Abstract

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Ambition in Innovation: Technological Stock and Vicarious Learning in the Nascent Electric Scooter Sector

**Keywords:** innovation; nascent industries; patents; vicarious learning; inter-firm similarity; firm-level capabilities
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ABSTRACT

The technology S-curve predicts that technological performance will improve sharply as technological effort is applied to this end. However, it remains unclear how firms individually apply technological resources and how firms with technological superiority should determine their product performance accordingly – particularly since technology advantage in an emerging sector seldom translates into market advantage. This study examines how firms with strong technological resources tamp down such market uncertainty using vicarious learning, with rivals possessing the same pre-entry experience serving as benchmark exemplars for this purpose. Using a unique hand-collected dataset from the nascent Taiwanese electric scooter market, we find that firms often strategically release lower-performing products than their capabilities might dictate. Vicarious learning centered on both similar firms (with the same pre-entry experience as a focal organization) and dominant firms in the sector moderate this direct effect. We contribute to the literature by shedding light on how firms use vicarious learning to determine product performance, subsequently facilitating their progression along the S-curve in a nascent market.
INTRODUCTION

The technology S-curve concept predicts how the performance of a new technology improves over time as engineering effort is applied to this end (Foster, 1986; Christensen, 1992; Nieto, Lopez, and Cruz, 1998). This literature focuses mainly on the changes in market dynamics as movement up the S-curve unfolds (Govindarajan and Kopalle, 2006; McGrath, 1998). Specifically, this model of technological change posits an initial stage in which the novelty of the technology and the lack of certainty regarding its future prospects make for slow progress in improvement. As greater understanding is developed regarding the technology and its potential to outperform existing competitive approaches is followed by the next phase technical improvements accelerate.

While these S-curve dynamics have been explored and confirmed in a wide variety of sectors (Becker and Speltz, 1983; Lee and Nakicenovic, 1988; Merino, 1990; Roussel, 1984), most of this research takes the overall industry as the key unit of analysis (McGrath, 1998). Technological change in these circumstances is viewed as an objective and natural progression, with its dynamics largely guiding the innovation activities of all firms within the industry (Carayannis and Roy, 2000). However, the notion that different firms in a given sector may interpret the pace of technological progress in dissimilar ways, and as a result pursue relatively distinct approaches to their innovation programs, cannot be discounted (Christensen, 1992).

These differential approaches to innovation based on firm-level interpretations of both S-curve dynamics and the broader competitive environment are particularly salient considerations in nascent markets – that is, industry sectors where technological progression begins to emerge from the initial stage of the S-curve to its more rapid technical improvement. In these stages, the accelerating pace of technological progress may conceal an ongoing lack of clarity regarding the
value proposition needed for a new innovation to actually meet customer needs (which may themselves be nebulous or latent in nature) and become established. Firms vying to deliver acceptable innovations to a nascent market face the need to negotiate these twin progressions (customer-based and technological) absent a clear final goal (Tongur and Engwall, 2014).

Without knowing in detail what specific performance parameters or product characteristics the market expects, a firm might seek to incorporate the best technology at its disposal into a new product; however, the resulting performance often far exceeds what the market needs (Peng and Sanderson, 2014). Further to this point, evidence from the automobile (Abernathy and Clark, 1985), the digital camera (Benner and Tripsas, 2012) and flat panel display (Wang and Seidle, 2017) sectors shows that firms in such nascent markets should not always aim for outright technological superiority, at least initially. Differences across firms regarding the presumed progression of the technology and its competitive implications may help to explain why even technically astute organizations introduce less ambitious innovations than their abilities might dictate. This being the case, what considerations determine the extent to which a firm is both willing and able to translate its technological advantage into product advantage in a nascent market?

We examine this question through an analysis of the new product performances – the degree of novelty or innovativeness that each new offering represents – introduced to market by firms in the nascent Taiwanese electric scooter market. In response to the role played by emissions from these and other vehicles in exacerbating air pollution in the country, the scooter industry moved to offer electric scooters in the early 2000s. Sales spiked after 2010 because more firms, both start-up and diversified, made sizable commitments to the market. Interestingly, though, as this market has evolved, major firms have introduced product offerings with a trait
that suggests that the overall technological potential of their underlying capabilities has not been fully harnessed.

While the technological resources that a given firm brings to bear on its product development activities are an important consideration in innovation, past research on the role of such resources in predicting either entry or early advantage in a newly forming sector offers conflicting conclusions (Schoenecker and Cooper, 1998; Robinson, Forell, and Sullivan, 1992). We submit that technological resources, while important per se, are not necessarily the decisive element in the degree of technological innovation undertaken by an organization. Indeed, market uncertainty is a key factor that slows down the pursuit of technology performance (Sainio et al., 2012) – and such uncertainty is rife in nascent product markets. Firms address this difficulty by observing relevant external actors (including similar firms or particularly successful rivals in the industry) and inferring lessons from the actions of these exemplars – that is, by engaging in a process of vicarious learning (Baum, Li, and Usher, 2000). We adopt a perspective centered on vicarious learning to argue that the presence of similar firms or the existence of a dominant firm moderates the effect of an innovating firm’s technological resources on innovative offerings. Firms often seek to infer information from their competitors’ action when uncertainties are high, with managers paying particularly close attention to leading firms or competitors with whom they share similarities on some key dimension (Benner and Tripsas, 2012; Haunschild and Miner, 1997). Accordingly, in the nascent Taiwanese electric scooter market we consider the roles of a dominant market leader and of organizations sharing the same pre-entry experience (Khessina and Carroll, 2008; Sarangee and Echambadi, 2014) as a focal firm in addressing the uncertainty inherent in a nascent sector. Firms with the same pre-entry experience evince similar approaches to adopting innovation that entails key changes in important technological parameters (McGrath,
1998), and such firms also exhibit the same learning behaviors (Benner and Tripsas, 2012; Zachary, Gianiodis, Payne, and Markman, 2015) when compared to those with dissimilar experience. The key point is that, through processes of vicarious learning oriented towards either successful or similar organizations, firms are better able to resolve the abiding uncertainty in an emerging market segment; as a result, such firms are also more ably positioned to make use of the resources at their disposal in determining the nature of their innovation activities. In short, we examine how technological resources are deployed as these relate to the ambition of product innovation undertakings under the scenario of high market uncertainty.

