Endogenous Capability Building and Start-Up Advantage in Creating New Markets

MohammadMahdi Hashemian
MIT
Sloan School of Management
mhashemi@mit.edu

Hazhir Rahmandad
MIT
Sloan School of Management
hazhir@mit.edu

Abstract
Startups play a major role in establishing many new markets. This is theoretically puzzling because existing firms have more resources and relevant core and peripheral capabilities that should advantage them in diversifying into new markets. Here, we explore one mechanism that differentiates startups from existing firms due to the stronger link between startups’ past performance and resources available for future capability building. Using a simulation model, we show that this reinforcing loop leads entrepreneurial financial markets to quickly focus on more promising startups and, despite initial disadvantage, enable the most promising startups to take over projects in well-endowed diversifying entrants. We analyze how different markets and technological opportunities can affect these dynamics.

Jelcodes:M13.O32
Endogenous Capability Building and Start-Up Advantage in Creating New Markets

ABSTRACT

Startups play a major role in establishing many new markets. This is theoretically puzzling because existing firms have more resources and relevant core and peripheral capabilities that should advantage them in diversifying into new markets. Here, we explore one mechanism that differentiates startups from existing firms due to the stronger link between startups’ past performance and resources available for future capability building. Using a simulation model, we show that this reinforcing loop leads entrepreneurial financial markets to quickly focus on more promising startups and, despite initial disadvantage, enable the most promising startups to take over projects in well-endowed diversifying entrants. We analyze how different markets and technological opportunities can affect these dynamics.

Keywords:
Organizational Capabilities, Disruption, Simulation modeling
Endogenous Capability Building and Start-Up Advantage in Creating New Markets

Introduction

The birth of new markets has significant impacts on firms’ survival and growth, employment trends, and economy in general. Those companies that lead in creating new markets can shape how the market is structured and perceived and benefit from various advantages that accrue to the market leader. Thus, both startups and existing firms compete in creating new markets, one to establish the foundation for a new and successful enterprise, the other to expand their boundaries and thrive in the face of competition in existing markets. One theoretically important and practically relevant question is whether startups or existing firms are better placed to succeed in starting a new market.

According to the resource-based view of strategy, existing firms are likely to have a significant advantage over the newcomers. Diversifying entrants\(^1\) are well endowed when compared to startups. For example, existing firms have more access to vital resources. At least, in the crucial early stages, they have access to greater human capital and higher financial resources. Moreover, these firms, in many cases, have experience in prior or neighboring technologies. For example, Klepper and Simons (2000) show that firms in Radio market had greater experience and thus advantage over newcomers in TV receiver manufacturing market. Based on the greater resources and the prior experience, existing firms can be expected to develop relevant core and peripheral capabilities faster. For instance, while the new technological capabilities should be developed in a new market, existing firms may leverage their established brand and well functioning

---

\(^1\) Since our focus is on creating new markets, we use the terms (diversifying) entrants and existing firms interchangeably.
distribution channels to aid their nascent project. Finally, existing firms have a network of relevant customers and suppliers that potentially can serve as a good base for exploring and spearheading the new market. In sum, diversifying entrants have access to potentially relevant resources, customers, and capabilities that are expected to give them a significant advantage against start-up firms in starting a new market.

Thus, one may expect that existing firms should dominate the launch of new markets. Yet, there is plenty of evidence that highlight the startups’ importance. Companies such as Uber, Dropbox and Airbnb, among others, are example of startups that have recently created large new market where existing firms abound. To go beyond only anecdotal evidence, we analyzed the commercialization of a set of 26 major innovations\(^2\) from 1979 to 2009 and found that in at least 50 percent of new markets startups were first to commercialize a notable product. Microprocessors (by Intel), DNA Sequencing (e.g. Illumina), Online shopping (e.g. Ebay and Amazon) and social networking (e.g. MySpace) are a few examples of new markets in our sample where startups led the market. Additionally, startups are often more successful in introducing existing innovations in new geographical areas (Neffke, Hartog, Boschma, & Henning, 2016). On the national scale, US economic data\(^3\) shows that startups are the major driver for growth and new jobs responsible for around 70% of gross job creation, though they also have very high failure rates (and corresponding job losses).

Why start-ups succeed in establishing many new markets where resource based view would give them little chance? Existing firms have access to potentially relevant resources, customers, and

---


capabilities that are expected to give them a significant advantage against start-up firms, and yet their track record offers suggests those advantages do not always translate to successful market creation. Understanding the mechanisms that promote start-ups in competitive markets are thus central to understanding sources of innovation, structures of emerging markets, and the competitive dynamics around new technological opportunities.

