Strategic fit, local financing, and startup growth

Nataliya Wright*

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Abstract

Prior work suggests that startups in less-financing-rich contexts grow less than others. Does this growth gap narrow or widen if these startups adopt strategic fit and therefore align their strategic choices with each other and their context? While fit can improve these startups' resource allocation, it can also be harder to achieve and constrain their flexibility. To address this theoretical ambiguity, this study interviews 253 software startups from 34 economies and scores the internal and external fit of their market, moat, and organizational choices, developing the first dataset of its kind. The study finds that performance differences between startups headquartered in less- versus more-financing-rich cities attenuate with strategic fit. This finding is driven by fit better predicting performance in less-financing-rich contexts, rather than by variance in the adoption of fit across these contexts. Additional analyses indicate that fit prevents poor organizational and moat investments, which otherwise penalize startups in less-financing-rich contexts but not in others. Together, these results suggest that strategic fit can help compensate for local financing constraints.

Keywords: Entrepreneurial Strategy, Technology Entrepreneurship, Entrepreneurial Scaling, International Entrepreneurship, Strategy

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1 Introduction

A growing body of research shows that venture capital is crucial for startup growth (Conti & Guzman 2021). Startups based in places with less access to venture capital funding, even with promising technologies that can benefit the global market, face a higher hurdle to scale their business. With less local venture capital money, it is hard to hire developers, build a product, and expand into other markets. Accessing venture capital from elsewhere is difficult because of home bias seen in both online and offline investment markets (Lin & Viswanathan 2023, Sorenson & Stuart 2001, Wright, Koning & Khanna 2023). And moving to venture capital-rich hubs to overcome these financing frictions is not feasible for everyone (Guzman 2023, Shi et al. 2024). Indeed, we see that many startups that successfully scale, like Airbnb and Slack, come from financing-rich contexts like Silicon Valley.

And yet, some startups from less-financing-rich places have still managed to scale into billion-dollar valued unicorns: Grammarly from Ukraine, Spotify from Sweden, and GoJek from Indonesia to name a few. These startups gain praise for their strategies that allowed them to achieve significant growth against all odds (Foo et al. 2020). And consistent with this view, prior work suggests that firm-specific choices, specifically a strategy that is fit for the company and its context, can help startups succeed no matter where they are located (Gans et al. 2019, Khanna et al. 2005, Porter 1996).

This begs the question: *How does strategic fit—the degree to which a company's strategic choices are aligned with each other (internal fit) and are appropriate in view of the context (external fit)*[1]*—shape the relationship between local financing*[2] *and startup performance?* This requires first answering a descriptive question that is the focus of this paper: Do performance differences between startups in contexts with less versus more supply of venture capital narrow or widen when startups have strategic fit? On the one hand, strategic fit can

[1]This definition of strategic fit is consistent with definitions in Siggelkow (2001) and Van den Steen (2017).

[2]Local financing refers to the volume of venture capital available in a startup's HQ, primarily defined on a city (hub) level, consistent with prior work in entrepreneurship (Kerr & Robert-Nicoud 2020).

help startups in less-financing-rich contexts succeed to the same extent as those in more-financing-rich contexts, attenuating performance differences between them. This might be because only higher quality startups from less-financing-rich contexts make it to the point in which they need strategic fit. And startups from these contexts might gain more value from avoiding bad investment (Van den Steen 2017), team coordination (Porter 1996), and imitation frictions (Rivkin 2000) that strategic fit affords given the steeper recovery costs they face.

But strategic fit might be less attainable for startups in less-financing-rich contexts—even higher quality ones. After all, it might take expensive experiments or trial-and-error to get to strategic fit (Gans et al. 2019, Lee & Kim 2024, Moeen et al. 2020, Ott et al. 2017, Pillai et al. 2020, Posen & Chen 2013). Even if accessible, it might constrain their flexibility, requiring a large financial cushion for startups to adapt to new markets or information (Aggarwal & Wu 2015, Aldrich & Ruef 2006, Siggelkow 2001). Changing any choice requires changing every other choice that is aligned to it (Chen et al. 2012). And so pivoting to better or new opportunities, even within the same market, can require more capital that is simply not feasible in less-financing-rich contexts. This would mean that strategic fit would exacerbate differences in performance between startups from less- versus more-financing-rich contexts.

Distinguishing between these possibilities is not easy. And this is particularly because directly measuring strategic fit—both internal and external—is non-trivial. It requires measuring how appropriate formulated choices are given the context (external fit) and in relation to one another (internal fit) (Siggelkow 2001, Van den Steen 2017). This is especially hard to do across international contexts to capture enough variation in local financing (Berry et al. 2010, Ghemawat 2001). Some empirical work has assessed strategic fit within specific geographic contexts, whether it be through in-depth qualitative case studies (Siggelkow 2001, Shankar & Shepherd 2019) or observable firm investments and surveys that map out particular configurations of choices (Naman & Slevin 1993, Nath & Sudharshan 1994, Peteraf & Reed 2007, Zajac et al. 2000, Zatzick et al. 2012). But these approaches can be difficult to apply systematically across the globe because there is often not a one-size-fits-all configuration of choices, even if the general definition of strategic fit could apply across borders.

To address this gap, this paper develops an approach to measure strategic fit across international contexts through a field methodology. The approach preserves the definition of strategic fit across borders to enable comparison, while allowing flexibility in the specific configuration of choices. Structured interviews ask executives about their market scope, moat, and organizational choices. Like the World Management Survey, the study quantitatively scores executives' interview responses according to a rubric (Bloom & Van Reenen 2007). Rather than scoring the use of specific practices or configurations of choices, however, evaluators measure the alignment and appropriateness of the choices to capture internal and external fit, respectively. These measures then aggregate to a numerical strategic fit score. Matching the strategic fit scores—validated with natural language processing techniques—with startups' headquarters (HQ) location and their subsequent performance enables this study to measure how strategic fit shapes the relationship between local financing and startup growth.

The resulting dataset covers the strategies of 253 software companies from over 30 countries and six continents. These high-growth companies, which received investments from top venture capital firms like Sequoia Capital, Y Combinator, Andreessen Horowitz, and the Founders Fund, make up over 12 percent of software Series A ($5–20 million) deals during January 2019–September 2021.[3] This dataset consists of roughly 190 hours of interviewing, a million words, and 63,000 coded observations. It is the first to systematically measure the strategic fit of a global sample of startups.

The study finds that strategic fit narrows the performance differences between startups in less- versus more-financing-rich contexts. This is driven not by higher quality startups in these less-financing-rich contexts being more likely to adopt strategic fit, but rather by strategic fit better predicting growth there. Additional analyses reveal that this lop-sided

[3]Excluding China, where it is difficult to get performance data.

relationship is driven by strategic fit helping startups avoid the costs associated with poor organizational and moat investments, which penalize firms when there is little venture capital nearby, but do little for those with plentiful access to such resources. The latter startups can relatively easily recover from these mistakes and learn from them. Consistent with this idea, strategic fit only meaningfully narrows performance differences between startups in less- versus more-financing-rich cities in contexts where high firing costs make bad organizational investments more costly. Together, these results suggest that strategic fit weakens the local financing-startup performance relationship because this fit matters more when there is less local financing available.

This study makes several contributions to strategy and entrepreneurship research. It contributes to work assessing the impact of market factors like venture capital availability on startup growth. By showing that strategic fit weakens the positive relationship between venture capital and startup growth that prior work shows (Conti & Guzman 2021), the study reveals that strategic fit is a partial substitute for venture capital. And this adds to other substitutes for local market conditions in startup growth and innovation found in research like university entrepreneurship programs (Fini et al. 2011) and access to data (Nagaraj et al. 2020) and in contrast to other factors like open source software (Wright, Nagle & Greenstein 2023) and crowdfunding (Dushnitsky et al. 2016) that serve as complements. As a result, investments in strategic fit may compensate for structural factors like the absence of a developed venture capital industry.

By showing that strategic fit weakens the relationship between local financing and startup performance because it is more valuable where there is less supply of local financing, this research also contributes to work assessing the impact of strategic fit on performance. Specifically, the paper finds that local venture capital weakens the relationship between strategic fit and performance that prior work suggests (Naman & Slevin 1993, Rivkin 2000, Porter 1996). Much of this prior work has focused on firms that rely on their own sale cycles or loans that they imminently need to pay back rather than venture-capital-backed firms. And this venture capital seems to dilute the value of strategic fit because it can help firms shoulder and learn from the bad investment costs that might result from not having such fit.

Moreover, the findings show how not only specific strategic choices but also their fit with one another varies across entrepreneurial firms as they grow. Research suggests that firms choose different market entry approaches (Alvarez-Garrido & Guler 2018, Bingham & Eisenhardt 2011), ways to position relative to competitors (Carlson 2022, Guzman & Li 2022, Marx et al. 2014), and organizational designs (DeSantola & Gulati 2017, DeSantola et al. 2022, Lee 2022). This study shows that how these choices fit together also varies across firms, with implications for performance.

Lastly, the research helps bridge the gap between the global emergence of innovative startups and entrepreneurship research that is still primarily US-focused. Through interviews with startup executives from over 30 countries and six continents, supplemented with human coding and natural language processing (NLP), the paper captures otherwise tacit strategic fit among growing ventures across international contexts. The approach combines the depth of qualitative methods with the generalizability of quantitative methods to expand our geographic lens of entrepreneurial strategy and scaling.

2 Theoretical framework

The following section discusses whether strategic fit narrows or widens differences in performance between startups in less- versus more-financing-rich contexts. Such a difference depends on how the adoption and value of strategic fit varies across these contexts. Specifically, whether higher quality startups are more likely to adopt strategic fit (selection) and whether that strategic fit has more value depending on the local venture financing (treatment) shape whether strategic fit narrows or widens the local financing-performance relationship. Figure 1 illustrates these possibilities and serves as a guiding framework for an abductive analysis. The null is that neither the adoption nor the value of strategic fit varies across financing contexts. This would mean that the difference in performance among startups in these contexts would remain the same with fit. Cell A depicts this scenario.

[Insert Figure 1]

2.1 The case for strategic fit widening performance differences

Differences in the adoption and value of strategic fit might widen performance differences between startups in less- versus more-financing-rich contexts. It might be the case that higher quality startups in more-financing-rich contexts are more likely to adopt strategic fit. Indeed, getting to strategic fit might require costly experimentation and trial-and-error (Gans et al. 2019, Lee & Kim 2024, Moeen et al. 2020, Ott et al. 2017, Pillai et al. 2020). Further, higher quality[4] startups might re-locate to financing-rich contexts (Kulchina 2016, Lee & Glennon 2023, Shi et al. 2024). And if they do so to target specific types of customers, investors, or talent (Alvarez-Garrido & Guler 2018, Guzman 2023), they might automatically have more strategic fit. Holding all else equal, this would widen the performance gap. Cell B shows this scenario.

Startups in more-financing-rich contexts might gain more value from strategic fit. This is because it is a more costly way to grow and therefore only beneficial when there is enough venture capital to go alongside it. When choices are so intertwined with one another and the initial market structure, changing any one single choice typically requires changing them all. And startups often need to iterate on their choices when they learn new information from experiments, tests, or advisors (Camuffo et al. 2020, Gans et al. 2019, Miller et al. 2023, Tidhar et al. 2024), even within the same market. So making these changes, anything from a small tweak to an actual pivot, requires changing many choices that can be costly.

For the same reason, it is also quite costly for startups to adapt to new markets, which they often do to grow (Bingham & Eisenhardt 2011, Chen et al. 2012). Adaptation requires

[4]Quality refers to the promise of the underlying startup idea and founders (Kaplan et al. 2009), which is conceptually separate from whether startups adopt strategic fit.

tweaking not only the system of choices given their alignment—but possibly also the logic behind the choices that might have been closely intertwined with the initial market structure (Aggarwal & Wu 2015, Aldrich & Ruef 2006, Cohen et al. 1972, Weick 1976). Given this cost, startups in resource-constrained contexts often have to navigate by bricolage (Baker et al. 2003, Baker & Nelson 2005), making the most of every opportunity at hand, even if comes at the expense of strategic fit. Holding adoption constant, this would widen performance differences between startups in less- versus more-financing-rich contexts. Cell D illustrates this scenario. And this is even more of the case if startups in more-financing-rich contexts are also more likely to adopt strategic fit, as shown in Cell E.

2.2 The case for strategic fit narrowing performance differences

But it also might be the case that we see narrower performance differences between startups in less- versus more-financing-rich contexts with strategic fit. Higher quality startups from less-financing-rich contexts might be more likely to adopt strategic fit. This could be because they face tougher requirements to get investment locally or from afar in order to get to a stage in which they actually need strategic fit (Chen et al. 2010). The startups that do manage to get funding might then be higher quality, and these higher quality startups might be more likely to have strategic fit by virtue of simply being more knowledgeable about strategy and their market. Higher quality startups might also deliberately re-locate to less-financing-rich contexts to target specific types of institutional voids (Khanna & Palepu 1997), access global talent (Kerr 2018), or learn from specific communities (Hernandez 2014). This would mean that higher quality startups in these less-financing-rich contexts would inherently achieve strategic fit because of this location selection. This would then narrow the performance gap between startups from less- versus more-financing-rich contexts. Cell C depicts this scenario.

It could also be that startups in less-financing-rich contexts gain more value from strategic fit. Startups in these contexts might have less access to venture capital needed to experiment to come to strategic fit, so they might be less likely to adopt strategic fit overall. The rarity of strategic fit in these contexts might therefore make it more valuable, for example, in venture financing evaluations (Barney 1991).

Further, venture capitalists in less-financing-rich contexts might be more conservative in their selection of startups. Knowing the relative scarcity in funds, they might invest in portfolio companies that have more fit and therefore are less likely to make investments that put the company at risk, even if there is a longer term learning value. Investors in more-financing-rich contexts, on the other hand, might pay less attention to fit upon selection because they realize that there is enough money available to allow startups to learn from any mistakes that they make in their commitments, *and* that learning might lead to actually more optimal decisions in the future. These investors could further make corrections to fit in the control they want to exert. Instead, they might look to select on people who would be able and willing to learn and adjust (Gompers et al. 2020, Kaplan et al. 2009). This would mean that startups with fit would raise more subsequent funding in less-financing-rich contexts but not necessarily in more-financing-rich contexts.

Strategic fit might also allow startups in these contexts to avoid costs that can be fatal without sufficient financial cushion to recover and learn. If the activities of the company are aligned with the strategy of the company, then team members are more likely to be on the same page (Porter 1996). Coordination becomes less costly and might even require less investments in formal organizational structures. Instead, team members are inherently aligned and make decisions that move the company toward their objective.

By virtue of having choices that reinforce one another, it is hard for competitors to imitate (Rivkin 2000). After all, it would take not just copying one choice, but copying them all to get to strategic fit. This means that startups who have strategic fit would need to invest less in forging defenses against competitors.

And if indeed companies pursue such aligned choices, the chances are that their subsequent choices and investments will continue to align whether deliberately or simply by inertia, holding any factors in the market constant (Ghemawat 2001, Siggelkow 2001, Van den Steen

2017). In such cases, startups would incur less expenses related to recovering from bad investments. These cost savings from strategic fit might be particularly important in less-financing-rich contexts where there are fewer recourse options. Indeed, prior work suggests that a strategy creating fit would be more important when commitments are more irreversible (Van den Steen 2017). But in financing-rich environments, the cost savings might not matter much. Such startups can afford to recover from bad investments because they can learn from them and make more optimal decisions in the future (Aldrich & Yang 2013, Bingham & Eisenhardt 2011).

This extra value to startups from less-financing-rich contexts would narrow the performance differences between the two types of startups, as shown in Cell G. This would especially be the case if startups from less-versus more-financing-rich contexts are also more likely to adopt strategic fit, as depicted in Cell I.

2.3 Summary

This 3x3 crucially shows that whether strategic fit narrows or widens startup performance differences in less- versus more-financing-rich contexts can reflect vastly different mechanisms with unique implications for theory and practice. Let's take the case of strategic fit widening the performance differences between startups in less- versus more-financing-rich contexts. The implications of this finding would be quite different if more adoption of strategic fit by higher quality startups in more-financing-rich contexts is driving the results, rather than startups from these contexts gaining more value from fit. In the first case, a practical implication would be to train more startups in less-financing-rich contexts to adopt strategic fit. In the latter case, the implication would be to help these startups that generally already have strategic fit to better shoulder the costs associated with it or to turn to alternative growth approaches. It is therefore crucial to disentangle the possibilities. The sections below proceed to do so.

3 Methodology

To test whether strategic fit attenuates or widens performance differences between startups in different financing contexts, the study assesses how the relationship between the volume of venture capital in startups' HQ cities varies by whether startups adopt strategic fit. To measure strategic fit, this study uses a field methodology that leverages structured interviews with startup executives that elicit their market scope, moat, and organizational choices, measuring the alignment (internal fit) of the choices and their appropriateness in light of a startup's context (external fit).

3.1 Structured interviews to measure strategic fit

The field methodology to create a strategic fit measure relies on interviews with executives of a global sample of software startups that are beginning to scale. These interviews elicited executives' market scope, moat, and organizational choices that map to value creation, capture, and delivery choices in corporate strategy frameworks (Harrigan 2011, Kaplan & Norton 1992, Teece 2010) and customer, competition, and resources/capabilities in entrepreneurial strategy frameworks (Gans et al. 2018).[5] Deriving this information from existing databases or third-party sources is otherwise virtually impossible. While such sources may show the commitments made by firms—perhaps intentionally or not—they generally do not allow scholars to isolate the formulation. Rather, they reflect both execution and formulation, which makes it difficult to capture strategic fit.

The interviews targeted software companies that had raised a Series A round (5–20M USD) since 2019. They focused on the software industry because companies in this sector often pursue standardized business models, such as software-as-a-service, that make cross-country comparisons feasible. This sector also drives high-growth entrepreneurship, accounting for many of the billion-dollar-valued unicorns that have emerged worldwide. The

[5]The study excludes the technology category from Gans et al. (2018)'s entrepreneurial strategy framework because it holds this generally fixed given the software industry sampling. This allows for an easier comparison across firms around the world.

interviews focused on the Series A phase because ventures generally have reached product-market fit within their early adopter market and are now actively thinking about scaling to a broader market. In this scaling phase, companies simultaneously face market and organizational choices that can be either aligned or misaligned, allowing one to detect the extent to which a company has strategic fit (Eisenmann & Wagonfeld 2014). Further, sampling on this funding stage allows for the controlling of a quality threshold, as companies undergo rigorous due diligence to get the Series A. Indeed, all of these firms are highly promising, and several received investments from prestigious venture capitalists like Sequoia Capital and Andreessen Horowitz.