This paper makes several contributions to both theory and managerial practice. First, while past work prescribes the key dimensions for successful adoption in settings such as disk drives, electric vehicle batteries, digital cameras, and MP3 players (Christensen, 1997; Govindarajan and Kopalle, 2006; McGrath, 1998; Peng and Sanderson, 2014), we focus on technology performance and explain how firms with technological resources determine the performance they offer. By shedding light on innovation dynamics in a nascent market (a setting characterized by a technological S-curve where performance is beginning to ramp up from its initially low levels), we show that technological resource is not the sole key factor pushing technology performance forward. Instead, we highlight the important condition of market uncertainty, and explain how firms use vicarious learning in response to this uncertainty to fine-tune their degree of innovativeness. We show the varying pace of technological progress that each firm manifests while the industry advances as a whole as technological S-curve predicts (Christensen, 1992). Relatedly, we explain why firms strategically embrace a less-than-perfect product, and demonstrate how such a practice presents a particular advantage to firms with superior technological capabilities. Second, prior literature highlights the similarity in firm
capabilities to explain firms’ product offerings, portfolio width, and survival rates (Christensen, 1997; Khessina and Carroll, 2008; Sarangee and Echambadi, 2014; Wezel and van Witteloostuijn, 2006). We offer complementary insights by underscoring how firms choose their benchmark exemplar(s) for learning purposes based on similarity of pre-entry experience. Third, research indicates how industry origin and background experiences influence product specification decisions (Khessina and Carroll, 2008; Dew, Sarasathy, Read, and Wiltbank, 2009; Katila, Chen, and Piezunka, 2012; York and Lenox, 2014). Our paper broadens this literature by showing how firms with different pre-entry industry experiences approach the demand in a nascent market segment, and what the presence of close rivalry means to them. Finally, studying the electric scooter market offers insights of potential use in other markets that are also shifting to new technological bases; these include, for example, the e-bike (Ruan, Hang, and Wang, 2014), hybrid bus (Sushandoyo and Magnusson, 2012), and cloud computing (Sultan, 2014) industries.

Our paper is organized as follows. In the next section we develop the reasoning behind our various hypotheses. Following this we describe the empirical setting, data collection, and methods employed in our analyses. Results are then reported, and we discuss our findings in greater detail. We conclude with implications of our research for theory and managerial practice.

THEORY DEVELOPMENT AND HYPOTHESES

Entry into an industry is increasingly recognized to be a process, rather than a single event (Markman and Waldron, 2014). While the technical expertise possessed by a firm has a significant bearing on the innovation initiatives that may be pursued (Cohen and Levinthal, 1990; Rotheraermel and Hess, 2007), an organization will fail if it commits to too sophisticated a product
specification before the market is ready (Christensen, 1997). The technologically capable firm therefore has to gauge the distance it should maintain between what it *can* do and what it *should* do in terms of developing and introducing its product innovations to market.

**Direct Effects: Technological Stock**

Technological expertise may not directly translate into superior product position. This is especially true within the context of an emerging product segment, as predicting the direction in which such a market will evolve is exceedingly difficult. Technologies that represent significant departures from established offerings and customer understandings are rarely the most successful initially, and in some cases even fail completely (Sainio et al., 2012). Facing this uncertainty, firms may purposefully choose a low product specification offering in order to control the cost of failure (Wang and Seidle, 2017). Such a decision can be particularly advantageous, however, when the focal firm possesses sufficient technological capabilities to either scale forward or scale back the ambitiousness of its innovative offerings.

While the focal firm’s own technological capabilities represent a valuable asset with which to pursue innovation, the corollary to this point is that the corresponding capabilities of its rivals are of equal importance to their product development initiatives. In particular, the extent to which other firms are able to identify and build upon a technical basis similar to that of the focal firm will have key implications for the approach to innovation of the latter. Rosenkopf and Almeida (2003) use patents to approximate the knowledge stock of semiconductor firms and study how firms draw upon each other’s knowledge stock. Taking a cue from their research, we introduce the term ‘technological stock’ to refer to this (potential or actual) mobilization of an organization’s technical expertise by competing firms in the emerging product category. The
notion of technological strength as a ‘stock’ or reserve in this sense connotes the idea that the value of such capabilities can be depleted over time if and when rivals are able to incorporate them into innovative product offerings of their own, whether in advance of or in response to the focal firm. Where evidence of this technological stock exists and can be observed, it offers the focal firm an opportunity to learn vicariously about the technological capabilities and possible competitive actions of rivals. Importantly, by observing the use of such ‘shared’ capabilities on the part of its rivals, the focal firm is also able to better infer the market potential of its own technology and its technical position vis-à-vis its competitors – with implications for the overall success and performance of the firm (McGahan and Silverman, 2006).

To take one example of this tendency, a firm seeing a high number of citations to its patents by rival firms would be better able to gauge its technological position vis-à-vis these competitors. Here the technical expertise of the firms in question – the ‘technological stock’ – would be abundant and available for competitors to tap, though the extent to which either firm could benefit from this situation depends on the innovation activities expected to be undertaken by the other. The relevant point for our purposes is that this information could subsequently affect the degree of performance advancement that the focal firm hopes to achieve with its innovative product. Specifically, we argue that the greater the extent of this technological stock, the lower the product performance advancement realized by a focal firm. The reasoning here is that a significant technological stock increases the likelihood that any new product offering – even one at the forefront of the market – could be replicated in fairly short order by the adept competitor in question. Releasing the best product may accelerate competitors’ catching-up, since the rivals here would tap on the stock to imitate and improve upon the offering.
The focal firm in this scenario may be forced to reevaluate the novelty of its product and to scale back the ambitiousness of its innovation efforts, possibly by continuing to internally develop its best technology for the time being. Rather than bringing to market the best possible (that is, the most technologically advanced) product, the firm will see greater benefit in treating its attempt as a first foray in the quest to establish its market foothold. This is in contrast to the conventional wisdom that dictates the need to release the one best product and garner market leadership in a single move.

