Endogenous Capability Building And Start-Up Advantage In Creating New Markets

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Submitted To The Department of Management on August 5th In Partial Fulfillment Of The Requirements For The Degree of Master of Science In Management Research

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: the stronger link between past performance and resources available for future capability building for startups than for existing firms. 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 overtake projects in well-endowed diversifying entrants. We analyze how different markets and technological opportunities can affect these dynamics.

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1. Introduction

The birth of new markets has significant effects on firms' survival and growth, employment trends, and the economy in general. Those companies that lead in creating new markets can shape how the market is structured and perceived and can 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 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 the Radio market had greater experience and thus advantage over newcomers in the TV receiver manufacturing market. Based on the greater resources and 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 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.

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1 For theoretical simplification, we make a clear distinction between “new” vs. “existing” markets. However, in practice there is a continuum of newness, for example, Helfat and Lieberman (2002) identify new industry, new product-market niche, different geographic location, and established market as points on this continuum.

2 Since our focus is on creating new markets, we use the terms (diversifying) entrants and existing firms interchangeably.
Thus, one may expect that existing firms should dominate the launch of new markets. Yet, there is plenty of evidence that highlights startups' importance. Companies such as Uber, Dropbox and Airbnb, among others, are examples of startups that have recently created large new markets where existing firms abound. To go beyond anecdotal evidence, we analyzed the commercialization of a set of 26 major innovations from 1979 to 2009 (based on Forbes, 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 (Illumina), Online shopping (Ebay and Amazon) and social networking (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 et al., 2016). On a national scale, US economic data shows that startups are the major driver for growth and are responsible for around 70% of gross job creation (2015), though they also have very high failure rates (and corresponding job losses).

Why do start-ups succeed in establishing many new markets when the 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 suggests that those advantages do not always translate to successful market creation. Understanding the mechanisms that promote start-ups in competitive markets is 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 mechanisms that directly or indirectly inform 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, and Dunkelberg, 1988; Dosi and Lovallo, 1997; McCarthy, Schoorman, and 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 cognitive frames limit existing firms (e.g., Kaplan and Henderson, 2005). Those frames, evolved through adaptive processes of capability building and routine formation (March and Simon, 1958; Nelson and Winter, 1982), guide information collection and processing by organizational decision makers. While much of this research focuses on competition between diversifying entrants and incumbents, similar mechanisms may inform the competition between startups and diversifying entrants in forming new markets. 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 and Barney, 1997; Koellinger, Minniti, and Schade, 2007; Palich and Bagby, 1995), and data from several markets supports the idea that biases and inertia slow down incumbents more than diversifying entrants (Henderson and Clark, 1990; Tripsas and Gavetti, 2000; Utterback, 1996). However, it is less clear whether 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, from core technical ones to marketing, brand name, talent acquisition, supply chain, and other peripheral 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 and Barney, 1997; Dunne, Klimek, and Roberts, 2005; King and Tucci, 2002; Klepper and Simons, 2000). This
observation is actually consistent with theories that suggest diversifying entrants may not be bound by the same inertia that holds incumbents back, and in many cases are successful in radical innovation (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 as 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.

2. 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 and Marengo, 2000; Helfat and Lieberman, 2002; Nelson and 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 and 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 and 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 and Montgomery, 1988; Markides and 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
and 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?

2.1 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 and 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” (Foster, 1988). When the fundamental limit is approached, 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. Indeed, different technological platforms targeting the same market opportunity may show very different trajectories as different platforms have different learning growth rates and limits. Thus firms may compete with each other while climbing different technological maturity curves.

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. While most organizational learning models endow competing actors with one search move per period, actual firms may have very different rates of exploration and/or exploitation. 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).
2.2 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 level of resources startups secure maybe less than projects inside a well-endowed firms, especially in the pre-commercialization stage. On the one 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 three reasons. First, projects inside an organizations share some expertise, systems, capabilities and resources with each other which prohibit full decoupling (Bresnahan, Greenstein, and 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, 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 push-back 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.