These interviews resulted from directly reaching out to startup executives and getting a positive response from a generally representative sample. From July to November 2021, I reached out to the primary contacts (generally CEOs and co-founders) of all of the startups in the software sector who raised a Series A ($5–20 million) round of funding since 2019 listed in PitchBook, among the most recognized and comprehensive startup databases on the market. I sent each of them a standardized email template inviting them to participate in a 45-minute interview as part of an academic project assessing how startups scale. These emails excluded companies from China because of the difficulty of getting performance data. Overall, 12 percent of such startups (253 companies) agreed to interview, exceeding the five-to-ten percent response rate seen in other research involving private sector surveys or interviews (Ben-David et al. 2013, Bloom et al. 2012). As of 2022, each startup had raised about $30 million in funding and employed 90 people on average.

The startups that agreed to interview appear similar to those that did not on most dimensions. There is not a systematic difference in initial and latest performance variables like valuations and financing size between startups that received an interview versus not (Table 1).[6] The interviewed sample generally looks like the non-interviewed sample in

[6] The latest valuations per employee variable is higher for non-interviewed startups, though the initial value known to the research team at the time of recruitment is no different. This difference is likely related to the lower representation of North American startups, since these startups tend to have higher valuations and hire less people given the generally higher local financing availability and labor costs. All other latest

terms of employee count distribution (Figure A.11) and first financing amount distribution (Figure A.12). While the relative shares of regions look similar among interviewed and non-interviewed companies (Figure A.10), startups headquartered in North America were less likely to conduct an interview (Table 1). Because of the high concentration of North American startups in the original population, sampling on a higher share of startups from elsewhere increases the variance of local venture financing to help address the research question. Slightly older startups were also less likely to interview, but the magnitude of the difference is fairly small—less than one year. Nevertheless, to account for these selection factors, a Heckman model includes the North American and age selection factors and finds consistent results in Table A10. The interviews occurred from July to November 2021.

[Insert Table 1]

Interview questions were open-ended and future-oriented. They were open-ended to ensure the accuracy of responses by minimizing "social desirability bias" and the leading of interviewees, consistent with studies measuring management and strategy in mature firms (Bloom & Van Reenen 2007, Yang et al. 2020). The questions were future-oriented to capture how executives think about scaling choices not yet made rather than retrospective accounts of decisions. Such an approach allows us to isolate the formulation (rather than execution) of choices and reduce measurement error. The questions elicited executives' objectives over the next 3–5 years, how they planned to expand their markets, what they saw as their biggest moat against competitors, how they planned to expand their organization, and how they defined their company's culture. Additional questions asked executives what they surmised to be their next three action items to reach their objectives, how they planned to use their Series A funding, and what they saw as their biggest uncertainties. The interviews also captured the

performance variables (valuations, funding, and successful exit) do not vary among non-interviewed and interviewed startups, indicating that any recent differences are likely small. While subsequent specifications evaluate all of the performance variables, we can interpret the results with these latter three performance proxies are more generalizable than those with valuations per employee. European-based startups were also weakly more likely to interview, which also is likely related to the lower representation of North American startups. The Heckman model with the North American selection factor helps account for this.

sources of information that executives used to develop their strategy and why they did not pursue particular alternative approaches. The Appendix shows questions from the structured portions of the interview. Pitch decks of a third of the firms and the organizational charts of a fourth of them helped corroborate interview information.

Independent evaluators coded the interviews in a double-blind manner. Five coders—MBA students and those with similar experiences—coded each interview transcript independently. To quantify strategic fit, the coding was based on a rubric[7] that measured the alignment of the choice responses (internal fit) and their appropriateness in light of the startup's context (external fit) on a scale of one to five. Evaluators also provided binary codes (0/1) to indicate the presence or absence of particular aspects of the strategy—such as expanding across geographies or verticals—to measure the strategy's content. The interviews were double-blind, consistent with other research scoring management and strategic practices across organizations (Bloom & Van Reenen 2007, Yang et al. 2020). Interviewed executives did not know that their responses would get quantitative scores. Interview coders also did not have performance information about the interviewed firms. Thus, neither the interviewees nor those doing the evaluation knew the relationship between a firm's strategic fit and its performance.

Using multiple independent evaluators validated the strategic fit coding. The coding rubric achieves a relatively high and stable inter-coder reliability: 0.9 correlation across all questions and 0.5 correlation among the questions coded one to five. This reliability is similar to correlations seen in past research (Bloom et al. 2012). In the final dataset, about one-fifth of the interviews received independent evaluations from two coders, and the final strategic fit score was the average of the two. Due to resource limitations, the rest of the interviews received evaluations from one coder each. Figure 2 illustrates the strategic fit coding approach.

[Insert Figure 2]

[7]This rubric was the consequence of (a) pilot interviews with colleagues who were startup executives but not in the final sample and (b) feedback sessions with the evaluators.

3.2 Data

The final dataset connects the startups' strategic fit scores with metrics of their HQ city financing and performance outcomes. Table 2 shows summary statistics. As we would expect, startups headquartered in cities with above-median volumes of venture capital get higher valuations, raise more funding, and get higher valuations per employee, consistent with the positive relationship between venture capital and startup performance that prior work suggests (Conti & Guzman 2021). They are also more likely to be in English-speaking contexts, likely reflecting being headquartered in US cities that exhibit the highest volumes of venture capital. Interestingly, they hired less employees at the time of the interview. This is likely driven by the lower labor costs in less-financing-rich contexts.

[Insert Table 2]

3.2.1 Measuring strategic fit

Measuring the alignment of executives' market scope, moat, and organizational choices (internal fit) as well as their appropriateness in light of a startup's context (external fit) creates a numerical strategic fit score. The score averages the external and internal fit of the choices to create a firm-level strategic fit measure, as shown in Equation (1):

$$strategicfit_i = \frac{externalfit_i + internalfit_i}{2} \tag{1}$$

$strategicfit_i$ is the overall strategic fit score of a company i. $Externalfit_i$ reflects how appropriate are the choices in light of the startup's context, as measured by how logical they are and how much they increase beliefs in the success of the company. Because the specific context of each startup varies, these questions allow us to more flexibly capture appropriateness. That being said, further robustness analyses with large language models (LLMs) prompted with direct questions on the appropriateness of the responses with the startup's market yield similar scores (Table A7). $Internalfit_i$ refers to how well the choices align with the executive's objective and the other choices.

Figure 3 provides an example of the coding. It shows two human resource (HR) software companies with choices that vary in internal fit, but that have similar external fit. The choices of these companies are appropriate given their HR context: They are generally logical and convincing. While having a similar external fit, they differ in their internal fit. Startup 2 has a higher internal fit because its objective and choices all align together around a customer focus. Startup 1 has a lower internal fit because its objective focuses on the user, while its market scope focuses on the customer and product and its organizational design on the product. These choices do not clearly align with one another. Appendix A.2 shows additional coding examples.

[Insert Figure 3]

The strategic fit score is robust to alternative coding. One alternative approach uses NLP techniques. An SBERT model, a word-embedding model that can capture the semantic meaning of the text at the sentence level (Carlson 2022, Devlin et al. 2018, Reimers & Gurevych 2019), is able to measure internal fit. Specifically, it measures the similarity between each of the market scope, moat, and organizational responses as well as the objective. An LLM measures external fit. The LLM evaluates each of the market scope, moat, and organizational responses individually according to the same prompts given to human coders. These prompts capture how appropriate are the responses in terms of being logical and increasing beliefs in the success of the company, and in robustness analyses, how appropriate they are in light of the startup's market. Aggregating the LLM-based external fit measures and the SBERT-based internal fit measures using Equation (1) creates an alternative strategic fit score. Table A4 shows that these LLM/SBERT-based measures positively correlate with the human-generated scores.

Robustness checks also show that the scores withstand differences in speaking styles. The length of responses, for example, does not predict the strategic fit score. This analysis reduces the concern that time constraints or speaking styles confound this measure. Later specifications also control for the English readability of the transcribed responses to ensure that language differences do not meaningfully affect score comparisons.

The final strategic fit variable indicates the 1–5 score that is then standardized to a mean of zero using interview data. This variable reflects the extent to which a company has strategic fit. Figure 4 plots the relatively normal distribution of the composite fit measure and of the internal vs. external fit sub-measures.

[Insert Figure 4]

The study measures local financing at the city level. This variable is the total amount of funding in software companies in 2018-2021 in each city using PitchBook data.[8] Figure 5 shows the financing values across headquarter cities in the sample.

[Insert Figure 5]

3.2.2 Measuring startup quality

Measuring startup quality is difficult (Kerr et al. 2014, Scott et al. 2020). In this case, startup quality reflects the potential of the inherent idea—the technology and market (the horse)—as well as the founder teams that create this idea (the jockey) (Kaplan & Norton 1992). These are conceptually different from the decision to pursue strategic fit, but admittedly are hard to disentangle empirically. To do so, we can assume that the initial funding raise and valuation incorporate the quality of the initial idea and founder team. We can therefore use these initial performance variables as controls to capture the quality of the companies. This is consistent with prior work assessing startup quality (Scott et al. 2020, Wright, Koning & Khanna 2023).

[8] This variable is on a city level. It reflects cities that are proximate and typically considered as part of the same startup ecosystem. For example, it maps San Francisco to other parts of the Bay Area, including Silicon Valley, Palo Alto, and Menlo Park. The results are similar without this aggregation.

3.2.3 Measuring performance

Several variables capture the performance of companies 18–24 months after the interview. These variables all come from PitchBook's database. The study controls for the initial level recorded in PitchBook of each corresponding performance measure to account for ex-ante differences *between* firms and better capture growth *within* a firm.

- **Logged valuation** indicates a company's post-money valuation, reflecting its expected value at the time of investment.
- **Logged total funding** indicates the logged total US dollar value of funding. This variable is a common proxy of startup performance in prior work (Guzman & Li 2022, Koning et al. 2022, Wright, Koning & Khanna 2023).
- **Logged valuation per employee** indicates valuation dollars per employee as a rough metric of productivity for these young ventures.
- **Successful exit** indicates whether a startup achieved an initial public offering (IPO) or acquisition. This is a common indicator of successful startup growth (Guzman & Stern 2020).

3.3 Empirical Specification

To assess whether strategic fit narrows or widens performance differences between startups in less- versus more-financing rich contexts, the study uses the following regression specification:

$$y_i = \beta_1 financing_i + \beta_2 strategy_{ij} + \beta_3 financing_i x strategicfit_{ij} + foundedyear_i + industry_i + evaluator_j + readability_{ij} + yinitial_i + region_i + topuni_i + \gamma_{ij} + \epsilon_{ij} \quad (2)$$

The dependent variable y_i is an array of performance variables 18-24 months after the interview. These variables include log valuation, log funding, log valuation per employee, and whether the startup successfully exited. $Strategicfit_{ij}$ indicates the standardized strategic fit score calculated using Equation (1) by a given evaluator j for company i. $Financing_i$

indicates the amount of venture capital invested in startups' HQ city from 2018-2021, $financing_i x strategicfit_{ij}$ indicates whether the relationship between local financing and performance varies across firms by the extent to which they have strategic fit.

The specification also includes a number of controls. $Foundedyear_i$ indicates firm i's founding year to control for differences in firm maturity.[9] $Industry_i$ indicates the industry cluster of firm i generated from a k-means clustering (unsupervised) machine learning model using the company's keywords. $Evaluator_j$ reflects evaluator fixed effects. $Readability_{ij}$ reflects (a) the English language quality of responses, based on the evaluator's attested understanding of the interview transcripts due to language barriers (irrespective of the content) and (b) the Flesch Reading Ease Score, using an NLP technique from the Python textstat library. This algorithm allows for a more objective measure of how feasible it is to read a body of text. γ_{ij} reflects whether the analysis filled in missing values for the strategic fit score of firm i with evaluator j's average evaluations for firm i. These missing values made up less than two percent of the codes.

$yinitial_i$ indicates performance corresponding to the dependent variable that was initially recorded in PitchBook. For example, for log valuation as the dependent variable, this initial performance variable would be the first logged valuation recorded for the company in PitchBook. For log total funding and successful exit, this performance variable would be the initial log total funding that company i received in PitchBook. Including these variables allows the study to control for initial observable quality differences between companies and capture what is closer to growth rather than the static performance of a company. $topuni_i$ indicates whether the interviewed executive attended one of the top 10 universities in each region of the startup sample, using the QS World University Rankings (2022), as a metric of human capital (Wright, Nagle & Greenstein 2023).[10] The study clusters standard errors

[9]The analysis groups firms founded in 2020 and 2021 to avoid singleton observations as there is only one firm founded in 2021. The results are similar without this grouping.

[10]These regions include North America, Latin America, Europe, Asia, and Africa, as categorized by (Rankings 2022). The source does not provide rankings explicitly for the Middle Eastern region, so the study instead uses the top universities ranked by QS in the individual HQ countries of startups in the region. If the educational information is not listed, the measure assumes that the executive did not have it. The

on the company level, given that a subset of companies get multiple evaluations. The main results are also robust to standard errors clustered on the HQ country and HQ city levels.

The coefficient of interest is β_3. This coefficient shows how the relationship between local financing and performance varies across firms by the extent to which they have strategic fit. A negative coefficient reveals that strategic fit narrows the difference in performance between startups based in less- versus more-financing-rich contexts.

4 Results

The nine scenarios in Figure 1 suggest that strategic fit can either narrow, widen, or not change the differences in performance between startups based in less- versus more-financing-rich contexts. The analyses below explore these possibilities. Figure 6 summarizes the flow of these analyses.

[Insert Figure 6]

4.1 How does strategic fit shape the relationship between local financing and startup performance?

I begin with assessing whether the relationship between local financing in the startup headquarters and their future performance varies among startups with a lower or higher strategic fit score.

Consistent with prior work suggesting that local financing is important for startup growth (Conti & Guzman 2021), Figure 7 shows that the volume of venture capital invested in 2018-2021 in the startup HQ city positively predicts performance, both in terms of logged valuation (left) and logged funding (right). Here, the difference in performance between startups is fairly steep: Those that are based in more-financing-rich contexts perform significantly better. However, when companies have an above-median strategic fit score, the

results are similar when excluding this missing sample (2% of companies).

performance differences between these cities narrow substantially. The margins plots reveal that this narrowing is *not* driven by startups with high strategic fit performing worse in more-financing-rich contexts—the standard error bars overlap at high local financing values on the x-axis. Rather, it is driven by startups with low strategic fit facing a penalty in less-financing-rich contexts, and thereby seeing a measurable drop in performance effects. Indeed, the high and low strategic fit lines diverge meaningfully only at lower local financing values. And consistent with this trend, Figure 8 shows that valuations and funding remain fairly high for startups in more-financing-rich contexts—with high or low strategic fit— and in less-financing-rich contexts with high strategic fit. But they drop measurably for those with low strategic fit in less-financing-rich contexts. This suggests the following 2x2 relationship:

	More-Financing-Rich Context	**Less-Financing-Rich Context**
High Strategic Fit	1. Higher Growth	2. Higher Growth
Low Strategic Fit	3. Higher Growth	4. Lower Growth

Quadrant 2 is perhaps the most noteworthy: It reveals that startups with high strategic fit reach similar growth levels to others, despite being in a less-financing-rich context.

[Insert Figures 7– 8]

Of course, these trends could just reflect that the quality of the company, its sub-sector, or its founders—rather than their strategic fit per se—is driving results. To account for these concerns, the study applies Equation (2).

Table 3 reports the results when applying Equation (2). Column 1 shows that, at baseline, without taking into consideration the interaction between strategic fit and local financing, local financing positively predicts valuations, consistent with prior entrepreneurship studies (Conti & Guzman 2021). Strategic fit does not meaningfully associate with valuations. Further analyses break down this relationship to see whether it is driven by the differential value of strategic fit in less- versus more-financing-rich contexts as discussed in the theoretical framework. The interaction term between local financing and strategic fit is negative, no matter whether using valuations (Columns 2–3), total funding raised (Columns 4–5), valuation per employee (Columns 6–7), or successful exit (Columns 8–9) as dependent variables.

[Insert Table 3]

The results are similar when including no controls or a full set of controls. They are also similar when accounting for the observable quality of firms across less- versus more-financing-rich contexts using coarsened exact matching based on firm age, industry, and founder education variables. Since startups might pursue different objectives and choices in less-financing-rich contexts (e.g., being more likely to expand their revenue by geography—the most common way to do so), it could be that this content is driving the results. To account for this, I control for the content of these choices and objectives using a LASSO model and find similar results (Table A8).

These patterns suggest that strategic fit narrows the differences in performance between startups based in less- versus more-financing-rich contexts. They are consistent with Cells C, F, G, H, and I and are not consistent with Cells A, B, D, and E in Figure 1.

4.2 Are higher quality startups more likely to adopt strategic fit in less-financing-rich contexts?

Figure 7 and Table 3 reveal that performance differences between startups based in less-versus more-financing-rich cities decline when startups have more strategic fit. While this rules out several scenarios in the predicted relationships in Figure 1, it leaves several other possibilities depending on whether adoption and/or the value of strategic fit varies across the two types of startups. Specifically, it could be that higher quality startups in less-financing-rich contexts are more likely to adopt strategic fit or that strategic fit generates higher value for these startups (or both).

To test between the possibilities in Cells C, F, G, H, and I, the study next assesses whether higher quality startups in less-financing-rich contexts adopt strategic fit more than those in financing-rich contexts. Table 4 shows how initial quality indicators of the startups, including initial financing size, valuations, and whether executives attended top universities, predict the strategic fit scores across financing contexts. Contrary to the prediction in Figure 1 Cells C and I, higher quality startups are not more likely to adopt strategic fit in less- versus more-financing-rich contexts, no matter whether using initial financing size (Column 1), initial valuations (Column 2), or whether executives attended a top university (Column 3) as quality proxies.

[Insert Table 4]

This suggests that higher quality startups being more likely to adopt strategic fit in less-financing-rich contexts is not driving the narrowing of performance differences seen in Table 3. This rules out Figure 1 Cells C and I. Cell G, indicating similar adoption of strategic fit but with a higher value to startups in less-financing-rich contexts, remains as the only consistent possibility.

4.3 Do startups in less-financing-rich contexts gain more value from strategic fit?

If adoption does not drive the narrowing in performance differences, this leaves the possibility that strategic fit is more valuable in less-financing-rich contexts. This finding would be consistent with the last remaining scenario: Cell G in Figure 1. To test for this possibility, I assess how the direct relationship between strategic fit and subsequent performance varies by startups based in less- versus more-financing-rich contexts.