Summarizing the above argument, we propose the following hypothesis:

**H1:** Technological stock is negatively associated with the degree of product performance of an innovative offering in an emerging product segment

**Moderating Effects: Market Uncertainty**

Organizations in emergent segments generally struggle with identifying demand – not knowing when, how and by whom the new technology will be deployed. In their study of the development of portable music player (MP3 player) technology, Peng and Sanderson (2014) conclude that pioneering firms in this then-nascent sector, whether large (Sony and Creative Labs) or small (Digital Cast and Diamond Media), struggled mightily to determine the price, size, weight, and storage technology of these new products that would be accepted by consumers in the market. Significant technological change, while typically helping to usher in the existence of new industries, is often fraught with such market uncertainties (Benner and Tripsas, 2012; Tongur and Engwall, 2014). This uncertainty becomes an important factor influencing innovation in nascent sectors, as the unpredictability of demand and competition in the market can both condition the product development initiatives pursued by a firm (Sainio et al., 2012).
We consider market uncertainty as a moderating (instead of a direct) effect because the presence of this uncertainty can influence the firm’s decision in two opposite ways: by signaling either resource abundance that encourages market entry or competitive pressure that discourages the firm from taking action or making irreversible commitments (Sainio et al., 2012). In either case, the effect will not be fully realized without factoring in vicarious learning, which determines how firms manage market uncertainty.

Owing to the substantial costs of obtaining information on all potentially valuable referents, organizations look for exemplars offering particularly salient lessons to emulate. Firms with the same pre-entry industry experience as the focal organization provide useful prospects in this regard, as does the market leader in this nascent sector. Firms sharing the same pre-entry experience usually harbor the same assumptions and develop similar approaches to a developing market (Benner and Tripsas, 2012). More generally, Bresman (2010: 86) discusses the value of similarity in his examination of external learning:

Vicarious learning activities allow teams to improve based on the experience of others. Thus, these activities involve others who have experiences associated with tasks that are similar enough to yield applicable lessons learned.

Decisions to deploy technological capital are not made in a vacuum, but rather need to be seen within the broader market environment within which they are undertaken (McKendrick and Wade, 2010). To this end, we consider what roles the number of organizations similar to the focal firm and the presence of a dominant firm play in influencing the degree of technological innovation. The former indicates the ease (or lack thereof) of transitioning organizational resources to the emerging segment, while the latter represents the competitor’s market power. Because firms sharing the same pre-entry experience are more likely to opt for the same learning
behavior and to possess similar capabilities (Benner and Tripsas, 2012; Zachary et al., 2015), we examine the role that similarity of pre-entry experience between a focal firm and its rivals in the new market plays in conditioning the impact of technological stock on innovation activities.

Below we posit the ways in which firms use vicarious learning to mitigate the peril of market uncertainty (Haunschild and Miner, 1997; Mezias and Eisner, 1997). Vicarious learning occurs when firms “faced with insufficient information to learn from their own experience, attempt to reduce uncertainty by attending to visible and comparable organizations’ actions for clues about how to interpret their own situation and act” (Baum, Li, and Usher, 2000: 767). In the absence of direct experience, firms make inferences by which they attribute observed outcomes to unobserved processes. As alluded to above and described in more detail next, inferences made with regard to similar firms or to a dominant market leader may be particularly illuminating for an organization dealing with the uncertainty that characterizes emerging market sectors (Srinivasan, Haunschild, and Grewal, 2007).

**Similar firms.** An increase in the number of similar firms in the emerging product segment suggests the appearance of market opportunity (in the form of both resources and demand) for the focal firm. Firms sharing the same pre-entry experience exhibit the same traits in determining product specifications (McGrath, 1998; Khessina and Carroll, 2008; Ruan et al., 2014), manifest similar proclivities for risk (Dew et al., 2009), and share information with or even mimic the actions of each other (Benner and Tripsas, 2012; Zachary et al., 2015). As similar firms establish themselves in greater numbers in the segment, the focal organization is presented with a host of templates for competitive action from which to draw, increasing the
value of its vicarious learning initiatives (Jiang, Holburn, and Beamish, 2014; Srinivasan et al., 2007).

While a high level of technological stock reflects the central importance of the firm’s technology, we have argued in our first hypothesis that it also attenuates the ambitiousness of innovation owing to the difficulty of capturing returns from the offering in the marketplace. This concern is reduced when many organizations with similar pre-entry experience to that of the focal firm have already moved into the sector. The focal firm can see in these activities proof of the viability of its own potential offerings as well as the fit of its own capabilities in the new market segment – and hence the value of pursuing a high degree of technological innovation.

In a related sense, the focal firm is emboldened to follow the lead of its competitors under the (mistaken) assumption that these rivals have access to valuable information not possessed by the firm itself (Simon and Lieberman, 2010). An increasing number of similar firms may thereby lead the focal firm to exaggerate the potential gain of market success. The firm is thus incentivized to move ambitiously with its product innovativeness because it may perceive lost market opportunity if holding back.

**H2**: The presence of similar firms positively moderates the effect of technological stock on the degree of product performance of an innovative offering in an emerging product segment

*Dominant firm.* Where a large firm has captured a significant segment of customer demand and controls channels of supply and distribution, the prospects of dislodging such an incumbent from its position may be particularly unfavorable. The situation will be particularly serious for organizations facing a large firm with the same pre-entry experience. Prior studies observe the similarity in product specifications of firms sharing the same pre-entry experience
(Khessina and Carroll, 2008; McGrath, 1998; Ruan et al., 2014), even where the level of demand for specific product characteristics and performance stays largely constant. The presence of a dominant firm offering similar products subsequently squeezes the market space available to other firms. These organizations will be forced to compete directly with the large firm for the same demand without, however, enjoying the same control over channels of supply and distribution. The staying power of the most successful firms tends to be high. In studying the entry of firms into the small satellite industry, Carayannis and Roy (2000) found that the motivation to roll out more innovation largely depends on the prospect of market success. Even with high technological stock, the focal firm may view the amount of effort needed to succeed and to recoup the often substantial investments in research and development that underpin innovation to be exceedingly onerous. Although the organization may still have the technical skills needed to introduce a competitive offering into the market, it will need to expend more resources to acquire a leading position as the market is under the strong grip of a dominant firm.