Prior research advances two distinct sets of arguments on this question. One strand of literature, building on psychological research, suggests that entrepreneurs are prone to over-confidence and escalation of commitment (e.g., Cooper, Woo, & Dunkelberg, 1988; Dosi & Lovallo, 1997; McCarthy, Schoorman, & Cooper, 1993). Therefore start-ups often enter new markets against the odds, the vast majority exit in failure, but by chance a few stumble upon effective new products ahead of existing firms, and come to lead the new markets. In this view, sheer luck and the large number of startups explains their widespread success.

A second, organizationally focused, perspective highlights how the cognitive frames limit existing firms (e.g., Kaplan & Henderson, 2005). Those frames, evolved through adaptive processes of capability building and routine formation (March & Simon, 1958; Nelson & Winter, 1982), guide information collection and processing by organizational decision makers. For example existing firms may explore only incremental improvements on existing platforms, missing the more promising radical changes in platforms (Henderson, 1993; Utterback, 1996), or underestimate the future value of new markets given their need for large revenue streams which are not satisfied in early markets (Christensen, 2000). Therefore, when new opportunities arrive or potentially disruptive technologies emerge, existing firms are late in recognizing those developments, offering the start-ups the first mover advantage.
Both these mechanisms are likely at work: experimental evidence of overconfidence among entrepreneurs is strong (e.g., Busenitz & Barney, 1997; Koellinger, Minniti, & Schade, 2007; Palich & Bagby, 1995), and data from several markets supports the idea that biases and inertia slow down incumbents more than diversifying entrants (Henderson & Clark, 1990; Tripsas & Gavetti, 2000; Utterback, 1996). However, it is less clear if these mechanisms fully explain startup advantage in *new markets*. For example, explaining startups’ success based on abundance of entrepreneurial entry and overconfidence implicitly assumes few existing firms with relevant core or peripheral capabilities compete for the new market. However, for every new opportunity, there are scores of firms with potentially relevant capabilities that could be leveraged in the new market. Similarly, in the absence of incumbents, theories of organizational inertia and constraining cognitive frames would require diversifying entrants to miss the new opportunities that may have little conflict with their existing businesses. However, empirical evidence suggests that many of the existing firms in fact compete in new markets (Busenitz & Barney, 1997; Dunne, Klimek, & Roberts, 2005; King & Tucci, 2002; Klepper & Simons, 2000) consistent with theories that suggest diversifying entrants may not be bound by the same inertia that holds incumbents back and are successful in radical innovation in many cases (Sosa, 2013; Utterback, 1996). Therefore, we suspect there are complementary mechanisms that work in favor of startups, countering resource and capability advantages of existing firms in shaping new markets.

In this study we explore one such mechanism that rests on differential rates of learning with endogenous growth across start-ups and existing firms. We view each competitor in a new market as engaged in searching a complex landscape of technological and business model configurations. We capture an important endogeneity in the search process: that startups and diversifying entrants search more or less rapidly depending on their access to resources, which in
turn is a function of their past performance perceived by resource-holders. For example venture capitals, as well as stock markets, reward promising start-ups with additional rounds of funding, and firms allocate more resources to the more promising research and development projects.

Focusing on the same opportunity for a new market, we analyze the competition among projects within existing firms and start-ups. By focusing on this competition we exclude the mechanisms related to inertia and lack of entry by existing firms into new markets and explore what mechanisms matter when start-ups compete head-to-head with projects in existing firms. Internal projects are distinguished from start-ups based on two features. First, following the resource-based literature we allow projects in existing firms to have access to additional resources compared to startups. These could be due to capabilities, network, talent, or financial resources that existing firms offer their internal projects with a discount or at no cost. Second, existing firms, due to organizational coupling and portfolio logic, follow a more egalitarian approach in allocating resources to internal projects, compared to how tightly financial markets couple startups’ resources to their perceived promise. While the first feature represents the existing theory, we hypothesize that the second feature activates an unexplored mechanism in which start-ups benefit from a stronger reinforcing feedback loop among Exploration, Outcomes, and Resources for Exploration. The start-ups that, by chance, arrive at better configurations earlier, are proportionally rewarded with more resources for further exploration and refinement of their promising idea. Parallel projects inside an incumbent firm may have more resources initially, but get a weaker boost in resources when they find a promising path. Therefore, promising startups can break out of competition faster and be the first to establish new markets. Rooted in differential learning rates in presence of endogenous resources, various technological opportunities, and the inherent uncertainty in learning and capability building, this mechanism is
dynamically complex. We therefore utilize simulation modeling to formalize and explore this mechanism in depth and establish its boundary conditions.