Table 5 reports the results. It shows that the coefficient on strategic fit is consistently positive and meaningful for startups based in less-financing-rich contexts for most of the performance proxies. In contrast, the coefficient on strategic fit is consistently negative, though only meaningful when log valuation per employee is the dependent variable, in more-financing-rich contexts (Column 6).

[Insert Table 5]

Consistent with Cell G in Figure 1, the differences between startups in less- versus more-financing-rich contexts are meaningful. Strategic fit predicts performance more in less-financing-rich contexts, suggesting that it brings startups in these contexts more value.

4.4 Why do startups in less-financing-rich contexts gain more value from strategic fit?

What makes strategic fit more predictive of performance in less-financing-rich contexts? The theoretical framework suggests several possibilities. One possibility is that strategic fit is simply rarer in financing-rich contexts because it requires investor resources that are not readily available locally. This rarity makes strategic fit a valuable capability (Barney 1991). If this were the case, we would expect to see that startups in less-financing-rich contexts are less likely to adopt strategic fit. Contrary to this prediction, Table 4 shows that strategic fit scores do not vary between startups across these contexts (Columns 4–5).

It might also be the case that investors in less-financing-rich contexts value strategic fit more than those in wealthier contexts. And because startups often have local investors, startups in less-financing-rich contexts would be more likely to get additional funding if they have strategic fit. If this was the case, then we would expect to see that strategic fit especially predicts performance among startups in less-financing-rich contexts that do not have any investors from financing-rich cities. To test this, Table A11 reports how the relationship between strategic fit and performance varies in less-financing-rich contexts by whether startups have investors in the top three cities for financing (San Francisco, New York, and London). In contrast to the prediction, for most performance proxies, startups without top financing hub investors do *not* see a stronger relationship between strategic fit and performance (Columns 1–3). The exception is for successful exit, where they see a weakly stronger relationship (Column 4). While not fully inconsistent, these results do not strongly support that differences in investor preferences drive strategic fit being more valuable in less-financing-rich contexts.

Another possibility is that strategic fit reduces frictions that can be costly to recover from in less-financing-rich contexts. But in financing-rich contexts, such frictions might be either negligible or, in fact, offer helpful learning opportunities to enable startups to make better decisions in the future. As mentioned in the theoretical framework, these costs can come in three forms, and two are related to internal fit. The first is regarding team coordination costs. By virtue of all choices being connected to a common objective and one another, we would expect that team members would be more likely to be on the same page and face less coordination frictions. The second cost that strategic fit might help startups avoid is around imitation. Indeed, prior work suggests that when choices are tightly interconnected, competitors would be less likely to imitate the strategy of the focal firm (Rivkin 2000). These two cost channels would suggest that internal fit rather than external fit would drive the narrowing of performance differences between firms in less- versus more-financing-rich contexts.

The third cost is related to external fit. By virtue of making choices that are appropriate given the context, we would expect that startups would be less likely to make bad investments, whether in terms of hires, moats, or markets, in isolation of the other choices. In this case, we would expect that external fit rather than internal fit would drive the narrowing of performance differences between firms in less and more-financing-rich contexts.

To test between these three cost channels, Table 6 repeats the analysis in Table 3, but decomposes the internal versus external fit sub-components. If internal fit drives the results, then this would be consistent with either team coordination or imitation cost channels. But if it is external fit driving the results, then this would be more consistent with the bad investment cost channel. The table shows that, irrespective of the performance proxy, it is external fit that drives the results. The interaction between external fit and local financing is larger in magnitude and more meaningful relative to that of internal fit and local financing. And in particular, external fit related to organizational and moat choices helps account for these results (Table A12).

[Insert Table 6]

These patterns are more consistent with the bad investment cost channel—particularly related to moat and organizational investments—rather than team coordination and imitation cost channels, driving the additional value of strategic fit for startups in less-financing-rich contexts. Consistent with imitation not driving this cost channel, Table A14 shows that the baseline results are not any stronger in sub-sectors with more competitors. And consistent with team coordination not driving this cost channel, the baseline results are not meaningfully stronger for firms in regulated sub-sectors that tend to face higher coordination costs (Table A15).

If this bad investment cost channel really does drive the results, we would expect that the narrowing of performance differences would happen in those contexts where the cost of recovery for such an investment is higher. Consistent with organizational external fit helping to drive the results (Table A12), one type of bad investment that the software startups in this sample mentioned was around hiring. A bad hire would require incurring the costs of firing and recruiting a new candidate. Building on the logic above, we would expect that when the cost of firing is higher that strategic fit—and particularly external fit—would narrow performance differences between startups in less-versus more-financing-rich contexts. Consistent with the prediction, Table 7, Table A13, and Figure 9 show that startup performance differences only narrow with strategic fit, and particularly external fit, when firing costs—using measures from Botero et al. (2004)—are higher. The coefficient on the interaction between fit and local financing is negative and meaningful only in these contexts for most of the performance proxies.

[Insert Table 7 and Figure 9]

Consistent with this bad investment channel, additional analyses suggest that startups that have more strategic fit are less likely to close offices, as one proxy of bad commitments. Indeed, Figure A.13 shows that startups with a higher strategic fit score closed less regional and subsidiary offices. Even when controlling for other quality factors about the firms, founders, and their original office locations in Table A16, a higher strategic fit score weakly predicts less office closures (Column 1). And this relationship is driven by external fit (Column 2) rather than internal fit (Column 3).

Qualitative evidence from the interviews triangulate this bad investment mechanism. Consistent with moat and organizational external fit driving the quantitative results (Table A12), startups in less-financing-rich contexts discussed how irreversible their product and hiring decisions were due to limited financing available locally. For example, a Brazilian startup discussed how important it was to get their product—their moat—right the first time because of the local financing constraints:

> In the Valley, you can validate an idea really fast. You can fail fast and you can try again...And you will find a path of funding pretty—not easy—but you have many options...In Brazil, you have, like, 10 VCs...And so you need to [consider], can I extract value from this product in 24 months or maybe 36 months...and use this to self-fund the next step?

The irreversibility in these less-financing-rich contexts makes any bad investment that much more costly and difficult to recover from. Startups in less-financing-rich contexts discussed how thinking through decisions better given their context—indicative of external fit—would have helped them avoid such bad investments. To illustrate, a South Korean startup discussed how they could have avoided a costly hiring mistake had they been "smarter earlier"—that is, had they thought through the decision more initially:

> One of the main mistakes that we actually made...right after Series A is that we went on a hiring spree. And the team went from 20 to actually 70 people in

> less than six months. And that...unexpectedly damaged our culture, because a lot of new people with different ideas and different working habits came in too fast...And so there was a lot of back progress that we have...gone through. And that's just time and money being spent not on the company, but rather fixing mistakes that if we were smarter earlier, then we probably wouldn't have made in the first place.

The company faced a steep penalty of “time and money" from not having external fit in this hiring decision, given how irreversible it is in the local context. Other startups outside of the top financing-rich contexts also discussed how costly a recruiting mistake was. For example, a startup based in Qatar mentioned: “[Our] objective is to make sure...I'm spending the money on the right talents. Any mistake here it's considered a disaster." Similarly, a startup based in Sweden mentioned:

> I think that when you have limited resources, you really spend it well, and you really think about where you put your talents, and which recruitment you prioritize. As opposed to when you have these big, big, big budgets, you know, like, you're allowed to make mistakes.

In contrast, companies in more-financing-rich contexts discussed how reversible their investments were. If anything, they served as learning opportunities to help them make the right investment in the future. The availability of local financing enabled them to try again, for example, by replacing bad hires. Without fit, these companies could make mistakes and could also afford a second chance. For example, one US company noted being able to afford making mistakes—such as hiring the wrong talent—and viewed such mistakes as a learning opportunity:

> Because you have access to money and capital, then you make a lot of mistakes. And those can be expensive mistakes...Some of the biggest mistakes and learnings for me is hiring people—the right role...and who you're really hiring for, cultural fit, and things like that.

The US company paid a relatively low penalty for making a mistake related to “hiring for fit." While a similar mistake was detrimental to the South Korean startup, the US startup perceived its own mistakes as harmless and even helpful for learning about its talent needs. This startup was not an exception in a more-financing-rich context like the US. Other startup executives from more-financing-rich contexts discussed the relatively harmless nature of mistakes, embracing them as learning opportunities. One executive noted that he “intentionally hired very smart people. So I let them be smart and execute. And I also let them make mistakes because that’s how you learn." Another US executive explained: “If a mistake happens, or like a true mistake...it’s fine...What are you going to do to fix it? Great—fix it. How to prevent it? Cool, I’m not going to ask you about it again."

These examples show how companies in less-financing-rich contexts perceive their commitments to be more irreversible. Amid this irreversibility, strategic fit becomes crucial. Without thinking through their choices thoroughly given their context as external fit enables, these companies are more likely to make bad hires, invest in the wrong technology, or make other bad commitments. Strategic fit therefore helps startups avoid getting it wrong the first time.

4.5 If startups in less-financing-rich contexts gain more value from strategic fit, why don’t they adopt it more?

Table 4 shows that startups in less-financing-rich contexts are not any more likely to adopt strategic fit. If anything, Summary Table 2 shows they are less likely to adopt external fit. This naturally raises the question: Why do they not adopt it more than others if they get more value from it?

The interviews suggest that scaling knowledge constraints may account for this. In less-financing-rich-contexts, startups face limited volumes of venture capital that constrain growth relative to other startups as prior work suggests (Conti & Guzman 2021) and is evidenced by the positive baseline relationship between local financing and startup growth (Table 3). As a result, in these contexts, there are less startups that have went through the scaling process and gained wisdom to inform other startups’ strategic fit in the ecosystem. In particular, these local scaling experiences offer the contextual knowledge (Gupta & Khanna 2019) and adaptation experience (Chen et al. 2012) to inform startups' external fit.

To this end, startups in less-financing-rich contexts discussed how challenging it was for them to find relevant expertise locally. A startup based in Australia noted: "In our part of the world, there wasn't really a lot of people that we could learn from in the earliest phases of the company." Similarly, a UK-based company acknowledged that: "[There is] not much [reliance on advisors]—for sure, not on the organizational setup—mostly because I don't think our investors had that experience, unfortunately." A German company described that such experience is important because it helps mentors not only offer advice, but know in what circumstances to offer it:

> Most of the mentors will advise you on the rest of the 50 percent, where they don't have the expertise...At least in Europe...Possibly [the] US is different. You have a high number of experienced founders in the market. They know exactly where they are good, [and] where they are not so good...That's where we see a more mature market in the US.

These examples show how the limited experience in scaling in less-financing-rich contexts makes it more difficult to find advisors with relevant expertise that can help local entrepreneurs achieve strategic fit, for example, related to organizational choices.

In contrast, companies in more-financing-rich contexts discussed how having those with scaling experience in the local ecosystem was helpful to inform their strategic fit. For example, one US-based startup emphasized how important it was for them to learn from such experience:

> My advisors...include a bunch of operators—people who have been successful and built their own companies before, companies that are later stage. So founders of...many other companies have been my friends and advisors. So they have helped us think through that. They're like, hey, we have gotten to this point. These are the challenges [that we] face next, and you should plan for that. And they have seen a step or two ahead of where we are at...None of this, by the way, is possible without the support and help of many people...In the Bay Area I have reached out to people that I didn't know at all. And I said, hey, can I have 30

> minutes of your time? I really want to learn this from you. And they gave me the time.

The deep market knowledge that came from this experience was particularly helpful. This market understanding helped companies achieve external fit. Indeed, another US-based startup mentioned:

> We had a lot of questions and perspectives shared by people who understood some pieces of what we were trying to do and offered insight to that...people with direct experience in alignment with where the market is going. And the ability to have them bought in to what you're trying to do without a strong conviction of driving it."

And in particular, the knowledge that these experienced advisors conveyed related to more tacit choices that are otherwise hard to learn about from public domains, for example, related to organizational design:

> And I talked to my investors and boards. Any investor that would talk to me, I'd be like, oh, I see you're invested in [big technology company]. How are they organized? How did they do it? Because generally, they know those sorts of things and can tell me things that you wouldn't be able to see publicly. It was really hard to figure that out, actually. Surprisingly hard to find models for how people are doing this and how people are doing this effectively, distressingly so...people don't publish their org charts, right? It would be one thing if everybody publishes their org charts and you could see, or there is like a book on here's how a multi-product company should be organized at the series A level.

These examples show that having experienced mentors and peers nearby was important for startups in more-financing-rich contexts to learn about how to achieve strategic fit, particularly external fit. Without access to this knowledge, startups struggle to achieve fit. Because there are less scaling successes in less-financing-rich contexts, consistent with the positive baseline relationship between local financing and startup growth, this expertise is more scarce there. And this scarcity in scaling knowledge that informs strategic fit may explain why startups in less-financing-rich contexts do not adopt fit more despite it being more valuable.

5 Discussion and conclusion

5.1 Summary

This paper shows that strategic fit narrows performance differences between startups in less- versus more-financing-rich contexts. This narrowing is driven not by higher quality startups in less-financing-rich contexts being more likely to adopt strategic fit, but rather by startups in these contexts gaining more value from it. This study's analyses suggest that this value comes from avoiding bad organizational and moat investments, which are otherwise more costly and difficult to recover from in these more-limited financial contexts. These results suggest that strategic fit weakens the relationship between local financing and startup performance and can therefore help compensate for local financing constraints.

5.2 Contributions to theory

The results contribute to a broader literature assessing both substitutes for and complements to local endowments in entrepreneurship. For example, prior work shows that open source platforms complement local resources like human capital and income in entrepreneurship (Wright, Nagle & Greenstein 2023). This paper reveals that strategic fit is a factor that interacts with local resources, specifically financing, serving as a substitute, joining other factors like peer advice (Chatterji et al. 2019) and access to data (Nagaraj et al. 2020). As a result, strategic factors like fit, while commonly thought to increase performance differences between firms (Rivkin 2000), may actually reduce ones that root from environmental factors like financing.

By showing that strategic fit weakens the relationship between local financing and performance because it brings more value in less-financing-rich contexts, the study also reveals that local financing is an important factor that weakens the relationship between strategic fit and startup performance, as suggested in prior work (Rivkin 2000, Porter 1996). Much of this prior work has focused on firms that rely on their own sales cycles or loans that they imminently need to pay back rather than venture-capital backed firms. And this equity-based financing seems to attenuate the value of strategic fit because it can help firms shoulder and learn from the bad investment costs that might result from not having fit.

The study also contributes to the debate on whether strategy matters for entrepreneurs (Bhide 2000, Delmar & Shane 2003, Dencker et al. 2009, Gans et al. 2019, Mintzberg & Waters 1985, Ott et al. 2017, Rivkin 2000). The paper's findings suggest that the value of strategic fit—an important aspect of strategy—is not equal across geographies: Local financing shapes the extent to which strategic fit matters for startups.

Lastly, this research reveals that institutional factors—including constrained capital markets (Khanna & Palepu 1997)—not only influence which strategies firms choose (Gao et al. 2017, Khanna et al. 2005, Khanna & Palepu 1997), but also whether strategic fit capabilities are valuable resources (Barney 1991, Wernerfelt 1984). Investing in an organization's capability to align may yield dividends for firms specifically situated in institutional and geographic contexts with constrained funding.

5.3 Limitations and opportunities

This work is a first step toward systematically measuring and understanding the role of strategic fit across startups from around the world. Future work may delve into specific choices underlying the fit—for example, related to expanding markets or structuring the organization—and how they systematically vary across international and sectoral contexts. Investigating this variance may enrich our understanding of how and when particular strategic choices matter for startups.

The study measures the extent to which startups have strategic fit, but not necessarily whether they have a good or bad strategy. To disentangle startups' choices from the conditions of the local environment, the strategic fit measure does not take into account ex-post outcomes. These ex-post outcomes would be important for evaluating the quality of the underlying strategy. However, in other research contexts, understanding this ultimate quality might be essential, for example, to test the ability of investors to detect “good" from “bad" strategies of startups they evaluate. Future work may take into consideration these ex-post outcomes to understand the quality of strategy.

The study also focuses on software companies to enable an international comparison of companies. The technologies in this sector tend to be inherently scalable, so startups can sell to global markets and are not as constrained by their local supply chains. Indeed, the largest share of startups in this sample sought to grow their revenue by expanding into new geographic markets (e.g., as opposed to expanding into new industry segments or adding products into the same market). They are also more likely to have distributed and remote models with employees disbursed around the world. That being said, companies from other sectors with hardware technologies that might not be as easily built and sold across international markets might face even higher irreversibility because they are more beholden to their local context for customers and talent. Strategic fit may serve an even bigger role for them. Future work may test such trends in these other sectors to better understand the boundary conditions of strategic fit's role as a substitute for local financing.

5.4 Practical implications

By showing that strategic fit narrows performance differences between startups in less- versus more-financing-rich contexts, the study offers an additional pathway through which policy-makers, entrepreneurs, and investors may fuel startup growth in these contexts. Investing in strategic fit—whether it be through mentoring, training, or internal exercises—may be another important way to nurture entrepreneurial scaling in startup ecosystems around the world, in addition to traditional approaches that focus on increasing access to finance and general business knowledge.

The study offers a way to measure strategic fit across companies that combines the depth of qualitative methods and the generalizability of quantitative methods. This method may be valuable for not only researchers, but also investors and managers to evaluate companies across international and sectoral contexts. For example, this method may inform managers whether they are growing with strategic fit. It may help investors decide on which startups to give funding to. And it may serve as a way for policymakers and accelerators to take stock of the strategy development capabilities of startups in their ecosystem and to measure the impact of their programs.

In conclusion, the study shows how strategic fit narrows performance differences between startups in less- versus more-financing-rich contexts and offers a novel way to measure strategic fit of companies across different contexts. In doing so, the study reveals how strategic fit may spur entrepreneurial growth in resource-constrained environments and opens the door to measuring strategic fit across a wide array of international and sectoral contexts.

