Received: 20 June 2022 | Revised: 24 January 2024 | Accepted: 6 February 2024

DOI: 10.1002/smj.3596

RESEARCH ARTICLE

SMS | Strategic Management Journal

WILEY

When do startups scale? Large-scale evidence from job postings

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Abstract

Research Summary: Scaling at the right time is a crucial challenge for startups. Conceptualizing "scaling" as the entrepreneurial process of acquiring and committing resources to implement the core business idea and expand the customer base, this study examines how scaling early may decrease imitation risk at the expense of increasing commitment risk. As startups typically hire managers and sales personnel when they begin to scale, we propose that this timing can be empirically measured by when startups first post these jobs. Leveraging a dataset of job postings, we find that early scalers are more likely to fail, but no evidence of a countervailing benefit in terms of successful exit. Additional analyses suggest that the commitment risk in scaling early outweighs the benefit of reducing imitation risk.

Managerial Summary: In recent years, a few high-growth startups (e.g., Facebook and Uber) that made their fortune by scaling early—an approach often referred to as "blitzscaling"—have received much interest among academics and practitioners. However, this study presents large-sample evidence that scaling early is positively associated with a higher rate of firm

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failure, especially for platform companies. These findings imply that, despite its potential benefits of preventing imitation by competitors, scaling early can suppress startup performance by prematurely curtailing learning through experimentation and committing to a business idea that lacks product-market fit. In sum, our work cautions startups against prioritizing scaling early before finding product-market fit, and instead highlights the importance of spending sufficient time on experimentation before scaling.

KEYWORDS

entrepreneurship, human capital, organization design, timing, venture scaling

1 | INTRODUCTION

> "Scaling at the right time is tough. Too early and you waste money and get distracted. Too late and you miss the market or run out of runway" (Marmer et al., 2011, p. 43).

Entrepreneurial ventures play a crucial role in creating jobs and spurring innovation (Decker et al., 2014; Gans et al., 2002). Unfortunately, however, most of these startups fail to grow to fulfill such a role (Choi et al., 2023; Guzman & Stern, 2020), more than often because they poorly time when to scale their business (Eisenmann, 2021; Furr & Ahlstrom, 2011; Hoffman & Yeh, 2018; Marmer et al., 2011). Just as Penrose (1959, p. 19) likens this growth process to a metamorphosis from "a caterpillar" to "a butterfly," scaling represents a significant organizational transformation that poses major administrative challenges to firms in the early stages of their life cycle. Given its strategic importance and challenges, this phenomenon has been the focus of a growing body of research. As Ott and Eisenhardt (2020), pp. 2308–2309 point out, this research has shed important light on its antecedents (e.g., founding conditions; Agarwal et al., 2020, Eisenhardt & Schoonhoven, 1990) or its consequences (e.g., changes in organizational design; DeSantola & Gulati, 2017, Lee, 2022).

However, little scholarly attention has, thus far, been paid to the timing of when startups begin to scale and undertake this organizational transformation. Like other temporal decisions (e.g., Lieberman & Montgomery, 1988; McDonald & Eisenhardt, 2020; Schilling, 2002), this timing of scaling could be consequential to startup performance because this time-bound decision can leave startups with narrow "windows of opportunity" (Davis et al., 2009, p. 419, Tyre & Orlikowski, 1994). When making such a decision, entrepreneurs, as boundedly rational agents with resource constraints (Chen et al., 2022; Cohen et al., 2019; Gans et al., 2019), can be susceptible to "jumping the gun" (Clydesdale, 2009) or "missing the boat" (Mullins & Forlani, 2005). In this vein, practitioner-oriented pieces have offered compelling yet opposing anecdotes (mostly in the context of two-sided platforms) on when startups should scale. While some argue that startups should scale early (Chen, 2021; Hoffman & Yeh, 2018), others suggest that scaling early can be detrimental to startup performance (Eisenmann, 2021; Furr &

Ahlstrom, 2011; Marmer et al., 2011). This conflicting anecdotal evidence has not been theoretically and empirically examined, partly due to a lack of consensus on the concept of scaling and an absence of a generalizable empirical measurement. Hence, several scholars remark that much remains to be learned about when this entrepreneurial process unfolds and its consequences (Dushnitsky & Matusik, 2019, pp. 442–443, Puranam, 2018, p. 111).

To investigate how the timing of scaling affects startup performance, we first draw upon the literature on the entrepreneurial process (e.g., Agrawal et al., 2021; Gans et al., 2019; Kirzner, 1997). This literature demonstrates that new ventures first engage in "experimentation"—that is, an iterative learning process of trial-and-error in testing and deciding the core business idea (Chen et al., 2022; Contigiani & Levinthal, 2019; Murray & Tripsas, 2004). Leveraging this notion of experimentation, we conceptualize "scaling" as the subsequent process in which startups primarily focus on acquiring and committing new resources to implement the chosen core business idea and expand their customer base. We then incorporate insights from both the academic literature and practitioner-oriented work on these two processes to formulate a theoretical framework for the timing of scaling (i.e., the point in time when a new venture shifts its primary focus from experimentation to scaling). Our framework suggests that, like other decisions during the entrepreneurial process (e.g., Ching et al., 2018; Contigiani, 2023; Gans & Stern, 2017), this timing can entail a tension between value appropriation (i.e., imitation risk) and learning (i.e., commitment risk). That is, while scaling early may allow startups to reduce imitation risk and appropriate more value from their business idea, it may prematurely curtail their learning through experimentation and thus result in a higher risk of committing to a business idea that lacks product-market fit. In particular, for two-sided platforms, these two opposing forces may be amplified because the salience of network effects and economies of scale can further reduce imitation risk (Katz & Shapiro, 1994; Saadatmand et al., 2019), while the complex interdependencies in two-sided markets may heighten the dangers of conducting insufficient experimentation and thus committing to a business idea with poor product-market fit (Büge & Ozcan, 2021; McDonald & Eisenhardt, 2020).

Building upon the literature on firm growth and organizational design, we then propose a methodological approach to measure the timing of scaling. More specifically, as this early-stage growth in resources and customer base generally exceeds the expertise or managerial capacity of the founding teams (Penrose, 1959, pp. 186–188), it presents unique administrative challenges to nascent firms—commonly referred to as "growing pains" (Flamholtz & Randle, 2015). To tackle these challenges, startups formally recruit specialized human resources: namely, managers and sales personnel (Kazanjian, 1988; Penrose, 1959). As new ventures typically hire these human resources before scaling their business (Hambrick & Crozier, 1985, p. 37), we suggest that the timing of scaling can be empirically measured using the first manager and sales postings.

To examine when startups begin to scale and the underlying tension between imitation risk and commitment risk, we develop new empirical measures of the timing of scaling using job postings. This dataset consists of 6.3 million job postings for more than 38,000 startups founded in the United States after 2010. As this dataset includes information on the date and the occupational family of each job posting, it allows us to measure precisely when each company posts its first manager and sales jobs. Furthermore, it enables us to observe company status (i.e., operating, acquired, IPO, or closed) and various organizational characteristics (e.g., founding year, location, funding, patent protection, competition, and industry).

Before applying these new measures, we undertake three different approaches to demonstrate that these measures indicate when startups begin scaling: (1) assessing the word occurrence of "scale" and "scaling" in the job postings, (2) analyzing when startups enlist their first manager and sales postings relative to their first venture capital (VC) funding, and (3) examining the case of PillPack. First, the word occurrence analyses reveal that, compared with the other ones, the first manager and sales postings show a disproportionate increase in the terms "scale" and "scaling," thus indicating startups' intention to begin scaling. Second, in line with the observation that startups receive financial resources from VCs to exponentially grow in terms of employees and sales (Bertoni et al., 2011), we find that the first manager and sales postings predominantly occur after the first VC funding. Finally, the case of PillPack, which provides rare documentation of the detailed timeline of scaling (e.g., Schoen & Farr, 2019; Stern & Fehder, 2019), offers anecdotal support for our measures as this company went on a nationwide hiring spree and grew to $100 million in revenue after its first manager and sales postings. Taken together, the results of these three analyses enhance the credibility of our empirical measures.

After substantiating our measures, we offer a descriptive analysis to establish stylized facts about the timing of scaling. We find that startups, on average, begin scaling 4 years after their founding. However, this timing of scaling varies significantly across these firms. Most notably, startups that scale early are less likely to engage in experimentation through A/B testing. In addition, contrary to the common belief that startups operating in a new market (i.e., no competitors before entry) should scale early to reduce the risk of imitation, they tend to scale later than those in a more established market. Moreover, this timing differs substantially with firm outcomes: that is, early scalers are associated with a higher likelihood of failure than their peers that scale later.

We further probe into this relationship between the timing of scaling and firm outcomes through a series of regression analyses. Our results show that startups that begin scaling in the first 6 or 12 months of their founding are 20–40% more likely to fail. However, we do not find any evidence of a countervailing benefit of scaling early in terms of a successful exit (e.g., IPO or large acquisition). We then examine the underlying mechanisms. Most substantively, consistent with the view that early scaling can increase commitment risk, we find that the amplified failure odds linked to scaling early are almost entirely driven by startups that do not engage in A/B experimentation. In contrast, we do not find meaningful evidence that scaling early can be beneficial by reducing imitation risk, which we measure using various proxies including patent protection and the degree of competition. Together, these results imply that, despite its potential benefits of decreasing imitation risk, scaling early can suppress startup performance by prematurely curtailing learning through experimentation and increasing commitment risk. Finally, we find that the association between scaling early and higher failure rates is more than three times stronger for platform startups than for their non-platform counterparts, while the likelihood of successful exit does not substantially vary.

Our study contributes not only to the burgeoning stream of research on the entrepreneurial process, but more broadly to the literature on firm growth, organizational design, and two-sided platforms. First, by integrating diverse insights from these prior studies, this study proposes a conceptualization of scaling that can facilitate future research on this phenomenon. Second, our work highlights that the timing of when startups (especially, two-sided platforms) begin to scale is a crucial temporal decision during the entrepreneurial process that has, thus far, received little scholarly attention. Third, this article sheds light on how this temporal decision can simultaneously affect both imitation risk and commitment risk—a fundamental tension underlying the entrepreneurial process (Contigiani, 2023; Gans et al., 2019) and two-sided platforms (McIntyre, 2011; Schilling, 2002). Fourth, by documenting the first large-scale analysis of when startups scale, this article stimulates new avenues of inquiry on its antecedents. Finally, we present a novel methodological approach using labor market data to empirically operationalize the timing of scaling. This approach enables future inquiry into the ensuing process of scaling. More generally, it illustrates that job postings are meaningful real-time events that reflect a firm's strategic intentions and organizational design changes, thus offering a building block for large-sample research that systematically explores evolutionary patterns of strategy and structure.