\[ \text{Learning Uncertainty} \]

\[ \text{Startuup j} \]

\[ \text{Capability Growth} \]

\[ \text{Endogenous Learning} \]

\[ \text{Resources secured for Startup j} \]

\[ \text{Perceived Promise} \]

\[ \text{Allocated to Project i} \]

\[ \text{Learning Uncertainty} \]

\[ \text{Project i} \]

\[ \text{Capabilities} \]

\[ \text{Management Perceived} \]

\[ \text{Endogenous Learning} \]

\[ \text{Resources Allocated to Project i} \]

**Figure 1:** Summary of feedback loops in dynamic competition among startups and existing firms.
3. Analyzing Competition in Creating New Markets

Capturing the qualitative mechanisms discussed in section 2, we model the competition among \( N (=5 \text{ in the reported results}) \) 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. This S-shaped function formalized in Equation (1) for projects represents the inherent features of each technology which we distinguish based on 1) its Technological limit or maximum and 2) the slope of growth at the beginning that affects how fast each technology improves early on. Startups of course have the same S-shaped function. Sample technology S-curve functions that vary on these two features are represented in Figure 6-A. Financial markets allocate resources to various startups by comparing their promise against other startups. Equation (2) 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 (3)). We capture the relative decoupling among internal projects, compared to the market’s decoupling among startups, using parameter \( (\alpha) \). Therefore, when \( \alpha \) gets closer to 1 the decision process inside the organization becomes more similar to the market. Smaller values of \( \alpha \) reflect managers’ decision to diversify their investment, more cautiously linking a project’s resources to its past performance.

\[
\text{Perceived Promise Project (i)} = \frac{\text{Technology limit}*\text{Project (i) Capabilities}}{\text{Project (i) Capabilities} + \left(\frac{\text{Initial Slope}}{\text{Technology limit}}\right)\text{e}^{\text{Project (i) Capabilities}}}
\]

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

\[
\text{Resources Allocated to Project (i)} = r \times \text{Base Investment} \times \frac{e^{\alpha g}*\text{Perceived Promise Project(i)}}{\sum_{k=1}^{N} e^{\alpha g}*\text{Perceived Promise Project(k)}}
\]

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

\[3 \text{ Full model documentation can be found in the appendix. Various analyses not fully reported in the paper.}\]
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.

**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>( \alpha )</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>10</td>
</tr>
<tr>
<td>SD</td>
<td>Uncertainty (Noise Standard deviation)</td>
<td>0.2</td>
</tr>
</tbody>
</table>

### 3.1 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.

\[\text{Figure 2- Sample simulation with } N=2, \alpha =0.1 \text{ and } r=1.5. \text{ The startups are in grey and red while projects inside the existing firm are in blue and green.}\]

\(^4\) 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).
3.2 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 and assuming they all explore the same technological platform. We then 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 simulations (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 medium decoupling ($\alpha=0.5$) the diversifying entrant requires over 1.6 times more resources to compensate for the stronger reinforcing loops that startups can activate.
3.3 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. To keep with the spirit of controlled experiments, we only vary one factor compared to the base case and thus assume every project and startup follow the same technological S-curve function. We change the Market aggressiveness parameter \( g \) from 10 to 5 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 \((a=1)\) we still see a 50 percent change. Similarly, we still observe that when \((a=1)\) and Diversifying Entrant has significant resource advantage \((r=2)\), it is able to clear out the competition.

![Start-up Winning Fraction](image)

**Figure 4.** Simulation results in case of Low Market Aggressiveness \((g=5)\)

However, comparing to the base case, here the relative impact of decoupling has faded. In low aggressive markets, the existing firms just needs 1.5 times more resources to compensate for no decoupling \((a=0)\). 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.

3.4 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 $t=1.9$, 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.

3.5 Competition in the Rugged Technological Landscapes

The base case results assumed startups and existing firm’s projects compete on the same
technological landscape and thus face the same learning curve. This may not be the case
in many realistic settings. For example in the alternative fuel vehicle market, hydrogen,
electric, and hybrid technologies promise different ideals of fuel efficiency, carbon
footprint, and costs. They also have very different trajectories of investment and
learning, with hybrid vehicles promising faster early improvements but likely lower
maximum benefits (Keith, 2012). Thus we systematically vary the s-shape function that
connects capabilities to the promise of each startup/project.