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Tables

Table 1: Summary table comparing interviewed and non-interviewed companies

	(1)					
	Not Interview Obs	Not Interview Mean	Interview Obs	Interview Mean	Difference	SE
North America HQ	1718	0.64	253	0.54	0.10**	0.03
Europe HQ	1718	0.21	253	0.26	-0.05+	0.03
English-Speaking HQ	1718	0.75	253	0.70	0.05	0.03
Age (Years - at Interview)	1700	6.15	253	5.63	0.52**	0.20
Num. Employees (at Interview)	1697	66.77	250	61.38	5.39	9.80
Funding Amount (Millions USD - at Interview)	1723	26.27	253	21.85	4.42	2.99
Valuation (Millions USD - Initial)	1290	24.06	179	21.87	2.19	6.08
Log Valuation (Initial)	1290	2.46	179	2.39	0.06	0.09
Financing (Millions USD - Initial)	1728	3.84	253	3.50	0.34	0.31
Log Financing (Initial)	1728	1.20	253	1.13	0.07	0.06
Valuation/Employee (Millions USD - Initial)	1280	1.16	178	1.39	-0.22	0.43
Log Valuation Per Employee (Initial)	1280	0.47	178	0.51	-0.04	0.04
Valuation (Millions USD - Latest)	1458	197.30	208	140.79	56.52	41.05
Log Valuation (Latest)	1458	4.27	208	4.20	0.07	0.09
Total Raised (Millions USD - Latest)	1724	46.20	253	41.74	4.46	5.56
Log Total Raised (Latest)	1724	3.32	253	3.23	0.09	0.06
Valuation/Employee Latest (Millions USD - Latest)	1450	1.97	207	1.51	0.46*	0.23
Log Valuation/Employee (Latest)	1450	0.86	207	0.76	0.10*	0.04
Successful Exit	1728	0.04	253	0.05	-0.01	0.01
N	1981					

The table compares interviewed versus non-interviewed firms in the sampling frame of software firms (outside of China) that raised a 5–20M USD Series A Jan. 1, 2019–Sep. 30, 2021. The sample size drops because of missing year founded, HQ country, and performance data from PitchBook.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Summary table comparing startups in less- versus more-financing rich contexts

	(1)					
	Low VC Obs	Low VC Mean	High VC Obs	High VC Mean	Difference	SE
Fit (Composite)	128	-0.06	125	0.07	-0.13	0.12
External Fit	128	-0.16	125	0.13	-0.29*	0.11
Internal Fit	128	0.04	125	-0.01	0.05	0.12
Whether Exec. Attended Top Uni.	128	0.28	125	0.45	-0.17**	0.06
Readability (NLP)	128	70.29	125	71.75	-1.47	0.83
Readability (Human)	128	0.09	125	0.01	0.09**	0.03
North America HQ	128	0.34	125	0.74	-0.39***	0.06
Europe HQ	128	0.25	125	0.26	-0.01	0.06
English-Speaking HQ	128	0.43	125	0.98	-0.55***	0.05
Age (Years - at Interview)	128	5.78	125	5.47	0.31	0.25
Num. Employees (at Interview)	125	75.33	125	47.42	27.90***	6.86
Funding Amount (Millions USD - at Interview)	128	19.46	125	24.29	-4.84	4.11
Valuation (Millions USD - Initial)	67	23.78	112	20.72	3.05	7.52
Log Valuation (Initial)	67	2.38	112	2.40	-0.02	0.18
Financing (Millions USD - Initial)	128	3.67	125	3.33	0.34	0.60
Log Financing (Initial)	128	1.15	125	1.11	0.05	0.11
Valuation/Employee (Millions USD - Initial)	66	2.15	112	0.93	1.22	0.77
Log Valuation Per Employee (Initial)	66	0.58	112	0.47	0.10	0.10
Valuation (Millions USD - Latest)	95	108.15	113	168.22	-60.08	34.12
Log Valuation (Latest)	95	3.97	113	4.39	-0.41*	0.16
Total Raised (Millions USD - Latest)	128	38.03	125	45.53	-7.49	8.16
Log Total Raised (Latest)	128	3.15	125	3.32	-0.17	0.12
Valuation/Employee Latest (Millions USD - Latest)	94	1.06	113	1.89	-0.83**	0.26
Log Valuation/Employee (Latest)	94	0.60	113	0.90	-0.29***	0.07
Successful Exit	128	0.07	125	0.12	-0.05	0.04
N	253					

Shows summary statistics for interviewed firms, broken up by whether firms are headquartered in less-financing-rich (left) versus more-financing-rich (right) cities. The sample size drops because of missing performance data from PitchBook.

$+ p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Strategic fit narrows performance differences between less- and more-financing-rich contexts.

	(1) Log Val.	(2) Log Val.	(3) Log Val.	(4) Log Total Raised	(5) Log Total Raised	(6) Log Val./ Employee	(7) Log Val./ Employee	(8) Success. Exit.	(9) Success. Exit
Log HQ City VC	0.127^{***}	0.125^{***}	0.123^{***}	0.060^{**}	0.060^{**}	0.055^{***}	0.031^{*}	0.003	-0.001
	(0.033)	(0.030)	(0.033)	(0.019)	(0.021)	(0.011)	(0.014)	(0.007)	(0.008)
Fit	0.013	0.607	0.636^{+}	0.548^{*}	0.638^{**}	0.112	0.215	0.193^{*}	0.167^{**}
	(0.083)	(0.389)	(0.345)	(0.266)	(0.234)	(0.097)	(0.131)	(0.075)	(0.062)
Fit x Log HQ City VC		-0.057	-0.066^{*}	-0.047^{+}	-0.058^{**}	-0.013	-0.024^{+}	-0.017^{*}	-0.015^{*}
		(0.035)	(0.032)	(0.024)	(0.021)	(0.010)	(0.012)	(0.007)	(0.006)
_cons	2.876^{***}	2.901^{***}	1.926^{*}	2.601^{***}	2.538^{***}	0.184^{+}	0.539	0.068	-0.004
	(0.342)	(0.316)	(0.908)	(0.192)	(0.668)	(0.101)	(0.409)	(0.064)	(0.218)
N	246	246	207	304	302	245	207	304	302
Evaluator FE	No	No	Yes	No	Yes	No	Yes	No	Yes
Year Founded FE	No	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	No	Yes	No	Yes	No	Yes	No	Yes
Initial Performance	No	No	Yes	No	Yes	No	Yes	No	Yes
Filled-In FE	No	No	Yes	No	Yes	No	Yes	No	Yes
Readability	No	No	Yes	No	Yes	No	Yes	No	Yes
HQ Sub-Region	No	No	Yes	No	Yes	No	Yes	No	Yes
Top Uni	No	No	Yes	No	Yes	No	Yes	No	Yes

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook and singleton observations.

$+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: The narrowing does not seem to be driven by higher quality startups in less-financing-rich contexts having fit.

	(1) Fit	(2) Fit	(3) Fit	(4) Fit	(5) Fit
Log HQ City VC	0.000	-0.005	0.024	0.015	0.014
	(0.033)	(0.055)	(0.026)	(0.022)	(0.024)
Log First Financing	-0.137				0.008
	(0.233)				(0.121)
Log First Financing x Log HQ City	0.018				
	(0.023)				
Log First Val.		-0.061			0.053
		(0.256)			(0.080)
Log First Valuation x Log HQ City		0.012			
		(0.024)			
Exec Top Uni			0.468	0.114	0.129
			(0.482)	(0.128)	(0.146)
Exec Top Uni x Log HQ City			-0.034		
			(0.047)		
_cons	0.702	0.373	0.356	0.463	0.047
	(0.584)	(0.828)	(0.535)	(0.532)	(0.705)
N	302	211	302	302	211
Evaluator FE	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation data from PitchBook and singleton observations.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Strategic fit positively predicts performance only in less-financing-rich contexts.

	(1) Log Val.	(2) Log Val.	(3) Log Total Raised	(4) Log Total Raised	(5) Log Val./ Employee	(6) Log Val./ Employee	(7) Success. Exit	(8) Success. Exit
Fit	0.149	-0.172	0.161^{+}	-0.069	0.107^{+}	-0.108^{*}	0.058^{*}	-0.026
	(0.146)	(0.124)	(0.094)	(0.081)	(0.055)	(0.050)	(0.023)	(0.034)
_cons	2.581	2.986^{*}	4.417^{**}	1.984^{*}	0.310	0.990^{+}	-0.020	0.108
	(1.770)	(1.284)	(1.318)	(0.776)	(0.697)	(0.573)	(0.243)	(0.392)
N	76	128	152	149	76	128	152	149
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Performance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Low VC	High VC	Low VC	High VC	Low VC	High VC	Low VC	High VC

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook and singleton observations.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: External fit drives the results.

	(1) Log Val.	(2) Log Val.	(3) Log Total Raised	(4) Log Total Raised	(5) Log Val./ Employee	(6) Log Val./ Employee	(7) Success. Exit	(8) Success. Exit
Log HQ City VC	0.125***	0.129***	0.062**	0.060**	0.032*	0.033*	-0.001	-0.001
	(0.034)	(0.030)	(0.021)	(0.021)	(0.015)	(0.013)	(0.008)	(0.008)
Internal Fit	0.109		0.335		0.006		0.085	
	(0.363)		(0.221)		(0.144)		(0.062)	
Internal Fit x Log HQ City VC	-0.021		-0.032		-0.005		-0.007	
	(0.033)		(0.020)		(0.013)		(0.006)	
External Fit		1.043**		0.683**		0.386**		0.193**
		(0.343)		(0.224)		(0.133)		(0.066)
External Fit x Log HQ City VC		-0.098**		-0.059**		-0.039**		-0.019**
		(0.031)		(0.020)		(0.012)		(0.006)
_cons	2.112*	1.636+	2.611***	2.523***	0.609	0.419	0.004	-0.016
	(0.906)	(0.906)	(0.669)	(0.675)	(0.400)	(0.409)	(0.217)	(0.221)
N	207	207	302	302	207	207	302	302
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Performance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook and singleton observations.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: External fit especially weakens the financing-performance relationship when in HQ contexts with higher firing costs.

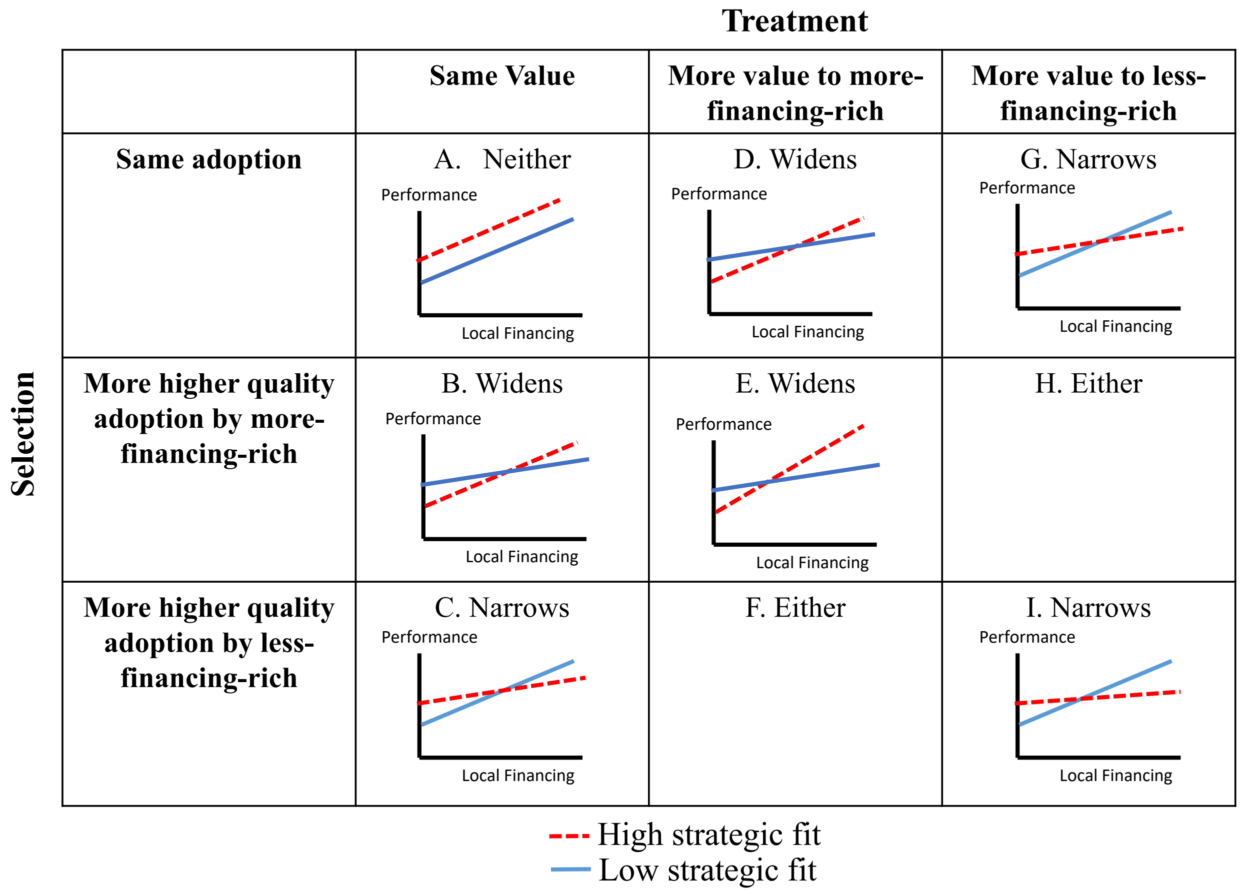
	(1) Log Val.	(2) Log Val.	(3) Log Val.	(4) Log Total Raised	(5) Log Total Raised	(6) Log Total Raised	(7) Log Val./ Employee	(8) Log Val./ Employee	(9) Log Val./ Employee	(10) Success. Exit	(11) Success. Exit	(12) Success. Exit
External Fit	0.264	2.000***	0.223	-0.261	0.616*	-0.235	0.039	0.737***	0.111	0.213	0.324**	0.298+
	(0.484)	(0.432)	(0.519)	(0.389)	(0.251)	(0.399)	(0.223)	(0.167)	(0.237)	(0.148)	(0.112)	(0.159)
Log HQ City VC	0.076*	0.085	0.080+	0.036	0.073*	0.045	0.015	0.009	0.028	-0.012	-0.010	-0.008
	(0.036)	(0.056)	(0.042)	(0.029)	(0.033)	(0.033)	(0.018)	(0.022)	(0.021)	(0.013)	(0.012)	(0.012)
External Fit x Log HQ City VC	-0.036	-0.200***	-0.030	0.014	-0.044	0.014	-0.009	-0.082***	-0.015	-0.018	-0.037**	-0.022+
	(0.043)	(0.045)	(0.046)	(0.031)	(0.029)	(0.033)	(0.020)	(0.018)	(0.020)	(0.012)	(0.012)	(0.013)
Firing Cost			-4.895**			0.741			-0.567			0.266
			(1.648)			(0.884)			(0.627)			(0.304)
External Fit x Firing Cost			1.387			2.070*			0.766+			0.057
			(1.091)			(0.829)			(0.432)			(0.303)
Log HQ City x Firing Cost			0.153			0.053			-0.003			0.028
			(0.123)			(0.093)			(0.052)			(0.031)
External Fit x Log HQ VC x Firing Costs			-0.126			-0.166*			-0.075+			-0.031
			(0.117)			(0.078)			(0.044)			(0.030)
_cons	1.433	2.909	2.688**	2.053*	3.390**	2.249**	0.546	0.970	0.590	0.035	-0.108	-0.086
	(0.993)	(2.919)	(0.924)	(0.787)	(1.257)	(0.716)	(0.508)	(0.920)	(0.428)	(0.331)	(0.286)	(0.229)
N	137	64	205	158	138	297	137	64	205	158	138	297
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Performance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Low Cost	High Cost	Full	Low Cost	High Cost	Full	Low Cost	High Cost	Full	Low Cost	High Cost	High Cost

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook, as well as singleton observations and missing firing cost data from Iceland, Qatar, Serbia, and Seychelles.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

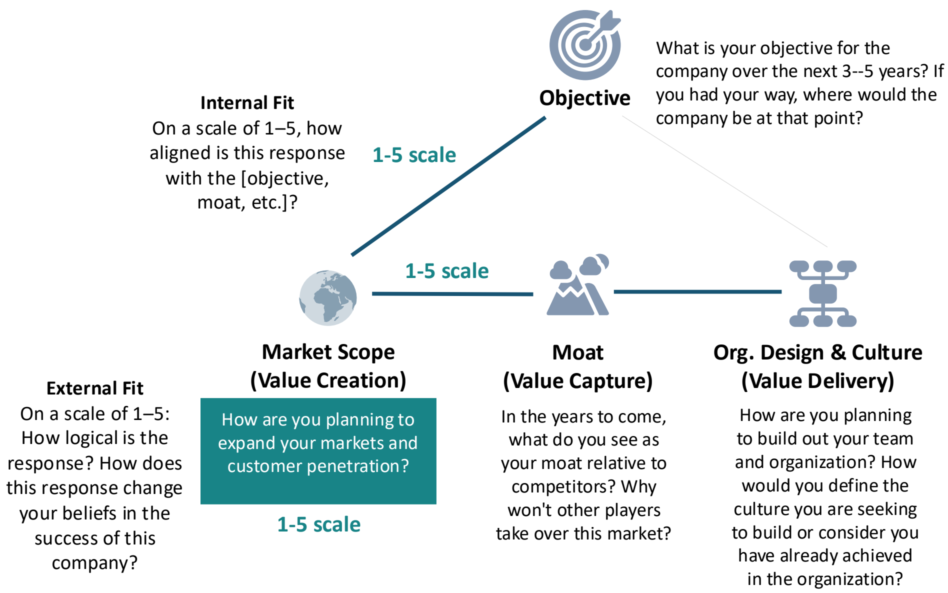
Figures

Figure 1: Predicted relationships between strategic fit, local financing, and startup growth



The figure shows several competing possibilities of how strategic fit shapes the relationship between local financing and startup performance depending on how and whether the adoption of strategic fit varies between less- versus more-financing-rich contexts (selection) and whether its value varies across these contexts (treatment). Cells B, D, and E show scenarios in which strategic fit widens performance differences between startups based in less- versus more-financing-rich contexts. Cells C, G, and I show scenarios in which strategic fit narrows these performance differences. Cells F and H show scenarios where the overall relationship is ambiguous because selection and treatment can offset one another. Cell A is the null hypothesis where neither the adoption or value of strategic fit varies across financing contexts.

Figure 2: Overview of strategic fit measure



The figure illustrates the field methodology and coding used to create the strategic fit measure. Additional NLP/LLM analyses test the robustness of the measure. In particular, they show that the measure is similar when using alternative evaluative questions, for example, for external fit, asking: "How appropriate is this response to the startup's market?" Appendix Tables A4 – A7 report these analyses.

