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Diversification as an Adaptive Learning Process: An Empirical Study of General-Purpose and Market-Specific Technological Know-How in New Market Entry

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An enduring trait of modern corporations is their propensity to diversify into multiple lines of business. Penrosian theories conceptualize diversification as a strategy to exploit a firm's fungible, yet "untradeable", resources and point to redeployment of technological know-how as an important driver thereof. However, less understood are the characteristics of technological assets that underlie firms' diversification decisions, and the impact diversification has on firms' subsequent development of technologies. In this paper, we expand the existing theories in two ways. First, we argue that central to understanding firms' diversification decisions is a distinction between their technological assets that are applicable to many markets and ones that are useful in only a limited number of contexts. To this end, we develop a novel way to characterize technologies along a continuum from highly general-purpose to highly market-specific. Second, we explore empirically the idea that diversification is an adaptive learning process involving both exploitation of existing capabilities and creation of novel ones. Using data on three decades of patenting and diversification histories of 28,376 firms, we find that: (1) a firm's possession of general-purpose technological assets is positively associated with its decision to diversify, (2) firms that enter a new industry through diversification develop technologies that are specialized to the target industry, and (3) the increase in the intensity with which a diversifying firm develops technologies specific to the target industry is positively associated with its longevity in that market. Our findings have implications for understanding firm growth, diversification, and evolution.

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INTRODUCTION

An enduring trait of modern corporations since their emergence in the mid-19th century is their propensity to diversify over time into multiple lines of business. The causes and consequences of such diversification have long fascinated scholars of organizations and strategy (Chandler 1990; Penrose 1959; Teece 1982). And of course, decisions about horizontal scope of the enterprise lie at the intellectual heart of the field of corporate strategy (Rumelt 1984). Following Penrose's (1959) seminal work on firm growth, current theories conceptualize diversification as a strategy to exploit fungible, yet "untradeable", resources (Montgomery and Wernerfelt 1988; Teece 1982). While there are many potential resources that might become relevant during the process of diversification (e.g., brand, distribution) technological know-how has been a focal point in both scholarly (Granstrand, Patel, and Pavitt 1997; Teece 1982) and practitioner-oriented writings (Hamel and Prahalad 1990). Empirical work has largely supported the general proposition that redeployment of technological assets plays a central role in diversification (Montgomery and Wernerfelt 1988), and that firms' diversification strategies demonstrate a degree of coherence around technological capabilities (Granstrand et al 1997; Lemelin 1982; Teece, Dosi, Rumelt, and Winter 1994).

Technological know-how, however, is a highly variegated construct. Beyond broad notions that difficult to transact know-how provides opportunities for diversification, existing research does not fully elucidate the specific kinds of technological assets that might underlie a firm's diversification decisions or create opportunities for diversification. Take the seemingly straightforward proposition that firms diversify into technologically "related" markets or around identifiable "core competences". This can be used to justify or explain virtually any diversification move. In addition, existing research has focused almost exclusively on exploitation of technological assets across markets, when both Penrose's original theory of diversification and case studies that followed suggest that diversification often requires both exploitation of existing technological assets and creation of new ones (Penrose 1959; Pisano 2018; Pisano and Shulman 2018).

In this paper, we attempt to sharpen the Penrosian theory of diversification in two ways. First, we probe more deeply into the nature of technological assets that underlie diversification. Following Pisano (2018), we characterize technological assets by their degree of market specificity. We develop a novel measure that enables us to characterize technological assets along a continuum from highly market-specific to highly general-purpose. We then use this measure to predict a firm's propensity for diversification. Second, we explore empirically the idea that diversification is an adaptive learning process involving both exploitation of existing capabilities and creation of novel ones.

Using data on three decades of patenting histories across 28,376 firms and their diversification strategies, we find the following: (1) a firm's possession of general-purpose technological assets is positively associated with its decision to diversify, (2) firms that enter a new industry through diversification develop technologies that are specialized to the target industry, and (3) the increase in the intensity with which a diversifying firm develops technologies specific to the target industry is positively associated with its longevity in that market. We discuss implications of these findings for theory and research on firm growth, diversification, and evolution.