In the base case, we assumed that every startup and project inside the diversifying
entrant follows the same S-shape path. This S-shape function has 1.5 as maximum and 1
as the slope of the curve at origin. Here, to simulate more rugged technological
Landscapes, we randomly assign a maximum to each startup/project drawn from a
uniform distribution, with a width of 1. We consider two different averages for this
maximum. In panel B we show results where maximum technology potential is Uniform
\([1,2]\), while in panel C we use Uniform \([0.5,1.5]\). The former case is consistent with the
base case results’ maximum technological potential. The latter is motivated by the
observation that in real markets some projects/startups are invested on platforms that lack potential for ultimate commercial success (i.e. reach performance threshold of 1 in our model) even if they fully ascent the learning curve. In both cases we draw the beginning slope randomly from a uniform distribution from ranges (0 2].

Results introduce two mechanisms compared with the base case. First, the existence of multiple technological platforms induces more randomness into who wins the competition. A project may receive a lot of resources, but be following an ill-fated technological trajectory, and another lean startup may succeed because by chance it has stumbled on a very promising trajectory with fast returns. This randomness thus reduces the impact of both additional resources and decoupling. For example compare the base case with Figure 6-B. With no decoupling (α=0) the diversifying entrant now has a 10% chance to win the competition with r=1.9, compared to about 1% in the base case. Similarly, when α=1, the startups chances of winning the competition increase from 1% to 10% when entrants have 60% more resources.

More interesting is the strength of endogenous learning mechanism in response to viability of technological platforms and the heterogeneity in initial promise of the technology. The initial promise of technology regulates the strength of the endogenous learning reinforcing loop. Those startups and projects building on technologies with a sharp initial return on investments (higher slopes) are likely to quickly attract more resources and dominate, especially if strong decoupling is present. This may suggest that start-ups, with higher decoupling, should generally do better in the presence of rugged technological landscapes.

This intuition is however correct, only if the majority of technological platforms are viable, i.e. could lead to a commercially successful product (e.g. Figure 6-B). In practice some technologies may actually look promising early on, but prove unviable later. In these settings an over-aggressive allocation of resources to projects with early promise may lead startups, and firms, down a dead-end, wasting resources that could have otherwise nurtured other technologies. In fact, if a substantial fraction of the technological platforms are unviable then too much decoupling could become a liability,
reducing the chances of startups compared to more egalitarian allocation mechanisms inside the entrant firm (Figure 6-C).

Therefore in Figure 6-C we note that given a level of resources, the incumbent benefits from decoupling, only to an extent, beyond which extra decoupling is harmful, reducing the entrants chances of success because they exceedingly pick the winner too early and hurt the more viable late bloomer technological platforms. In Figure 6-D we show the entrant’s winning fraction as a function of different decoupling levels they chose, in the case where 50% of technological platforms are not viable (similar to Figure 6-C set-up).
We notice that the best decoupling level is both under 1, and decreasing with the amount of resources available. As entrants’ access to resources increase, they are better off keeping a more egalitarian allocation in place allowing them to discover the real long-term benefits of technological platforms before they converge on one. This mechanism offers a more functional explanation why entrants may prefer to have lower decoupling among their projects than is mandated by the market.

3.6 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 and 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.

4. 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 observation. 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.

We initially justified the key difference between startups and entrants, the level of decoupling among competing projects, based on organizational and political pressures that constrain resource allocation among projects inside a firm. Interestingly, once we consider the existence of unviable technological platforms, the entrant firms may actually be better off not decoupling among their projects to the extent the market does. Therefore there may be a more functional explanation for the coexistence of different decoupling levels and resulting distribution of success among startups and entrants. Under market pressures startups operate with stronger endogenous learning loop, and
when the startup with initial promise is lucky and on an overall viable technological trajectory, then the startup is more likely to win the competition. However, avoiding premature convergence on a technology which will not pan out later, the entrants are better off with more egalitarian allocation, discovering the more viable long-term platform at the expense of giving up some markets to startups.

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 and 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 and 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 et al., 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 project.
References:


Appendix- Model Formulations:

**Entrant Capability[EN,Random]** = INTEG ( ECapabilityGrowth[EN,Random, Init EN Cap[EN]])

Units: dmnl
This variable on an aggregate level represents the organizational capabilities that each project accumulates.

**Startup Capability[SU,Random]** = INTEG ( SCapabilityGrowth[SU,Random, Init SU Cap[SU]])

Units: dmnl
This variable on an aggregate level represents the organizational capabilities that each startup accumulates.