Figure 3: Example of HR startups with similar external but different internal fit scores

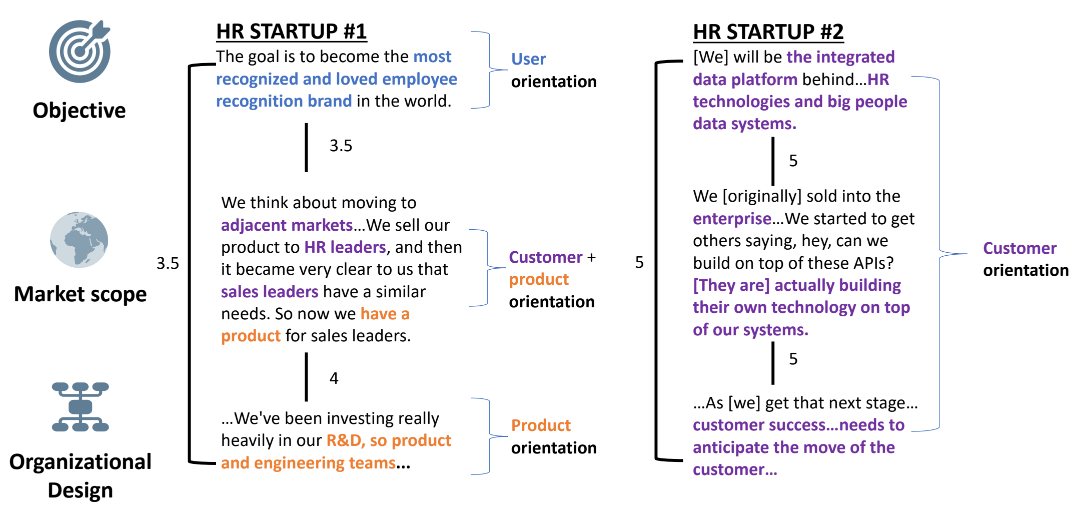


Figure 4: Histogram of strategic fit scores

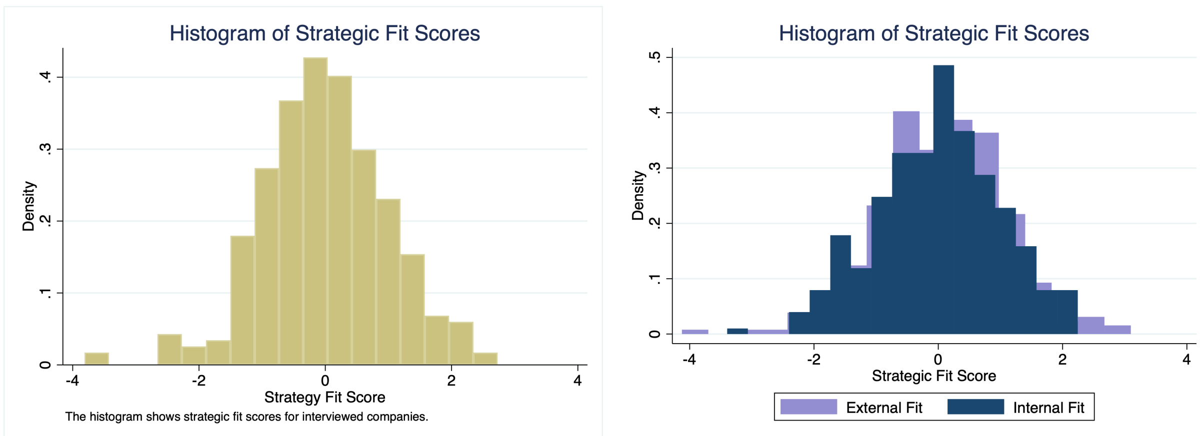


Figure 5: The VC index by HQ city

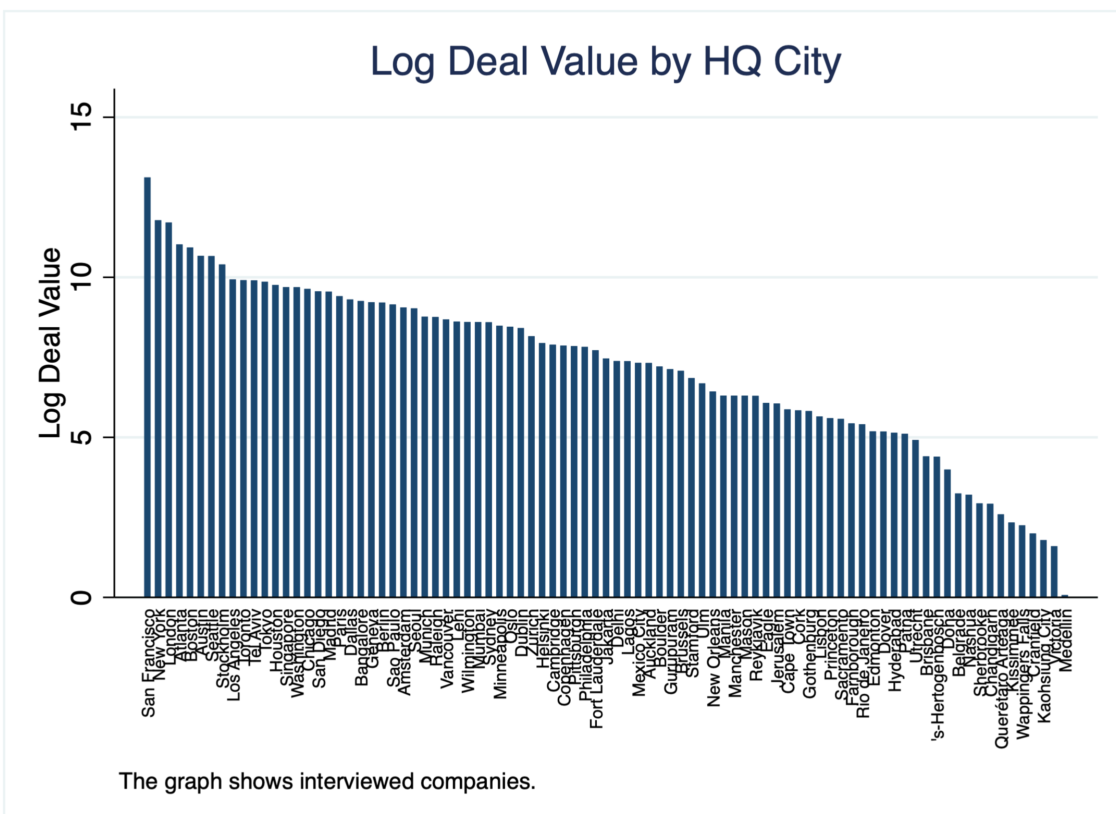
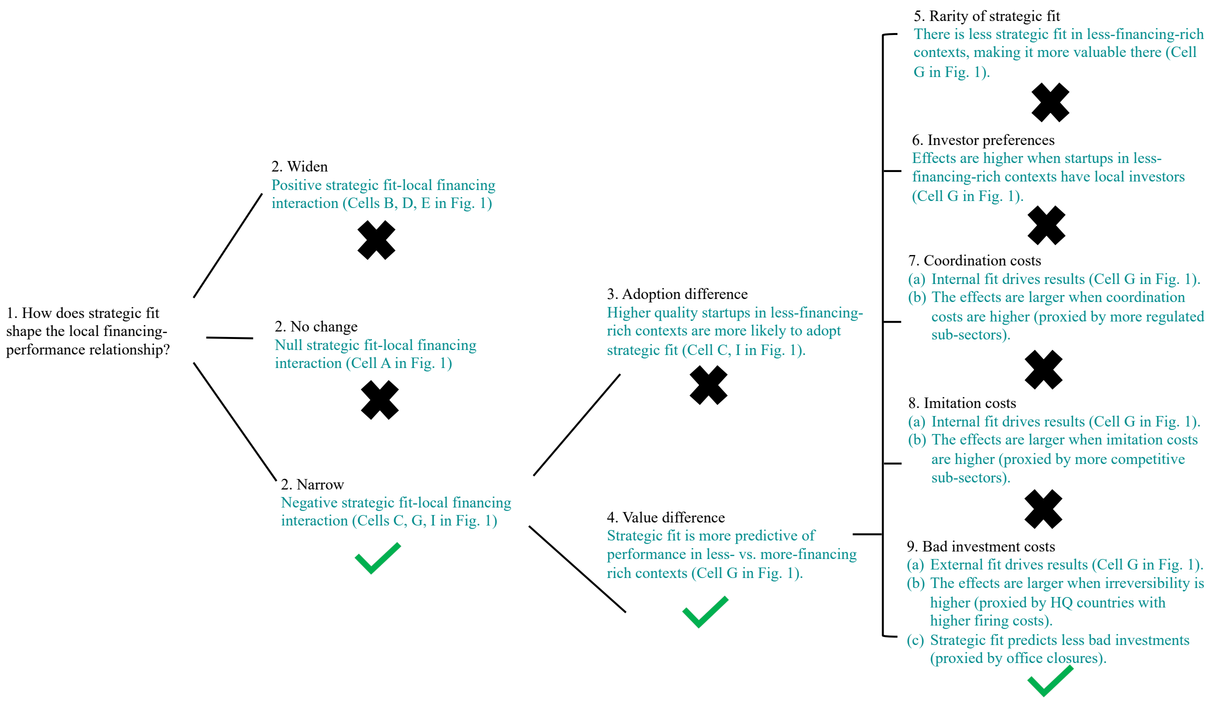
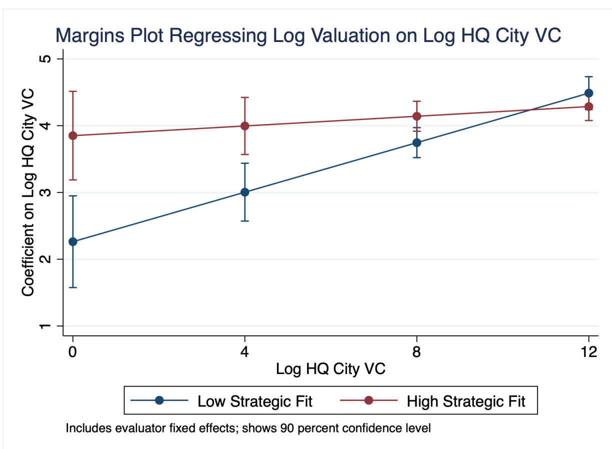


Figure 6: Analysis summary



The diagram summarizes the abductive analysis process. The black text indicates potential mechanisms, the teal text indicates the predicted empirical trend consistent with that mechanism, and the check/X-marks indicate whether the study finds this empirical trend or not, respectively.

Figure 7: Strategic fit narrows performance differences between less- and more-financing-rich contexts in terms of logged valuations (left) and logged funding (right).



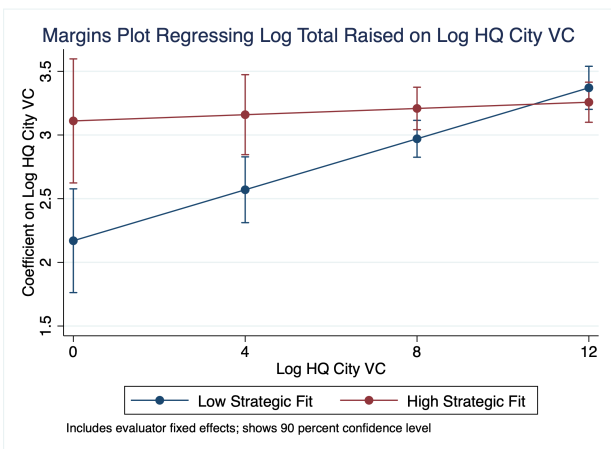
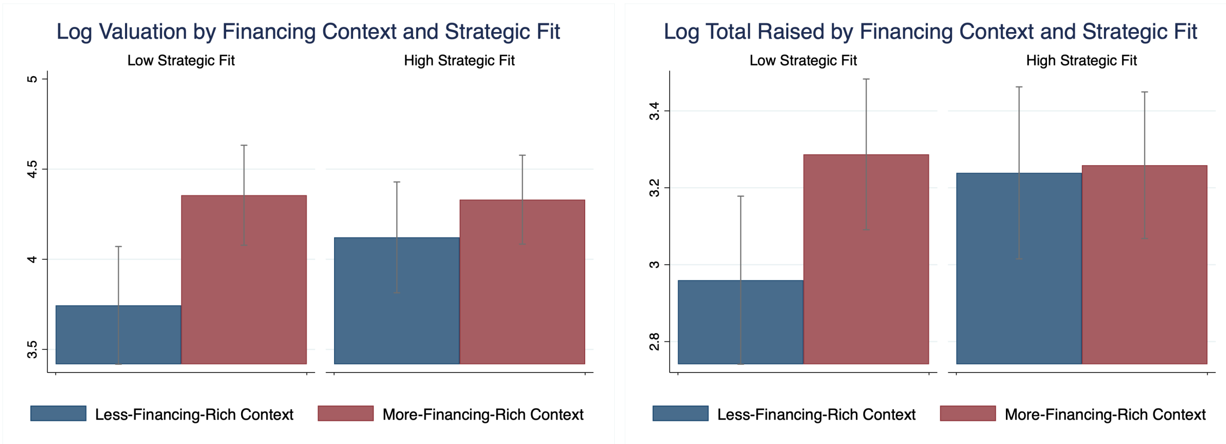


Figure 8: Strategic fit narrows performance differences between less- and more-financing-rich contexts in terms of logged valuations (left) and logged funding (right).



"Less-financing-rich context" and "more-financing-rich context" indicate below-median and above-median volumes of local financing in the HQ city, respectively. "Low strategic fit" and "high strategic fit" indicate below-median and above-median strategic fit scores, respectively.

Figure 9: External fit only meaningfully narrows performance differences between startups in less- vs. more-financing-rich contexts among firms in HQ countries with higher firing costs.

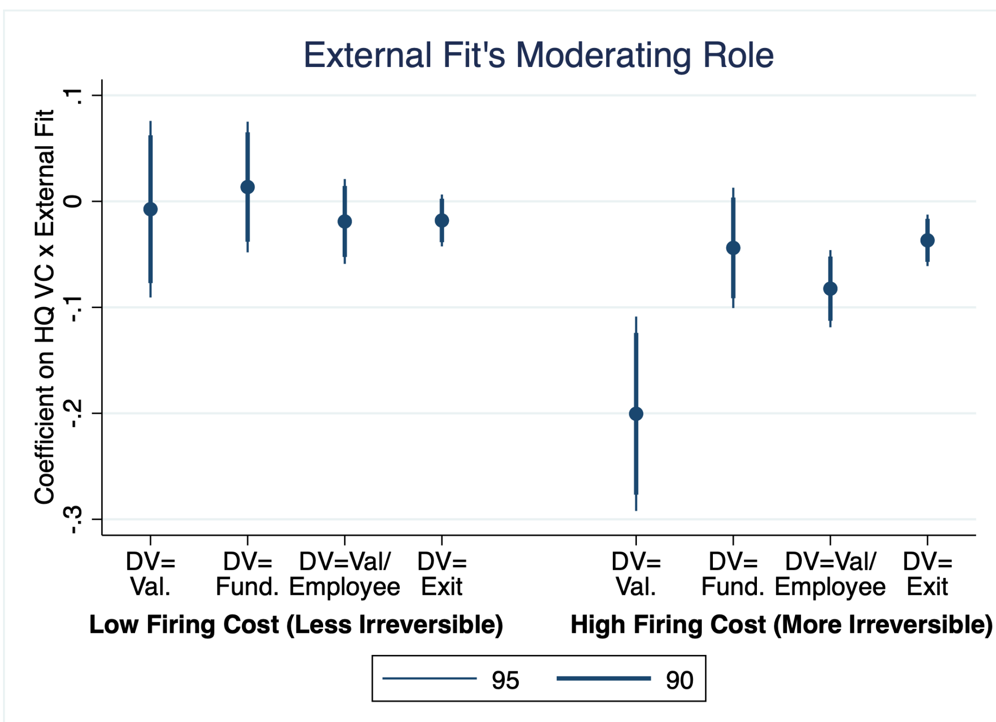


Table 7 reports the regression results corresponding to this figure.

A Appendix

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A.1 Interview protocol and scoring

Measuring strategic fit relied on structured interviews with executives of software companies that leveraged a standardized interview protocol of open-ended questions asking executives to recount their companies' objectives, market scope, moat, organizational design, and organizational culture choices. Supplementary questions elicited how the executives prioritized their next three action items, how they were using Series A funding, what they perceived as their biggest uncertainties, and why they did not pursue particular alternative approaches, for example, expanding across geographies rather than across industries. These questions are below.

- Objective
  - What is your objective for the company over the next 3–5 years? If you had your way, where would the company be at that point?
- Market scope (Value creation)
  - How are you planning to expand your markets and customer penetration?
- Moat (Value capture)
  - In the years to come, what do you see as your moat relative to competitors? Why won't other players take over this market?
- Organizational design and culture (Value delivery)
  - How are you planning to build out your team and organization? How would you define the culture you are seeking to build or consider you have already achieved in the organization?
- Supplementary questions
  - At the beginning of the conversation, you mentioned your objective for the company. If you could boil it down to the three actions you need to take to make that objective possible, what would they be?
  - How are you using or planning to use your Series A funding?
  - What is the biggest source of uncertainty that faces your company in the next 3–5 years? How are you addressing it?
  - Why did you not pursue [insert particular alternative] to [expand your market or design your organization]?

Research associates (MBA students and those with similar experience) evaluated the transcribed responses to the above questions and used the following scoring rubric to evaluate them.

- **External fit**:
  - On a scale of 1–5, how logical is the response? (1= response is illogical—the conclusion DOES NOT at all follow from assumptions; it is internally inconsistent. 3= response is somewhat logical, but has some internal inconsistencies. 5= response is logical.)
  - On a scale of 1–5, how does this response change your beliefs in the success of this company? (1= reduces your beliefs; 3= doesn't change your beliefs; 5 = increases your beliefs.)
- **Internal fit**:
  - On a scale of 1–5, how aligned is this response with the executive's [objective, market scope, organizational design, etc.]? (1=not aligned; 3 = somewhat aligned; 5 = very aligned)?

A.2 Coding examples

The following section shows examples of market scope, moat, and organizational responses and their strategy scores. For simplicity, the section focuses on scoring the appropriateness of these responses (external fit) and alignment with executives' objectives (part of internal fit).

Market scope examples

Table A1 shows examples of companies' market scope responses and scores. A France-based company developing a video communication tool (third row) has a relatively low market scope score. Its plan to expand its market scope through direct sales and gradual internationalization from Europe to the US are reasonable independently but are misaligned with one another. One might expect that grabbing the biggest market in the US first (rather than in Europe) would be important for solidifying market share and would be more fitting with the direct sales approach to get customers with "bigger revenue...and less churn." This misalignment between two independently reasonable approaches results in an average external fit score. By pushing off entry into a market with high-value customers and risking its stake in that market, the company also risks its ability to achieve its objective to "build a new category of product" and correspondingly achieve a "1 billion-plus valuation." The misalignment between the market scope approach and the objective results in a lower internal fit score.