In this situation, the presence of a dominant firm produces more market uncertainty (in terms of the prospects for future survival and success) for the focal firm. The cost of failure to a focal firm can be very high if it relates to this organization’s best product – that is, if an offering at the frontier of its technological expertise is released but does not succeed in the marketplace. Given these high stakes in the presence of a dominant firm, the focal organization may see the benefit in introducing a product incorporating relatively less performance advancement to establish a foothold in the market and to gain knowledge (Christensen, 1997; Lynn, Morone, and Paulson, 1996). Additionally, the cost of building a foothold is lower than the cost of aggressive attack (Jayachandran, Gimeno, and Varadarajan, 1999). The focal firm essentially chooses to
compete in a relatively low-risk fashion at the lower end of the segment, biding its time in anticipation of a more favorable competitive stance vis-à-vis the market leader.

**H3:** The presence of a dominant firm negatively moderates the effect of technological stock on the degree of product performance of an innovative offering in an emerging product segment

**METHODS**

**Industry**

We chose the scooter industry in Taiwan to study a firm’s decision to enter a nascent (electric scooter) market. Electric scooters present an attractive opportunity to aspiring entrants as the potential market size in Taiwan is thirteen million units in domestic demand, with export units adding considerably to this total. The demand for electric scooters is a threat to existing scooter and motorcycle manufacturers as the product requires different sets of technological expertise. On one hand, electric scooters represent market potential that attracts new entrants having expertise in electrical and battery management systems. On the other hand, sales of electric scooters directly erode the sales of gasoline engine scooters. Incumbents are thus caught in a dilemma of hefty investment and cannibalization, a situation that opens the door for new entrants into the nascent sector.

**Industry Evolution**

*1990-2000.* Scooters and motorcycles are the primary means of transportation in Taiwan due to the sub-tropical climate and high population density of this country. On average every person owns 0.92 scooters (or motorcycles), compared with 0.34 vehicles.\(^1\) Annual industry production is about 1.2 million units, making Taiwan one of the major scooter and motorcycle

\(^1\) Figures from the Ministry of Transportation and Communications of Taiwan. Data accessed April 13, 2018.
manufacturers in the world. Due to this prevalence, emissions from scooters and motorcycles are a major source of air pollution. As a result the Taiwanese governments, both central and local, have implemented a series of initiatives to encourage the adoption of electric scooters since 1991.

The Industrial Technology Research Institute, a non-profit organization, has developed three prototypes of electric scooters referred to as EC1, EC2, and EC3, respectively. Leading scooter and motorcycle manufacturers and their suppliers formed a joint venture tasked to commercialize EC2 in 1997.

**2000-2010.** Despite the favorable regulatory and demographic environment existing in the early days of this sector, the adoption of electric scooters was initially slow due to concerns over low horse power, limited cruising range, and uncertain availability of charging stations. The EC2 joint venture was shutted in 2002. Meanwhile, the total number of gasoline-powered scooters and motorcycles approached fifteen million units. Exhaust from these engines became a major source of air pollution and the Taiwanese government again sought to clamp down on this problem. Stringent new emission regulations went into force in 2007, and a new wave of governmental policies aimed at developing the entire supply chain for electric vehicle manufacturing in 2008 breathed new life into the electric scooter market.

Besides changes in government policies, two factors – one technology-push and one market-pull in nature – increased the demand for electric scooters. First, manufacturers now have better batteries to overcome horse power and cruise range limitations, due primarily to advances in lithium-ion batteries (McGrath, 1998; Ruan et al., 2014). A group of firms specialized in battery management find their technological capabilities particularly fit to produce electric scooters. Second, the market-pull factor in the form of demand for electric vehicles has recently gained momentum. The popularity of electric vehicles as a general class helped to shift
consumers’ initial skepticism about electric scooters into more positive impressions. Younger generations are more willing to consider electric scooters over traditional scooters since the former are more eco-friendly and align more closely with their concerns regarding the health of the physical environment. Coupling market-pull with technology-push considerations, the electric scooter market witnessed increasing entries, making this industry a particularly appropriate setting for our purposes.

2010-present. The market experienced significant sales growth after China Motor, a leading Taiwanese vehicle manufacturer, entered the electric scooter market in 2010. Figure 1 illustrates the trend of the industry’s annual production, which increased from 1,280 units in 2005 to 20,026 in 2016. Besides the growth in production units, the market became less concentrated as the Herfindahl index dropped from almost 1 to 0.4.

![Figure 1: Number of Firms and Industry Herfindahl Index, 2005 Through 2016](image)

**FIGURE 1: NUMBER OF FIRMS AND INDUSTRY HERFINDAHL INDEX, 2005 THROUGH 2016**
As expected given these unfolding economic opportunities, the rise of market demand summarized above attracted market entries. Although firms that at the time also manufactured scooters were represented here, start-ups and diversified entrants made up the bulk of new entries. Diversified entrants range from battery management firms to fitness equipment manufacturers, golf car manufacturers, and suppliers to scooter manufacturers. As noted at the outset of this paper, we classify firms based on their pre-entry experience: 1) *start-up firms* that produce and sell only one product – in this case, electric scooters; 2) *incumbents* that sell traditional scooters and motorcycles in addition to electric scooters; and 3) *diversified firms* that, while present in this segment, also earn some portion of their overall sales from outside of the motorcycle and scooter industry. Although the literature typically examines newly established and diversified firms belonging to the same start-up category, our categorization uses three categories following Sosa (2013), who pointed out how R&D performance diverges among them. We find such a taxonomy to be particularly important for electric scooters since the correlation between product performance and patent citations appears to be related to pre-entry experience. We could identify a clearer trend in Figure 2. Incumbents are more conservative on product specification although they receive more patent citations. In contrast, start-up firms receive low patent citations but are more aggressive in product specification. Finally, diversified firms perform lower on both dimensions.
Figure 3 illustrates the breakdown of firms active in the electric scooter market by pre-entry experience. The market was first characterized by entries from diversified entrants, followed by a period from 2006 through 2009 when only a few firms maintained their interest in the nascent electric scooter market. Entries then jumped in 2010. While diversified entrants made up the majority of firms at the time, more start-ups subsequently joined the industry. Unlike their competitors, many of these start-ups received funding from venture capital sources, demonstrating dynamics broadly similar to those of the technology firms founded in Silicon Valley. Compared with start-ups that generally possessed a strong conviction to have electric scooters accepted as a mainstream product, incumbents seemed more ambivalent towards electric scooters – or, at the very least, showed a tendency to hedge their bets with regard to the emergent
sector. Despite the fact that almost all current scooter and motorcycle manufacturers added electric scooters to their product lineup, their focus remained on traditional scooters and motorcycles.