TECHNOLOGICAL KNOW-HOW IN DIVERSIFICATION

Early writings of Edith Penrose (1959) speculate that a firm's horizontal expansion will be precipitated by development of assets that are currently underutilized but could be leveraged in other markets. Central to this theory is the idea that a diversifying firm has the opportunity to take advantage of economies of scope by redeploying its assets at a low marginal cost (Panzar and Willig 1981; Teece 1982), economies of scale, which exist if a firm currently does not capture cost advantages associated with scale of its operations, and transaction cost economics, so long as diversification is the more profitable way to capture rents on its assets than licensing (Williamson 1975). Building on those insights, strategy scholars justify existence of the multiproduct firm (Teece 1982) and provide boundary conditions for profitable diversification (Helfat and Eisenhardt 2004; Hill, Hitt, and Hoskisson 1992; Markides and Williamson 1994; Montgomery and Wernerfelt 1988; Teece et al. 1994).

Redeployment of existing assets to new contexts is at the center of Penrosian theories of diversification and has till date received the vast share of scholarly attention. However, although much of Penrose's own discussion focused on the exploitation of existing capabilities, she also hints that diversifying firms create new resources to carry out their expansion: "In planning expansion a firm considers two groups of resources—its own previously acquired or 'inherited' resources, and those it must obtain from the market in order to carry out its production and expansionary programs" (Penrose 1959:86). Additional case study evidence suggest that diversification involves creation of new capabilities as much as it involves exploitation of existing ones (Pisano 2018). A prolific diversifier like the Virgin Group, for instance, leverages its brand in a variety of business (air travel, train travel, cruises, fitness centers, financial services, etc.) but must also develop new capabilities in each of those businesses.

While there are many potential capabilities (for example, human capital (Farjoun 1998) or managerial know-how (Farjoun 1998; Penrose 1959; Prahalad and Bettis 1986)) that might be exploited and created during the process of diversification, technological assets are often at the center of a firm's opportunities for entry to a new industry (Miller 2006; Robins and Wiersema 1995; Teece 1982; Wernerfelt and Montgomery 1988). This is because technological know-how's low marginal costs of use and difficulty of exchange through contractual means (Teece 1982) position it as a resource that is especially likely to lead to profitable diversification when leveraged across business segments (e.g., Teece 1980). Further, developing technologies that grant a firm the ability to compete and innovate in its target market plays an important role in its subsequent longevity in the new industry (e.g., Rosenberg 1994; Schumpeter 1975).

Much less understood are the specific ways in which a firm's knowledge base influences its decision to diversify, and how that decision impacts its future accumulation of capabilities. There is evidence that a firm's patterns of diversification demonstrate a degree of "coherence" (Teece, Dosi, Rumelt, and Winter 1994). That is, firms from the same industry tend to have similar diversification "footprints" (i.e., they diversify into similar industries). These patterns suggest some common underlying resources across firms from the same industry. While tantalizing in their implications, these findings leave many questions unanswered. What are those common underlying resources? Why might some firms from the same industry exhibit different patterns of diversification? And why might there be differences in post-diversification performance? To begin to address these questions, we examine more deeply the nature of underlying technological assets that might lie at the heart of firms' diversification strategies.

General-Purpose vs. Market-Specific Know-How Innovation is a problem-solving process that both draws on past accumulated knowledge and produces knowledge available for future problem-solving efforts. Innovative capacity is thus highly history-dependent (Landini, Lee, and Malerba 2017; Malerba, Nelson, Orsenigo, and Winter 2008; 2016). A firm's capacity for innovation depends at least partially on the know-how it produced in past efforts. Following Pisano (2018), we distinguish technological assets by the degree to which they can be utilized across applications or markets. At one extreme, some technological assets – what Pisano (2018) referred to as "market-specific" – are useful only within a very narrow range of industries. The specific design of the suspension system for a Ford F150 pick-up truck is a relatively specialized asset. It is quite valuable when used in the Ford F150, and may be potentially useful on similar vehicles, but its value drops considerably if considering other types of vehicles that are not cars (e.g., motorcycles, airplanes, and trains), and it likely has little direct value outside of vehicles. Of course, designing that suspension system both requires and generates additional insights and know-how about fundamental principles of designing complex mechanical systems under dynamic loads. This broader knowledge could be in turn useful for a wider range of application, and thus represents a "general-purpose" capability.