As an example of a high market scope score, the US-based company developing a recruiting platform (first row) is expanding its market by partnering with enterprise human resource systems to enable others to build on top. By gaining customer value from incumbents and innovations from third-party entrants in the "quarter-of-a-trillion-dollar market" in HR technologies, the company conveys a plan that fits well with its assumptions of increasing value across markets. Unlike the gradual international expansion approach planned by the France-based company, this company targets the big players in the business first so it can get the first-mover advantage to be the data infrastructure on which others can build. The "API-first" approach enables the company to reach major HR systems seamlessly. This interoperable approach aligns well with its objective to be an "integrated data platform behind many of the HR technologies and big people data systems."

The Brazil-based company (second row) pursuing a document automation platform takes a direct sales approach, like the other two companies above. Unlike the deliberate approach pursued by the US company, the Brazilian company started with enterprise sales because it was familiar with the approach and thought it would be "easy." However, it soon realized it was mistaken; this was a market with “complicated sales cycles." The executive admitted that “it [would have been] better to start with the middle or SMB market." However, by focusing on a shorter-term feasible customer approach first, the company chose an option that ended up being difficult to sustain in Brazil, resulting in an average external fit score. The company has the potential to achieve substantial financial outcomes by targeting large enterprises in Brazil, where there is a promising market opportunity to “solve a huge bureaucracy problem." This market focus fits with the company's objective to get “over 100 million reais in revenue" and an IPO. It would be even more fitting if the company addressed how it would mitigate risks around the “complicated sales cycles." Together, this plan has a relatively strong fit with the executive's objective, resulting in a high internal fit score.

Table A1: Market scope examples

Internal, External Fit Scores	**Desc.**	**Objective**	**Market Scope**	**HQ**
5, 5	Recruiting platform using AI/ML to provide talent to enterprises	In the next three to five years, [the company] will be the integrated data platform behind many of the HR technologies and big people data systems.	We created integrated partnerships with the largest HCMs. And this has been really helpful, because our whole message was, we're going to make your system better. And it caused those systems to want to sell us...And because the whole technology was built as an API-first business, we started to get others saying, hey, can we build on top of these APIs? And then there's about a quarter of a trillion dollars in HR tech that's out there in the world.	US

4.5, 3.5	Platform using AI to automate procurement of documents in Brazil for companies.	…For the next three to five years…we will achieve over 100 million reais in revenue…which means, probably, we could see some IPO in the next three or five years.	It's hard because here in Brazil, what we are trying to do is solve a huge bureaucracy problem. So more than understanding our market, we are creating disruptive products. And it's a B2B enterprise market. So the sales cycle [is] more complicated. So we sell for the huge—the most important banks in Brazil, real estate companies, and also agro-companies. So I think the strategy is to focus on outbound sales. And we spend a lot of money to get this whole market, the enterprise market. And after that, for the next round, and to get scale, probably, we will divide our product…to have more standalone products and go to the middle and SMB markets.	Brazil
2, 3	Video communication tool for companies	The main proxy for all the rest is to build a new category of product...KPIs that will probably be attached to a goal of...revenue probably around 100 billion ARR [and]...1 billion plus valuation.	Investing a lot in sales...so reaching out instead of depending on the inbound demand. Second thing is obviously expanding to different markets. We've been really present in...Europe. We'll continue to actually expand in Europe...And also the US, North America in general is actually super interesting, really mature market, a lot of competition that's fairly—we haven't really scratched the surface as a company yet...And so once we have done successfully those two regions that we see, we will probably expand to new ones or most likely APAC and so on.	France

Moat examples

Table A2 shows examples of moat responses and scores from three companies. The Singapore-based company creating a mobile-based alternative credit scoring platform (third row) conceives a moat centered around its data from mobile devices to improve the predictive power of customers' models. Its external fit is weak. The company does not articulate why other players would be unable to build their mobile data moat. While the company notes that it can coexist with other companies providing telco data because customers use both, it is unclear why other players would not have an incentive to produce mobile-derived data. These players could achieve economies of scope by providing both types of data to customers. Further, the mobile-derived data moat does not directly fit with the objective of being a "global company." Whether the mobile-derived data can ensure international adaptability or relevance is questionable.

In contrast to the Singapore-based company that focused its moat on the "process" of its data collection, the US-based company creating a recruiting platform (first row) pursued a moat focused on the ultimate value that the data would create. The company's data, which are "prohibitively expensive" for even large players to collect, can improve recruitment outcomes by "identifying" and "matching" people in a much better way. The response has a high external fit because it shows how the company's data create value and are difficult for others to acquire. Further, this hard-to-get data that create value enable the company to expand its reach to customers in the recruiting space, aligned with its objective to be behind "many of the HR technologies and big people data systems." The HR-data nature of the moat targets the same HR customers that are core in its objective. This alignment contrasts with the mobile-data nature of the Singapore company's moat that does not necessarily fit with the global nature of its customers, resulting in the US company achieving a higher internal fit score.

The Finland-based company creating a product-testing technology (second row) perceived its moat to be a combination of the technical nature and user-friendliness of the product. It is unclear why these capabilities are a "winning combination." Specifically, the executive does not articulate the value the capabilities create for customers and why other competitors would not be able to take over the space, resulting in a weaker external fit. The "plug and play" nature of the technology that can be applied to international audiences somewhat fits with the company's objective to be a "global player." However, it is unclear how it would create sufficient barriers to entry to allow it to achieve "revenue of 100 million euros." The response therefore achieves an average external fit score.

Table A2: Moat examples

Internal, External Fit Scores	**Descr.**	**Objective**	**Moat**	**HQ**

4.5, 5	Recruiting platform using AI/ML to provide talent to enterprises	In the next three to five years, [the company] will be the integrated data platform behind many of the HR technologies and big people data systems.	Data... The problem with talent data is it's huge. And those are prohibitively expensive for even a multi-billion-dollar organization to try and structure data that way. So we instead were... going to build one, which was a risk. And once we pulled that off, we really started to see that we could identify people in this much better way... We could also match people much better for organizations based on capability. And the people that we were putting there were so much more diverse.	US
4, 3	Creator of technology to spur creation and testing of products and services	We want to become a global player in our arena...We aim to grow, especially in Europe...But our key goal now with the A round is really to establish a great position in Europe. And after that, the aim is to take the next step and enter the US market...Our five-year plan is to reach a revenue of 100 million euros.	We are a plug-and-play platform. That makes it possible that everyone can really run advanced consumer research and testing and thereby be fast and successful with their innovation process. So combining this super-easiness to use with expert approach and methods, I think that's the winning combination...And of course, then thinking a bit longer-term perspective, since we are focusing on a certain domain, we are also developing our AI capabilities...So of course the data combined with our algorithms [will be] a strong asset.	Finland
2, 2	Mobile-based alternative credit-scoring platform to enable financial inclusion and access for underbanked consumers	My ambition [is] to bring [the] company [to the] global level.	[Our moat is] data that would increase the predictive power of [customers'] models...So there are companies who are developing scorecards based on telco data. We don't consider them as a direct competitor because we have clients who are using both, right? Scorecards developed based on device, mobile device data. That is [our company]. So we can coexist together.	Singapore

Organizational examples

Table A3 shows examples of organizational responses and scores from different companies. The Brazil-based startup creating a platform to automate procurement of documents (third row) seeks to bring in technology, business, and senior-level talent. The response is not very appropriate given the context (external fit) because these different types of talent do not appear to bring much value in the startup's market. Further, the response does not mention why technology, sales, or senior executives would help the company better reach customers to increase revenue and ultimately get an IPO, as noted in its objective. As a result, the response also earns a relatively low score for fit with the objective (internal fit).

The US-based startup creating a recruiting platform (first row)—with a similar B2B platform model and type of talent as the Brazil-based startup—pursued an aligned organizational design. The approach of moving from a tech team to an increasingly commercial team with API business experience aligns with the objective of wanting to be the "integrated data platform" underlying "many of the HR technologies and big people data systems." The technology team can create a data platform that initially brings value to the early adopter market that automatically provides feedback. Subsequently, the API-experienced customer success and sales side can bring that value to mainstream companies who are less forthcoming with their feedback. Customer success then becomes important to "anticipate the move of the customer." Therefore, the company can have the space to first develop a great technology with minimal outside pressure and only then make it known to the world (the "Trojan horse" approach). This close fit between customer needs in the market and the organizational design response results in a high external fit score.

The Qatar-based startup creating a one-stop-shop (second row) focused its organizational design on getting intelligent, young, and experienced people from around the world. This talent mix of global experience and aptitude is compelling. Employees need to bring expertise to excel in their duties but also bring new ideas. Global sourcing is particularly valuable in a smaller country like Qatar, where such experienced and high-potential talent is difficult to find. Therefore, the combination of intelligence and expertise that the company brings to the team fits well with its assumptions about local labor market conditions, resulting in a high external fit. However, the approach fits weakly with the objective of being "a regional app with multiple services." One might expect that the company would be focusing on the "local" nature of talent in different domains to fit its goal of building a "super regional app" in the Middle East. The discrepancy between the global nature of the organizational design and the local nature of the objective drags down the response's internal fit.

The Seychelles-based startup creating a crypto network (fourth row) pursued an organizational design that strongly aligns with its objective. Building a network of developers with crypto-specific skills and interests fits with the objective of creating “decentralized unchained governance" that is core to a crypto innovation. The company is pairing a decentralized team structure with a decentralized objective by choosing an open-source network-like organizational structure. The decentralized approach allows the company to get technical contributions relatively quickly and cheaply for its near-term product goals. However, the transactional nature of interaction with developers raises questions about how the company will retain talent and tacit knowledge over time to be “scalable." The discrepancy between the transactional approach and the scalable rationale results in a lower external fit score.

Table A3: Organizational examples

Internal, External Fit Scores	**Desc.**	**Objective**	**Organizational Response**	**HQ**
4, 5	Recruiting platform using AI/ML to provide talent to enterprises	In the next three to five years, [the company] will be the integrated data platform behind many of the HR technologies and big people data systems.	In the beginning, tech and products were 80 percent of our team... Most startups start the opposite way. We don't ever market things...We appreciate much more of the Trojan horse approach... We are now going to be much more even keel on a 50-50 percentage. My focus is also...[an] incredibly strong customer success... to anticipate the move of the customer. And we are going to bring in some experts that come from API-first businesses.	US
3, 4.5	One-stop-shop for online shopping, food, etc.	Our aim, to be a super regional app with multiple services [in the Middle East].	I had to steal people from similar business model. So in every specific area, I make sure I have 40 percent been there, done that. Now I have employees coming from Colombia to handle my customer experience department. I was making sure people have been there, done that. However, I bring in young people also...So how can I bring experienced people with know-how, and at the same time, bring the smartest people from university together? So this is my strategy.	Qatar
4, 4	Platform using AI to automate procurement of documents in Brazil for companies	For the next three to five years... we will achieve over 100 million reais in revenue... which means, probably, we could see some IPO in the next three or five years.	We are in three [areas]. It's the tech team of course, it's the number-one. And we face a challenge here...So we're thinking in the rest of the world, it's the same problem....The sales team we probably will spend more money on. And also, we need to hire more senior executives to our teams. So we develop our senior leadership.	Brazil

5, 3.5	Crypto network for Web 3.0	Our goal is to...eliminate ourselves as a company in three years. And since we're in this process, we will try to stabilize the protocol, make it very concrete, resistant to the change of environment, both from technical and market condition perspectives. And once we're quite sure the protocol will evolve...the core team will transfer the right privilege to the community to realize what we call decentralized unchained governance.	Once someone [is] convinced by our idea and they believe we're doing the right thing and they have the required capability to help with this...crypto-network building things, they can join...And we will provide incentives in various ways...First, we tried to find some mechanism to incentivize hundreds or even thousands of people to join our network and make contributions relatively—it can be comparable with open source software development...It's much more important and scalable than recruitment.	Seychelles

A.3 Sampling checks

This study interviewed more than 12 percent of the software companies (outside of China) that received Series A funding ($5–20 million) from January 2019–September 2021. There may be a concern that these 253 companies are different than those not interviewed in this sample, biasing the results. For example, perhaps only the worst companies agreed to an interview because they wanted to get advice on how to improve their operations. Alternatively, we could imagine that only the best companies agreed to the interview so as to market their success.

To help account for this potential bias, measuring differences between the interviewed companies and others in the sampling frame is valuable. While Table 1 shows that performance metrics like employee count, valuations, and first financing size do not predict whether a startup was interviewed in the sample, there might still be a concern that the overall distributions vary. Further, because North American startups were less likely to interview (Table 1), there might be concern that the overall regional distributions are different among interviewed and non-interviewed companies.

To address this concern, histograms reveal how the overall distributions vary among interviewed and non-interviewed companies for several key variables, where we might be concerned about selection. Figure A.10 shows that the regional distribution of the interviewed sample of companies looks similar to that of the non-interviewed companies. Figure A.11 shows that the distributions of the number of employees at the time of the interview are similar for interviewed and non-interviewed companies. Figure A.12 shows that the distributions of initial financing size among interviewed and non-interviewed companies in the sample are also similar.

Figure A.10: Regional distribution of non-interviewed sample is similar to that of the interviewed sample.

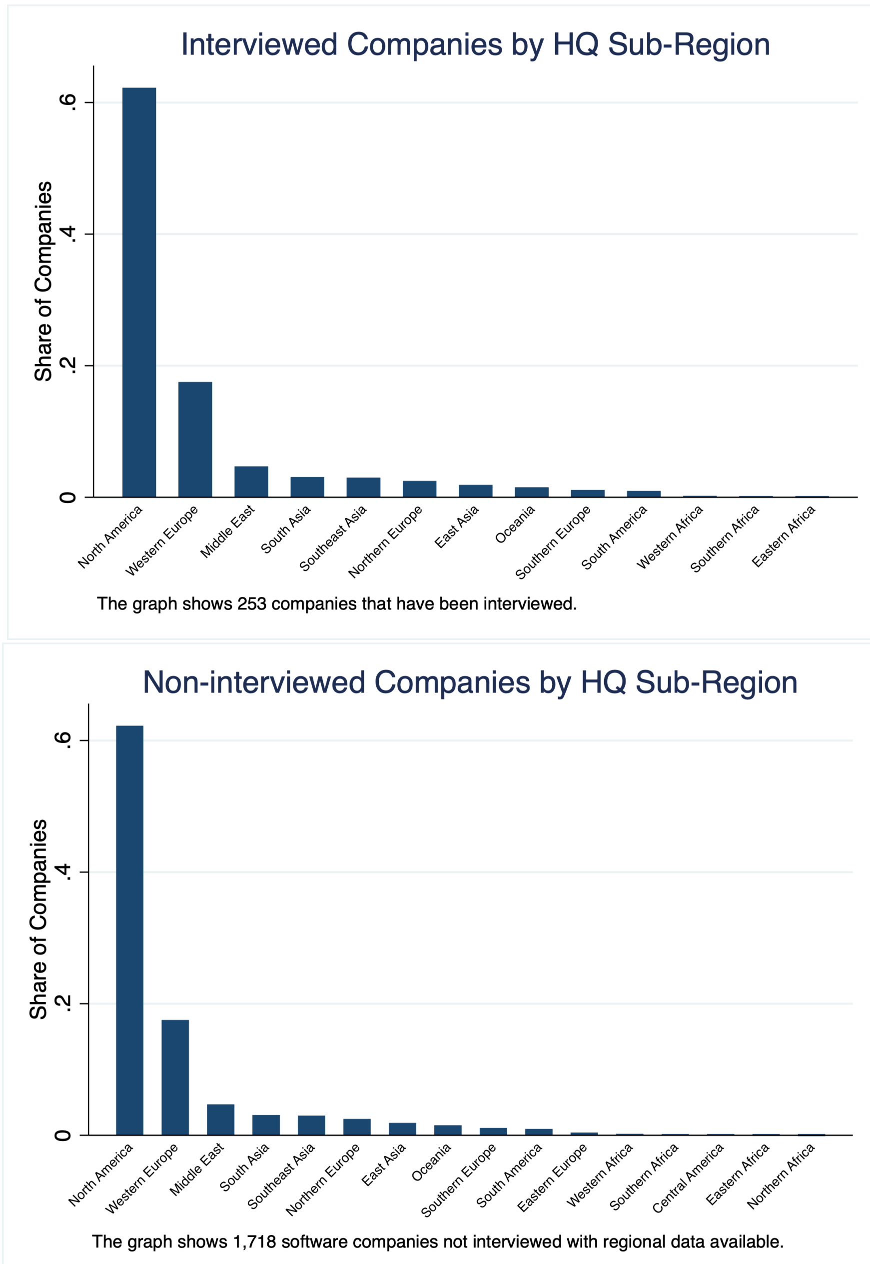


Figure A.11: Employee distribution of non-interviewed sample is similar to that of the interviewed sample.