2 | THEORETICAL BACKGROUND

2.1 | The entrepreneurial process

Organization scholars have long argued that, as firms grow and develop over time, they undertake different processes, addressing different organizational needs and problems and acquiring different resources and capabilities (Greiner, 1972; Helfat & Peteraf, 2003; Penrose, 1959). In particular, entrepreneurship research demonstrates that newly established firms typically engage in two important processes: *experimentation* (Chen et al., 2022; Contigiani & Levinthal, 2019; Koning et al., 2022; Murray & Tripsas, 2004) and *scaling* (DeSantola & Gulati, 2017; Eisenmann, 2021; Furr & Ahlstrom, 2011; Sutton & Rao, 2014). In Figure 1, we illustrate the theoretical framework of how these two stylized processes, in theory, proceed.[1]

First, new ventures face the problem of reducing uncertainty and finding the core business idea that fits the market and creates value (Kirzner, 1997). Thus, they focus on the process of *experimentation*, which refers to a series of trial-and-error in testing the parameters of the core business idea (Chen et al., 2022; Contigiani & Levinthal, 2019; Murray & Tripsas, 2004). During this learning process, these new ventures make explicit assumptions, which act as scientific hypotheses subject to falsification (Zellweger & Zenger, 2023). To validate these hypotheses, they run A/B tests, conduct interviews with focus groups, and consult with experts and friends (Bennett & Chatterji, 2023, pp. 9–10, Koning et al., 2022). When they receive feedback that refutes their hypotheses, these firms may choose to pivot away from these unsupported assumptions or strategically reorient their whole business idea (Kim & Kim, 2024; Kirtley & O'Mahony, 2023; McDonald & Gao, 2019), and cycle through this process until they believe that their core business idea fits the market (Agrawal et al., 2021; Chen et al., 2022; McDonald & Eisenhardt, 2020). If these companies fail to find such a business idea through this iterative process, they may choose to exit and discontinue their operation (Chen et al., 2022). This scientific approach of experimentation can thus reduce commission error and, ultimately, improve startup performance (Camuffo et al., 2019; Koning et al., 2022).

Once they have chosen a core business idea through experimentation, new ventures encounter the subsequent problem of implementing the chosen core business idea to capture value (Gans et al., 2019). To address this problem, these startups shift their main focus to the process of *scaling*: that is, acquiring and committing new resources to implement the chosen

[1]Prior research on entrepreneurship has used various other terminology to describe these two processes. For example, Kazanjian (1988) refers to these processes as "conception and development" and "growth," while Ott and Eisenhardt (2020) distinguish between "strategy formulation" and "scaling." In practitioner-oriented work, Sutton and Rao (2014) make the distinction between the process of "uncovering and meeting customer needs" and the process of "scaling up," whereas Eisenmann (2021) does so between "launching" and "scaling." However, it is important to note that the distinction between these processes does not imply that new ventures completely discontinue experimentation after scaling. Instead, it suggests that, once these firms have experimented and chosen a core business idea, their primary focus shifts to scaling and implementing the chosen business idea (Contigiani & Levinthal, 2019, p. 554). Although new ventures may continue to experiment with and fine-tune their chosen core business idea after scaling, pivoting the whole business idea post-scaling can be prohibitively costly as these companies have already committed new resources and made irreversible investments during scaling (Chen et al., 2022, Furr & Ahlstrom, 2011, Gans et al., 2019, p. 741).

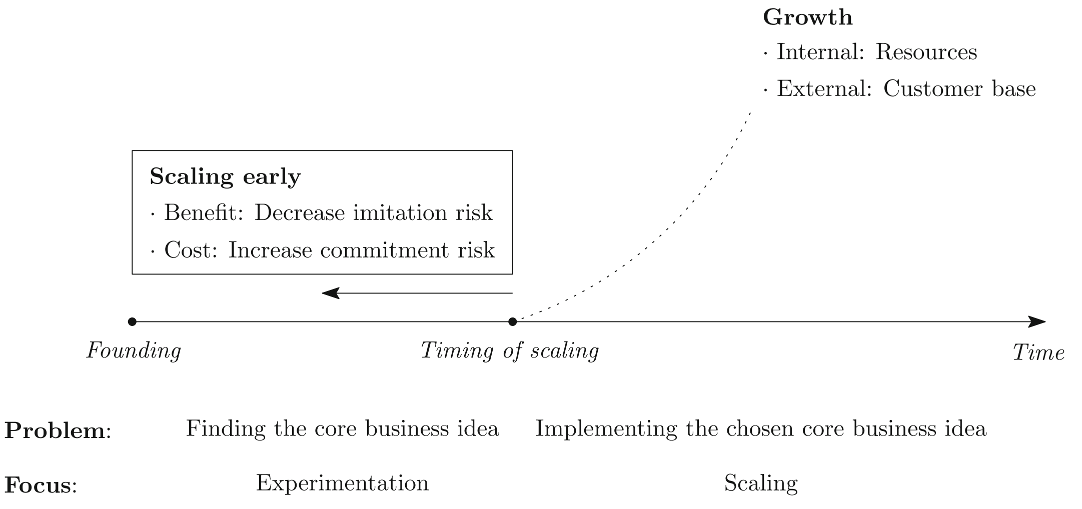

FIGURE 1 Summary of our theoretical framework. Here, experimentation refers to the iterative process of testing and pivoting the key parameters of the core business idea, whereas scaling is defined as the process of acquiring and committing new resources (e.g., new employees) to implement the chosen business idea and expand the customer base. In turn, the timing of scaling denotes the point in time when a new venture shifts its primary focus from experimentation to scaling.

business idea and expand their customer base. As Kazanjian (1988, pp. 262–264) finds in his in-depth case study, "all ventures go through a period during which the primary focus of the entrepreneur … is on the invention and development of a product [i.e., experimentation]. … If a product is technically feasible and achieves market acceptance, a period of high growth [i.e., scaling] will typically result" (comments added). Similarly, Eisenmann and Wagonfeld (2012, p. 1) suggest that "after a startup has found product-market fit—that is, after it has validated its business model and has a repeatable monetization process—it usually begins scaling up." Chen et al. (2022, p. 10) exemplify this transition in the case of Spotify: "Once sufficient learning [through experimentation] took place to establish demand, Spotify fully entered the market, *scaling* their operations and music collection to serve a mass market" (comment and emphasis added). Penrose (1960, p. 1) thus highlights that "[this] growth is governed by a creative and dynamic interaction between a firm's productive resources and its market opportunities."

Hence, scaling constitutes an informed and intentional process of internal and external growth (Ott & Eisenhardt, 2020, p. 2308, Penrose, 1959, p. 2). Here, internal (or supply-side) growth involves an increase in resources (e.g., new employees beyond the founding team), whereas external (or demand-side) growth reflects an increase in customer base beyond the early adopters.[2] As this growth accompanies a disproportionate increase compared to their existing resources and customer base, new ventures encounter new levels of administrative

[2]This concept of scaling is distinct from two related constructs: "scalability" and "economies of scale." First, scalability points to the phenomenon in which the value of a resource does not decrease with the magnitude of firm operations over which it is applied (Levinthal & Wu, 2010, p. 781). In turn, economies of scale refer to the phenomenon in which a firm's number of output units (i.e., "scale") decreases its average unit cost of inputs (Stigler, 1958). Unlike these two phenomena, which are independent of firm age, scaling centers on the growth process of new ventures. Although this early-stage process may prioritize the attainment of scalable resources and economies of scale (Giustiziero et al., 2023; Piaskowska et al., 2021), scaling may not necessarily achieve these goals, as it typically requires non-scale-free resources (e.g., specialized human resources) and incurs a disproportionate increase in costs (e.g., salary).

complexity. To address this increased complexity, they undertake an organizational transformation that is distinct from growth in the later stages of their life cycle (DeSantola & Gulati, 2017; Lee, 2022). As Penrose (1959, p. 19) describes:

> With increasing size, both the managerial function and the basic administrative structure have undergone fundamental changes which profoundly affect the nature of the "organism." The differences in the administrative structure of the very small and the very large firms are so great that in many ways it is hard to see that the two species are of the same genus … we cannot define a caterpillar and then use the same definition for a butterfly.

Like other temporal decisions (e.g., Lieberman & Montgomery, 1988; McDonald & Eisenhardt, 2020; Schilling, 2002), when startups begin to scale and undertake this transformation can be consequential to their performance because this decision is time-bound (Delmar & Shane, 2004, p. 407, Wood et al., 2021). When making such a decision with narrow "windows of opportunity" (Davis et al., 2009, p. 419), entrepreneurs, as boundedly rational agents with resource constraints (Chen et al., 2022; Cohen et al., 2019; Gans et al., 2019), could be susceptible to "jumping the gun" (Clydesdale, 2009) or "missing the boat" (Mullins & Forlani, 2005). Accordingly, practitioner-oriented pieces (e.g., Eisenmann, 2021; Furr & Ahlstrom, 2011; Hoffman & Yeh, 2018; Marmer et al., 2011) have presented compelling yet conflicting anecdotes (primarily in the context of two-sided platforms) on how this temporal decision can affect startup performance. In what follows, we synthesize anecdotal insights and prior scholarly research to assess the theoretical link between the timing of scaling and subsequent startup performance. This framework suggests that this temporal decision of when startups begin scaling may simultaneously affect imitation risk and commitment risk.

2.2 | Why the timing of scaling may affect startup performance

On the one hand, scaling early could be beneficial to startups because it can reduce the risk of imitation, which is a fundamental problem that they face when appropriating the value of their core business ideas (Contigiani, 2023, p. 2, Gans et al., 2002, p. 573).[3] The more a startup delays its scaling and spends time on experimentation to explore and fine-tune its core business idea (e.g., by running A/B tests, conducting interviews with focus groups, or consulting with experts and friends), the more likely that it discloses its core business idea to and thus imitated by its competitors (Agrawal et al., 2021, p. 5516, Contigiani, 2023). This imitation can substantially erode the value captured by the startup (Gans et al., 2002; Gans & Stern, 2017). One approach to mitigate this erosion and improve value appropriation is to leverage patents or other forms of intellectual property rights (Posen et al., 2023, p. 82). However, these rights can take a significant amount of time and cost to acquire and, when granted, provide weak protection against imitation—especially for such small firms (Lanjouw & Schankerman, 2004)—as competitors can "reverse engineer" or "invent around" the disclosed intellectual property (Gans & Stern, 2003, p. 339, Mansfield et al., 1981, p. 907). Thus, rather than spending more time on

[3]In this study, we adopt Posen et al.'s (2023, p. 6) definition of imitation: that is, "a firm's purposeful attempts to reproduce, in whole or part, another firms' products, processes, capabilities, technologies, structures, and/or decisions in its pursuit of competitive advantage."

experimentation and/or pursuing intellectual property rights, startups may scale early and speed up their execution (Ching et al., 2018; Gans & Stern, 2017) to quickly gain alternative mechanisms that deter imitation (i.e., "entry/mobility barriers" or "isolating mechanisms"; Caves & Porter, 1977, Rumelt, 1984, p. 568). While scaling early may not necessarily outright prevent imitation, doing so can reduce the cost associated with potential imitation (i.e., risk) by allowing the startup to "get ahead and stay ahead" (Ching et al., 2018, p. 390).