For ease of exposition, in this article we often characterize technologies in dichotomous terms, as either general-purpose or market-specific. However, in reality, technological assets are best described along a continuum. In addition, as the example above implies, any given problem-solving activity can generate a mixture of both general-purpose and market-specific know-how. Attempts to solve a specific problem may generate knowledge applicable to a broader range of problems. Firms may also have different strategies with regard to the search for general-purpose versus market-specific technological assets. The location of firms' research labs might serve as one example of a strategic choice that influences their propensity to create different types of know-how. For instance, firms with centralized research labs (such as Corning) may explicitly seek to create general-purpose technological capabilities as a mean to generate future growth options (Bowen and Purrington 2008). Conversely, other firms may explicitly seek to focus their efforts only on the most applied problems within their specific market domains (Intel is an example of a company that historically followed this R&D strategy (Pisano, Collis, and Botticelli 1997)).

Differentiation between general-purpose and market-specific technologies is important because the two likely play a fundamentally different role during a firm's diversification process. On the high-level, a firm's general-purpose technologies enable it to have opportunities for diversification in the first place. This is because a firm might be able to leverage its general-purpose technologies across existing and new business segments and thus take advantage of economies of scope and scale. However, in our framework, market-specific technologies are also important. We theorize that development of technologies specific to a new market is necessary for a firm to exercise its options for diversification. Research shows that successful entry into a new industry environment, even one related to a firm's existing business segments, ultimately requires development of highly-complex context-specific technologies (Christensen 1997; Henderson and Clark 1990; Von Hippel 1994). Consequently, we theorize that development of both general-purpose and market-specific technologies plays a role in the diversification process.

General-purpose technologies constitute a mechanism that underlies the relatedness hypothesis which predicts why a firm diversifying into a related industry will create more value than a firm entering a more distant market (Teece 1980). In our theorizing, we follow Scherer and conceptualize relatedness in terms of technological opportunity (1965). The core idea is that technology fosters exogenous connections between industries (Robins and Wiersema 1995) and thus, from as firm's perspective, its general-purpose technologies serve as links between its existing assets and other markets to which those assets might be applicable. Those industries, by extension, constitute a set of related markets and thus potential diversification targets. A firm that has developed technologies that are on average more general-purpose should thus be more likely to diversify that one with more market-specific technologies. Consequently, we hypothesize that general-purposeness of a firm's technological assets will be positively associated with its decision to diversify.

Hypothesis 1: General-purposeness of a firm's technological assets is positively associated with its decision to diversify.

General-purpose capabilities create options to enter new industries, but alone are not sufficient for entry. Diversification is an adaptive learning process whereby general-purpose know-how acquired in one industry is adapted to the specific requirements of the target industry and new, target-industry specific know how is created. Google's much discussed foray into autonomous vehicles is an example with strong parallels to the Virgin example we noted earlier. Google's software development capabilities, and particularly its deep expertise in artificial intelligence, are the general-purpose assets creating the opportunity to develop an autonomous vehicle. But developing any vehicle requires skills in a broad range of traditional automotive engineering disciplines (even the most sophisticated automotive vehicle is still a highly complex mechanical device requiring mechanical systems integration, powertrain design, suspension systems, active safety features, climate control, to name a few). Consequently, while stocks of general-purpose capabilities might have provided a firm like Google with options to diversify, entry into a new market generally also requires development of additional capabilities specific to the target industry.

The reason why development of technological know-how specifically applicable to a firm's new markets is an important component of diversification is connected to the fact that even related industries are ultimately characterized by unique environments which influence the specifics of technologies that are necessary to successfully compete within them. While some technologies are general-purpose and thus applicable across markets, the vast majority of technologies necessary for sustained presence in an industry are shaped by problems that arise within it and thus are useful to the extent that they help a firm respond to those environment-specific challenges (Cyert and March 1963). Considered together, those insights lead us to two hypotheses. First, diversification into an industry is associated with development of technologies specifically applicable to that market. Second, development of technologies specific to the target industry is positively associated with a diversifying firm's longevity in the new market.

Hypothesis 2: Diversification into an industry is associated with development of new technologies specifically applicable to that industry.

Hypothesis 3: Development of new technologies specifically applicable to a target industry is positively associated with a diversifying firm's longevity in the new market.