**Init EN Cap[EN] = Init SU Cap[SU] = 0**

Units: dmnl
These two variables are the initial values for the two stocks of capabilities.

**ENActualPromise[EN,Random]** = SCURVE2(Entrant Capability[EN,Random], EnMax[EN,Random], EnSlope[EN,Random], 1)

Units: dmnl
This is the Actual promise or potential based on the capabilities each project has been building.

**SUActualPromise[SU,Random]** = SCURVE2(Startup Capability[SU,Random], SuMax[SU,Random], SuSlope[SU,Random], 1)

Units: dmnl
This is the Actual promise or potential based on the capabilities each startup has been building.

**EPerceivedPromise[EN,Random]** = Entrant Signal to Noise ratio * ENActualPromise[EN,Random] + (1 - Entrant Signal to Noise ratio) * (sum(ENActualPromise[EN!,Random]) / ELMCOUNT(EN)) * Max(0, Pink Noise EN2[EN,Random])

Units: dmnl
This is the perceived promise of each project based on actual potential, the accuracy of managers perception and a noise parameter.

**SPerceivedPromise[SU,Random]** = Market Signal to Noise ratio * SUActualPromise[SU,Random] + (1 - Market Signal to Noise ratio) * (sum (SUActualPromise[SU!,Random]) / ELMCOUNT(SU)) * Max(0, Pink Noise SU2[SU,Random])

Units: dmnl
This is the perceived promise of each startup based on actual potential, the accuracy of VC perception and its the noise

**Market Signal to Noise ratio** = **Entrant Signal to Noise ratio** = 1
Units: dmnl
These variables represent the accuracy by which the market or entrant can perceive startups or projects.

**Resources Allocated to Projects** [EN, Random] = (Internal Investment in Market [Random] * EXP(Internal Aggressiveness * EPerceivedPromise [EN, Random])/ (sum(EXP(Internal Aggressiveness * EPerceivedPromise[EN!, Random])) + SW Consider Other Side * vmax (EXP(Internal Aggressiveness * EPerceivedPromise[SU!, Random]))) * (0 + if then else(vmax(SPerceivedPromise[SU!, Random]) >= Starting Point, 1 , 0))
Units: $/Month
The resources allocated to each project is determined by the its relative capability while capturing the fact in later stages of the race resources are allocated more aggressively.

**Internal Aggressiveness** = Market Aggressiveness * Relative Internal Agg
Units: dmnl
This is the ultimate decoupling between entrant project based on its decoupling strength and market aggressiveness.

**External Investment in Market** [Random] = BaseInvestment * (1 - DominantDesignEmerged [Random])
Units: $/Month
This is the Resources that the entrant would pour into the this competition

**Resources secured for Startups** [SU, Random] = External Investment in Market [Random] * EXP(Market Aggressiveness * SPerceivedPromise[SU, Random])/ (sum(EXP(Market Aggressiveness * SPerceivedPromise[SU!, Random])) + SW Consider Other Side * vmax (EXP( MarketAggressiveness * EPerceivedPromise[EN!, Random])))
Units: $/Month
The resources allocated to each startup is determined by the its relative capability while capturing the fact in later stages of the race resources are allocated more aggressively.

**SW Consider Other Side** = 0
Units: dmnl
This is switch by which be we can select whether startups and entrant can see each others promise or not.

**Internal Investment in Market** [Random] = Extra Internal Resources * BaseInvestment * (1 - DominantDesignEmerged [Random])
Units: $/Month
This is the Resources that the entrant would pour into this competition:

**External Investment in Market [Random]** = BaseInvestment*(1-DominantDesignEmerged [Random])

Units: $/Month

This is the Resources that the investors would pour into this competition:

**BaseInvestment** = $10^6

Units: Month

This parameter represents the Base investment in this market:

**ECapabilityGrowth [EN,Random]** = Resources Allocated to Projects[EN,Random]*EN Prod* Technological Uncertainty EN[EN,Random]

Units: 1/Month

This is the capability boost each one of the entrant projects in each round based on resources they could get and technological uncertainty.

**Technological Uncertainty EN[EN,Random]** = Max(0,Pink Noise EN[EN,Random])

Units: dmnl

This is the uncertainty in building capabilities for Entrant projects.

