Bottleneck Resources, Market Relatedness, and the Dynamics of Organizational Growth

Abstract
Entering a new product market requires assembling a bundle of resources. Because missing a single resource can foil the entire entry effort, we argue that bottleneck resources – those most difficult to obtain or sell externally – anchor the direction of firm growth. We characterize market resources as bottlenecks to product-market entry because they are (on average) more challenging to obtain and sell than technological resources, and we articulate why the importance of market resources varies with the strength of external markets for technology. Using cross-industry data linking firms' product portfolios with patents, we find resource dynamics whereby market resources drive the strategic decision to enter, and firms fill technological gaps using both internal R&D and external acquisitions (joint ventures and alliances). Our study underscores the importance of resources for firm growth dynamics and specifically highlights market resources as the bottleneck that constrains and directs the direction of product market entry.

Keywords: product market entry; diversification; resource-based view; demand-side strategy, markets for technology

There are many ways to center a business. You can be competitor focused, you can be product focused, you can be technology focused, you can be business model focused, and there are more. But in my view, obsessive customer focus is by far the most protective of Day 1 vitality.

– Jeff Bezos in his 2016 letter to Amazon shareholders

1. Introduction

What determines the direction of a firm's new product market entry and growth? In examining this question, the resource-based view (RBV) describes a firm as a bundle of resources (Wernerfelt, 1984). Prior research suggests that firms leverage resources from current markets to facilitate entry into new product markets (Penrose, 1959; Helfat and Lieberman, 2002; Sakhartov and Folta, 2014). This focuses entry behavior on adjacent or "related" businesses where the value of extant resources can be profitably redeployed, creating path-dependence and coherence to a firm's growth trajectory. However, we often observe product-market entries that seemingly do not build on existing resources and demand significant new investments that diverge from a firm's existing strengths. As firms can hardly be expected to pursue every potential redeployment use for the resources they already possess, there should be important latent heterogeneity in which resources do and do not lead to product market entry. This speaks to the need for a more general theory providing coherence to entry behavior and the role of resources.

To develop a theory about the resources that do and do not lead to entry, we focus on the process of completing the resource bundle necessary to introduce a new product (Wu, Wan, and Levinthal, 2014; Speckbacher et al., 2015). This process entails combining resources that the firm already controls with newly developed or acquired resources that fill necessary gaps. Because lacking a single resource in the bundle can prevent entry, we argue that it is not necessarily the most valuable resource in the firm's current resource bundle but the hardest-to-acquire (and by extension, hardest-to-sell) resource that determines the direction of product market entry. We define these difficult-to-acquire resources as *bottleneck resources*, borrowing from Teece's discussion of complementary assets as a potential "choke point" in a firm's value chain to profiting from technological invention (2006:1138) and Keum's analysis of the bottleneck activities to implementing a successful strategic change (2020).[1] Firms that lack a bottleneck resource are constrained from entering a market because of the difficulties in acquiring the bottleneck resource. Conversely, firms that already possess a bottleneck resource have the incentive to enter the product market to capture value from the resource given the challenges in otherwise monetizing the bottleneck resource's potential. In translating the broad theory of bottleneck resources to market entry, we propose that market resources (e.g., customer relationships, distribution channels, brand names) are likely to serve as bottlenecks based on the significant challenges to obtaining or trading them externally (Day, 1994; Lord and Ranft, 2000). Meanwhile, the growth of markets for technology through licensing, patent transfer, and alliances (Pavitt, 1984; Arora et al., 2001) has increased the transferability of technological resources and reduced their potential to be bottleneck resources.

This focus on bottleneck resources yields novel predictions on the dynamics of resource and firm growth. First, in contrast to the dominant characterization of market resources as playing only a secondary role, we propose that market relatedness, or the extent to which the firm's existing market resources are similar and fungible across product-market boundaries, is an independent and critical predictor of product market entry decisions. Market knowledge, including the understanding of the preferences and needs of key customers in the product market, has long been recognized as a critical complementary resource (Teece, 1988; Helfat and Lieberman, 2002), but there has been a surprising lack of theoretical and empirical research that explicitly links market relatedness to firm entry behavior. This is not to suggest that market resources are always bottlenecks and that other resources are always easy to obtain, but *on average* and across industries, we expect market resources to be more likely to function as bottlenecks. Second, we expect significant heterogeneity in the importance of market resources as a bottleneck. The difficulty of completing the rest of the bundle should vary across firms and markets, especially with respect to building technological resources that are at least on par with competitors. The importance of market relatedness should increase as firms have easier access to requisite technology (Pavitt, 1984;

[1] For analogous discusions of bottleneck *firms* in an ecosystem, refer to Von Hippel (1994), Jacobides and Tae (2015), and Hannah and Eisenhardt (2018).

Arora et al., 2001) but decrease as technological resources become more central to product-market success (Arora and Nandkumar, 2011). This suggests the strengths of markets for technology as an important contingency that changes the bottleneck resource within and across firms. Third, firms entering a product market by redeploying market resources will need to access and strengthen relevant technological resources. This suggests intriguing and novel temporal dynamics in organizational growth where extant market resources drive entry into a related product market, while the decision to enter (and the need to complete the resource bundle) triggers the internal and external acquisition of new technological resources relevant to the entering market.