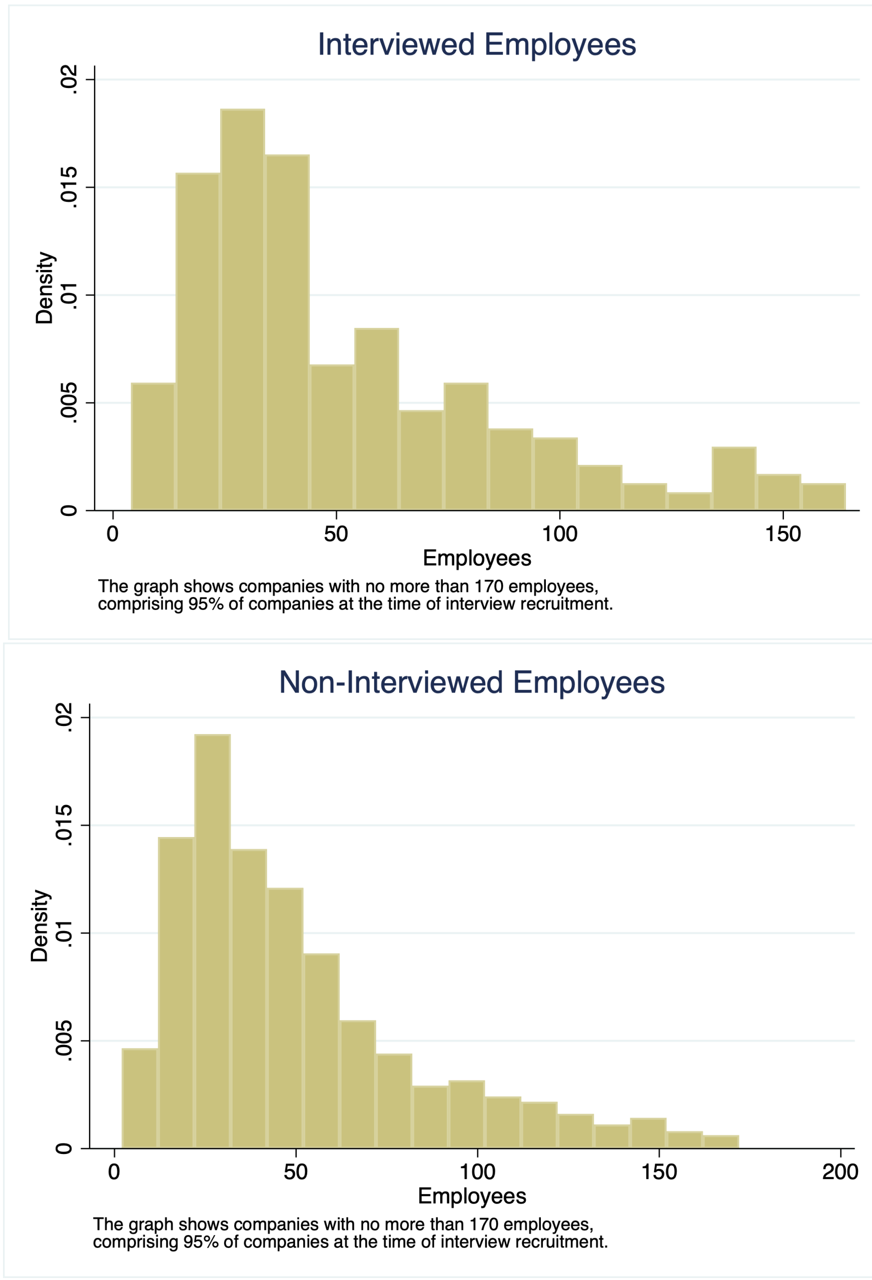
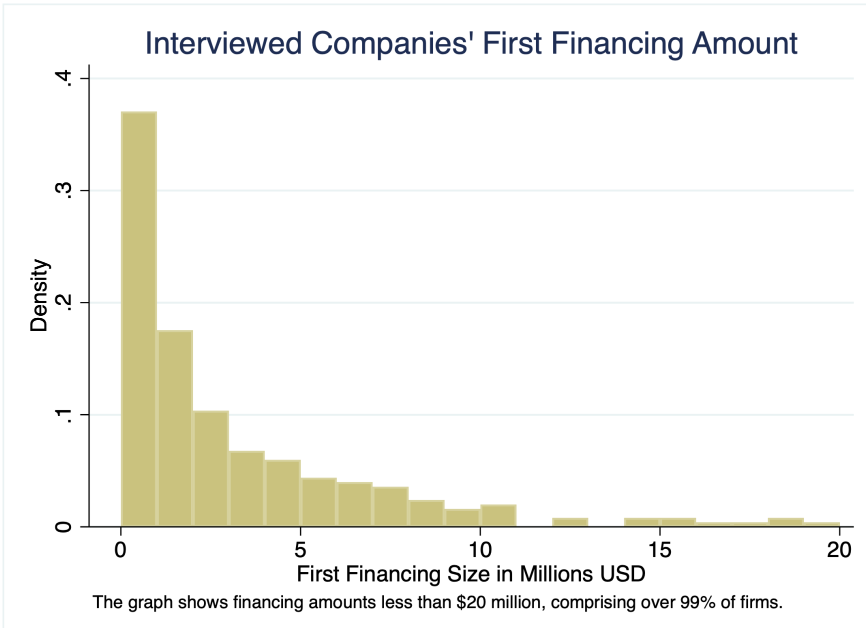
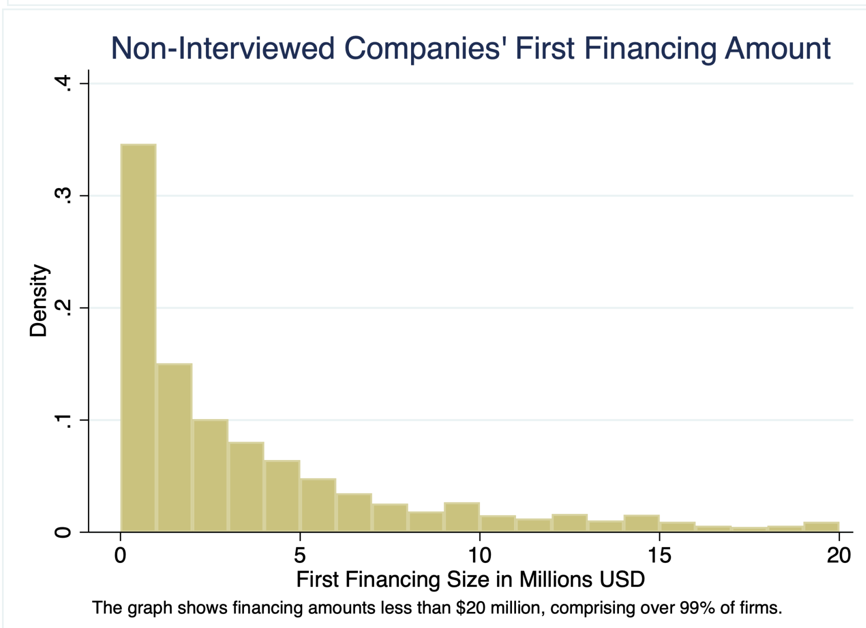


Figure A.12: First-financing-size (in USD) distribution of non-interviewed sample is similar to that of the interviewed sample.





A.4 AI approach to strategic fit score

Could the strategic fit measure be fraught with human error? AI, and, specifically, NLP techniques make it possible to create an alternative strategy measure to test the robustness of the human coding. Specifically, OpenAI's LLM (ChatGPT)—trained using reinforcement learning from human feedback (OpenAI, 2022)—allows for the measuring of the external fit of startups' market scope, moat, and organizational responses. The LLM followed similar prompts as given to human coders—to measure how appropriate are each of the responses—in order to construct a numerical score of external fit.

An SBERT model is suited to measure the internal fit among the responses. This model measures the similarity of text, taking into account the semantic meaning of sentences by assessing words in the context of their sentences (Devlin et al. 2018, Reimers & Gurevych 2019). It allows for researchers to assess the similarity of each of the choices to the objective and to one another.

Like the algorithm using the human-coded measures in Equation (1), averaging the LLM-based external fit score (standardized to a mean of zero) and the SBERT-based internal fit score (also standardized to a mean of zero) across choices and normalizing them creates an AI-based composite strategic fit score. This score excludes missing values.

Table A4 shows that the final composite score positively correlates with the primary strategy measure used in the paper (Column 1). The subscores using the LLM and SBERT models for each choice element are also positively associated with the corresponding human-coded subscores (Columns 2–4). Table A6 shows that the SBERT-created internal fit scores positively correlate with the human-coded internal fit scores. Table A5 shows that the LLM-created external fit scores positively correlate with the human-coded external fit scores. The results are similar when using an alternative prompt to external fit based on whether the response is appropriate for the startup's market, as shown in Table A7.

These positive correlations between the human-coded and computer-generated scores suggest that the human evaluations are not spurious. They help validate the strategic fit scores.

Table A4: Human and AI calculations of strategic fit are positively correlated.

	(1) Strategic Fit Human	(2) Market Fit Human	(3) Moat Fit Human	(4) Org. Fit Human
Strategic Fit AI	0.237***			
	(0.065)			
Market Fit AI		0.179**		
		(0.061)		
Moat Fit AI			0.252***	
			(0.072)	
Org. Fit AI				0.200**
				(0.069)
_cons	0.003	0.000	0.010	0.000
	(0.057)	(0.062)	(0.061)	(0.062)
N	253	253	249	253

Robust standard errors (in parentheses) are clustered at the company level.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Human and AI calculations of external fit are positively correlated.

	(1) External Fit Human	(2) Market External Fit Human	(3) Moat External Fit Human	(4) Org. External Fit Human
External Fit LLM	0.224**			
	(0.069)			
Market External Fit LLM		0.049		
		(0.070)		
Moat External Fit LLM			0.296***	
			(0.064)	
Org External Fit LLM				0.249***
				(0.065)
_cons	-0.000	0.000	0.015	0.000
	(0.061)	(0.063)	(0.060)	(0.061)
N	253	253	249	253

Robust standard errors (in parentheses) are clustered at the company level.
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: Human and AI calculations of internal fit are positively correlated.

	(1) Internal Fit Human	(2) Market Internal Fit Human	(3) Moat Internal Fit Human	(4) Org. Internal Fit Human
Internal Fit SBERT	0.080**			
	(0.030)			
Market Internal Fit SBERT		0.172**		
		(0.063)		
Moat Internal Fit SBERT			0.152*	
			(0.065)	
Org Internal Fit SBERT				0.097
				(0.062)
_cons	3.922***	0.000	-0.001	-0.000
	(0.029)	(0.062)	(0.063)	(0.063)
N	253	253	249	253

Robust standard errors (in parentheses) are clustered at the company level.
+ p < 0.10, * p < 0.05, ** p< 0.01, *** p < 0.001

Table A7: Human and AI calculations of external fit when directly eliciting appropriateness with context are positively correlated.

	(1) External Fit Human	(2) Market External Fit Human	(3) Moat External Fit Human	(4) Org. External Fit Human
External Fit LLM (Alt.)	0.152*			
	(0.076)			
Market External Fit LLM (Alt.)		-0.003		
		(0.075)		
Moat External Fit LLM (Alt.)			0.173**	
			(0.064)	
Org External Fit LLM (Alt.)				0.220***
				(0.062)
_cons	0.000	0.000	0.015	0.000
	(0.062)	(0.063)	(0.062)	(0.061)
N	253	253	249	253

Robust standard errors (in parentheses) are clustered at the company level.
+ p < 0.10, * p < 0.05, ** p< 0.01, *** p < 0.001

A.5 Results hold when controlling for observable firm differences and the content of strategy.

A concern with the results in Table 3 is that they actually reflect systematic differences in the quality of the firms or the nature of the strategy that confound the value of strategic fit with its adoption. While Table 4 helps disentangle the adoption effects by assessing whether higher quality firms are more likely to adopt strategic fit in less-financing-rich contexts, there might still be concern that some aspects of the startups or their strategy are accounting for their selection into strategic fit.

To help address this possibility, Table A8 repeats the analyses from Table 3, accounting for observable differences between firms, including firm age, industry, and founder education using coarsened exact matching. It also accounts for the content of strategy, including the objective, market, moat, and organizational approaches using LASSO models. The results are similar with these models: Strategic fit narrows differences in performance between startups in less- versus more-financing-rich contexts.

Table A8: Strategic fit narrows performance differences between less- and more-financing-rich contexts even when controlling for observable differences between firms and strategy content.

	(1) Log. Val (CEM)	(2) Log Val. (LASSO)	(3) Log Total Raised (CEM)	(4) Log Total Raised (LASSO)	(5) Log Val./ Employee (CEM)	(6) Log Val./ Employee (LASSO)	(7) Success. Exit (CEM)	(8) Success. Exit (LASSO)
Log HQ City VC	0.159^{*}	0.117^{***}	0.039	0.050^{*}	0.036	0.041^{***}	0.003	0.003
	(0.061)	(0.030)	(0.035)	(0.020)	(0.027)	(0.012)	(0.015)	(0.007)
Fit	1.008^{+}	0.416	0.658^{+}	0.641^{*}	0.391^{*}	0.137	0.116	0.198^{**}
	(0.558)	(0.318)	(0.365)	(0.251)	(0.177)	(0.108)	(0.093)	(0.067)
Fit x Log HQ City VC	-0.095^{+}	-0.046	-0.062^{+}	-0.056^{*}	-0.040^{*}	-0.019^{+}	-0.010	-0.018^{**}
	(0.050)	(0.029)	(0.034)	(0.022)	(0.016)	(0.011)	(0.009)	(0.006)
_cons	1.022		2.458^{*}		0.545		0.368	
	(1.298)		(1.124)		(0.569)		(0.311)	
N	104	209	152	304	104	208	152	304
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Performance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEM Matched	Yes	No	Yes	No	Yes	No	Yes	No
Strategy Content	No	Yes	No	Yes	No	Yes	No	Yes

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook and singleton observations.
$+\ p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.6 Results hold with economy-level proxy of local financing.

To ensure the robustness of the city financing measures, Table A9 repeats the analysis in Table 3 using economy-level measures of venture capital deal flows in 2018-2021 as reported in PitchBook. Table A9 shows that strategic fit's moderating effects generally hold. Strategic fit narrows the difference in performance between startups in less- versus more-financing-rich contexts.

Table A9: Strategic fit narrows performance differences between less- versus more-financing-rich contexts.

	(1) Log Val.	(2) Log Val.	(3) Log Val.	(4) Log Total Raised	(5) Log Total Raised	(6) Log Val./ Employee	(7) Log Val./ Employee	(8) Success. Exit	(9) Success. Exit
Log HQ Country VC	0.067	0.065	0.315*	0.008	-0.003	0.061***	0.085*	0.012+	0.030**
	(0.045)	(0.045)	(0.122)	(0.024)	(0.048)	(0.015)	(0.037)	(0.007)	(0.011)
Fit	0.031	0.977	1.610**	0.779*	0.904*	0.396*	0.773***	0.135	0.094
	(0.098)	(0.612)	(0.598)	(0.374)	(0.353)	(0.180)	(0.180)	(0.083)	(0.096)
Fit x Log HQ Country VC		-0.076	-0.128**	-0.056*	-0.069*	-0.035*	-0.063***	-0.010	-0.007
		(0.046)	(0.046)	(0.028)	(0.027)	(0.014)	(0.015)	(0.007)	(0.008)
_cons	3.306***	3.354***	-1.254	3.096***	3.112***	-0.011	-0.335	-0.049	-0.343
	(0.578)	(0.579)	(1.831)	(0.305)	(0.889)	(0.185)	(0.648)	(0.081)	(0.250)
N	246	246	207	304	302	245	207	304	302
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Performance	No	No	Yes	No	Yes	No	Yes	No	Yes
Filled-In FE	No	No	Yes	No	Yes	No	Yes	No	Yes
Readability	No	No	Yes	No	Yes	No	Yes	No	Yes
HQ Sub-Region	No	No	Yes	No	Yes	No	Yes	No	Yes
Top Uni	No	No	Yes	No	Yes	No	Yes	No	Yes

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.7 Results hold with Heckman model accounting for sample selection.

Table 1 shows North American startups and slightly older startups were less likely to interview for this study (Column 1). To account for this selection criteria, Table A10 repeats the analysis from Table A9, but now includes these North American and age selection factors in the first stage. It shows similar results. Strategic fit negatively moderates the positive relationship between local city venture capital and performance.

Table A10: Strategic fit attenuates the positive relationship between HQ city venture capital and startup growth even when accounting for selection criteria.

	(1) Log Val. North America Selection	(2) Log Val. Age Selection	(3) Success. Exit North America Selection	(4) Success. Exit Age Selection
main				
Log HQ City VC	0.131***	0.132***	0.004	0.004
	(0.028)	(0.027)	(0.007)	(0.006)
Fit	0.565*	0.407	0.182**	0.182**
	(0.277)	(0.326)	(0.070)	(0.070)
Fit x Log HQ City VC	-0.052*	-0.045	-0.017*	-0.017*
	(0.025)	(0.030)	(0.007)	(0.007)
_cons	-25.143	2.006+	23.399	23.401
	(72.612)	(1.041)	(20.526)	(20.510)
strategy_sample				
north_america	0.084		-0.255**	
	(0.064)		(0.078)	
age		-0.041**		-0.042***
		(0.014)		(0.013)
_cons	-1.289***	-0.990***	-0.884***	-0.783***
	(0.060)	(0.094)	(0.060)	(0.083)
/				
athrho	1.946***	-0.071	-0.010	-0.000
	(0.263)	(0.563)	(0.438)	(0.016)
lnsigma	0.745***	0.021	-1.244***	-1.244***
	(0.112)	(0.064)	(0.089)	(0.089)
N	1927	1909	2022	2004
Evaluator FE	Yes	Yes	Yes	Yes
Year Founded FE	Yes	No	Yes	Yes
Initial Perform.	Yes	Yes	Yes	Yes

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing year founded and/or valuation data from PitchBook. The models use a smaller set of fixed effects to enable convergence and given data availability. Column 2 excludes the year founded fixed effect to allow for convergence.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.8 Differences in investor preferences do not seem to drive results.

The theoretical framework suggests that one reason strategic fit is more valuable in less-financing-rich contexts is that investors in more-financing-rich contexts care *less* about strategic fit as a criterion for subsequent investment. They might either perceive it as constraining for growth or simply care more about other factors like the quality of the founders. This would mean that startups in these contexts with investors from more-financing-rich contexts would see less value in strategic fit. Table A11 tests this possibility by assessing how the relationship between strategic fit and performance varies by whether a startup based in a less-financing-rich context has an investor from the top three financing cities in the sample (San Francisco, New York, and London). It shows that there are no meaningful differences in the value of strategic fit for startups with or without these investors. These results are not consistent with the idea that investors in more-financing-rich contexts prefer strategic fit less.

Table A11: Differences in investor preferences do not seem to drive results.

	(1) Log Val.	(2) Log Total Raised	(3) Log Val./ Employee	(4) Success. Exit
Fit	0.084	-0.048	0.098	0.133*
	(0.439)	(0.193)	(0.144)	(0.063)
Top Hub Investor	0.371	0.270	0.389*	-0.110^{+}
	(0.440)	(0.180)	(0.172)	(0.060)
Fit x Top Hub Investor	-0.193	0.183	-0.026	-0.083
	(0.475)	(0.224)	(0.154)	(0.065)
_cons	1.060	4.164**	-0.853	0.141
	(1.834)	(1.471)	(0.571)	(0.301)
N	67	136	67	136
Evaluator FE	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Initial Performance	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes	Yes
Sample	Low VC	Low VC	Low VC	Low VC

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook, as well as singleton observations.
$+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.9 Moat and organizational external fit drive the results.

Table 6 shows that external fit drives the results. This suggests that preventing bad investments, rather than coordination or imitation costs, might help explain why strategic fit matters more in less-financing-rich contexts. What types of bad investments really matter?

To assess this question, Table A12 repeats the same exercise as Equation (2), but it breaks down the external fit measure into its three underlying components: market, moat, and organizational approaches. It shows that the negative moderating role of external fit is driven by organizational external fit for logged valuations as the performance variable (Columns 1–3). For total funding and probability of exit as performance variables, both organizational and moat organizational fit drive the results (Columns 4–9).

Together, this table suggests that moat and organizational external fit matter particularly for less-financing-rich contexts. These results are consistent with the idea that strategic fit helps startups in less-financing-rich contexts avoid bad moat and organizational investments, for example, related to their differentiating technology or hires, which can otherwise be difficult to recover from.