![Figure 3: Number of firms by pre-entry experience, 2005 through 2016](image)

**FIGURE 3: NUMBER OF FIRMS BY PRE-ENTRY EXPERIENCE, 2005 THROUGH 2016**

Data

We collect our data from multiple sources. The primary data source is the Automobile and Motorcycle Industry Yearbook, the annual publication of the Industry & Technology Intelligence Services, from 2003 to 2011. This source provides detailed information about the industry dynamics with regards to manufacturers’ activities and new product launches in both the conventional and electric scooter segments. Other supplementary resources include: the Taiwan Transportation Vehicle Manufactures Association database, which provides annual sales data on all scooter and motorcycle models from 1979 to 2017; the Environmental Protection
Administration of Taiwan, which provides the records of electric scooters’ technical specifications; the Industrial Development Bureau of Taiwan, which provides market share data specifically for electric scooters; and, finally, the Intellectual Property Office of Taiwan, which maintains patent data.

Variables

The dependent variable in this analysis, degree of product performance, is measured as the power output of electric scooters, in Watts (McGrath, 1998). A higher product specification indicates a relatively more ambitious innovative undertaking on the part of a focal firm. Our research indicates that power output is a key criterion in purchasing decisions for two reasons. First, power output is proportional to an electric scooter’s cruising range. Although the average daily travel distance is 7.75 miles, a long cruising range allows for fewer charges during the week. Second, high power output allows scooters to climb steeper slopes. Electric scooters are usually parked in the underground garages of high rise buildings. Some earlier models with lower Watts are reported to have trouble climbing these garage ramps. Given these considerations, power output is a critical technical feature influencing the purchasing decision.

Our independent variables are technological stock, the presence of similar firms, and the presence of a dominant firm. Our first step in constructing the technological stock variable entails collecting patent data. The centrality of intellectual property to the technical expertise of

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2 In addition to power output, type of battery and mode of charging are arguably additional key criteria in making purchasing decisions. First, the lead-acid battery was the default battery type in the first few years when electric scooters and vehicles were first introduced to the market (McGrath, 1998). Lithium-ion batteries soon replaced lead-acid batteries due to their inherent technological superiority. The decision between lead-acid and lithium-ion batteries was essentially settled by 2010, when sales of electric scooters experienced substantial growth as shown in Figure 1. Second, direct charging and battery swap are the two available modes of charging. Although battery swap failed to gain adoption from electric vehicles (Noel and Sovacool, 2016), the technology remains promising for electric scooters due to demand characteristics. Nevertheless, mode of charging has no effect on the power performance of scooters. For these reasons our model does not explicitly consider these two attributes as measures of technical performance.
organizations in many sectors represents an opportunity for potential learning. Patent citation suggests the technical foundation upon which another firm can subsequently develop new knowledge and file its own patent. Researchers have used patent citations as a measure of the flow of ideas and knowledge production (Huang and Murray, 2009; Rosenkopf and Almeida, 2003). Given the value of patents as a source of competitive intelligence (Rawat and Saluja, 2007), patent citation data can be mobilized for the purpose of measuring vicarious learning.

A patent is related to electric scooter design or manufacturing if it falls into one of the following International Patent Classes: B60G B60L B60R B60T B60W B62D B62H B62J B62K B62M F01P F16D F21V G01R G05F G06F G06Q G07C H01F H01H H01L H01M H01R H01T H02B H02H H02J H02K H02M H02P H03F H03K H04L H04M H04R H04W H05B H05K. These patent classes are representative of electric scooter technologies, and start-ups in our sample mostly file patents only in these patent classes. We use the total number of citations that a firm has received for its electric patents since founding until year $t$ to measure technological stock. Patent data is public information and is a valuable means by which firms can gain a peek into competitors’ technologies. Each granted patent represents a new body of knowledge, and citations to these patents provide the originating firm with an indication of the extent to which other organizations may be building upon its technical expertise for innovation purposes.

Next we identify sub-categories of firms sharing the same pre-entry experience as the focal firm. The presence of similar firms is a count measure of the number of firms sharing the same pre-entry experience as the focal firm in year $t$. The operationalization of pre-entry experience includes three categories: start-up, incumbents, and diversified, as defined earlier.

Finally, we cluster firms based on their pre-entry industry experience. In each cluster, we separately measure the presence of a dominant firm using the maximum market share that a firm
controls in the electric scooter market in year $t$. We calculate market share by dividing the unit sales for a firm in year $t$ by the market’s total annual unit sales.

We include firm age and patent count to control for the influence of overall firm experience on the degree of product performance advancement. *Firm age* is measured as the difference between year $t$ and a firm’s founding year. The firm minimum age in the data set is greater than zero because start-up firms in the sample do not report sales in their first years. *Patent count* measures the total number of electric scooter patents possessed by a firm. With this variable we calculate the cumulative number of electric patents that have been granted to the focal firm from its founding until year $t$. 
Model

We use a random effects two-stage least squares model to test our hypotheses.\(^3\) We first control for whether a firm joins the electric scooter market, and subsequently test its choice of product performance. Thus the dependent variable in our selection equation (the first stage equation) is a binary variable, \textit{entry}, coded 1 if a firm reports sales from the electric scooter market in a given year. The instrumental variables are the firm’s market share from the traditional scooter market in year \(t\), the total annual production units of the electric scooter in year \(t\), and a dummy coded 1 if the firm previously attempted to commercialize the electric scooter prototype EC2, available from government funded research. A handful of incumbents had attempted to form a joint venture to mass produce the prototype. This initiative was dissolved in 2002. We test hypothesized effects in the second stage, with the degree of product performance as the dependent variable.

RESULTS

Summary statistics are shown in Table 1. Two variables, technological stock and patent count, report correlations higher than 0.7. To check whether multicollinearity produces biased estimates, we drop the affected variables in turn from the models and still receive consistent and significant estimates. The mean variation inflation factor (VIF) is 2.91, with patent count and technological stock reporting values of 6.61 and 5.04, respectively; both figures are well below the common cutoff value of 10 above which multicollinearity is seen to become problematic.