**SCapabilityGrowth [SU,Random]** = Resources secured for Startups [SU,Random]* Technological Uncertainty SU [SU,Random] * SU Prod

Units: 1/Month

This is the capability boost each one of the startups in each round based on resources they could secure and technological uncertainty.

**Technological Uncertainty SU [SU,Random]** = Max(0,Pink Noise SU [SU,Random])

Units: dmnl

This is the uncertainty in building capabilities in startups.

**SU Prod** = INITIAL(EN Prod*SUProdMultiplier)

Units: 1/$

This variable determines how much capability would be gain by 1 dollar of investment:

**SUProdMultiplier** = 1

Units: dmnl

This is the relative productivity of investment in Startups comparing to Entrant.

**EN Prod** = 2*e^-7

Units: 1/$

This variable determines how much capability would be gain by 1 dollar of investment:

**SUWinner [Random]** = if then else(vmax(SUActualPromise[SU!,Random])>1,1,0)
This variable identifies if one of the startups has reached the winning threshold

$$\text{ENWinner[Random]} = \text{if then else}\left(\text{vmax(ENActualPromise[EN!,Random])}>1,1,0\right)$$
Units: dmnl

This variable identifies if one of the entrant project has reached the winning threshold

$$\text{DominantDesignEmerged[Random]} = \text{Min}(1,\text{ENWinner[Random]}+\text{SUWinner[Random]})$$
Units: dmnl

This variables is a switch that will turn on when on of the startups or project reach the threshold associating with winning the market.

$$\text{ENWinRatio} = \frac{\text{SUM}(\text{ZIDZ(ENWinner[Random!],SUWinner[Random!]}) + \text{ENWinner[Random!]})}{\text{ELMCOUNT(Random)}}$$
Units: dmnl

The average Ratio of Entrant winning with fixed relative aggressiveness and resources in different random runs

$$\text{SUWinRatio} = \frac{\text{SUM}(\text{ZIDZ(SUWinner[Random!],SUWinner[Random!]}) + \text{ENWinner[Random!]})}{\text{ELMCOUNT(Random)}}$$
Units: dmnl

The average Ratio of Startups winning with fixed relative aggressiveness and resources in different random runs

$$\text{MaxPH} = \text{Mean of Max Promises} + \text{"Half-Range of Max Promises"}$$
Units: dmnl
This is the upper limit to technological limit.

$$\text{MaxPL} = \text{Mean of Max Promises} - \text{"Half-Range of Max Promises"}$$
Units: dmnl
This is the lower limit of the technological limit.

$$\text{Mean of Max Promises} = 1.5$$
Units: dmnl
This the average of technological limit. In the base case its 1.5 but in runs with some unviable projects it could be lower.

$$\text{Half-Range of Max Promises} = 0.5$$
Units: dmnl
This variable determines the range above or below the average technological limit.

$$\text{SGL} = 1$$
Units: dmnl
This is the initial slope lower limit

\[ \text{SGH} = 1 \]
This is the initial Slope higher limit

\[
\text{EnMax}^{\text{EN,Random}} = \text{VECTOR ELM MAP}(\text{SUInitialMax}[S1,R1], (\text{EN}-1)^*\text{ELMCOUNT}(\text{Random})+\text{Random}-1) \\
\text{Units: dmnl} \\
\]
Each project will have the max of an equivalent startup.

\[
\text{EnSlope}^{\text{EN,Random}} = \text{VECTOR ELM MAP}(\text{SUInitialSlope}[S1,R1], (\text{EN}-1)^*\text{ELMCOUNT}(\text{Random})+\text{Random}-1) \\
\text{Units: dmnl} \\
\]
Each project will have the initial Slope of an equivalent startup.

\[
\text{SuMax}^{\text{SU,Random}} = \text{RANDOM UNIFORM}(\text{MaxPL, MaxPH, NoiseSeed[Random]}) \\
\text{Units: dmnl} \\
\]
This is the S-curve max or the technological limit for startups.

\[
\text{SuSlope}^{\text{SU,Random}} = \text{RANDOM UNIFORM}(\text{SGH, SGL, NoiseSeed[Random]}) \\
\text{Units: dmnl} \\
\]
This is the S-curve initial slope for startups.