DATA AND METHODS

Data We investigated a relationship between a firm's general-purpose and market-specific technological know-how and its diversification activities using a sample of publicly traded firms that applied for at least one patent with the United States Patent and Trademark Office (USPTO) between 1975 and 2004 and whose information appeared in the University of Virginia's The Global Corporate Patent Dataset (Bena, Ferreira, Matos, and Pires 2017), The Derwent World Patents Index, and the Compustat Historical Segment database. Our full sample included 28,376 firms from 448 industries and 5,933 instances of diversification. We determined a firm's and its business segments' industry membership using its Standard Industrial Classification (SIC) assignment.

Methods We used different empirical approaches to evaluate our three hypotheses. We will describe them in turn. To test hypothesis 1, we longitudinally analyzed patenting and diversification histories of firms in our sample from 1976 to 2004. Our first step was to use the Compustat Historical Segments database to find each year when firms diversified into a new industry. *Diversification* is the outcome variable predicted in our analyses evaluating hypothesis 1. It is measured on yearly basis. *Diversification* equals 1 for each year when a firm added a business segment in an industry that was not represented in its business segments in the prior year and 0 otherwise. In analyses testing hypothesis 1, we predicted the likelihood of *Diversification* from the average general-purposeness scores of a firm's patents. In those analyses, we included all firms in our sample, both those that did and did not diversify during the span of time covered by our data.

Our second step was to use patent data to construct yearly measures of general-purposeness of each firm's technologies. We followed an established convention, advantages and disadvantages of which are well known, and used patents developed by a firm to operationalize its technological assets (e.g., Argyres and Silverman 2004; Kotha, Zheng, and George 2011; Sampson, 2005; Sears and Hoetker 2014; Zheng, Liu, and George 2010). We began by building a dataset of all successful patents that each firm in our sample applied for between 1975 and 2004. We focused on successful patents because our theoretical predictions concern a firm's technological assets, which, by definition, are its usable technologies (Sears and Hoetker 2014) as opposed to its attempts at technological innovation. In accordance with earlier literature on this topic, we defined successful patents as those that received at least one forward-art citation (e.g., Sears and Hoetker 2014; Singh and Fleming 2010).

Next, to place each patent developed by a firm on a continuum from highly general-purpose to highly market-specific, we examined the forward-art citations that a patent received from future-art patents developed between 1975 and 2013.[1] Examining industry membership of firms that developed each forward art patent citing the patent in question gives us information about whether a given technology was applicable to a narrow range of industries, i.e., it was a market-specific technology, or a wide range of industries, i.e., it was a general-purpose technology. Consider the following example. An automobile company develops a patent that receives forward citations exclusively from other automobile

[1] We used forward-art patents developed during this time period because prior research showed that there exists a lag of approximately two to three years between patent application and granting dates and that forward citations that a patent receives typically plateau three years after its grant year (Jaffe et al. 1993). Thus, determining general-purposeness score of a patent from its forward-art citations over six years after its application date allowed us to capture the vast majority of the forward-art citations that the patent is expected to receive (Jaffe et al. 1993).

companies. That patent would be score as highly "market-specific" under the presumption that both the patent originator and the forward citers are from the same industry. In contrast, consider another patent, developed by the same auto company, that receives forward citations from companies in a broad range of markets (e.g. aircraft, software, electronics, etc.). Our measure would rate this patent on the general-purpose end of the scale under the presumption that it was relevant to firms from a wide range of other industries. Placing a technology on a scale from highly general-purpose to highly market-specific by looking directly at the industries where it was useful differentiates our work from earlier studies on this topic in an important way. In prior studies, breath of a diversifying firm's technological capabilities is based on *technological domains* (indicated by patent technological classes) to which its technologies belong (e.g., Miller 2004; 2006). While using patent technological domains is quite helpful for many empirical questions, it is less useful for exploring questions related to market-specificity. Comprehensive investigation into the relationship between a firm's technological assets and its diversification decisions requires detailed industry-applicability data on historical patent portfolios of a large number of firms. In the past, a major challenge to such analyses presented inconsistencies in firm names in the USPTO's records. However, recent advances in algorithmic text disambiguation techniques significantly improved matching between firms and their patents, which in turned enabled us to trace a given technology's industry applicability (Bena, Ferreira, Matos, and Pires 2017).