\(^3\) We choose a random effects model because the Hausman test statistics fail to reject the null hypothesis of no systematic difference in coefficients.
### TABLE 1: SUMMARY STATISTICS

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Product performance advancement</td>
<td>1555.1</td>
<td>959.83</td>
<td>348</td>
<td>6400</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Dominant firm</td>
<td>34.27</td>
<td>32.06</td>
<td>0</td>
<td>98.99</td>
<td>-0.12</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Similar firms</td>
<td>3.44</td>
<td>2.11</td>
<td>0</td>
<td>7</td>
<td>-0.09</td>
<td>0.47</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Patent count</td>
<td>84.85</td>
<td>149.67</td>
<td>0</td>
<td>593</td>
<td>0.00</td>
<td>-0.06</td>
<td>-0.12</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Technological stock</td>
<td>34.69</td>
<td>56.83</td>
<td>0</td>
<td>192</td>
<td>0.05</td>
<td>-0.07</td>
<td>-0.20</td>
<td>0.87</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Firm age</td>
<td>28.98</td>
<td>17.74</td>
<td>3</td>
<td>62</td>
<td>-0.26</td>
<td>0.15</td>
<td>0.14</td>
<td>0.57</td>
<td>0.33</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>Entry</td>
<td>0.18</td>
<td>0.38</td>
<td>0</td>
<td>1</td>
<td>-0.10</td>
<td>0.19</td>
<td>0.09</td>
<td>-0.16</td>
<td>-0.15</td>
<td>-0.20</td>
</tr>
</tbody>
</table>
Hypothesis testing results are reported in Table 2. Model 1 is the simple effects model, including the direct hypothesized effect (Hypothesis 1) and control variables only. Models 2 and 3 add the moderating terms to test Hypotheses 2 and 3.

**TABLE 2: HYPOTHESIS TESTING RESULTS**

<table>
<thead>
<tr>
<th>Dependent variable is the degree of product performance</th>
<th>Model 1 H1</th>
<th>Model 2 H3</th>
<th>Model 3 H2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry</td>
<td>-233.666</td>
<td>-522.142</td>
<td>-572.026</td>
</tr>
<tr>
<td>Firm age</td>
<td>(-0.31)</td>
<td>(-0.53)</td>
<td>(-0.68)</td>
</tr>
<tr>
<td>Similar firms</td>
<td>-31.196</td>
<td>-19.765</td>
<td>-52.797</td>
</tr>
<tr>
<td>Dominant firm</td>
<td>-1.098</td>
<td>-0.458</td>
<td>4.172</td>
</tr>
<tr>
<td>Patent count</td>
<td>8.067***</td>
<td>7.367***</td>
<td>7.538***</td>
</tr>
<tr>
<td>Technological stock</td>
<td>-19.891***</td>
<td>-16.274***</td>
<td>-20.442***</td>
</tr>
<tr>
<td>Similar firms x technological stock</td>
<td>-0.074</td>
<td>(-0.05)</td>
<td>(-0.05)</td>
</tr>
<tr>
<td>Dominant firm x technological stock</td>
<td></td>
<td></td>
<td>-0.105***</td>
</tr>
<tr>
<td>Constant</td>
<td>2111.899**</td>
<td>2422.523**</td>
<td>2422.975**</td>
</tr>
</tbody>
</table>

Observations 96 96 96

z statistics in parentheses
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

As predicted, the estimate for technological stock is negative and significant (β=-19.891, p-value=0.00, Model 1). Hypothesis 1 is supported. A one unit increase in technological stock will reduce the degree of product performance incorporated in a new offering by 17.869 (Watts). It is difficult to know beforehand exactly what customers prefer and their willingness to pay (Benner and Tripsas, 2012; Christensen, 1997; Peng and Sanderson, 2014; Tongur and Engwall, 2014). The firms with higher technological stock – that is, those organizations whose existing
capabilities are built upon more frequently by other firms as revealed by citation rates – are
generally more capable of addressing customer concerns in a timely manner. They can do so
because their technological capability allows them to test new features and respond to critical
concerns in tandem (Hawk, Pacheco-De-Almeida, and Yeung, 2013). This finding casts light on
the factors determining how firms improve their product performance post-entry. Our results
reveal that the responsiveness enabled by higher technological stock manifests itself in more
incremental forms of innovation than would be possible given the technical expertise of the firm;
in short, the firm may deliberately scale back the technological ambition of its product
development efforts.

Hypothesis 2 fails to receive statistical support. The estimate for the presence of similar
firms in Model 2 has no significant positive moderating effect on technological stock as it relates
to the resulting degree of product performance. In our hypothesis development we assume that
the number of similar firms will enhance the effect of vicarious learning. The focal firm will
presumably know more about the market by observing the strategic approaches taken by similar
firms (Baum et al., 2000); coupled with technological stock, this market information should
encourage firms to act more aggressively. However, the results from Model 2 suggest that
vicarious learning does not have a direct implication for technology specification. In order to
further explore this unexpected finding we perform additional analyses in the next section.

As predicted, Hypothesis 3 is supported. The presence of a dominant firm negatively
moderates the effect of technological stock on the degree of product performance incorporated in
a new offering ($\beta=-0.105$, p-value=0.00, Model 3). The post estimation of the moderating effect
is plotted in Figure 4 by the mean of market share of the dominant firm in each pre-entry
experience category over the sampling period. The positive effect of technological stock
increases when the dominant firm presence is weak (i.e., max market share is lower than the mean); while the positive moderating effect diminishes when the presence turns stronger (i.e., max market share is above the mean). That is, high technological stock leads the focal firm to become more aggressive in pursuing product novelty only when its top competitors lack control over the market; its ambition dissipates if a leading rival commands a firm grip over the market.