**Dynamics of Capability Building**

Most new markets are launched when a firm develops both a technological solution for an unmet need and a business model that can realize and scale up the potential for the new solution. There is no general prescription for this process and existing Literature suggests that learning and experimentation is at the heart of finding a product design that starts a new market (Dosi & Marengo, 2000; Helfat & Lieberman, 2002; Nelson & Winter, 1982). The result of this learning process is more effective organizational capabilities in the form of routines (Winter, 2000) that enable firms to enhance their performance and profitably and meet the needs of an emerging customer base (Helfat & Peteraf, 2003). Therefore understanding how different firms learn and build their capabilities differently can help explain the performance heterogeneity not only in mature markets (Gibbons & Henderson, 2012) but also firms success and survival in waves of creative destruction.

Firms competing to start a new market can include both startups and projects inside existing firms. Both types of players seek resources to search and develop effective capabilities in order to differentiate themselves as the first who offers a viable product and business model, attracts customers, and thus launches a new market. This first-mover advantage can help startups become profitable, benefit from first mover advantages (Lieberman & Montgomery, 1988; Markides & Sosa, 2013) and pay back the entrepreneurs and early investors handsomely. On the other hand existing firms who succeed in starting new markets enhance their chances of survival and strategically renew their capabilities, and retain a high leverage position in their industry (Lieberman & Montgomery, 1988). Therefore both startups and existing firms often find
themselves in direct competition when it comes to establishing new markets. This raises the question: which type of firm is more likely to succeed in building the requisite capabilities more rapidly, and why?

**Endogenous Capability Building**

Extant literature offers two relevant insights into this process of capability building. First, the relationship between cumulative investment in capabilities and performance follows an S-shape curve (Foster, 1988). In the initial phases, the return on investment is low as distant exploration is pursued, the needs and tastes of customers are assessed, multiple alternative solutions are sampled, but no promising technological path is established. As capabilities build, firms’ knowledge base grows, and early uncertainties are resolved, performance gains speed up as a function of capability learning. Once a technological platform is finalized a more focused process of search and learning by doing pursues and the typical learning curve dynamics kick in (Argote & Epple, 1990). In this regime the return on learning slows down as low hanging improvement opportunities are discovered first and the learning organization approaches the “fundamental limit of the technology”. When performance arrives near that fundamental limit, further investment in capabilities yield few improvements and those improvements matter less for customers (Christensen, 2000). The specifics of this process are a function of the underlying technology and market, as different platforms have different learning growth rates and limits.

Second, there is uncertainty in the process of capability building. Some investments prove fruitful while others offer little improvement in the underlying capabilities and the resulting promise of the firm/project. This probabilistic feature comes from two separate but related sources of uncertainty. First, some explorations, while helpful in learning about the problem at hand, never pay off in terms of actual efficiency gains. Moreover, there is large variation both in
the potential returns of different improvement activities and the organizational effectiveness in realizing those returns. Building on these two features of capability building dynamics we view firms as engaged in an adaptive learning process that is uncertain and bounded by the technological trajectory they choose to explore.

Our model of organizational learning is distinguished from the existing models in the literature by capturing the endogeneity in the speed of search. Specifically, the resources available to startups and internal projects for search and capability investment depend, partially, on their past performance. The more promising the progress of a start-up, the better its prospects for securing the next round of funding that enables further capability building and refinement. Similarly, how managers perceive the promise of internal projects for future investment depends on projects’ past performance. Managers approve higher budgets and allocate more organizational resources to projects that have shown higher promise.

The endogeneity in the resources for capability investment is due to the resource allocation by financial markets among multiple startups, and by existing firms among multiple projects. Specifically, comparing the perceived promise of multiple startups active in a new market, venture capitals and other investors have to decide on their allocation according to the perceived promise of each contender. A similar mechanism determines the allocation of organizational budget among multiple R&D projects. Thus, markets and internal decision makers allocate resources not only based on the focal firm/project’s promise, but also those of the other alternatives. As a result, if past investments have resulted in higher capabilities and perceived promise for one alternative compared to competitors, new resources are more likely to flow in the direction of that alternative, creating a reinforcing loop, which we call Endogenous Learning. Figure 1 provides a stylized causal loop diagram for our model (Sterman, 2000).
Securing Resources in a Competitive Environment