Table A12: Moat and organizational external fit drive the results

	(1) Log Val.	(2) Log Val.	(3) Log Val.	(4) Log Total Raised	(5) Log Total Raised	(6) Log Total Raised	(7) Success. Exit	(8) Success. Exit	(9) Success. Exit
Log HQ City VC	0.407*	0.552**	0.864***	0.186	0.439***	0.361*	0.033	0.109**	0.127**
	(0.165)	(0.202)	(0.245)	(0.127)	(0.119)	(0.172)	(0.035)	(0.035)	(0.049)
Market External	0.763+			0.361			0.081		
	(0.445)			(0.355)			(0.106)		
Market External x Log HQ City VC	-0.074+			-0.033			-0.009		
	(0.044)			(0.033)			(0.010)		
Moat External		1.188+			1.166**			0.316**	
		(0.604)			(0.368)			(0.098)	
Moat External x Log HQ City VC		-0.119*			-0.106**			-0.031**	
		(0.054)			(0.033)			(0.010)	
Org. External			2.339***			1.066*			0.372**
			(0.670)			(0.486)			(0.130)
Org External x Log HQ City VC			-0.198**			-0.081+			-0.034**
			(0.064)			(0.046)			(0.013)
_cons	-0.855	-2.305	-7.094*	1.299	-1.751	-1.408	-0.282	-1.167**	-1.406**
	(1.973)	(2.349)	(2.841)	(1.425)	(1.511)	(2.032)	(0.418)	(0.438)	(0.536)
N	207	207	207	302	302	302	302	302	302
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Performance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation data from PitchBook, as well as singleton observations.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.10 Strategic fit weakens the financing-performance relationship when in contexts with higher firing costs.

The theoretical framework suggests that avoiding bad investments might be one reason why strategic fit would matter in less-financing-rich contexts. One type of “bad" investment that startups in these contexts mentioned was difficult to reverse was around hiring the wrong talent. If this were the case, we would expect that strategic fit, especially external fit, would narrow performance differences between startups in less-versus more-financing-rich contexts when it is costly to fire, making bad hires that much more irreversible.

Consistent with this prediction, Table A13 and Table 7 show that strategic fit—particularly external fit—narrows performance differences between startups in less- versus more-financing rich contexts only when HQ country firing costs—drawn from Botero et al. (2004)—are above the sample median. The countries with the highest firing costs include The Netherlands, Indonesia, India, and South Korea. The countries with the lowest firing costs include New Zealand, Nigeria, Canada, and the US.

The differences are particularly meaningful even with the continuous version of the firing cost variable when assessing external fit that also drives the main results (Table 7).

Table A13: Strategic fit weakens the financing-performance relationship when in HQ contexts with higher firing costs.

	(1) Log Val.	(2) Log Val.	(3) Log Val.	(4) Log Total Raised	(5) Log Total Raised	(6) Log Total Raised	(7) Log Val./ Employee	(8) Log Val./ Employee	(9) Log Val./ Employee	(10) Success. Exit	(11) Success. Exit	(12) Success. Exit
Fit	-0.443	1.433**	-0.407	-0.161	0.367	-0.109	-0.275	0.387+	-0.212	0.134	0.277*	0.192
	(0.347)	(0.483)	(0.384)	(0.392)	(0.318)	(0.425)	(0.195)	(0.217)	(0.182)	(0.102)	(0.117)	(0.129)
Log HQ City VC	0.072*	0.094	0.074+	0.042	0.088*	0.044	0.015	0.021	0.025	-0.016	-0.007	-0.012
	(0.036)	(0.064)	(0.042)	(0.027)	(0.035)	(0.032)	(0.018)	(0.026)	(0.021)	(0.014)	(0.011)	(0.013)
Fit x Log HQ City VC	0.020	-0.144*	0.014	0.003	-0.020	-0.000	0.015	-0.039	0.007	-0.010	-0.031*	-0.015
	(0.032)	(0.058)	(0.035)	(0.032)	(0.038)	(0.036)	(0.017)	(0.024)	(0.017)	(0.008)	(0.013)	(0.011)
Firing Cost			-5.803***			0.231			-1.082+			0.103
			(1.549)			(0.993)			(0.585)			(0.327)
Fit x Firing Cost			1.806*			1.682+			0.852*			0.045
			(0.811)			(0.963)			(0.371)			(0.287)
Log HQ City x Firing Cost			0.176			0.081			0.015			0.043
			(0.128)			(0.096)			(0.055)			(0.033)
Fit x Log HQ VC x Firing Costs			-0.125			-0.127			-0.053			-0.014
			(0.092)			(0.095)			(0.042)			(0.030)
_cons	1.746+	2.215	2.992***	2.052**	3.346**	2.295**	0.671	0.553	0.742+	0.087	-0.148	-0.043
	(0.926)	(2.858)	(0.863)	(0.752)	(1.234)	(0.703)	(0.477)	(0.981)	(0.410)	(0.335)	(0.274)	(0.229)
N	137	64	205	158	138	297	137	64	205	158	138	297
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Performance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Low Cost	High Cost	Full	Low Cost	High Cost	Full	Low Cost	High Cost	Full	Low Cost	High Cost	Full

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook, as well as singleton observations and missing firing cost data from Iceland, Qatar, Serbia, and Seychelles.

$+\ p < 0.1$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

A.11 The results are not stronger in more competitive sub-sectors, suggesting that imitation costs are not driving the results.

Table 5 reveals that strategic fit is more valuable for startups in less-financing-rich contexts. One possibility for this is that these startups are able to deter imitation risk because of how complicated their set of interconnected activities are, and it might be harder to recover from imitation risks outside of major financing hubs. If this was a driving mechanism behind strategic fit narrowing performance differences between startups in less- versus more-financing-rich contexts, we would expect that internal fit would drive the results—since this interconnected set of activities makes imitation quite challenging (Rivkin 2000). This does not appear to be the case—external fit, in fact, consistently drives the results, as shown in Table 6.

An additional test to confirm whether the reduction in imitation risk is driving the results is to see whether the baseline results are larger in more competitive sub-sectors. We would expect this to be the case if a key value of strategic fit is to reduce the risk of imitation, which would be higher in sub-sectors with more competitors. Table A14 conducts this analysis and finds that the negative moderating role of strategic fit is not any stronger in sub-sectors with more competitors. These results are not consistent with the reduction in imitation risk driving the results.

Table A14: The results are not stronger in more competitive sub-sectors.

	(1) Log Val.	(2) Log Val.	(3) Log Val.	(4) Log Total Raised	(5) Log Total Raised	(6) Log Total Raised	(7) Log Val./ Employee	(8) Log Val./ Employee	(9) Log Val./ Employee	(10) Success. Exit	(11) Success. Exit	(12) Success. Exit.
Fit	0.811	-0.104	0.460	0.740*	0.236	0.907*	0.135	0.075	-0.108	0.254*	0.076	0.256*
	(0.530)	(0.341)	(0.575)	(0.351)	(0.282)	(0.370)	(0.213)	(0.184)	(0.210)	(0.099)	(0.087)	(0.124)
Log HQ City VC	0.158***	0.024	0.211***	0.068*	-0.002	0.092**	0.056*	-0.007	0.067**	-0.001	-0.019	-0.005
	(0.045)	(0.057)	(0.048)	(0.030)	(0.041)	(0.033)	(0.022)	(0.020)	(0.021)	(0.008)	(0.018)	(0.010)
Fit x Log HQ City VC	-0.070	-0.013	-0.040	-0.057^{+}	-0.026	-0.074*	-0.015	-0.013	0.005	-0.024**	-0.006	-0.025*
	(0.051)	(0.031)	(0.056)	(0.032)	(0.025)	(0.035)	(0.020)	(0.016)	(0.020)	(0.009)	(0.009)	(0.011)
Competitors			0.000**			0.000			0.000*			0.000
			(0.000)			(0.000)			(0.000)			(0.000)
Fit x Competitors			-0.000			-0.000			0.000			-0.000
			(0.000)			(0.000)			(0.000)			(0.000)
Log HQ City x Competitors			-0.000*			-0.000			-0.000*			0.000
			(0.000)			(0.000)			(0.000)			(0.000)
Fit x Log HQ VC x Competitors			0.000			0.000			-0.000			0.000
			(0.000)			(0.000)			(0.000)			(0.000)
_cons	2.236^{+}	0.702	2.548**	3.025***	2.611*	2.110**	0.731	-0.492	0.209	-0.241	0.666	-0.011
	(1.319)	(1.528)	(0.952)	(0.883)	(1.164)	(0.740)	(0.550)	(0.736)	(0.424)	(0.216)	(0.471)	(0.246)
N	117	89	245	174	126	302	117	89	244	174	126	302
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Performance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Less Comp.	More Comp.	Full	Less Comp.	More Comp.	Full	Less Comp.	More Comp.	Full	Less Comp.	More Comp.	Full

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook, as well as singleton observations.

$+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.12 The results are not stronger in more regulated sub-sectors, suggesting that coordination costs are not driving the results.

Another possibility for why strategic fit might be more valuable for startups in less-financing-rich contexts (as shown in Table 5) is that these startups are better able to coordinate their teams, and these team coordination costs can be harder to recover from without sufficient financial support. If this was a driving mechanism behind strategic fit narrowing performance differences between startups in less- versus more-financing-rich contexts, we would expect that internal fit would drive the results, since the organizational structure and culture would be connected with the objective of the company, keeping everyone on the same page (Porter 1996). This does not appear to be the case—external fit, in fact, consistently drives the results, as shown in Table 6.

Another test to confirm whether the reduction in team coordination costs is driving the results is to see whether the baseline results are larger in more regulated sub-sectors where coordination costs would be higher, for example, because of the need to liaise between public and private stakeholders (Mahon & Murray Jr 1981). We would expect this to be the case if a key value of strategic fit is to reduce the risk of team coordination failures, which would be higher in sub-sectors with more need for coordination. Table A15 conducts this analysis and finds that the negative moderating role of strategic fit is not any stronger in more regulated sub-sectors. These results are not consistent with the reduction in team coordination costs driving the results.

Table A15: The results are not stronger in more regulated sub-sectors.

	(1) Log Val.	(2) Log Val.	(3) Log Val.	(4) Log Total Raised	(5) Log Total Raised	(6) Log Total Raised	(7) Log Val./ Employee	(8) Log Val./ Employee	(9) Log Val./ Employee	(10) Success. Exit	(11) Success. Exit	(12) Success. Exit.
Log HQ City VC	0.086*	0.205*	0.100**	0.084***	-0.031	0.081***	0.021	0.051^{+}	0.027^{+}	0.000	0.004	-0.004
	(0.036)	(0.080)	(0.034)	(0.022)	(0.039)	(0.022)	(0.017)	(0.029)	(0.015)	(0.011)	(0.012)	(0.009)
Fit	0.532	0.920	0.617	0.391	1.307*	0.425^{+}	0.131	0.239	0.211	0.153*	0.298	0.158*
	(0.514)	(0.698)	(0.444)	(0.237)	(0.580)	(0.239)	(0.170)	(0.305)	(0.153)	(0.073)	(0.198)	(0.075)
Fit x Log HQ City VC	-0.063	-0.082	-0.066^{+}	-0.040^{+}	-0.115*	-0.045*	-0.017	-0.024	-0.024^{+}	-0.011^{+}	-0.032	-0.011
	(0.045)	(0.064)	(0.039)	(0.023)	(0.054)	(0.023)	(0.015)	(0.028)	(0.014)	(0.006)	(0.019)	(0.007)
Regulated			-0.842			0.881*			-0.190			-0.034
			(0.733)			(0.405)			(0.290)			(0.134)
Fit x Regulated			0.002			1.004			0.001			0.049
			(0.796)			(0.625)			(0.341)			(0.191)
Log HQ City x Regulated			0.084			-0.072^{+}			0.017			0.007
			(0.068)			(0.038)			(0.027)			(0.014)
Fit x Log HQ VC x Regulated			0.002			-0.077			-0.001			-0.012
			(0.071)			(0.057)			(0.031)			(0.018)
_cons	1.039	2.377^{+}	2.084*	1.441^{+}	4.655***	2.179**	-0.227	1.091^{+}	0.585	0.180	-0.057	0.035
	(1.390)	(1.405)	(0.930)	(0.842)	(1.315)	(0.712)	(0.559)	(0.622)	(0.427)	(0.337)	(0.321)	(0.203)
N	113	89	207	167	130	302	113	89	207	167	130	302
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Performance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Not Regulated	Regulated	Full	Not Regulated	Regulated	Full	Not Regulated	Regulated	Full	Not Regulated	Regulated	Full

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of missing valuation and/or employee data from PitchBook, as well as singleton observations.
$+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.13 Strategic fit predicts less office closures.

Research suggests that strategic fit can help companies prevent bad investments (e.g., Van den Steen 2017; Porter 1996). Correlating the strategic fit scores with bad commitments can empirically shed light on this. But getting data on whether companies made a bad commitment is difficult. One proxy of a bad commitment that is possible to get from existing data (PitchBook) is whether companies closed an office or subsidiary.

Figure A.13 shows a negative relationship between the strategic fit score (on the x-axis) and the number of regional office and subsidiary closures (on the y-axis). Even when controlling for other initial differences between firms like the initial founding amount, Table A16 shows that a higher strategic fit score is weakly associated with less regional and subsidiary office closures alone (Column 1). Consistent with external fit driving the performance results in Table 3, external fit (Column 2) rather than internal fit (Column 3) also drives the reduction in the number of closed offices. Together, the negative relationship between strategic fit and regional office closures is consistent with the idea that strategic fit can help companies avoid bad commitments.

Figure A.13: Strategy negatively predicts offices closures

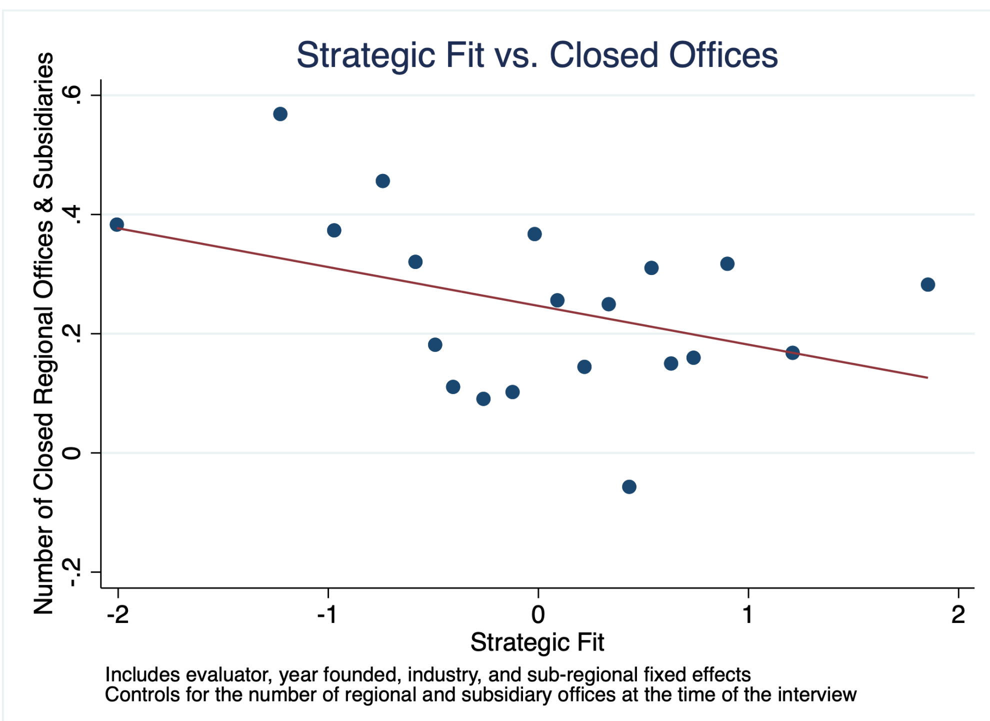


Table A16: Strategic fit weakly negatively predicts future office closures.

	(1) Num. Closed Offices	(2) Num. Closed Offices	(3) Num. Closed Offices
Fit	-0.068^{+}		
	(0.038)		
External Fit		-0.080^{+}	
		(0.042)	
Internal Fit			-0.050
			(0.042)
_cons	-0.120	-0.152	-0.119
	(0.318)	(0.313)	(0.319)
N	302	302	302
Evaluator FE	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes
Readability	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes
Top Uni	Yes	Yes	Yes
Initial Num. Offices	Yes	Yes	Yes
Initial Log Total Raised	Yes	Yes	Yes

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of singleton observations.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.14 Startups in less-financing-rich contexts have similar objectives as those in more-financing-rich contexts.

Could it be that startups in more-financing-rich contexts are more growth-oriented accounting for the differences in results? If this were the case, we would expect them to be less likely to have strategic fit because this fit might come at the expense of moving quickly.

We would expect that that strategic fit scores would be lower for startups in more-financing-rich contexts. Table 4 shows that there are not meaningful differences between the two, which is inconsistent with this alternative mechanism.

To further assess this possibility, Table A17 shows how the stated objective of executives varies by their local financing context. The key "growth" objectives cited from prior work—getting acquired and going public (Guzman & Stern 2020)—do not vary among startups in less- versus more-financing-rich contexts. While startups in more-financing-rich contexts are more likely to want to be a unicorn and market leader, they are actually less likely to want to become global and grow users. There is no difference in their objectives to grow revenue, become profitable, raise more funding, or achieve a social impact objective. These results suggest that there are not consistent differences in growth motivations between the two contexts.

Table A17: Startups in more-financing-rich contexts are not more like to be growth-oriented.

	(1) Increase Revenue	(2) Get Acquired	(3) Go Public	(4) Grow Users	(5) Become Global	(6) Market Leader	(7) Create Market	(8) Unicorn (Bil.+ USD Val.)	(9) Become Profitable	(10) Raise More Funding	(11) Social Impact
Log HQ City VC	-0.002	-0.006	0.012	-0.031*	-0.044***	0.018^{+}	-0.009	0.009*	0.004	-0.005	0.003
	(0.013)	(0.006)	(0.008)	(0.013)	(0.011)	(0.010)	(0.008)	(0.004)	(0.006)	(0.009)	(0.007)
_cons	0.534	0.180	0.069	0.294	0.276	0.711*	0.085	-0.263^{+}	0.069	0.153	-0.017
	(0.374)	(0.160)	(0.255)	(0.405)	(0.261)	(0.324)	(0.209)	(0.140)	(0.173)	(0.338)	(0.179)
N	302	302	302	302	302	302	302	302	302	302	302
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Founded FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Filled-In FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Readability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Sub-Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors (in parentheses) are clustered at the company level. The sample size drops because of singleton observations.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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