First, early scalers may preemptively amass a diverse set of scarce, difficult-to-imitate resources (Dierickx & Cool, 1989; Knott et al., 2003), such as specialized inputs, superior human capital, complementary assets, or geographic location. For instance, Beyond Meat, a U.S. startup producing plant-based meat substitutes, was able to procure long-term contracts with its suppliers and lock up a large percentage of the world's supply of its key inputs (e.g., pea proteins; Eisenmann, 2021, p. 44). Second, they may have a head start in learning new knowledge that is difficult to imitate (Posen & Chen, 2013) due to, for example, its tacitness (Kogut & Zander, 1992), causal ambiguity (Ryall, 2009), complexity (Rivkin, 2000), or interdependence (Lenox et al., 2007). Third, by accumulating such resources and knowledge in production early, these startups may enjoy greater returns to scale and learning (Leiblein et al., 2023; Spence, 1981; Stigler, 1958). Fourth, by intricately developing their business, these firms may make it costly and difficult for their imitators to fully observe, understand, and reproduce their business (Posen & Martignoni, 2018). Fifth, early scalers may secure a dominant market position by aggressively acquiring the buyers (e.g., using word-of-mouth referrals), establishing brand reputation and image, and locking in these buyers by increasing their switching costs with firm-specific product features (e.g., loyalty programs). Finally, they may do so through network effects by introducing a product whose value increases with the number of buyers (Katz & Shapiro, 1994). Hence, this line of reasoning suggests that startups that begin to scale their business early will experience higher performance.

On the other hand, scaling early could be detrimental to startups because it can inevitably reduce the time spent on the iterative learning process of experimentation, thereby increasing the risk of committing to a business idea with poor product-market fit. As this learning process is crucial for reducing commission error and enhancing startup performance (Camuffo et al., 2019; Koning et al., 2022), new ventures should, in theory, shift their primary focus from experimentation to scaling their business once they develop a product that best fits the market and creates value (Contigiani & Levinthal, 2019, p. 9, Chen et al., 2022). As one founder emphasizes: "Only when a startup *objectively* demonstrates that product-market fit is achieved and a pattern of revenue generation is *clearly* identified, it makes sense to scale the business model and grow" (Marmer et al., 2011, p. 12). However, as entrepreneurs are boundedly rational and resource-constrained (Gans et al., 2019), they tend to underestimate the time required for experimentation and satisfice prematurely across many decisions (Chen et al., 2022; Cohen et al., 2019). Consistent with this line of reasoning, Eisenmann (2021, p. 10) observes that, in many cases, "entrepreneurs, beguiled by the enthusiasm of a few early adopters, incorrectly extrapolate strong demand to the mainstream market and step on the gas." Although startups may continue to experiment after scaling to fine-tune their core business idea, pivoting the whole business idea post-scaling becomes prohibitively expensive as these companies have already made irreversible investments while scaling their business (Chen et al., 2022, p. 10, Gans et al., 2019, p. 741). These irreversible investments can make these entrepreneurs fall prey to the sunk-cost fallacy (Eisenmann et al., 2013, p. 19) or the escalation of commitment (Staw, 1981) to a business idea with poor product-market fit. As Furr (2011) explains:

> Scaling actually makes you less agile. Specifically, when you start hiring people and investing in your product, you become organizationally and mentally committed to your current approach—you've paid money and obligated yourself to a particular product or strategy and doing this makes it worlds harder to change.

Because early scalers not only lack organizational legitimacy as a new venture (Delmar & Shane, 2004; Stinchcombe, 1965) but also have committed to an insufficiently experimented, questionable business idea, they may encounter more difficulties in persuading resource providers (e.g., employees, investors, suppliers, complementors) to render their assets and in attracting the mainstream market beyond their early adopters. While facing these difficulties, early scalers may hastily exhaust their scarce resources at hand in fueling their premature commitment, thereby leading to a greater likelihood of firm failure. As one entrepreneur explains: "Premature scaling killed us. … [E]xtend your runway as long as possible until you've found product-market fit" (Loayza, 2015). Therefore, this alternative view implies that scaling early will be associated with lower performance.

2.3 | Mechanisms underlying the consequence of the timing of scaling

To explore the above mechanisms—namely, a decrease in imitation risk versus an increase in commitment risk—we consider a set of moderators that can serve as proxies for these mechanisms. Below, we discuss the theoretical underpinnings of these moderators.

2.3.1 | The benefit of decreasing imitation risk

In Section 2.2, we discuss how scaling early can benefit startups by reducing the risk of imitation. The extent to which startups face imitation risk and appropriate the value of their business idea would vary with two important factors: (1) patent protection and (2) the degree of competition.

First, patent protection can partially hinder imitation (Gans et al., 2002, Posen et al., 2023, p. 82). In their empirical study of the chemical, drug, electronics, and machinery industries, Mansfield et al. (1981, p. 913) find that, although "patent protection does not make [imitation] impossible, or even unlikely … [it] generally increases imitation costs." Therefore, startups with patent protection on their business idea may experience a lower risk of imitation, which enables them to devote more time to experimentation before scaling (Agrawal et al., 2021, p. 5516, Contigiani, 2023). In contrast, startups that do not have such protection, and thus face a higher imitation risk, may consider scaling early as an alternative approach to addressing the imitation risk (Ching et al., 2018). In other words, startups without patents can reap greater benefits from scaling early. Thus, this view suggests that the positive association between scaling early and startup performance will be greater for startups without patent protection prior to scaling, compared to those with such protection.

In contrast, the risk of imitation can increase with the degree of competition. When firms compete in the same industry or product-market space, these competitors are likely to imitate when the targets of imitation are relatively weak to react or are not capable (or credible) of doing so. New ventures can fall into this category of imitation targets (Gans et al., 2002) because they are resource-constrained, lack organizational legitimacy, and have little market power (Delmar & Shane, 2004, Stinchcombe, 1965). Hence, prior research (for a review, see Posen et al., 2023) suggests that incumbents (i.e., competitors who were established before the focal startup's entry) can quickly imitate these startups to limit future rivalry and leverage their existing resources (in particular, complementary assets) to capture value from the imitated business idea, while followers (i.e., competitors who are founded after the focal startup's entry) do so to learn vicariously, reduce uncertainty, and establish the legitimacy of their businesses. When there are more pre- and post-entry competitors, startups are likely to face a greater risk of imitation (Contigiani, 2023, p. 8) and may thus benefit more from scaling early. Hence, this argument implies that the positive association between scaling early and startup performance will be greater for startups facing a higher degree of pre- and post-entry competition, compared to those with a lower degree of such competition.

2.3.2 | The cost of increasing commitment risk

In Section 2.2, this study articulates how scaling early can be detrimental to startups by curtailing learning through experimentation and increasing the risk of committing to a business idea that lacks product-market fit. While spending more time on experimentation may reduce commitment risk and improve startup performance (Camuffo et al., 2019; Koning et al., 2022), this iterative learning process can be time-consuming and costly to implement (Gans et al., 2019). One prominent method that startups have adopted to drastically reduce the time and cost of experimentation is A/B testing tools (e.g., Optimizely.com). Relative to the more traditional methods (e.g., interviews with focus groups or experts; Bennett & Chatterji, 2023, pp. 9–10), these tools leverage the recent advances in digital infrastructure and technologies (e.g., Internet connectivity, online websites, cloud computing, and big data analytics) to measure and manipulate specific parameters of their business idea, deploy experiments, and gather feedback at scale, in parallel, in real-time, and at a relatively low cost. Thus, A/B testing tools make it relatively inexpensive for resource-constrained startups to identify promising parameters, drop non-valuable ones, and optimize their business idea (Koning et al., 2022). Given this increase in effectiveness and efficiency, new ventures that employ A/B testing tools to experiment before scaling may require less time for experimentation than those that did not. Put differently, these startups may not encounter an increase in commitment risk in scaling early. In sum, this discussion suggests that the negative association between scaling early and startup performance will be attenuated for startups that deploy A/B testing tools to experiment prior to scaling, compared to those that do not.

2.4 | The consequence of the timing of scaling for two-sided platforms

Given the opposing arguments on the timing of scaling, a particularly intriguing context is two-sided platforms. Although platforms and non-platforms differ in many aspects, both the benefit and cost of scaling early are expected to be amplified for platform companies. On the one hand, by scaling early, platform startups may reduce imitation risk through network effects and economies of scale. First, network effects play a crucial role for platforms in deterring imitation and creating a sustainable competitive advantage (Rysman, 2009) because the value for each participant increases with the number of other participants on the same side of the platform (Katz & Shapiro, 1994). This value from *direct* network effects can be augmented by *indirect* network effects, whereby a participant on one side benefits from the number and characteristics of participants on the other side (Lee et al., 2010). Moreover, platforms may enjoy economies of scale by establishing a standardized governance mechanism that ensures compatibility and efficient coordination among participants (Saadatmand et al., 2019). By scaling early and expediting the initiation of network effects and economies of scale, platform startups may reduce imitation risk and enhance their performance.

On the other hand, scaling early can be harmful to platform startups because these firms may require more time for experimentation in learning and optimizing the complex interdependencies on both sides of their market (Ott & Bremner, 2021). Furthermore, as many platforms (e.g., Amazon, Facebook, Uber) operate in markets where they must contend with regulatory complexity, these companies may need to carefully evaluate potential regulatory risks and assess policy dynamics before scaling their business (Büge & Ozcan, 2021). For example, in their multiple-case study of social investing platforms, McDonald and Eisenhardt (2020) show that these startups needed to engage in a series of experimentation to not only learn the supply- and demand-side of their market but also address the regulatory hurdles and gain approval from the securities and exchange commission. By prematurely committing to a business idea that fails to address these interdependencies, early scaling platforms may encounter difficulties entering and competing in their target market (Schilling, 2002). Even if an early scaler with an inferior business idea initially tips the market in their favor by attracting early participants, this initial advantage may not persist (Zhu & Iansiti, 2012), as competitors can quickly catch up by learning from the early scalers' costly investments in both the market and regulatory contexts and by securing the mainstream market (Eisenmann et al., 2006). Thus, for platform startups, scaling early may escalate commitment risk and ultimately diminish their performance.

3 | METHODS

3.1 | Measuring the timing of scaling through job postings

Although it remains theoretically inconclusive how the timing of scaling affects startup performance, there has been “a paucity of empirical work” (DeSantola & Gulati, 2017). A key reason is that it is difficult to develop a generalizable large-sample measure of the timing of scaling. Although the increase in employees or customers is commonly regarded as an indicator of firm growth (Azoulay et al., 2022, p. 79, Penrose, 1959, p. 1), using this internal and external growth to measure this timing has several potential limitations. First, as the growth in employees and customers is an outcome in and of itself (Choi et al., 2023, Penrose, 1959, p. 2), measuring the timing of scaling with this outcome selects on startups that managed to successfully scale. Furthermore, it cannot distinguish between startups that failed to scale and those that chose *not* to scale. Second, as this early-stage growth process arises not in a discrete manner but rather exponentially (Penrose, 1959, pp. 186–188), it is difficult to pinpoint when exactly scaling began. Finally, the extent to which this process is exponential can vary by firm characteristics (Ott & Bremner, 2021, Penrose, 1959, p. 186), making it challenging to come up with a measure generalizable across a large sample of firms.

To overcome these methodological challenges and derive a measure of when startups begin to scale, we extend our discussion in Section 2.1 by further drawing upon the literature on organizational growth and design. This literature has demonstrated that new ventures, in their early stages, rely heavily on their founding team and are yet to formalize their organizational structure (Kazanjian, 1988, p. 263, Stinchcombe, 1965). Such reliance on the founding team and lack of formal structure may not impose a significant constraint during the experimentation process (Lee, 2022). However, as startups transition from experimentation to scaling and grow internally and externally, they face new levels of administrative complexity that extend beyond the expertise and managerial capacity of their founding team (Hambrick & Crozier, 1985), thus potentially resulting in a "crisis of leadership" (Greiner, 1972, p. 41) and "growing pains" (Flamholtz & Randle, 2015).