Our key predictor variable testing hypothesis 1 is *General-Purposeness of an Average Technology* in a firm's portfolio, which we calculated on yearly basis. It operationalizes how general-purpose, on average, are the technologies that a firm develops each year. To build this measure we first calculated a general-purposeness score of each patent that a firm applied for in a particular year, *General-Purposeness of a Technology*$_i$. To do so, we drew on an approach suggested by Hall, Jaffe, and Trajtenberg (2001), which includes a bias correction method that allowed us to account for the variability in the number of forward-art citations received by patents[2]. Our measure provided information about the

[2] Bias correction methodology is adopted from Hall, Jaffe, and Trajtenberg (2001:45-46)

industries where a particular technology was useful and thus allowed us to characterize an invention as one that reaches many markets, i.e., is general-purpose, as opposed to one that is useful in only a limited number of industries, i.e., is market-specific. To calculate *General-Purposeness of an Average Technology*, the variable used in our models, we averaged the bias corrected values of *General-Purposeness of a Technology$_i$* across all patents that a firm applied for in the same year. *General-Purposeness of a Technology$_i$* was calculated as follows:

$$\textit{General-Purposeness of a Technology}_i = 1 - \sum_{s=1}^{S} \left(\frac{n_{is}}{n_i}\right)^2$$

where n_i denotes the total number of forward citations received by patent i, and n_{is} denotes the number received from patents which belong to firms from industry s. The value of this variable will be low when a patent is referenced by forward-art patents belonging to firms from a small number of industries, and it will be high when the opposite is true.

Our analyses testing hypothesis 1 also included several control variables. First, a firm's size might influence its diversification decisions since large firms may be especially likely to gain benefits due to scale. Therefore, we included two variables to approximate a firm's size. First, *Employees* (measured in thousands) indicates a yearly number of a firm's employees. Second, *EBIT* (measured in millions USD) indicates a firm's annual earnings before interests and tax and serves both as an additional approximation of its size as well as an indicator of its profitability, which could also be used as a proxy for approximating the quality of a firm's management.[3] Next, because a firm's age might positively influence the stock of tacit knowledge it is able to leverage during diversification activities (Gittelman and Kogut 2003), we controlled for a firm's *Age. Age* indicated the firm's age at the time of a patent's application date and was calculated by subtracting a firm's founding date from its patents' application dates. We have

[3] In a secondary set of analyses, we also included a firm's revenue (measured in millions USD) as one of the controls. The measure of revenue neither changed statistical significance of our results nor included meaningful information beyond those encompassed by the *Employee* and *EBIT* variables. At the same time, it was highly correlated with both the *Employee* and *EBIT* variables. Consequently, we excluded it from our models to avoid problems associated with multicollinearity.

also included in our analyses the total number of patents that a firm developed in a given year, *Total Patents*, because a firm who is a prolific innovator might be better able to develop technologies that are useful in diversification than a firm that is not. Lastly, we included a measure of a firm's *R&D Budget* (in millions USD). R&D budget can directly influence a firm's ability to develop technologies, thus, controlling for it in our analyses is essential for accomplishing our goal of illuminating how a firm's technological assets are associated with its decisions to diversify. Following an established convention in literature on firm technologies and strategic outcomes (e.g., Lahiri and Narayana 2013; Yanadori and Cui 2013) our predictor variable as well as all control variables used in our analyses were lagged by a year relative to the date of predicted *Diversification* to approximate the most directly the types of technologies that a firm was developing before its entry to a new market as well its other characteristics at the time. Further, in all our models we included firm and year fix effects. Table 1 includes summary statistics of all our variables used for testing hypothesis 1 and Table 2 shows their correlations. Table 3 shows results of our analyses testing hypothesis 1.

Now, we move on to describing our methodology for evaluating hypothesis 2, in which we predicted that diversification into an industry is associated with development of new technologies specifically applicable to that industry. Our first step in testing hypothesis 2 was to group firms in our sample based on their "origin" industries, meaning their primary pre-diversification SIC codes. Next, we eliminated from our analyses industry groups which did not have a single company that diversified into a different industry during the time span of our data. Left with industry groups which had at least one diversifier, we tagged all instances of diversification based on the year in which an entry to a new industry occurred and the "target" industry where it occurred.