Focusing on endogenous learning and capability building as the core mechanism to understand capability building and performance in new markets, we need to specify how the two types of players differ in their allocation of resources. Specifically, we focus on the differences between projects in existing firms and startups in securing resources to build their respective capabilities. Startups acquire much of their resources from financial markets, e.g. angel investors and venture capitals. In contrast, projects inside existing firms rely on the parent firm for their resources. Usually resource holders (either venture capitals or higher managers) rely on many similar cues, such as technology maturity, market size, business model coherence, team quality, intellectual property, and financial projections to assess the perceived promise of both startups and internal projects. However, there are important differences between the two. First, the levels of resources startups secure maybe less than projects inside well-endowed firms, especially in the pre-commercialization stage. On the other hand, existing firms often have significant financial resources at their disposal, which can give their internal projects a leg up. Moreover, from technological expertise to test equipment, market research, human resource systems, and supply chains, existing firms own various resources and capabilities that could benefit new projects with limited costs, increasing the return on investments in internal projects’ capabilities.

Second, there is a significant difference in how the resources are being allocated inside a firm vis-à-vis the market. Different startups are largely independent of each other, and thus decoupled in the eyes of financial markets. Early-on markets may allocate resources to multiple start-ups with varying promise levels due to uncertainties in technologies and assessment of promise, but as market matures, venture capitals quickly cut their losses and focus on the most promising platforms.
We expect decoupling among internal projects to be significantly less for at least four reasons. First, projects inside an organization share some expertise, systems, capabilities, and resources with each other, which prohibits full decoupling (Bresnahan, Greenstein, & Henderson, 2011). For example, an investment in firms' human resource systems impacts all internal projects, and it is costly to design and build separate systems for each internal project.

Second, the power to commit resources and formulate organizational strategy is distributed (Bower & Doz, 1979). Middle managers can use existing organizational resources to make progress in new projects without top management official consent, especially in earlier stages that require fewer resources (Bower & Gilbert, 2007; Burgelman, 1983). This increases the chance that multiple projects work on similar ideas and keep using limited organizational resources for their respective projects' advancement. Additionally, extant research suggests that top management resource allocation decisions are based on a combination of both project attractiveness and the organizational credibility of the manager proposing the project (Bower, Doz, & Gilbert, 2005). Therefore, more time and organizational resources might be needed in an existing firm to identify best projects. For example, if a highly credible manager proposes a project with medium promise, another less credible manager with a superior project needs to show further results (and therefore requires more time) to persuade top management for more resources.

Third, there are organizational and psychological pressures against full decoupling. The members of different internal projects see themselves as parts of the same organization, and as such expect to be rewarded based on their effort and overall organizational performance, and not their luck in establishing a new market, which is very uncertain. Thus, these members will likely feel mistreated when their rewards and resources are tied to the perceived performance of their
project rather than the efforts they have put into it, creating a pushback against such decoupling inside the large firm.

Finally, a diversifying entrant investing on multiple projects in a new opportunity space is likely to draw on the logic of portfolio management to keep investing in multiple internal projects, with less regard for their immediate perceived promise, in the hope that with more eggs in the basket they will ultimately have a winning project in the market. Such investment policy not only spreads the inherent risk of investing in new markets, but also builds the absorptive capacity inside the firm for potential future acquisitions or expansion in the emerging dominant design when the market is created. In sum, we expect that financial markets sift through startups aggressively to find the startup with the highest potential, but existing firms continue investing in multiple projects for longer time rather than narrowing down their focus to the most promising project early on.

---

**Insert Figure 1 about here**

---

**Analyzing Competition in Creating New Markets**

Capturing the qualitative mechanisms discussed in section 2, we model the competition among N (=5 in the reported results) startups and N projects inside a diversifying entrant firm. Each startup/project has a stock of capabilities that accumulate through investment in search and adaptation. The capability levels inform the perceived promise of each alternative in the eyes of relevant resource-holder (financial market or management) using a S-shaped function. Financial markets allocate resources to various startups by comparing their promise against other startups. Equation (1) formalizes this decision and allows for different levels of aggressiveness in the
market (parameter g). Similarly, managers in the diversifying entrant allocate resources to their internal projects based on the relative promise of each project (Equation (2)). We capture the relative decoupling among internal projects, compared to the market’s decoupling among startups, using parameter (α). Therefore, when α gets closer to 1 the decision process inside the organization becomes more similar to the market. Smaller values of α reflect managers’ decision to diversify their investment, more cautiously linking a project’s resources to its past performance.