**FIGURE 4: POST ESTIMATION OF MODERATING EFFECT OF MAX MARKET SHARE ON PATENT CITATIONS**

**DISCUSSION**

This finding allows us to draw the following inferences. In the presence of a dominant firm, competing firms expect to experience more difficulty in acquiring demand. This difficulty will lead firms to release good enough products as soon as possible in order to test demand and to accelerate learning (Moogk, 2012). The development of such ‘minimum viable product’ is based on the notion that firms faced with the uncertainty characteristic of an emerging sector are
well-served by attempting to “do things quickly, act before everything is known, learn while doing, involve real customers early, prototype iteratively, collaborate extensively and actively, and be prepared for the unexpected” (Huizingh, 2017: 44). As evidence of this tendency, an increasing number of software firms choose to release beta versions, i.e., products with bugs, reasoning that it is less advisable to wait if it takes too long to fix all bugs and if some of these imperfections are not overly important to customers. Firms in this circumstance choose to expedite their product release and accelerate learning to reduce market uncertainty (Moogk, 2012). Based on market feedback, firms can subsequently focus on fixing only those bugs that receive the most critical complaints. That is, firms may strategically release lower-performing products than they are capable of developing so as to attain faster product launch and market grabbing. This can be seen as an effort to chip away over time at the strong standing of a dominant firm in the industry. The quick release forces firms to compromise on product performance, even when doing so inevitably decreases the value of the product in the eyes of the consumer. Such a move is considered to be an affordable loss with “decision makers estimating what they might be able to put at risk and examining what they are willing to lose in order to follow a particular course of action” (Dew et al., 2009: 110). In essence, the loss is worthwhile if the learning from ‘market experiments’ helps the firm to configure the product features for optimal value. This loss is especially affordable for technologically capable firms since they can more quickly address technical issues following customer complaints; ideally, then, the resulting compromise of product performance will only be temporary. Firms with strong technological capabilities are thus more advantaged in a nascent sector because they can afford to pace their product releases (Hawk et al., 2013). The ability to sustain prolonged competition accordingly may be an especially important consideration with the presence of a dominant firm.
The control variable receiving statistical significance is patent count. The positive estimate suggests that the more patents a firm has, the more advanced the product performance will be. It can be inferred that patent count prompts firms to place bigger innovation bets, in order to aim for more ambitious product performance. Alternatively, the investment associated with R&D may present a financial pressure which leads managers to seek improved return on investment more aggressively.

Additional Analyses

We performed additional analyses to better understand the unanticipated results of Hypothesis 2. We re-run Model 2, but limit the samples to observations having three or more firms with the same pre-entry industry experience as a focal firm. Results are reported in Model 4 in Table 3.
**TABLE 3: ADDITIONAL ANALYSES**

Dependent variable is the degree of product performance

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Limited samples</td>
<td>Three-way interaction</td>
</tr>
<tr>
<td>Entry</td>
<td>-172.719</td>
<td>-1351.806</td>
</tr>
<tr>
<td></td>
<td>(-0.18)</td>
<td>(-1.58)</td>
</tr>
<tr>
<td>Firm age</td>
<td>-21.739</td>
<td>-19.586</td>
</tr>
<tr>
<td></td>
<td>(-0.75)</td>
<td>(-0.94)</td>
</tr>
<tr>
<td>Similar firms</td>
<td>-24.955</td>
<td>-61.171</td>
</tr>
<tr>
<td></td>
<td>(-0.19)</td>
<td>(-1.24)</td>
</tr>
<tr>
<td>Dominant firm</td>
<td>-2.457</td>
<td>8.189**</td>
</tr>
<tr>
<td></td>
<td>(-0.57)</td>
<td>(2.72)</td>
</tr>
<tr>
<td>Patent count</td>
<td>9.595***</td>
<td>1.695</td>
</tr>
<tr>
<td></td>
<td>(5.17)</td>
<td>(0.56)</td>
</tr>
<tr>
<td>Technological stock</td>
<td>-27.299**</td>
<td>-1.555</td>
</tr>
<tr>
<td></td>
<td>(-3.19)</td>
<td>(-0.22)</td>
</tr>
<tr>
<td>Similar firms x technological stock</td>
<td>2.134+</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.71)</td>
<td></td>
</tr>
<tr>
<td>Dominant firm x technological stock</td>
<td></td>
<td>-0.104***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-6.01)</td>
</tr>
<tr>
<td>Start-up</td>
<td>721.134</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.53)</td>
<td></td>
</tr>
<tr>
<td>Dominant firm x start-up</td>
<td>-13.771</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.75)</td>
<td></td>
</tr>
<tr>
<td>Technological stock x start-up</td>
<td>-3.224</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.12)</td>
<td></td>
</tr>
<tr>
<td>Technological stock x dominant firm x start-up</td>
<td></td>
<td>0.947*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.35)</td>
</tr>
<tr>
<td>Constant</td>
<td>2148.161</td>
<td>2252.311***</td>
</tr>
<tr>
<td></td>
<td>(1.36)</td>
<td>(3.62)</td>
</tr>
<tr>
<td>Observations</td>
<td>64</td>
<td>96</td>
</tr>
</tbody>
</table>

* z statistics in parentheses
+ *p < 0.1, **p < 0.05, ***p < 0.01, ****p < 0.001

With the limited sample set, we find a marginally significant and positive estimate of similar firms x technological stock (β=2.134, p-value=0.087, Model 4), corroborating Hypothesis 2. Past studies suggest that there is a threshold number of similar organizations needed in order for firms to rely more on vicarious learning (Jiang et al., 2014; Srinivasan et al., 2007). In our
sample set, the number is three. For a lower number, the focal firm may not view firms with the same pre-entry industry experience as potential rivals from whom to learn – or, more likely, there may be a lack of observations needed to meaningfully engage in vicarious learning related to the sector. With only one or two firms present, the focal organization may ‘see’ only random firms testing new markets. However, when the number becomes greater, the focal firm interprets the behavior of firms with the same pre-entry industry experience differently, perhaps reasoning that it should become more serious about participating in this market. Furthermore, the focal firm cannot discern a pattern or a trend unless there is a certain number of similar firms exhibiting the same behavior in the market. It can also be inferred that business secrecy can easily be maintained within a handful of firms. Although firms disseminate market information, it takes a critical mass for information to spread more widely. Taken together, the benefit of vicarious learning will not be realized until the market reaches a critical mass needed to generate and exchange information. Only when the number of similar firms reaches a certain threshold does the focal firm benefit from vicarious learning and plan its own strategy, using technological stock to its advantage. Combining the findings from Models 2 and 4, we reason that the impact of information cascade (Simon and Lieberman, 2010) does not take effect until the number of firms passes a certain threshold, at which point firms are convinced that there are strategic merits to following their peer.