Evaluating our theory requires identifying relatedness in market resources that do not neatly fall into the existing industry structure. Notably, SIC codes group together businesses using similar input resources even if they result in dissimilar products or outputs.[2] Hence, we build a novel dataset linking the product portfolios of US high-tech firms from the CorpTech Directory of Technology Companies with NBER's patent database. The resulting dataset allows us to track changes in product and patent portfolios for more than 5,000 high-tech firms across over 300 product markets from 1997 to 2005. Our main empirical finding is summarized in Figure 1: there are robust and consistently positive effects of market relatedness on entry across various levels of technological relatedness. In contrast, while technological relatedness does affect the likelihood of *technological* entry (Breschi, Lissoni, and Malerba, 2003), we find no evidence of an effect on *product market* entry. We also find that market relatedness matters more for firms and industries that can readily access relevant technological resources internally or externally. Finally, we find that while technological resources do not drive entry, the strategic decision to enter drives firms to acquire technological resources relevant to the entered market through both internal R&D and external collaborative arrangements, such as joint ventures and alliances.

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Our study offers and empirically explores a more nuanced understanding of Penrose (1959) and

[2] https://www.census.gov/eos/www/naics/reference_files_tools/NAICS_Update_Process_Fact_Sheet.pdf

the RBV (Wernerfelt, 1984). Market resources serve as an independent driver of product market entry for high-tech firms because they are difficult to both obtain and sell. On average, firms enter product markets to capture the value from their market resources, acquiring relevant technological resources through internal development as well as markets for technology (Arora et al., 2001). We expect the increasing sophistication of markets for technology to accelerate this trend by further shifting the bottleneck and the basis of a firm's competitive advantage toward downstream market resources. More broadly, this study emphasizes the importance of taking a more balanced perspective that incorporates consumers and product-market contexts into resource-based research that has singularly focused on technology and other supply-side considerations (Priem and Butler, 2001). The notion of bottleneck resources provides a theoretical foundation for the long-standing emphasis on customers as the basis of firm growth, the diversification and alliance patterns of technological firms, and the strategic importance of debates regarding the control over customer data with regulatory agencies.

2. Bottleneck Resources and the Direction of Product Market Entry

The RBV describes firm growth and expansion as a process of exploiting the firm's existing resources with imperfect factor markets (Penrose, 1959). The specialized nature of firm resources, while impeding competitive imitation and protecting their value in the existing market, increases the cost of adjusting them to fit the requirements of the new market (Miller and Shamsie, 1996). Such costs are substantial even across products with seemingly similar resource requirements, for example, reducing the potential profits of diversifying from the taxi to the limousine market by sixteen percent (Rawley, 2010). As a result, firms direct new product market entry to "adjacent" markets where extant resources can be redeployed with minimal modification, leading to theories of related diversification (Sakhartov and Folta, 2014).

We build upon the central tenet of the RBV that resources and their relatedness to the requirements of a new opportunity underpin entry but suggest that the relatedness (or redeployability) of the firm's resources will not all matter equally. In particular, our theory emphasizes the bundled nature of resources to identify which resources drive entry into a new product market. Introducing a new product requires assembling multiple extant resources that are scattered across multiple parts of a firm's value chain (Porter, 1985; Helfat and Raubitschek, 2000; Karim, 2012) as well as accessing new resources. Lacking even a single resource in the requisite bundle can thwart a firm's ability to enter a new product market, which suggests that the "acquirability" of resources may play a key role in understanding firm behavior. Varied streams of research document that the control over bottlenecks delivers a disproportionate share of overall value and becomes the focal point of competition and value capture in existing product markets (e.g., Von Hippel, 1994; Teece, 2006; Jacobides and Tae, 2015; Hannah and Eisenhardt, 2018; Aggarwal, 2020).[3] We borrow from this ecosystem and intra-organizational perspective on bottlenecks to characterize bottleneck resources in the context of new product market entry.

Consider a firm possessing two resources (*a*) and (*b*). Either resource provides a potential basis for creating a new product, but must be paired with another resource that the firm currently does not possess: (*a*) with (*A*) and (*b*) with (*B*). Determining whether the firm will create a product *P*(*a, A*) or *P*(*b, B*) depends on its ability to obtain (*A*) or (*B*). If resource (*B*) can be readily developed or obtained on the open market while (*A*) cannot, for example, due to market frictions or the tacit nature of the information, then the firm is constrained to creating *P*(*b, B*). This simple model suggests that resources that cannot be bought or sold determine the direction of a new product market entry (Dierickx and Cool, 1989), similar to Von Hippel's (1994) claim that innovation revolves around "sticky" information that is most difficult to move. As Penrose (1959) notes, diversification relies on resources that can be productively redeployed yet lack a well-functioning factor market. In contrast to the requirement for redeployability, the impact of well-functioning (or poorly functioning) factor markets on entry decisions remains scarcely considered. We define a bottleneck resource as a resource that is vital to the introduction of a new product, but that cannot be readily acquired or sold in the factor market. As noted earlier, this does not mean that the bottleneck resource is more valuable, or that the non-bottleneck resource can be acquired at little cost to

[3] Despite representing a minuscule requirement in terms of their quantity and nominal cost, much of US-China trade tension has revolved around rare earth minerals that constitute an essential and difficult-to-acquire input to manufacturing processes.

the acquiring firm. Instead, the term "bottleneck" builds directly on Penrose's (1959) second resource-based criteria for diversification – bottleneck resources do not have well-functioning factor markets.