\[
(1) \quad Resources\ Secured\ for\ Startup\ (j) = Base\ Investment \times \frac{e^{g \cdot Perceived\ Promise\ Startup(k)}}{\sum_{k=1}^{N} e^{g \cdot Perceived\ Promise\ Startup(k)}}
\]

\[
(2) \quad Resources\ Allocated\ to\ Project\ (i) = r \times Base\ Investment \times \frac{e^{a \cdot g \cdot Perceived\ Promise\ Project(i)}}{\sum_{k=1}^{N} e^{a \cdot g \cdot Perceived\ Promise\ Project(k)}}
\]

We capture the endowment (financial and non-financial) difference between startups and internal projects by varying the level of resources available to diversifying entrant’s projects compared to startups. Specifically, parameter r reflects the ratio of total resources allocated to the portfolio of internal projects compared to what market allocate to the group of competing startups. Theoretical arguments often suggest r is higher than one, that is, existing firms have more resources to allocate to their projects, or can offer various capabilities and assets to their internal projects at discounted costs. This parameter can also capture the differences in productivity of those investments, for example lower-than-one r-values could be justified in settings where diversifying entrants have no relevant capabilities or resources, and startups are more agile and productive in using their existing resources. Finally, we capture the uncertainty in the search and learning process using an auto-correlated noise process that regulates capability growth. Table 1 summarizes the main parameters of the model and their values in the base case simulations.
**Basic Dynamics**

To build intuition about the core mechanism in our model we first provide a sample simulation, with N=2 startups and 2 parallel projects inside a diversifying entrant. Figure 2 summarizes these results. Here the projects inside the diversifying entrant are endowed with 50% more resources \((r=1.5)\). Moreover, the managers in the firm are assumed reluctant to decouple the internal projects \((\alpha=0.1)\). As a result internal projects (blue and green lines) start by faster capability investment rates early on. Yet the randomness in capability growth, due to the uncertainty in returns on investment has given a leg up to one of the startups (the red one), which allows this startup to gain even more traction in the financial market early on. This leads to an increasing shift of investment resources towards this project and away from the other startup (the gray one). The internal projects also see a similar decoupling in resource allocation, but much slower than the startups. As a result, after a while, the red startup catches up with the better performing internal project, enhances its capability further, and ultimately beats all the players and establishes the new market first\(^4\). The key mechanism that promoted a startup here, despite its resource disadvantage, is the reinforcing loop of endogenous learning that was more strongly active for the startup, compared to the internal projects, due to \(\alpha<1\). Yet the core mechanism is also moderated by the uncertainty in the capability building, the extra resources available to the internal projects, and the shape of the technological landscape underlying the competition. We explore these factors using large sample simulations in the following sections.

---

\(^4\) We identify the successful competitor as the one first reaching a promising performance threshold that can sustain positive cash flow in the market (defined as the promise level of 1 in the model).
Startup advantage in creating new markets

In this section we report how the chances of startups in establishing a new market depend on the resource advantage of existing firms ($r$) and the decoupling level ($\alpha$). Keeping all other parameters the same across startups and entrants, we change the two parameters of interest by increments of 0.1, simulate 200 random markets in each setting, and report the startups winning fractions (across those 200 simulations) using a contour plot that summarizes the 24200 resulting simulation (Figure 3).

When the diversifying entrant has no resource advantage ($r=1$) and it is able to imitate market’s allocation by fully decoupling the internal projects ($\alpha=1$), we expect no difference between startups and internal projects of the entrant, leading to a startup success fraction of 0.5. When the diversifying entrant has twice more resources as startups ($r=2$) and is able to fully decouple its projects, as expected we see the vast majority of winners come from the diversifying entrant. As $\alpha$ decreases from 1 to zero however, we see increasing opportunities for the startup’s success. This advantage works against the entrants resource advantage, so for example with no decoupling ($\alpha=0$) the diversifying entrant requires over 1.6 times more resources to compensate for the stronger reinforcing loops that startups can activate.

Impact of Market Aggressiveness

In this section, we report the impact of the market aggressiveness on startup advantage. In our model market aggressiveness captures the speed with which financial markets rally around the
emerging top startup. One may expect more transparency in the market, higher discount rates, and stronger competition among different investors would trigger more aggressive treatment of the pool of existing startups. Therefore it is instructive to assess the sensitivity of results to this parameter. More specifically, we compare the case where we have a less aggressive market to the base case and track how the impact of extra resources \((r)\) and decoupling \((\alpha)\) on startup advantages changes. We change the Market aggressiveness parameter \((g)\) from 5 to 2, holding everything else identical to the base case.