Next, we focused in on each instance of diversification present in our data and compared technologies developed by a diversifying firm during a period before and after the new market entry date with technologies developed by its origin industry peers during the same time periods. Our first step was to analyze the portfolio of patents that a diversifying firm developed a year before entering a new industry, i.e., "pre-diversification patents" and a year after, i.e., "post-diversification patents". In this analysis, we compared industry membership of firms that created the forward-art patens that cite the diversifying firm's patents developed in the "pre" and "post" time periods. Specifically, we calculated the proportion of citations that the diversifying firm's pre-diversification patents and post-diversification patents received from firms belonging to the target industry. Then, we calculated the percent change in those proportions. We did this for every instance of diversification that appeared in our data. Next, we calculated standard errors of this citations ratio percent change statistic to find out whether in the year after diversification, the diversifying firm developed technologies that are more, less, or similarly applicable to the target industry as compared with technologies that it developed a year before diversification. Once we had those results, we turned to other firms from the diversifying firm's origin industry which did not diversify into its target industry during the same time period and calculated the same statistics for them. We averaged the non-diversifiers' statistics across all firms from the diversifying firm's origin industry and they became our comparison set to evaluate hypothesis 2. Figure 1 shows results of analyses testing hypothesis 2.

We now explain our approach for testing hypothesis 3, in which we predicted that development of new technologies specifically applicable to a target industry is positively associated with a diversifying firm's longevity in the new market. Our first step in conducting these analyses was to track all instances of diversification in our data. Specifically, we looked at the firms that entered a new industry, the year in which they entered, and the target industry which they entered. Then, for each instance of diversification, we examined the patents that a diversifying firm developed during a time period of one year before entering a new market and one year after. Using the same method that we have described above; we calculated the percent change in proportion of citations each diversifying firm's "pre-" and "post-diversification" patents received from firms belonging to its target industry. Next, we went back to the Compustat Historical Segment database and checked for which instances of diversification, the new segment that a diversifying firm added was still represented in its business segments five years after the entry date. We labeled as "successful" diversification those instances of diversification when a firm still had business in the new segment five years after the entry date, and when the opposite was true, we marked it as “unsuccessful” diversification. To evaluate hypothesis 3, we calculated standard errors of our citation ratio percent change statistic for the successful and unsuccessful instances of diversification. This allowed us to find out whether successful diversification was associated with different focus on development of technologies specific to the new market than unsuccessful diversification. We present results of analyses testing hypothesis 3 are in Figure 2.

RESULTS

Hypothesis 1 states that general-purposeness of a firm’s technological assets will be positively associated with its decision to diversify. Our analyses confirm this prediction. As shown in Table 3, the average general-purposeness score of a firm’s technological assets is positively associated with its decision to diversify. First, in Model 1, the coefficient on *General-Purposeness of an Average Technology* predicting a firm’s likelihood of diversification is positive and statistically significant. This provides evidence that a firm that develops technologies that are on average more general-purpose than those developed by its industry peers is more likely to diversify than a firm that produces more narrowly applicable technologies. Next, Model 3 shows that this association remains statistically significant even when we control for a firm’s size, age, R&D budget, and the number of patents it develops per year. As a robustness check, we have repeated those analyses including the average general-purposeness score of a firm’s patents developed over the span of the three years leading up to diversification as opposed to one year and received similar results. Our analyses thus suggest that developing technologies that are applicable to many industries is indeed positively associated with a firm’s decision to diversify. This finding provides support for hypothesis 1.

Our data also support hypothesis 2, which predicts that diversification into an industry is associated with development of new technologies applicable to that industry. As shown in Figure 1, firms that diversified into a new industry intensified development of technologies specific to that industry at a significantly greater rate than peers from their origin industry that did not diversify. In this analysis, we examined technologies that diversifiers and non-diversifiers from the same origin industry developed one year before and one year after each instance of diversification that appeared in our data. Specifically, we compared between new industry entrants, i.e., diversifying firms, and non-entrants the percentage change in proportions of citations that their patents developed during those two time periods received from firms belonging to the target industry focal in a particular instance of diversification. Our data show that, for new industry entrants, this citations ratio statistic increased on average by 62.24% between the "pre-" and "post- diversification" time periods while for non-entrants the average change in the statistic across these two time periods was only 10.19%. We find that the difference in these two means is statistically significant at the 95% confidence level. This result provides support for our prediction that diversification is a process during which firms develop new technologies specific to the target industry.