To address the increased complexity and avert an early crisis in scaling, startups seek to decompose tasks (DeSantola & Gulati, 2017, Penrose, 1959, pp. 47–49) and allocate them to specialized human resources formally recruited from the labor market (Clough et al., 2019; Hurst et al., 2023; Kim, 2018). In particular, new ventures hire managers to accommodate internal growth and coordinate the increased number of employees. Accordingly, the core of Penrose's (1959) thesis is that these managers are the key enabler and bottleneck of firm growth. Hence, the hiring of managers is "the *first* critical choice in an organization's development" (Greiner, 1972; emphasis added). Supporting this line of reasoning, Lee (2022) shows that these managers can help startups coordinate their increasing number of employees and achieve better commercial success.

In tandem, to acquire new customers and achieve external growth, startups employ sales personnel. As Penrose (1959, p. 65) highlights, "the new resources required [for firm growth] are, of course, not only managerial, but include other types of personnel, such as … salesmen." As startups encounter considerable challenges in attracting and building stable relationships with consumers (Delmar & Shane, 2004; Stinchcombe, 1965), dedicated sales personnel can help organizations enlarge the customer base by efficiently catering to different market segments (Bennett, 2013, p. 2017, Penrose, 1959, p. 83). In this vein, Kazanjian (1988, p. 264) finds that, to address "marketing crisis" and meet their sales goals, new ventures recruit "a person with an extensive marketing background."

To summarize, when transitioning from experimentation to scaling, new ventures aim to hire these two specialized human resources. As Hambrick and Crozier (1985, p. 37) articulate, "as with their managers, [new ventures] seek to acquire this expertise [i.e., sales personnel] *before it is needed*, recognizing that at the rate they are growing it will be needed very soon, and that it is more difficult to correct chaos than to prevent it by having good talent available" (comment and emphasis added). Thus, we propose that a startup's decision to recruit for these specialized human resources—rather than their actual employment, which is an outcome in and of itself—reflects the firm's intention to begin scaling. Hence, to proxy for the timing of scaling, we leverage data on job postings.

3.2 | Data

Our data are compiled from two sources (as of October 2020): Burning Glass Technologies (BGTs) and Crunchbase (CB). BGT, a labor market analytics company that collects information from more than 23,000 online job sites around the world, provides a dataset of 164 million online job postings between 2010 and 2019 for more than three million companies in the United States, which is representative of the U.S. labor market (Cammeraat & Squicciarini, 2021). This dataset consists of detailed information on each job posting, including its date, occupational code, employer, and geography. In turn, CB offers a database of 1.2 million companies in the United States, which is considered "the premier data asset on the tech/

startup world" (Dalle et al., 2017, p. 5). It presents comprehensive information (e.g., company website, founding date, funding, geography, and industry), the quality of which has improved significantly after 2008 (Koning et al., 2022).

These datasets were matched by the following process. First, from CB's dataset, we removed (1) startups founded before 2010, (2) investment firms, and (3) non-profit organizations. We then found exact matches in BGT's dataset based on the company name and location (i.e., state in the United States). For the companies in CB's dataset without an exact match, we used a fuzzy string-matching algorithm (i.e., Python's fuzzymatcher with a similarity threshold of −1 to account for minor differences) to find the most accurate match among those in the same location in BGT's dataset. These fuzzy-matched observations were manually checked to remove false or ambiguous matches. Finally, for both exact and fuzzy-matched observations, we used the company name to include job postings in BGT's dataset that were listed outside the founding location. This process yielded a sample of 38,217 startups that were founded in the United States after 2010 and posted 6.3 million jobs.

Despite its extensive coverage of online job postings, our dataset may not capture offline and informal ones (e.g., jobs posted through the founders' social connections). Although such informal postings may be common in the inception stage, leveraging such informal networks reaches its limit as startups scale their business and grow beyond their founding team. Thus, these firms typically formalize their human resource processes and recruit talent from the labor market (Clough et al., 2019, Kazanjian, 1988, p. 261). Although a startup's first formal postings for manager and sales represent its need for these specialized human resources required for scaling, our dataset is unable to distinguish whether these positions were filled. However, regardless of whether they were actually filled, these postings indicate the startup's intention to transition from experimentation to scaling and thus proxy for when startups begin scaling.[4]

3.3 | Measurement

3.3.1 | Timing of scaling

We measure when startups begin scaling using the time at which a startup first posts its manager or sales job. We operationalize this variable by first normalizing each job posting's date as the number of months since the founding date of the startup reported in CB's dataset. We then identify the first manager and sales postings using the occupational codes in BGT's dataset. Specifically, we consider the two-digit codes "11: Management Occupations" and "41: Sales and Related Occupations" in the Standard Occupational Classification System.[5]

[4]To address the concern that the first manager and sales postings could be weak precursors to scaling, we descriptively show the rapid increase in the number of job postings after these job postings (see Online Appendix A5) and present robust results using the number of job postings in each time window (see Table A15 in Online Appendix A11). The results are also consistent if we assume that a position was filled when a job with the same job title was not posted again within the following 6 months. Note that the absence of a manager or sales posting does not necessarily indicate that an organization does not engage in any managerial or sales tasks. Rather, it implies that the organization is yet to formalize its division of tasks, and thus the founding team "wears multiple hats" (Baron et al., 1999).

[5]As "11-2022: Sales Manager" is both a managerial position (in terms of vertical division of tasks) and a sales position (in terms of horizontal division of tasks), we include the job postings for 11-2022 when measuring both the first manager and sales postings. The results are consistent when excluding or isolating the 11-2022 postings (see Table A10 in Online Appendix A11).

3.3.2 | Startup performance

We examine two measures of startup performance. First, we identify firm failure using the information on company status (i.e., "Closed," "Operating," "Acquired," or "IPO") reported in CB's dataset (as of October 2020). However, as "Closed" accounts for only 3% of the sample and thus appears to be under-reported considering the high failure rate among startups, we improve this measure using the information on the company website in CB's dataset. Here, we assume that continued online presence with a company website is a low-cost commitment and is, therefore, a conservative proxy for active startups. Hence, we classify a startup as failed if its website returns an error (e.g., HTTP Error Code 4xx or 5xx). In contrast, if its website is properly loaded (i.e., HTTP Status Code 2xx) or redirected to another website (e.g., due to domain name change or acquisition; i.e., HTTP Status Code 3xx), the startup is considered active. With this method, the rate of firm failure increases to 27%. Second, we measure successful exit based on whether the firm achieves an IPO. Unlike acquisitions, which contain both successful exits and fire sales, IPOs are regarded as an unambiguous measure of startup success (Gompers et al., 2016; Kim, 2022, 2023).[6]

3.3.3 | Founding characteristics

For each startup, we consider its founding year (between 2010 and 2019) and location (i.e., state in the United States). To account for the startup's human and social capital, we measure its founding team's size by counting the number of its members whose roles contain the term "founder" in CB's dataset on individuals. We also control for serial entrepreneurship by determining whether at least one of these members has prior founding experience. Finally, we include the number of job postings (both pre-scaling and post-scaling) to proxy for firm size.

3.3.4 | VC financing

For financial resources, we measure VC funding as a set of binary variables equaling one if the startup raises a specific round of funding—namely, *Seed*, *Series A*, and *Series B and onward*. To account for its timing, we distinguish VC funding occurring before or after the month at which the startup begins scaling. In some of the descriptive analyses, we normalize the timing of VC funding relative to the startup's founding date.

3.3.5 | Patent protection

For patent protection, we merged data from the U.S. Patent and Trademark Office with CB's dataset using the company (or assignee) name and location. We then measure whether a

[6]The results are robust when using CB's dataset (i.e., "Closed") to measure firm failure or when using both large acquisitions (i.e., greater than $100 million) and IPO to measure successful exit (see Table A8 in Online Appendix A11). Furthermore, the results are consistent when using employment growth, which is more granular than the binary measures of firm failure and successful exit (see Table A9 in Online Appendix A11).

startup is a patenting firm ($\infty[Count>0]$), distinguishing whether the patent application date is before or after the startup's timing of scaling.

3.3.6 | Industry

As industries may vary in the extent to which they rely on managers and sales to scale, we leverage CB's overlapping classification of 47 industry groups.[7] We use this classification to create 47 binary dummies equaling one if a startup is in a certain industry group.

3.3.7 | Competition

Because most companies have multiple industry groups (e.g., PayPal is in "Financial Services," "Payments," "Commerce and Shopping," "Internet Services," "Mobile," and "Software"), there are more than 42,000 unique combinations, which allow us to characterize each startup's competition in two ways. First, using all 1.2 million firms in CB's database, we proxy for pre-entry competition by computing the natural logarithm of the number of companies that were founded *before* the startup and have the same set of industry groups. Second, we measure post-entry competition by calculating the natural logarithm of the number of companies that were founded within 1 year *after* the startup and have the same set of industry groups.

3.3.8 | A/B testing

Following prior studies (e.g., Koning et al., 2022, p. 5), we gathered data from https://builtwith.com/BuiltWith.com, which provides information on whether a startup used an A/B testing technology (e.g., Optimizely.com) to experiment with its product. We then found exact matches (based on the company website) between this database and CB's dataset. We then create a binary variable that equals one if a startup used at least one A/B testing technology; zero, otherwise.

3.4 | Verifying the measures for the timing of scaling

As we present a novel measurement of the timing of scaling, we undertake considerable efforts to verify this measurement. We do so by taking three different approaches: (1) text analysis of job postings, (2) descriptive analysis of comparing the timing of scaling with the timing of the first funding round, and (3) case analysis of PillPack. Taken together, these analyses help

[7]The industry groups in CB's dataset include: "Administrative Services," "Advertising," "Agriculture and Farming," "Apps," "Artificial Intelligence," "Biotechnology," "Clothing and Apparel," "Commerce and Shopping," "Community and Lifestyle," "Consumer Electronics," "Consumer Goods," "Content and Publishing," "Data and Analytics," "Design," "Education," "Energy," "Events," "Financial Services," "Food and Beverage," "Gaming," "Government and Military," "Hardware," "Health Care," "Information Technology," "Internet Services," "Lending and Investments," "Manufacturing," "Media and Entertainment," "Messaging and Telecommunications," "Mobile," "Music and Audio," "Natural Resources," "Navigation and Mapping," "Payments," "Platforms," "Privacy and Security," "Professional Services," "Real Estate," "Sales and Marketing," "Science and Engineering," "Software," "Sports," "Sustainability," "Transportation," "Travel and Tourism," "Video," and "Other."

substantiate that our measures of the first manager and sales postings indicate when startups begin scaling.