Results depicted in Figure 4 show a similar tradeoff as the base case, but with weaker impact of the mechanism that promotes startups. When the Diversifying Entrant has no resource advantage \((r=1)\) and similar decoupling in the allocation process \((\alpha=1)\) we still see a 50 percent change. Similarly, we still observe that when \((\alpha=1)\) and Diversifying Entrant has significant resource advantage \((r=2)\), it is able to clear out the competition. However, comparing to the base case, here the relative impact of decoupling has faded. In low aggressive markets, the existing firms just needs 1.2 times more resources to compensate for no decoupling \((\alpha=0)\). This result is due to the weakening of the Endogenous Learning reinforcing loop across the board when we reduce \(g\).

In the extreme, when \(g=0\), neither financial markets nor the internal managers attend to perceived promise in allocating resources. With a fixed share of investment guaranteed, the outcome of search and capability building is solely a function of total resources allocated and luck. More generally, when market is less aggressive, the diversifying entrant has sufficient time to improve performance of projects by using its resources advantage before the most promising startup can differentiate itself from the rest and get comparable resources. As a corollary, this mechanism puts even more pressure on investors in startups to be aggressive in their resource allocation, since that increases their chances of funding a successful startup.
Competition in highly uncertain markets

In this section, we report how the level of uncertainty in capability building impacts the chances of startup success. The maturity stage of new technologies, the closeness of the new market to existing markets (and thus the clarity of needs of potential customers), and the extent to which the technology and market are subject to influences outside of the model boundary, among others, regulate the level of uncertainty in search and capability building. To assess the sensitivity of results to different levels of uncertainty, we double the noise standard deviation from the base case (SD=0.2 to SD=0.4). We hold everything else the same as the base case to isolate the impact of increased uncertainty on startup advantage.

Results are reported in Figure 5. As expected, we see the same basic dynamics of increased startup chances when Entrant’s decoupling and resource advantage are less. Compared to the base case we see increased chances for startups success when \( r \) and \( \alpha \) are higher. For example, the fraction of startups winning reaches 0.1 when \( \alpha=1 \) and \( r=1.6 \), compared to the base case where we see a much steeper decrease in startups chances (from 50 percent to 10 percent when \( r=1.3 \)). On the other hand, we see increased chances of Entrant’s success when it has less resource advantage and is not able to decouple much between the projects. For example, in the base case, the entrant had almost no chance when \( r<1.1 \) and \( \alpha<0.2 \). In the case of highly uncertain markets however, Entrants chances never pass below 1 percent even when there are no more resources(\( r=1 \)) and no decoupling (\( \alpha=0 \)).

Two mechanisms explain these results. First, by increasing uncertainty in search and capability building success becomes more a matter of chance than the core model mechanisms. Therefore,
the probabilities of success come closer to 50% across the board, reducing the sharp distinction in the extremes (e.g. $\alpha=0$ with $r=1$ and $\alpha=1$ with $r=2$). On the other hand, the startup advantage due to the endogenous learning loop is only observed when the symmetry among startups is broken by randomness in investment returns. Increasing uncertainty thus triggers this mechanism earlier and helps startups win a larger fraction of simulated markets (thus the shift from $r=1.6$ to $r=1.9$ for the breakeven point under $\alpha=0$).

Competition in the Rugged Technological Landscapes

In this section, we systematically manipulated the s-shape function that connects capabilities to each startup/project promise. Different technologies may have widely different trajectories. For example in the alternative fuel vehicle domain, hydrogen, electric, and hybrid technologies promise different ideals of fuel efficiency, carbon footprint, and costs. They also have very different trajectories of investment, with hybrid vehicles promising faster early improvements but likely lower maximum benefits (Keith, 2012). So far we had used the same s-shape curve connecting the level of capability to the perceived promise, but different startups and projects may actually follow different architectures with various underlying capability-promise curves. This s-shape function represents the inherent features of each technology including its fundamental limit or maximum, the promise level at the inflection point where the maximum marginal gain from capability investments occur, and the slope of that maximum marginal gain which regulates how fast that technology reaches its maximum. These features are highlighted in Figure 6.a.
In the base case, we assumed that every startup and projects inside the diversifying entrant follow the same S-shape path. This S-shape function has 1.5 as maximum, 1 as the inflection point and 1 as the slope. Here, to simulate more rugged technological Landscapes, we randomly assign a maximum to each startup/project uniformly from 1 to 2. Similarly, we draw the inflection point and slope randomly from a uniform distribution from ranges [0.5 1.5] and [0.5 1] respectively.

Results depicted in Figure 6.b show that, while we see similar patterns with the base case, startups winning fraction has increased across the board. For example, with no decoupling (α=0) the diversifying entrant requires even more than 2 times more resources to compensate (compared to r=1.6 in the base case). Similarly, when Entrant is able to fully decouple between projects (α=1), chances of startup success decreases to around 1 percent when entrant has 80 percent more resources(r=1.8). In the base case, startups chances reaches the same 1 percent point by just 50 percent more resources (r=1.5).