Lastly, analysis presented in Figure 2 provides support for hypothesis 3. In it, we used a similar analytical approach to the one described above for testing hypothesis 2, but this time, we compared a diversifying firm's focus on development of technologies applicable to a newly entered market in successful and unsuccessful instances of diversification. Our results show that on average, in the successful instances of diversification, the proportion of forward-art citations that a firm's technologies developed a year after entering a new market received from firms beloning to its target market was on average 81.31% greater relative to its technologies developed a year before diversification. This result is in stark contrast to the average 9.02% change in those two proportions in the unsucessful instances of diversification. We find that the difference in these two means is statistically significant at the 95% confidence level. Thus, consistent with hypothesis 3, our results support our prediction that development of new technologies specifically applicable to a target industry is positively associated with a diversifying firm's longevity in the new market.

DISCUSSION AND CONCLUSION

While case studies have suggested that diversification is an adaptive learning process involving both redeployment of general-purpose technological assets and creation of new market-specific assets, systematic empirical evidence has been lacking. This was the gap we sought to redress in this paper. Our findings are consistent with the idea that diversification is an adaptive learning process. They also highlight the challenge of diversification. Diversification not only requires the production of general-purpose technological assets, but also the capacity to create highly specialized know-how in completely new domains. Posed in familiar language of organizational theory, diversification requires organizations to be both excellent exploiters (of general-purpose know-how) and excellent explorers (of market-specific know-how relevant to their target-industry). This dual challenge may explain why successful diversification is relatively rare.

Our study of course has limits, and normative conclusions should only be drawn with the greatest of care. As acknowledged at the outset, our study has all the limits of using patent data as a measure of innovative activity. This issue, of course, has been widely discussed in the past literature. We are comforted by the fact that our empirical study covers a large sample of firms and yields insights consistent with richer, more descriptive case studies. Further large sample quantitative studies and additional case studies would certainly be a worthwhile endeavor. A major limit of our study is that it was designed to show only associations and not causal relations. We have no evidence that general-purpose assets *cause* diversification, or that diversification *causes* the subsequent creation of market-specific technologies. We feel however that this was a worthwhile attempt to identify patterns between technological asset accumulation and corporate diversification strategies. Thus, our study should be read as a step in a much longer research program to understand the important link between knowledge creation, knowledge diffusion, and firm strategies. Further insights of these issues are central to understanding of technological and industry evolution, and the role that firms play in these processes. The potentially important implications for both theory, management practice, and public policy make this a rich stream for future work.

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TABLES AND FIGURES

Table 1. Summary statistics of variables used in models in Table 3.

	Observations	Mean	Standard Deviation	Minimum	Maximum
Diversification	19,403	0.106	0.308	0	1
Employees	18,422	22.764	58.728	0	905.766
R&D Budget	17,114	195.085	631.846	0	12,183
EBIT	19,372	463.611	1,795.010	-10,537	52,205
Age	19,402	17.954	14.694	0	54
Total Patents	19,401	40.540	149.392	1	4040
General-Purposeness of an Average Technology	19,401	0.468	0.256	0	1

Table 2. Correlation table of variables used in models is Table 3.