3.4.1 | Text analysis of job postings

To corroborate our measurement, we first leverage the text data in the job postings and assess the word occurrence of "scale" or "scaling." We expect that these two terms should more likely be mentioned in the first manager and sales postings than in others because these first postings reflect startups' intention to begin scaling (e.g., of actual job postings with the terms "scale" or "scaling," see Figure A1 in Online Appendix A1). To examine whether this is the case, we regress the likelihood of word occurrence of these two terms on whether a job posting is the first manager or sales posting, relative to other postings before and after them. Because their word occurrence would systematically vary by industry (e.g., "scaling" is a medical procedure in the dental industry), we include industry fixed-effects. The results are reported in Figure A2 in Online Appendix A2. Here, the left panel plots the estimates using the first manager postings as the focal point. As expected, these postings are roughly 35% more likely to include the terms "scale" and "scaling" than the others before and after. This pattern is robust when using the first sales postings, as shown in the right panel. In sum, these text analyses unveil that terms relevant to scaling are significantly more salient in the first manager and sales postings, thereby helping substantiate our measures.[8]

3.4.2 | Descriptive analysis of comparing with the timing of the first funding round

We further support our measurement by comparing it with the timing of the first round of VC funding, because VCs provide financial resources to scale businesses (Bertoni et al., 2011). Hence, we expect startups' first VC funding to precede their first manager and sales postings. As expected, Figure A3 in Online Appendix A2 shows that the vast majority of VC-backed startups post their first manager or sales job after raising their first round of VC funding. Considering the time lag between posting a job and successfully hiring an employee for that position, these results imply that the first round of VC funding generally precedes when startups hire managers and sales professionals to scale their business. Hence, this sequence of events offers more credence to our measures.

3.4.3 | Case analysis of PillPack

In general, it is difficult to find specific information on when and how a startup has evolved. Fortunately, PillPack, an online pharmacy startup founded in 2013 and later acquired by

[8]In Figure A2, the occurrence rate of these two keywords appears lower for the postings that come "after" than "among" the first manager or sales job postings. One potential reason is that, unlike the latter, the former includes all types of jobs (i.e., not only manager and sales jobs but also, e.g., engineering and legal). To examine whether this is the case, we run additional analyses by limiting the sample to manager and sales job postings, and find that the word occurrence of these keywords remains constant in the first and the latter manager and sales job postings, once a startup begins to scale (see Figure A5 in Online Appendix A3).

Amazon in 2018, offers a rare opportunity to anecdotally verify our measurement because the detailed timeline of its scaling is not only observable in our dataset but also well-documented in studies by other scholars and practitioners (e.g., Schoen & Farr, 2019; Stern & Fehder, 2019). According to these studies, its founders developed the initial business idea of digital pharmacy at the MIT Hacking Medicine hackathon and subsequently founded PillPack in 2013. They then spent the first few years on experimentation to better understand the market and carefully develop PillPack's product. These efforts included participating in a startup accelerator program (Techstars) to receive strategic guidance on market opportunities and business models, collaborating with IDEO to fine-tune the product design, and launching an experimental store in New Hampshire for initial hypothesis testing. In 2016, PillPack started scaling its business by undertaking a nationwide hiring spree, opening stores across 31 states, launching PharmacyOS (i.e., its supply-chain management software for pharmacies), and later achieving $100 million in revenue. Our dataset shows that PillPack started scaling as such, after it posted its first manager and sales jobs in 2016 (i.e., 37 and 39 months, respectively, after its founding; see Figure A4 in Online Appendix A2). Albeit a single case, this analysis provides anecdotal support to our measurement of the timing of scaling.

4 | RESULTS

4.1 | Descriptive statistics

We begin our analysis by documenting descriptive statistics at the firm level.[9] Table 1 displays the characteristics of 38,217 startups in our dataset that posted at least one job. Among these observations, 73% are active (i.e., "Operating," "Acquired," or "IPO"), while 27% have failed (i.e., "Closed"). Also, 41% of our startups received some form of VC funding with a large variation in the amount of funding raised. Similarly, 7% were granted at least one patent, but these companies significantly vary in the number of granted patents. While 30% are associated with the software industry, our observations are associated with various other industries, including healthcare, pharmaceutical, and platforms. Most faced significant pre-entry and post-entry competition. In addition, 11% used at least one A/B testing technology. As we limit the observations to startups founded after 2010, their firm age ranges from 0 to 10. Unsurprisingly, 40% were founded in California, New York, and Massachusetts. Because of CB's limited data on individuals, we were able to identify at least one founder for only 39% of our sample. Among these observations, the average team size is 1.6, and roughly 8% contain at least one serial entrepreneur. Given potential concerns of sample selection, we exclude these variables from our main analyses.[10]

In terms of the timing of scaling, we find that startups, on average, enlist both their first manager and sales postings 49 months after their founding. This remarkable similarity helps verify that both of these specialized human resources reflect a startup's intention to begin scaling. Thus, we document that startups, on average, begin scaling their business roughly 4 years after their founding. This average timing of scaling is comparable to qualitative observations by

[9]For the job-level descriptive statistics, see Table A1 in Online Appendix A4. In turn, for the number of job postings per active startup over time, see Figure A6 in Online Appendix A5.

[10]The results are robust when including these founding team characteristics (see Table A16 in Online Appendix A11).

TABLE 1 Descriptive statistics at the company level.

	No. Obs.	Mean	Std. dev.	Min	Max
Status					
Operating	38,217	0.630		0	1
Acquired	38,217	0.087		0	1
IPO	38,217	0.014		0	1
Closed	38,217	0.270		0	1
VC financing					
∞[Funding>0]	38,217	0.414		0	1
Funding (USD millions)	15,817	40.228	279.085	0.001	21,246.699
Patents					
∞[Count>0]	38,217	0.070		0	1
Count	38,217	1.809	145.499	0	28,319
Industry					
Software	38,217	0.302		0	1
Healthcare	38,217	0.121		0	1
Pharmaceutical	38,217	0.047		0	1
Platforms	38,217	0.018		0	1
Government and military	38,217	0.011		0	1
Competition					
Pre-entry	38,217	5.696	3.021	0	10.849
Post-entry	38,217	4.249	2.324	0.693	8.803
A/B testing	38,217	0.110		0	1
Founding year	38,217	2013.450	2.432	2010	2019
Founding location					
California	38,217	0.252		0	1
New York	38,217	0.109		0	1
Massachusetts	38,217	0.041		0	1
Founding team					
Size	14,782	1.639	0.830	1	11
Serial entrepreneur	14,782	0.083		0	1
Months to the first job postings					
Any	38,217	40.367	27.674	0	119
Manager	17,625	49.250	28.306	0	119
Sales	18,806	49.423	28.296	0	119

Ott and Bremner (2021) that startups typically begin scaling after spending a few years on experimentation.

It is worth noting that 40% of our observations did not post a manager or sales job between 2010 and 2019. We presume that this can be attributed to two main reasons. First, because startups generally begin scaling several years after their founding, the more recently established ones may not have scaled within the time frame of our dataset. Consistent with this presumption, we find that the likelihood of posting a manager or sales job monotonically decreases with the year of firm founding (see Table A2 in Online Appendix A6). Second, some startups may choose *not* to scale for various reasons (Penrose, 1959, pp. 193–194). Thus, there may be considerable heterogeneity at the extensive margin of whether a startup scales. Nonetheless, as our study is primarily concerned with the timing of scaling, we focus on startups that post at least one manager or sales job.

4.2 | Exploratory analyses

We move on to explore the variation in the timing of scaling conditional on posting at least one manager or sales job (see Figure 2). Interestingly, this distribution is yet again identical regardless of whether using the first manager or sales posting, thereby further supporting our empirical measurement. Figure 2 demonstrates that, while its average is 49 months (as shown in Table 1), the timing of scaling significantly varies across firms. This firm-level variation has also been observed by Ott and Bremner (2021), who find that eight platform companies in their qualitative study differed in terms of when they started growing their complementors and users.[11]

Given this heterogeneity in the timing of scaling, we examine various pre-scaling organizational characteristics that may correspond to startups' decisions on when to scale. Table 2

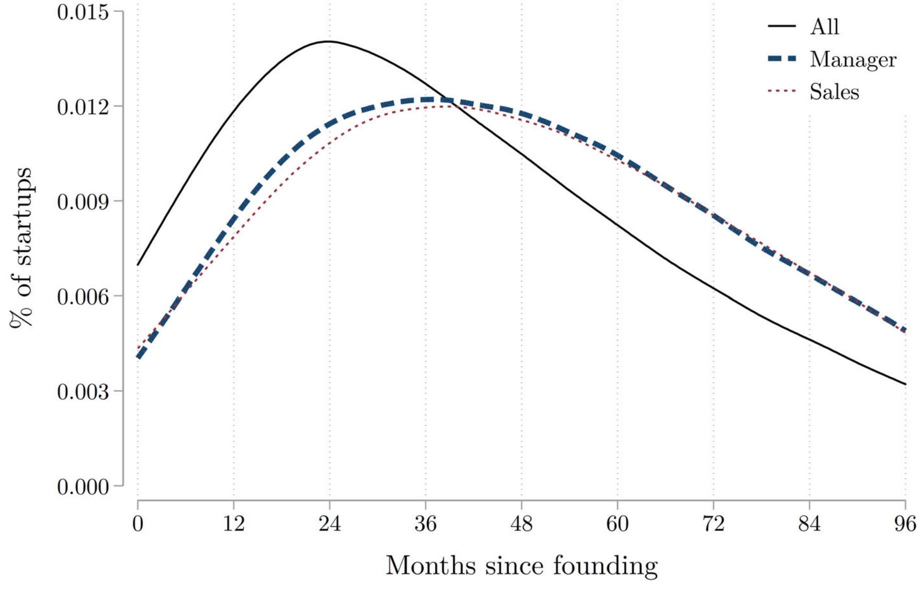

FIGURE 2 The distribution (kernel density) of the timing of scaling, which is remarkably identical regardless of whether this timing is measured by when startups enlist their first job posting for a manager (in blue dashed line) or a sales personnel (in red dotted line). This figure shows that while startups, on average, scale 49 months after their founding, they vary widely in their timing of scaling. In addition, it demonstrates that this timing can be measured consistently using the first manager and sales postings.

[11]For the industry-level variation in the timing of scaling, see Online Appendices A7 and A8.

presents these characteristics based on their timing of scaling into five bins: 0–6, 7–12, 13–18, 19–24, and 25+ months since the founding. Regardless of whether this timing is measured by the first manager or sales posting, the results are again remarkably consistent. First, we find that scaling early is relatively uncommon: only 4% began scaling in the first 6 months, while more than 77% did so after 24 months. Second, the comparison of means across the five bins suggests a positive association between the timing of scaling and whether VC funding was raised before scaling. Specifically, whereas only 0.1% of the startups that scaled in the first 6 months raised at least one round of VC funding, 19% of those that scaled after 24 months were funded by VCs. Third, Table 2 reveals that when startups began scaling and whether they had at least one patent granted before scaling are positively correlated: the share of those with at least one patent before scaling increases from roughly 2% (0–6 months) to 5% (25+ months). Fourth, the timing of scaling also varies with the measures of competition. While firms facing less pre-entry competition generally scale later, the association with the degree of post-entry competition is noisy, both of which are seemingly inconsistent with the perspective that scaling early mitigates the risk of imitation. Fifth, the proportion of startups that used A/B testing technologies increases with the timing of scaling, which is aligned with the view that scaling early increases commitment risk. Finally, we observe that, although startups with a larger founding team or with serial entrepreneurs may have the capabilities to scale early, the proportion of these startups generally increases with the timing of scaling.