These results are regulated by the heterogeneity in the strength of endogenous learning loop that is introduced in rugged technological landscapes. Specifically, increasing the maximum potential and the slope both speed up the reinforcing loop while earlier inflection point brings forward in time the operation of that loop in favor of startups. Thus, by introducing heterogeneity in these parameters, we are more likely to come across startups that benefit disproportionately from the endogenous learning loop, and thus are more likely to take over the otherwise identical internal project. Therefore, not only randomness in the search process but also randomness in the shape of technological landscape can enhance the chances of startups in establishing new markets.

---

Insert Figure 6 about here
---
One important assumption in the analyses presented above is that all startups and projects have the potential to successfully create a new market. Specifically, in previous analyses we set the minimum fundamental technological limit to be always greater than or equal to the threshold for winning the (market creation) competition of 1. In this part, we relax this assumption by randomly assigning a maximum to each startup/project uniformly from 0.5 to 1.5 (instead of [1, 2] Figure 6.a). Figure 7 depict the simulation results for the rugged landscape with just 50% viable technologies.

Results show that while the results are similar in low levels of investment and aggressiveness, increasing aggressiveness can become counterproductive for the entrant. To illustrate this point, Figure 7.b. exhibits the optimal level of aggressiveness with three different levels of investments. Aggressively investing resources on projects that show early promise and success can therefore be very risky. To explain this counterintuitive result, it’s important to note that unviable trajectories increase uncertainty and risk associated with focusing on one project. Therefore, when rugged landscapes increase the chances of failure, high levels of decoupling can actually hurt due to premature abandoning of promising alternatives.

**Robustness of Results**

Besides the results reported above, we conducted sensitivity analysis on all the model parameters and key structural features, finding no significant qualitative change in the results. Various nuances were revealed in the sensitivity analysis process. For example, we tested how access to information about the other side of the competition will affect the results. Interestingly, knowing about the promise of the other side (e.g. startup funders knowing about the promise of internal
projects and vice versa) can actually discourage investments when the other side has an early advantage by chance or due to extra investments. If this visibility is symmetric (both sides can observe the promise of the other), the net result supports internal projects that often start ahead due to extra resources. But the potentially more realistic asymmetric visibility, where startups are observable by all parties but internal projects are opaque to outsiders, can actually enhance startup advantage. Additionally, we also replicated the results using the NK model structure commonly applied in strategy research (Ganco & Agarwal, 2009; Levinthal, 1997) to model the same phenomenon and observed qualitatively similar results, so opted for the simpler, more flexible, and computationally more efficient model structure reported here. Overall our results are robust to key structural assumptions and parameter values in sensible ranges and the most important sensitivities are discussed in more detail in the previous sections.

**Discussion and conclusions**

Startups regularly succeed in creating new markets despite the presence and investments of well-endowed and capable existing firms who can benefit from the launch of a new market for their strategic renewal. Existing firms should have a significant advantage according to resource-based view of strategy, reducing drastically the odds of any startup succeeding in such a competition. Existing research provides key insights into why incumbents might not invest enough, or in time, in new opportunities. However, we know much less why diversifying entrants do not usually succeed in cases where they do invest and do so in time, especially in new markets in which the risk of the cannibalization and organizational inertia are lower than established markets.

We propose a novel mechanism to explain this puzzle. This mechanism captures the endogeneity in the search process: not only greater investment will result in building more capabilities, but also higher performance based on those capabilities will attract and enable more investments.
Building on this feedback loop, we argue that startups can speed up their learning process faster because existing firms cannot fully decouple between internal projects. This means that better performing projects inside the diversifying entrant get somewhat similar resources, less dictated by their performance growth, and as such they start to fall behind the fastest-growing startups that fully utilize this endogenous learning feedback loop.

In sum, our results show a distinct opportunity for start-ups to succeed even when competency traps and other sources of inertia do not weigh down existing firms. We explore the strength of our proposed mechanism under various levels of complexity in the technological landscape, aggressiveness of external markets in funding startups based on their perceived promise, and different incumbent strategies in internally providing resources for various projects. While we see interesting nuances based on these sensitivity analyses, our core results are robust in a wide range of parameter settings and assumptions.