In order to see how vicarious learning varies among firms with different pre-entry experience, we perform a three-way analysis, adding an additional interaction effect to Model 3. The three-way term we test is the presence of a dominant firm, technological stock, and pre-entry experience (start-up firms, incumbents, and diversified firms). We create a binary variable coded 1 based on a given pre-entry experience (e.g., start-up), otherwise 0 in each test, and we repeat
the tests three times for all three pre-entry experience categories. We only find significant estimates from the model interacting with the start-up dummy, reported in Model 5 in Table 3. While the interacting term dominant firm x technological stock remains negative, the three-way interaction term with the start-up dummy turns positive ($\beta=0.947$, p-value<0.05, Model 5). This finding suggests that start-up firms under conditions of high technological stock pursue product performance more aggressively than do other firms when their peers have captured more market share. That is, start-up firms are more attuned to peer performance than are incumbents and diversified firms in the existing market. On one hand, start-up firms tend to be more responsive to market changes and more risk-taking (Khessina and Carroll, 2008). On the other hand, start-up firms seem to be more open to the effects of vicarious learning. They are more likely to be convinced that peers’ success indicates the presence of substantial market opportunity, and to consider introducing a more ambitious product offering as a means to replicate the dominant firm’s standing in this emergent sector. Conversely, diversified firms and incumbents are generally reluctant to jump to deploy solutions of greater scale (Christensen, 1997; Katila, et al., 2012; Sosa, 2013), and are more likely to attribute peers’ market success to unobservable market uncertainties.

**CONTRIBUTIONS AND CONCLUSION**

The paper is motivated to understand how technology performance was improved when the technology S-curve climbs from the initially low and the varying pace of technological progress that each firm manifests while the industry advances as a whole as technological S-curve predicts. Although the S-curve predicts technology performance to drastically improve to gain adoption (Christensen, 1997; Govindarajan and Kopalle, 2006; McGrath, 1998), scare
scholarly attention has been paid to explain how firms determine product performance as they climb the curve. Past research has shown that large R&D investments (Robinson et al., 1992; Wang and Seidle, 2017) or superior technology performance (Abernathy and Clark, 1985; Benner and Tripsas, 2012; Sainio et al., 2012) do not always yield market advantage. We thus focus on explaining and predicting how firms with technological stock determine the performance they offer. We underscore the similarity in pre-entry experience a key factor to construct the linkage between technological advantage and product advantage, especially so for firms in a nascent market where market situation remains murky.

The extant literature has found that firms search for similar others to emulate (Bresman, 2010). Past research has measured similarity based on such dimensions as organizational size (Baum et al., 2000; Haveman, 1993; Kraatz, 1998; Srinivasan et al., 2007), market position (Kraatz, 1998; Rhee, Kim, and Han, 2006), common membership in an industry sector (Baum and Dahlin, 2007), and geographic proximity of competitors (Kim and Miner, 2007). In addition, a number of prior studies have considered the ways in which experiential and vicarious learning serve to complement or substitute for each other across a variety of organizational phenomena (Aranda, Arellano, and Davila, 2017; Giachetti and Dagnino, 2015; Li, Qian, and Yao, 2015; Schwab, 2007). However, consideration of the competitive dimension in studies of learning and imitation has only rarely been undertaken (Li et al., 2015). We address this shortcoming by theorizing and examining the potential usefulness of specific competitive firm characteristics – namely, similar pre-entry industry experience and market leadership – for purposes of vicarious learning in an emerging sector.

A relatively recent new stream of literature focuses on the boundary conditions under which “a particular entry-timing position is expected to provide performance advantages”
(Klingebiel and Joseph, 2017:1003). That is, the advantage of early movers and late movers is not comparable. Instead, our evidence shows that firms’ decisions regarding the degree of performance advancement of an innovative offering is based on their pre-entry experience. Prior literature mobilizes the similarity in firm capabilities to explain firms’ product offerings, portfolio width, and survival rate (Christensen, 1997; Khessina and Carroll, 2008; Sarangee and Echambadi, 2014; Wezel and van Witteloostuijn, 2006). We complement this line of reasoning by underscoring how firms choose their benchmark exemplar(s) for learning purposes based on the similarity in pre-entry industry experience. Start-up firms typically associate themselves with the emerging industry, while diversified firms identify themselves through the existing market and suppliers (York and Lenox, 2014). A difference in this identification likely leads to differences in how firms choose the benchmark organizations they emulate. Through our analyses, we find corroborative evidence in start-ups firms, the only group that will aggressively pursue a high degree of performance advancement in innovation when their peers are gaining more market share.

This is where vicarious learning becomes immensely important, as firms would have to observe similar firms to formulate a strategy based on their idiosyncratic capabilities. Benner and Tripsas (2012), who find that firms do not always imitate competitors for all product features they release, attribute this result to commonly held beliefs and assumptions shared among firms with the same pre-entry experience. We build upon this insight by showing how firms fine-tune the fit between product performance and firm capabilities. We shed light on how vicarious learning in the presence of firms with the same pre-entry experience and a market leader affects how organizations decide upon the degree of product performance of their innovative offerings, and how technological stock influences this effect.
We can conclude from our findings that technological stock becomes an exceedingly important consideration in many present-day industries because technical advancement usually takes several technology generations to complete. Each new generation offers better product features and technological performance. For example, software companies often release a beta version of their offerings with the express intent of enrolling user communities into product improvements that are reflected in subsequent iterations of the tool. The increase in design complexity that characterizes sectors such as software forces organizations to improve technical performance in incremental steps. In addition, users are already in the habit of installing ‘patches’ after the initial purchase or performing system updates periodically. Microsoft even formalized the term Patch Tuesday to refer to security patches released for its software products on Tuesdays.

At today’s speed of technology progression, firms very likely will lose customers to rivals if they force these clients to wait for the ‘perfect’ product. Incorporating a significant degree of performance advancement in each new offering, while perhaps an attractive goal, may rarely yield long-lasting benefit – particularly where technological stock reveals the potential for rivals to match such initiatives. In this sense, and perhaps in contrast to the prevailing wisdom that greater ambition in innovation efforts is generally advisable, the admonishment not to let the perfect be the enemy of the good (or the good enough) may ring especially true for innovating firms looking to compete in nascent sectors.
REFERENCES