The descriptive patterns above may imply that these organizational characteristics are antecedents of the timing of scaling. For example, startups with a larger founding team may tend to scale later because their founding teams have learned through experience that scaling early can be detrimental. However, these patterns may simply reflect the fact that smaller founding teams face less coordination friction and are thus able to execute and scale more quickly.[12] Because a more thorough investigation that goes beyond the scope of this study is required to systematically assess whether these patterns can be causally interpreted and to tease out their underlying mechanisms, we leave this inquiry for future research and account for these differences in our regression analyses.

Next, we explore how the timing of scaling varies with firm outcomes. Considering that startups face a significant risk of firm failure (Guzman & Stern, 2020), we compare the distributions of the timing of scaling for failed startups (i.e., "Closed") and for active ones (i.e., "Operating," "Acquired," or "IPO"). As illustrated in Figure A9 in Online Appendix A9, we find that failed startups, compared with active ones, display a left-shift in their timing of scaling. This left-shifted distribution implies a strong positive correlation between scaling early and firm failure. The two distributions cross at roughly 32 months of founding, after which failed startups account for a smaller share of the distribution relative to active ones. Again, these patterns are almost indistinguishable when using the first manager or sales posting to measure the timing of scaling.

4.3 | Regression analyses

Though our analyses above make significant headway in understanding the empirical patterns in the timing of scaling, a key question for scholars and practitioners is whether and how the

[12]Alternatively, larger founding teams may hire managers and sales personnel later because they may already possess such capabilities, though continued scaling efforts are expected to exceed the founding team's capacity.

TABLE 2 Descriptive statistics at the company level by the first manager and sales postings.

The first posting for	Manager					Sales				
Months since founding	**0–6**	**7–12**	**13–18**	**19–24**	**25+**	**0–6**	**7–12**	**13–18**	**19–24**	**25+**
#. job postings (pre-scaling)	0.087	0.279	0.241	0.209	1.480	0.240	0.226	0.798	0.247	1.922
VC financing (*pre-scaling*)										
None	0.999	0.988	0.981	0.975	0.810	0.999	0.992	0.982	0.969	0.814
Seed	0.001	0.007	0.012	0.010	0.097	0.001	0.004	0.012	0.016	0.101
Series A	0	0.005	0.006	0.013	0.054	0	0.003	0.006	0.013	0.049
Series B and onward	0	0	0.001	0.002	0.039	0	0	0.001	0.002	0.036
Patents (*pre-scaling*)										
∞[Count>0]	0.019	0.014	0.017	0.019	0.051	0.023	0.010	0.016	0.013	0.045
Count	0.380	0.798	0.198	0.228	0.581	1.264	0.174	0.198	0.351	0.541
Competition										
Pre-entry	6.304	6.218	6.167	6.054	5.564	6.103	5.987	5.931	5.783	5.494
Post-entry	4.382	4.427	4.470	4.405	4.209	4.196	4.233	4.284	4.261	4.155
A/B testing	0.093	0.085	0.122	0.140	0.161	0.082	0.090	0.133	0.133	0.163
Founding year	2014.912	2014.830	2014.784	2014.724	2012.821	2015.127	2015.090	2014.938	2014.602	2012.861
Founding location										
California	0.211	0.234	0.278	0.267	0.277	0.201	0.238	0.271	0.272	0.266
New York	0.098	0.119	0.121	0.121	0.109	0.102	0.137	0.127	0.118	0.110
Massachusetts	0.033	0.055	0.054	0.056	0.046	0.029	0.042	0.036	0.043	0.042
Founding team										
Size	1.595	1.526	1.618	1.663	1.698	1.533	1.524	1.606	1.619	1.717
Serial entrepreneur	0.049	0.081	0.095	0.091	0.090	0.065	0.091	0.092	0.082	0.088
No. observations	724	867	1160	1259	13,615	755	910	1245	1297	14,599

timing of scaling is related to startup performance. An ideal empirical approach to study this relationship would be to either randomly assign or find an exogenous source of variation in the timing of scaling across startups. Unfortunately, however, such randomization is not practically feasible, and a startup's decision to scale is inherently an endogenous choice that could be driven by a myriad of factors (e.g., the founders' experience, the firm's resources, or the industry's competition). Albeit unequipped with an exogenous variation, we examine the correlational link between the timing of scaling and firm outcomes. We do so not only to highlight the potential importance of the variation in the timing of scaling but also to examine the opposing arguments on when startups should scale.

To assess how the timing of scaling is associated with startup performance, we apply a linear probability model to estimate the following equation for firm i in industry j, located in state s, and founded in year t:

$$Y_{ijst} = \sum_{k=1}^{5} \beta_k \times d[k] + \mathbf{X}'\Pi + \gamma_j + \delta_s + \rho_t + \varepsilon_{ijst} \quad (1)$$

where Y is a binary dummy for firm outcomes (i.e., *Failure* or *IPO*) and $\mathbf{X}$ is a vector of firm characteristics. To separately estimate the different windows for the timing of scaling, we construct the following set of binary indicators $d[k]$ based on the time between founding and the first manager or sales posting: 1 if before 7 months; 2 if between seven and 12 months; 3 if between 13 and 18 months; 4 if between 19 and 24 months; and 5 if after 24 months. In the regressions, the last group (i.e., 25+ months) is the reference group against which other groups are compared.[13]

The results are displayed in Table 3 (for the full table, see Table A3 in Online Appendix A10). We first examine firm failure as the outcome as shown in Models 1–4. In Models 1 and 2, the timing of scaling is measured by the first manager posting. These models show strongly positive estimates for scaling in the first 0–6 or 7–12 months ($p = .084$ and $p < .001$, respectively) relative to the omitted group of scaling later (i.e., 25+ months). These estimates are noticeably lower for later time windows (i.e., 13–18 and 19–24 months), suggesting that the positive association between scaling early and firm failure is primarily driven by the startups that begin scaling in the earliest time windows. As Model 1 indicates, these results are robust to accounting for innate differences across industries, founding years, and states. Interestingly, after adding a series of controls in Model 2, our estimates of the timing of scaling modestly increase. Furthermore, the economic magnitudes are large: compared to scaling after 24 months (a baseline rate of 24%), scaling in the first 6 months is associated with a 30% higher rate of firm failure.

In turn, Models 3 and 4 repeat these analyses using the first sales posting. These models show consistent patterns with even higher magnitudes associated with scaling early. Model 4 shows that scaling in the first 6 months is linked to a nine percentage-point increase in the likelihood of firm failure, which represents a 39% increase relative to the baseline rate ($p = .008$). Though not necessarily causal, these results demonstrate a strong positive relationship between scaling early and firm failure. In sum, Models 1–4 show that scaling early is positively associated with firm failure.

[13]As the precise dates of firm failure are unobservable, we are unable to apply the Cox proportional hazards model. The results are consistent when using a continuous variable for the timing of scaling (i.e., the months since founding; see Table A11 in Online Appendix A11) or when using the logistic specification (not reported here).

TABLE 3 Main results for the regression of the timing of scaling on firm outcomes.

Outcome	Failure				IPO			
	Manager		Sales		Manager		Sales	
The first posting for	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Timing of the first job posting								
0–6 months	0.050 (0.026)	0.072 (0.023)	0.080 (0.028)	0.094 (0.028)	0.018 (0.012)	−0.003 (0.013)	0.020 (0.008)	0.004 (0.009)
7–12 months	0.050 (0.007)	0.065 (0.014)	0.086 (0.015)	0.093 (0.016)	0.015 (0.009)	0.002 (0.009)	0.008 (0.007)	0.000 (0.007)
13–18 months	0.025 (0.014)	0.036 (0.016)	0.056 (0.018)	0.064 (0.021)	0.015 (0.005)	0.005 (0.005)	0.004 (0.002)	−0.004 (0.004)
19–24 months	0.032 (0.015)	0.042 (0.017)	0.026 (0.021)	0.031 (0.022)	0.009 (0.004)	0.001 (0.005)	−0.006 (0.003)	−0.009 (0.003)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Fixed-effects								
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding location	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	16,891	16,891	17,992	17,992	16,891	16,891	17,992	17,992
R-squared	.026	.031	.027	.032	.092	.120	.085	.113

Note: Standard errors clustered by founding year and location in parentheses.
[Correction added on 2 April 2024, after first online publication: Table 3 has been updated in this version.]

A possibility is that scaling early is a high-risk-high-reward strategy: that is, while scaling early can elevate commitment risk by curtailing experimentation, it may simultaneously enhance the likelihood of successful exit by mitigating imitation risk. To examine whether scaling early is positively related to successful exit, we repeat our analysis using IPO as the dependent variable in Models 5–8. In general, we find that scaling early is not systematically related to the likelihood of an IPO (p>.1). Although scaling in the first 6 months in Model 7 shows a positive association (p = .036), this association is attenuated toward zero when including fixed-effects and controls in Model 8 (p = .576). Overall, we do not find a systematic relationship between the timing of scaling and the likelihood of an IPO.

4.4 | Testing the mechanisms

We move on to discuss various analyses to test the underlying mechanisms (i.e., a decrease in imitation risk vs. an increase in commitment risk). As discussed in Section 2.3, we first interact the timing of scaling with (1) patent protection and (2) the degree of underlying competition. We expect that the positive relationship between scaling early and startup performance will be lower for startups with patent protection compared to those without it, as such protection can reduce the risk of imitation. In contrast, we expect this positive relationship to increase with the level of pre- and post-entry competition, as a higher level of such competition can escalate imitation risk.

The results are reported in Table 4 (for the full table, see Table A4 in Online Appendix A10). In Models 1 and 2, the baseline effects represent the estimates for startups without a patent before scaling on the likelihood of firm failure. These estimates remain strongly positive for scaling in the first 0–6 or 7–12 months (p = .006 and p = .003). Although the interaction effects are negative, they are imprecisely estimated from zero (p = .397 and p = .891 in Model 1). In turn, Models 3 and 4 present negative relationships between scaling early and IPO likelihood—a pattern that is consistent with the notion that scaling early can be especially beneficial for startups without a patent given the heightened imitation risk. Although these associations are robustly negative for the first 6 months (p = .004 and p = .001), they are not distinguishable zero for the next 6 months (p = .865 and p = .614). Taken together, we do not find any evidence that, compared to those with a patent, startups without a patent experience a greater reduction in the likelihood of firm failure when scaling early. Moreover, we find mixed evidence in terms of increased odds of successful exit. Therefore, these results fall short of providing consistent support for the benefits of scaling early.

Next, we discuss the moderating effect of competition, which was measured before (Models 5–8) and after (Models 9–12) each startup's founding year. The baseline effects, which represent startups that do not face any competition, are consistent with our main findings in Table A3. But, regardless of which measure of competition we use, the interaction effects are generally noisy (p>.1). In other words, the relationship between scaling early and the likelihood of firm failure or IPO does not systematically vary with the degree of pre- and post-entry competition. Overall, consistent with Eisenhardt and Schoonhoven (1990, pp. 525–526), the results in Table 4 do not compellingly support the argument that early scalers can improve startup performance by reducing imitation risk.