Our analyses suggest that the endogenous learning mechanism is most salient when developing the new market is complex, uncertain, subject to increasing returns, and contested by multiple start-ups and entrants. More specifically the analysis provides a set of propositions on the market conditions that favor startups, including complex technological landscapes, limits to the applicability of diversifying entrant’s existing knowledge in the new opportunity, markets with strong reinforcing loops, availability of external funding mechanisms, and tightly coupled administrative systems inside existing firms.

Some of these predictions coincide with those of the existing theory, but others offer opportunities to empirically tease out the alternative mechanisms. For example, while spreading risk across a portfolio is a cornerstone of conventional finance and resource allocation strategies, our model predicts that the benefits of portfolios may break down when resources for learning
depend on past performance. It also suggests that entrepreneurial spin-offs can be successful by combining the benefits of both being a startup and having roots in a well-endowed firm (Christensen, 1993; Dosi, 1984; Klepper, 2001; Klepper & Sleeper, 2005). On the other hand, existing firms may be able to improve their odds of succeeding in new markets by decoupling across their projects, for instance through internal venture capitals (Chesbrough, 2000).

Our model, while providing interesting insights, is quite stylized and limited in scope. There are many other dynamics that can influence startups and existing firms’ competition. For example, we assume all the startups and projects inside the existing firms launch at the same time. This assumption provides us a platform to focus on our main mechanism. However, in many cases how soon existing firms recognize and engage in new market creation plays a significant role (Christensen, 2000; Henderson & Clark, 1990; Utterback, 1996). Moreover, we imply that fast learning and capability building are always desirable. However, existing literature suggests that the getting big fast strategies might backfire and create significant problems in execution and loss of credibility for a startup (Sterman, Henderson, Beinhocker, & Newman, 2007). For example, some firms may try to enhance their perceived promise without building the necessary capabilities, leading to cheating, corner cutting, and other risks we did not explore.

Moreover, we limited our analysis to the competition among startups and existing firms. The relationship between the two types is more complex however. Some existing firms do not enter new markets early on in the hope of acquiring a promising startup later. While as the fog of uncertainty clears, the laggard firms find fewer highly profitable acquisition opportunities, this strategy points to a more complex relationship between the two types. Indeed, some existing firms may sustain less promising projects internally to enhance their environmental scanning for identifying promising startups early on and to have the absorptive capacity in case they acquire a
new startup. These nuances point to a higher level competition among existing firms who invest in new technological areas not only counting on the likelihood of building a successful new product internally but also to strengthen their chances of acquiring promising startups before their competitors do. This potential mechanism offers one answer to the question: why existing firms invest in new markets if they can see a significant startup advantage due to endogenous learning mechanism? Formalizing this intuition and exploring its implications offers an opportunity to extend the current study.

Future research can also assess the impact of endogenizing both market’s and firm’s resource allocation. Specifically, over time one can expect that VCs and other funders of early stage businesses adjust their level of emphasis on past performance as indication of a firm’s chances of success, to maximize their own expected return on investment. Similarly, managers inside the existing firms may increase investments in projects or may attempt more decoupling in later stages when and if they observe signs of startups surpassing their projects.
References:


FIGURE 1
Summary of Feedback Loops in Dynamic Competition among Startups and Existing Firms.

![Diagram showing feedback loops between startups and existing firms]
TABLE 1

Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value/Range</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>Number of startups and projects inside the Diversifying entrant</td>
<td>5</td>
</tr>
<tr>
<td>α</td>
<td>Entrant’s Allocation Decoupling</td>
<td>[0 1]</td>
</tr>
<tr>
<td>r</td>
<td>Entrant’s Extra Internal resources</td>
<td>[1 2]</td>
</tr>
<tr>
<td>g</td>
<td>Market Aggressiveness</td>
<td>5</td>
</tr>
<tr>
<td>SD</td>
<td>Uncertainty (Noise Standard deviation)</td>
<td>0.2</td>
</tr>
</tbody>
</table>
FIGURE 2

Sample Simulation with N=2, A=0.1 and R=1.5. The Startups are in Grey and Red while Projects inside the Existing Firm are in Blue and Green.
FIGURE 3

Simulation Results of the Dynamic Competition between Startups and A Diversifying Entrant for the Base Case
FIGURE 4

Simulation Results in Case of Low Market Aggressiveness (G=2)
FIGURE 5

Simulation Results in Case of Highly Uncertain Markets (SD=0.4)
6.a. Randomness in the Technological S-Curves

6.b. Simulation Results of Competition in the Rugged Technological Landscape
FIGURE 7

7.a. Simulation Results of Competition in the Rugged Technological Landscape with 50% Viable Projects

7.b. Change in Optimal level of Aggressive without the 100% Viability Assumption