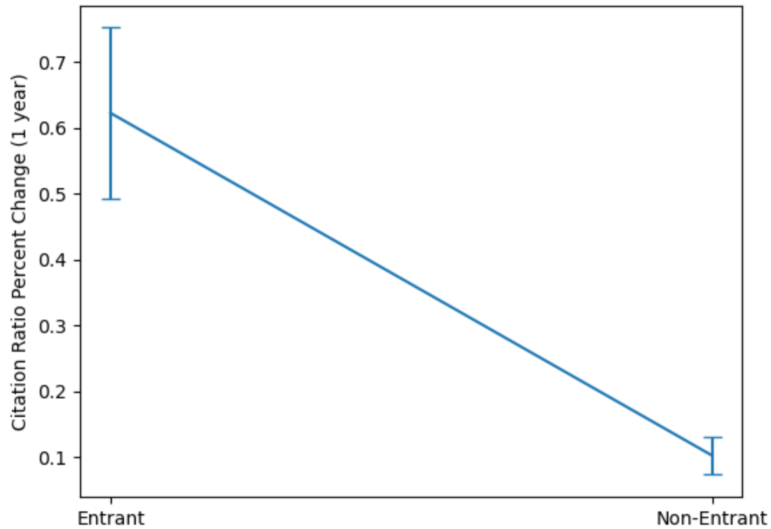
	Diversification	*Employees*	*R&D Budget*	*EBIT*	*Age*	*Total Patents*
Diversification	1.000					
Employees	0.119	1.000				
R&D Budget	0.075	0.656	1.000			
EBIT	0.071	0.582	0.601	1.000		
Age	0.125	0.243	0.175	0.253	1.000	
Total Patents	0.069	0.448	0.617	0.402	0.171	1.000
General-Purposeness of an Average Technology	0.054	0.054	-0.020	-0.028	-0.001	0.031

Table 3. Longitudinal logistics regression predicting a firm's likelihood of diversification. (*Employees, R&D Budget, EBIT, Age, Total Patents, General-Purposeness of an Average Technology* have been lagged by one year relative to the diversification date)

Model	(1)	(2)	(3)
Dependent variable	*Diversification*	*Diversification*	*Diversification*
Regression model	Logistic time series	Logistic time series	Logistic time series
General-Purposeness of an Average Technology	0.389*		0.529**
	(0.164)		(0.191)
Employees		0.001	0.001
		(0.001)	(0.001)
R&D Budget		$-5.691 \times (10^{-6})$	$-1.17 \times (10^{-5})$
		(0.000)	(0.000)
EBIT		$1.14 \times (10^{-5})$	$1.09 \times (10^{-5})$
		(0.000)	(0.000)
Age		0.002	0.003
		(0.011)	(0.011)
Total Patents		0.001*	0.001*
		(0.000)	(0.000)
Firm fixed effects	Included	Included	Included
Industry fixed effects	Included	Included	Included
Observations	10,036	8,594	8,594
Chi^2	462.49	429.66	437.40
Log Likelihood	-3,209.2164	-2719.8139	-2715.9447

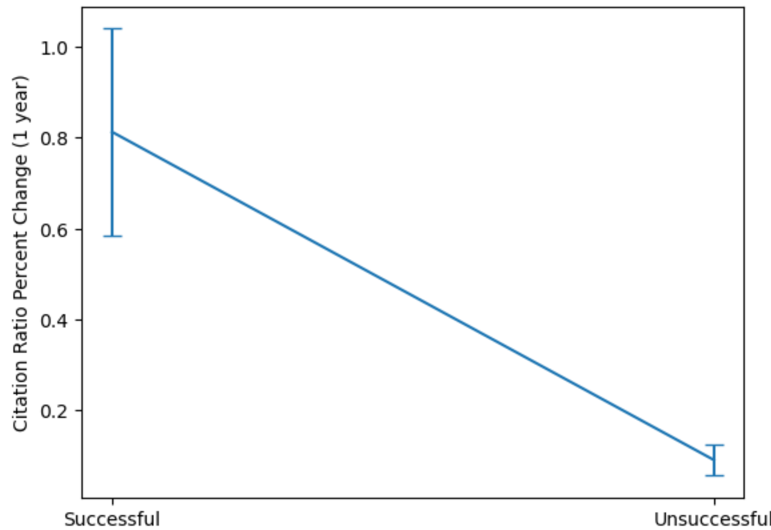
*$p < 0.05$, ** $p < 0.01$*

Figure 1. Comparison between firms that entered a new industry and non-entrants from their origin industries in the focus on development of technologies applicable to the diversifying entrant's target market (incl. 95% Confidence Interval)



	Number of unique firms	Mean	Standard Error
Entrant	2,227	62.24%	6.48%
Non-Entrant	26,148	10.19%	1.46%

Figure 2. Comparison in a diversifying firm's focus on development of technologies applicable to a newly entered market in successful and unsuccessful instances of diversification (incl. 95% Confidence Interval)



	Number of unique instances of diversification	Mean	Standard Error
Successful	2,762	81.31%	11.37%
Unsuccessful	3,171	9.02%	1.74%