Now, we turn to the negative mechanism of scaling early (i.e., an increase in commitment risk). As discussed in Section 2.3, we expect the negative relationship between scaling early and startup performance to be lower for startups that used A/B testing tools to experiment before

TABLE 4 Results for the interaction with three measures of imitation risk.

Proxies for imitation risk	**Pre-scaling patents (∞[Count>0])**				**Pre-entry competition**				**Post-entry competition**			
Outcome	**Failure**		**IPO**		**Failure**		**IPO**		**Failure**		**IPO**	
The first posting for	**Manager**	**Sales**	**Manager**	**Sales**	**Manager**	**Sales**	**Manager**	**Sales**	**Manager**	**Sales**	**Manager**	**Sales**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
Timing of the first job posting												
0–6 months	0.075	0.099	−0.001	0.007	0.083	0.120	0.006	0.014	0.069	0.117	0.013	0.016
	(0.021)	(0.026)	(0.012)	(0.008)	(0.041)	(0.063)	(0.018)	(0.017)	(0.034)	(0.055)	(0.018)	(0.017)
7–12 months	0.065	0.094	0.001	0.000	0.072	0.143	0.012	0.014	0.067	0.121	0.010	0.016
	(0.016)	(0.017)	(0.008)	(0.007)	(0.022)	(0.020)	(0.019)	(0.010)	(0.023)	(0.018)	(0.018)	(0.010)
13–18 months	0.037	0.066	0.006	−0.003	0.062	0.058	−0.005	0.005	0.049	0.051	−0.004	0.006
	(0.016)	(0.023)	(0.005)	(0.004)	(0.025)	(0.027)	(0.008)	(0.009)	(0.021)	(0.023)	(0.009)	(0.008)
19–24 months	0.042	0.031	0.001	−0.009	0.025	0.013	−0.012	0.002	0.031	0.012	−0.012	0.003
	(0.016)	(0.022)	(0.006)	(0.003)	(0.036)	(0.036)	(0.010)	(0.006)	(0.033)	(0.037)	(0.010)	(0.007)
Imitation risk × Timing of the first job posting												
0–6 months	−0.122	−0.173	−0.086	−0.098	−0.002	−0.004	−0.001	−0.002	0.001	−0.006	−0.003	−0.003
	(0.137)	(0.113)	(0.022)	(0.022)	(0.006)	(0.010)	(0.002)	(0.002)	(0.006)	(0.011)	(0.002)	(0.003)
7–12 months	−0.024	−0.041	0.062	0.020	−0.001	−0.009	−0.002	−0.002	−0.000	−0.007	−0.002	−0.004
	(0.173)	(0.153)	(0.118)	(0.115)	(0.004)	(0.005)	(0.002)	(0.001)	(0.005)	(0.007)	(0.003)	(0.002)
13–18 months	−0.044	−0.074	−0.046	−0.037	−0.004	0.001	0.002	−0.001	−0.003	0.003	0.002	−0.002
	(0.079)	(0.097)	(0.049)	(0.040)	(0.004)	(0.004)	(0.002)	(0.002)	(0.005)	(0.004)	(0.002)	(0.002)
19–24 months	−0.002	0.056	0.007	−0.004	0.003	0.003	0.002	−0.002	0.002	0.005	0.003	−0.003
	(0.104)	(0.136)	(0.045)	(0.047)	(0.004)	(0.004)	(0.002)	(0.001)	(0.006)	(0.005)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 4 (Continued)

Proxies for imitation risk	Pre-scaling patents (∞[Count>**0**])				Pre-entry competition				Post-entry competition			
Outcome	**Failure**		**IPO**		**Failure**		**IPO**		**Failure**		**IPO**	
The first posting for	**Manager**	**Sales**	**Manager**	**Sales**	**Manager**	**Sales**	**Manager**	**Sales**	**Manager**	**Sales**	**Manager**	**Sales**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
Fixed-effects												
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding location	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	16,891	17,992	16,891	17,992	16,891	17,992	16,891	17,992	16,891	17,992	16,891	17,992
R-squared	.031	.032	.120	.114	.031	.032	.120	.113	.031	.032	.120	.113

Note: Standard errors clustered by founding year and location in parentheses.

TABLE 5 Results for the interaction with A/B testing.

Moderator	A/B testing			
Outcome	**Failure**		**IPO**	
The first posting for	**Manager**	**Sales**	**Manager**	**Sales**
	Model 1	**Model 2**	**Model 3**	**Model 4**
Timing of the first job posting				
0–6 months	0.068 (0.025)	0.094 (0.028)	−0.003 (0.012)	0.000 (0.009)
7–12 months	0.068 (0.014)	0.098 (0.017)	0.002 (0.009)	0.002 (0.007)
13–18 months	0.039 (0.016)	0.071 (0.024)	0.005 (0.005)	−0.003 (0.003)
19–24 months	0.042 (0.018)	0.030 (0.023)	0.001 (0.005)	−0.009 (0.004)
A/B testing	−0.065 (0.011)	−0.055 (0.009)	−0.001 (0.005)	−0.001 (0.004)
A/B testing × Timing of the first job posting				
0–6 months	−0.008 (0.071)	−0.068 (0.077)	0.002 (0.026)	0.039 (0.033)
7–12 months	−0.097 (0.039)	−0.120 (0.036)	−0.003 (0.021)	−0.026 (0.009)
13–18 months	−0.057 (0.029)	−0.068 (0.038)	−0.000 (0.014)	−0.006 (0.011)
19–24 months	−0.021 (0.028)	−0.012 (0.017)	−0.002 (0.012)	0.000 (0.012)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Industry	Yes	Yes	Yes	Yes
Founding year	Yes	Yes	Yes	Yes
Founding location	Yes	Yes	Yes	Yes
No. observations	16,891	17,992	16,891	17,992
R-squared	.034	.035	.120	.113

Note: Standard errors clustered by founding year and location in parentheses.

scaling, compared to those that did not. The results are presented in Table 5 (for the full table, see Table A5 in Online Appendix A10). When estimating the likelihood of firm failure, Model 1 measures the timing of scaling with the first manager posting, whereas Model 2 uses the first sales posting. Regardless of which measure we use, the baseline effects of scaling early (i.e., the estimates for startups that do not engage in A/B testing) remain strongly positive for the first 0–6 ($p = .023$ and $p = .009$) and 7–12 months ($p = .001$ and $p < .001$). However, the interactions with A/B testing are negative albeit with varying degrees of precision. Among startups that engage in A/B testing, scaling in the first 6 months does not seem to exhibit a meaningful effect ($p = .910$ and $p = .399$), while scaling in 7–12 months of founding shows a reduction of 9.7–12 percentage points in the likelihood of failure ($p = .034$ and $p = .009$). In turn, Models 3 and 4 display the estimates on the likelihood of an IPO. In line with the main results in Table 3, these results do not show any meaningful associations with scaling early ($p > .1$), regardless of A/B testing. In sum, Table 5 implies that the relationship between scaling early and firm failure is largely driven by startups that do not engage in A/B testing. Thus, these findings lend support to the argument that scaling early can hamper startup performance by increasing commitment risk.

4.5 | Heterogeneous effects for two-sided platforms

As we discuss in Section 2.4, although platform and non-platform companies are different in many aspects, platforms offer an intriguing context where scaling early is expected to heighten both its benefit (i.e., a decrease in imitation risk through network effects and economies of scale) and its cost (i.e., an increase in commitment risk by curtailing experimentation). Thus, to examine whether the observed relationships between the timing of scaling and firm outcomes differ for platform startups, we interact the timing of scaling with whether a startup is in the platform industry.

The results are displayed in Table 6 (for the full table, see Table A6 in Online Appendix A10), which excludes the industry fixed-effects as "Platforms" comprise an industry group in CB's database. In Models 1 and 2, the dependent variable is firm failure. First, for both the first manager and sales postings, we find that the baseline estimates of scaling early for non-platform companies are positive ($p<.05$). The interaction terms show that platforms that begin scaling in the first 6 months experience a 22–27 percentage-point increase in the likelihood of firm failure relative to the baseline failure rate of 25% ($p=.032$ and $p=.073$). The estimates are noticeably attenuated for later windows of the timing of scaling. In short, these results show that platform startups are associated with a disproportionately high increase in the risk of firm failure when scaling early.

TABLE 6 Results for the interaction with platforms.

Moderator	**Platforms**			
Outcome	**Failure**		**IPO**	
The first posting for	**Manager**	**Sales**	**Manager**	**Sales**
	Model 1	**Model 2**	**Model 3**	**Model 4**
Timing of the first job posting				
0–6 months	0.072 (0.023)	0.091 (0.028)	−0.007 (0.014)	−0.000 (0.008)
7–12 months	0.062 (0.013)	0.090 (0.015)	0.002 (0.010)	−0.002 (0.007)
13–18 months	0.036 (0.015)	0.066 (0.020)	0.006 (0.006)	−0.004 (0.003)
19–24 months	0.041 (0.016)	0.034 (0.021)	0.001 (0.005)	−0.009 (0.003)
Platforms	−0.065 (0.015)	−0.054 (0.021)	0.001 (0.008)	−0.002 (0.007)
Platforms × Timing of the first job posting				
0–6 months	0.273 (0.108)	0.223 (0.110)	0.013 (0.017)	−0.009 (0.020)
7–12 months	0.179 (0.136)	0.120 (0.123)	−0.013 (0.018)	−0.008 (0.012)
13–18 months	0.138 (0.144)	0.008 (0.109)	−0.009 (0.013)	0.004 (0.011)
19–24 months	0.012 (0.152)	−0.128 (0.078)	−0.010 (0.013)	−0.001 (0.010)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Founding year	Yes	Yes	Yes	Yes
Founding location	Yes	Yes	Yes	Yes
No. observations	16,891	17,992	16,891	17,992
R-squared	.025	.026	.063	.063

Note: Standard errors clustered by founding year and location in parentheses.

We repeat the above analyses by using IPO as the outcome. Models 3 and 4 show that both the baseline estimates of scaling early for non-platform startups and the interaction effects for platform startups are imprecisely estimated (p>.1). Again, in line with our main results, we do not find a systematic relationship between the timing of scaling and the prospect of a successful exit.

4.6 | Robustness checks

Even with a suite of controls and fixed-effects, our results on scaling early and firm outcomes could have alternative explanations. First, these results may be subject to survival bias because startups that fail early, by construction, could not have scaled later. Second, these results may be sensitive to how we measure our variables. Third, our measure based on job postings is silent on whether the position was successfully filled, which can independently influence performance outcomes. Fourth, our discrete measures of the timing of scaling may fail to accurately portray startups that begin scaling early but choose not to ramp up their intensity of scaling efforts until later. Fifth, founding team characteristics may be important omitted variables. Finally, we examine whether our results are driven by business-to-business companies. In Online Appendix A11, we discuss these concerns in more detail and provide an extensive array of robustness tests. Overall, these tests show consistent sets of results, thereby granting more credence to our original findings.

5 | DISCUSSION

When startups should scale their business is a key area of inquiry for both organization scholars and practitioners. To address this question, our study integrates prior conceptualizations of scaling, offers a theoretical framework for the timing of scaling, and derives a novel empirical measurement to assess when startups begin scaling. Applying this measurement to a dataset of job postings, this study provides the first large-sample analysis of the timing of scaling. We find that startups that begin scaling within the first 12 months of their founding are 20–40% more likely to fail. Our results show that this positive correlation between scaling early and firm failure is negated for startups that engage in experimentation through A/B testing. However, we find no evidence that the relationships between scaling early and firm outcomes (both firm failure and successful exit) vary by whether a startup has patent protection for its business idea and by the degrees of its pre-entry and post-entry competition. Taken together, these results suggest that the commitment risk in scaling early outweighs the benefits of reducing imitation risk. Finally, our results show that the positive relationship between scaling early and firm failure is more than three times stronger for two-sided platforms than for non-platform companies. However, regardless of whether a startup is in the platform industry, we find no evidence to suggest that scaling early increases the likelihood of successful exit. We discuss the theoretical and managerial implications of our findings below.

5.1 | Contributions

Our study contributes to the literature on the entrepreneurial process, firm growth, organizational design, and two-sided platforms. First, this study clarifies the notion of scaling. This process has been increasingly regarded as a crucial step in achieving successful entrepreneurship and thus received growing interest among scholars and practitioners. However, given the complexity in and around this phenomenon, what exactly constitutes scaling has been a subject of much discussion but has, to date, lacked a precise agreement. Integrating these prior definitions (e.g., DeSantola & Gulati, 2017, p. 641, Eisenmann & Wagonfeld, 2012, p. 1, Ott & Eisenhardt, 2020, p. 2308, Sutton & Rao, 2014, p. 3) and bridging the concept of experimentation (i.e., the iterative learning process of testing and pivoting the core business idea; Chen et al., 2022, Contigiani & Levinthal, 2019, Murray & Tripsas, 2004), we characterize "scaling" as the entrepreneurial process in which a startup primarily focuses on acquiring and committing new resources to implement its chosen core business idea and expand its customer base. Thus, this study provides a conceptual building block for future research to explore the various dimensions of scaling: for example, whether a startup attempting to scale should acquire resources and customers organically, through acquisitions, or through alliances (i.e., mode), which location it should deploy its resources and expand into (i.e., geography), and which other products it should leverage its resources to (i.e., scope).

Second, this article highlights that the timing of when a startup shifts its focus from experimentation to scaling and undertakes its organizational metamorphosis from "a caterpillar" to "a butterfly" (Penrose, 1959, p. 19) is a crucial strategic decision for new ventures. Prior research has argued that, as bounded rational agents with resource constraints, entrepreneurs often make strategic commitments and irreversible investments at a suboptimal point in time (Chen et al., 2022; Cohen et al., 2019; Gans et al., 2019). In line with this argument, practitioner-oriented pieces (e.g., Eisenmann, 2021; Furr & Ahlstrom, 2011; Hoffman & Yeh, 2018; Marmer et al., 2011) have offered compelling anecdotes that such an imperfect decision on when startups begin to scale their business can be consequential to their performance. Despite this potential strategic implication, much of the research on scaling, to date, has paid little attention to its timing, focusing instead on its antecedents and consequences (Ott & Eisenhardt, 2020, pp. 2308–2309). Our study fills in this gap by showing that scaling early within the first year is significantly more likely to result in firm failure but not more likely to lead to a successful exit. This finding counters the prevailing perception among practitioners that scaling early—commonly referred to as "blitzscaling" (Hoffman & Yeh, 2018)—is an effective strategy for successful entrepreneurship. Thus, our study suggests that the timing of when startups begin to scale deserves more attention than it has so far received in the literature on the entrepreneurial process. By shedding light on this important yet understudied temporal decision, this study complements the burgeoning stream of research on scaling (e.g., DeSantola & Gulati, 2017; Lee, 2022) and answers the call for more research on this complex phenomenon (Dushnitsky & Matusik, 2019, pp. 442–443, Puranam, 2018, p. 111).

Third, by synthesizing insights from both scholarly and practitioner-oriented work, we offer a theoretical framework for the timing of scaling. This framework illustrates how this temporal decision can simultaneously influence imitation risk and commitment risk—a fundamental tension underlying the entrepreneurial process (Ching et al., 2018, Contigiani, 2023, p. 26, Gans & Stern, 2017, Gans et al., 2019) and two-sided platforms (McIntyre, 2011; Schilling, 2002; Tellis et al., 2009; Zhu & Iansiti, 2012). We also provide suggestive evidence that reducing imitation risk through scaling early (especially, for two-sided platform startups) may be insufficient to compensate for the risk of committing to a core business idea with poor product-market fit. Put differently, this study's theoretical framework and empirical findings imply that the internal fit between a firm's strategy, structure, and process is just as germane to startup performance as the external competition that the firm encounters. Hence, this study helps advance our understanding of one of the key tensions that arise in entrepreneurship and two-sided platforms.

Fourth, this article documents the first large-scale descriptive analysis of when startups begin to scale their business. We find that startups, on average, begin scaling 4 years after their founding. However, this timing of scaling varies significantly across firms. For example, although startups with a larger founding team or with serial entrepreneurs may have the capabilities to scale early, these firms are more likely to scale later than their counterparts. In addition, contrary to the common belief that startups operating in competitive markets should scale early to reduce imitation risk and capture the value of their business ideas, they tend to scale later than those in more established ones. Finally, although experimentation is crucial for startup success (Camuffo et al., 2019; Chen et al., 2022; Koning et al., 2022), new ventures that scale early are less likely to conduct experimentation using A/B testing tools. These and other descriptive results (for more details, see Sections 4.1 and 4.2) stimulate new avenues of future inquiry on the antecedents of the timing of scaling.

Finally, this article presents a methodology to empirically operationalize an important dimension of scaling: namely, its timing. Although firm growth has been commonly measured by the increase in employees and customers, using these measures for the timing of scaling has potential empirical limitations in data availability, sample selection, measurement error, and generalizability (as discussed in Section 3.1). To develop an alternative measure, we build upon existing theories on organizational growth and design. Specifically, as startups tend to formally hire managers and sales personnel before scaling their business (Colombo & Grilli, 2013; Hambrick & Crozier, 1985; Kazanjian, 1988; Penrose, 1959), we propose and verify that the timing of when startups scale can be measured by the first job postings for these specialized human resources. Hence, these measures enable future studies to explore other aspects of scaling that unfold after its beginning (listed in Section 2.1).

Beyond the phenomenon of scaling, our methodological approach using job postings holds promise for large-sample research on the evolution of strategy and structure. To date, prior research on firm growth and development has largely been conceptual or anecdotal (e.g., Greiner, 1972; Helfat & Peteraf, 2003; Penrose, 1959), primarily due to the empirical challenges in identifying the critical milestones or benchmarks that distinguish each stage (Weinzimmer et al., 1998). We argue that, as different stages require different human resources, these milestones and benchmarks can be captured by a firm's job postings. Thus, by exploring when a firm posts a managerial or functional position that it did not previously have (e.g., corporate development professionals), future studies may investigate how its strategy and structure evolve. With this methodological insight, future research can leverage job posting data to isolate a firm's strategic intent from its realized outcomes to not only provide a clearer ex-ante measure but also examine when and why organizations may experience a gap between the two.

5.2 | Managerial implications

> "One of the biggest causes of premature death in a startup is premature scaling of the team—hiring good people at the wrong time" (Furr & Ahlstrom, 2011).

In recent years, high-growth startups that made their fortune by scaling early (e.g., Facebook and Uber) have garnered much interest among academics and practitioners. Drawing upon these success stories, LinkedIn co-founder Reid Hoffman and entrepreneur Chris Yeh came up with the notion of "blitzscaling" (Hoffman & Yeh, 2018), arguing that it is essential for startups (especially, two-sided platforms) to prioritize scaling early to capture their market. In an interview, they claim that "if you are not the first to scale, ... you're likely to ultimately lose out and become irrelevant" (Greylock Perspectives, 2018). They go so far as to generalize this "fast and furious" strategy to firms of any size or type and in any region or industry (Hoffman & Yeh, 2018, pp. 240–275).

This narrative has lately drawn scrutiny from numerous practitioners. For instance, O'Reilly (2019) argues that "blitzscaling is not really a recipe for success but rather survivorship bias masquerading as a strategy." Similarly, Sherman (2019) raises the concern that "the consequences of investing too much, too soon in unproven businesses can be catastrophic." Consistent with these concerns, Marmer et al. (2011) find in their survey of high-tech startups that investing too much, too soon—in particular, hiring managers or sales personnel too early (p. 15)—is the most common reason for startup failure. Supporting this line of reasoning, our study provides large-sample evidence that scaling early is positively correlated with a higher rate of firm failure, even for platform companies.

5.3 | Limitations and future work

This study has some limitations. First, given the motivation, this study focuses on one dimension of scaling: the timing of when it begins. Future research could extend our analysis by investigating the other dimensions that unfold after its beginning: for example, mode (i.e., whether a startup scales organically, through acquisitions, or through alliances), geography (i.e., which location it scales into), and scope (i.e., which other products it leverages its resources to). Second, while our study provides descriptive analyses of how startups vary in their timing of scaling, it does not dig deeper beyond documenting potential antecedents that may explain this variation. These potential antecedents include characteristics of the founding team (e.g., serial entrepreneurs), the firm (e.g., technological capabilities), the industry (e.g., degree of competition), and the environment (e.g., changes to intellectual property regime). A deeper assessment of their associations with the timing of scaling merits further scholarly attention. Third, our empirical approach focuses on the supply-side growth of scaling—that is, hiring decisions inside firms. Future studies could complement this study by exploring the demand-side growth of scaling, such as revenues and market share. Finally, as exogenous variation in the timing of scaling was difficult to find, this study presents correlation estimates between timing and firm outcomes. Future research can revisit and advance these patterns by incorporating experimental or quasi-random variation in the timing of scaling.

5.4 | Conclusion

In sum, our work integrates prior conceptualizations of scaling, offers a theoretical framework and an empirical measurement for its timing, and documents the first large-sample analysis of when startups scale and its consequences. Yet, many insights remain to be uncovered regarding the scaling of entrepreneurial ventures. We hope our efforts serve as a promising foundation for future exploration of this phenomenon.

ACKNOWLEDGMENTS

The authors would like to thank Oliver Alexy, David Clough, Felipe Csaszar, Waverly Ding, Tom Eisenmann, Cheng Gao, Claudine Gartenberg, Brent Goldfarb, Jorge Guzman, David Hsu, Manav Raj, Chris Rider, Nicolaj Siggelkow, Olav Sorenson, Evan Starr, and Scott Stern for their valuable comments. Also, the authors acknowledge the helpful suggestions from the seminar participants at the Wharton School, Maryland Smith Entrepreneurship Research Conference, Strategic Management Society Annual Conference, Academy of Management Annual Meeting, Industry Study Association Conference, INSEAD Doriot Entrepreneurship Conference, Strategy Science Conference, LBS Sumantra Ghoshal Strategy Conference, and Wharton People and Organizations Conference. Finally, the authors gratefully acknowledge the research support from Analytics at Wharton. All errors in this article are the sole responsibility of the authors.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Burning Glass Technologies, Crunchbase, and Revelio Labs.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Lee, S. (R.), & Kim, J. D. (2024). When do startups scale? Large-scale evidence from job postings. *Strategic Management Journal*, *45*(9), 1633–1669. https://doi.org/10.1002/smj.3596