The concept of a bottleneck resource raises several novel implications for the dynamics of resource development and market entry. First, the resources most valuable in existing markets and those that drive firm growth need not be the same. In the model above, even if resource (*a*) is more valuable in existing markets, the ready access to (*B*) makes resource (*b*) more relevant to new market entry. This holds true even if the market potential for *P*(*a*, *A*) is greater than *P*(*b*, *B*). Firms try to maximize the value of their overall resource bundle, not a single resource (Levinthal and Wu, 2010). Our hypothetical firm can capture the most value by licensing or selling (*a*) to a firm that already possesses (*A*) while focusing its own product market efforts on offering *P*(*b, B*).

Second, our discussion extends the RBV's focus on extant resources to include missing resources when discussing diversification. Because entry cannot happen without (A) or (B), the direction of product market entry depends jointly on extant resources *and* the firm's ability to access new resources. This creates the potential for substantial heterogeneity in the direction of growth even among firms that currently possess a similar set of resources based on their ability to acquire missing resources.

Third, our focus on bottleneck resources provides a more nuanced consideration of resource fungibility and its effects on market entry. On the surface, there is a conflict because much of the recent work on resource redeployment emphasizes the importance of flexibility, while we focus on stickiness (or the lack of flexibility) as driving entry. However, redeployment research focuses on the ability to transfer resources toward a new task *within* firm boundaries (e.g., Helfat and Lieberman, 2002; Sakhartov and Folta, 2014; Uzunka, 2018; Stagni, Santalo, and Giarranta, 2020). In contrast, we focus on the difficulties in transferring resources *across* firm boundaries, which captures the ability to both sell an extant resource externally and acquire a missing resource. This distinction becomes more salient as the discussion moves from the level of individual resources to the level of "product-as-resource-bundle," where the concept of the external factor market takes primacy in the discussion of entry dynamics.

Lastly, our focus on bottleneck resources qualifies the assertion that "resources and products are two sides of the same coin" (Wernerfelt, 1984:171), as firms can monetize resources both through product market entry and through factor markets. Firms face resource constraints that prevent them from introducing an unlimited number of new products, which provide an incentive to sell (license) some resources in factor markets. This provides a viable business model for so-called patent trolls, who collect and license patents. Firms also develop technologies for the purpose of coordinating and monitoring networks of specialized external suppliers and "know" more than they make (Brusoni et al., 2001; Kapoor and Adner, 2012). This further weakens the link between firm resources and product market entry and reinforces the idea that some types of resources can create value and be monetized without market entry.

The overall theory of bottleneck resources is summarized by the following two propositions on the positive and negative direction of firm growth:

> Proposition 1: *The bottleneck resource, which is the most difficult to obtain or sell externally, rather than the most valuable resource, anchors the direction of product market entry.*
>
> Proposition 2: *In the absence of a bottleneck resource, entry does not occur even when a firm possesses other relevant resources*.

Below, we apply these two propositions to the distinction between market and technological resources and examine the dynamics of firm growth.

2.1. Market Resources as Bottleneck Resources

As firms are bundles of resources, many of which could potentially be the basis for growth, an extensive body of research tries to identify key characteristics of individual resources that drive new product market entry. In particular, in line with Teece's (1988) definition of a firm's competence as a set of differentiated *technological* resources and complementary assets, prior RBV research has placed technological resources at the center of entry and firm growth. Technological relatedness – the ability to transfer and reuse existing technological resources – affects all facets of organizational growth, including the introduction of new products within existing markets (Katila and Ahuja, 2002), entry into new markets (Silverman, 1999), the mode of product market entry (Helfat and Lieberman, 2002), and post-entry firm performance (Nerkar and Roberts, 2004; Sosa, 2009). Breschi, Lissoni, and Malerba (2003) also show that firms typically move into technological spaces that are proximate to the technological spaces in which they are already active, creating path dependency in the evolution of technological resources.

We expand the analytical focus to market resources. To the extent that "benefits from economies of scope can also be formulated in terms of demand-side benefits related to outputs" (Helfat and Eisenhardt, 2004: 1219) as opposed to only costs and supply-side benefits, we expect diversification to be built around the reuse and fungibility of market resources, in particular existing customer relationships and the understanding of customer preferences (Helfat and Lieberman, 2002). Indeed, many of the foundational studies have theorized on market knowledge as an independent resource that increases product market entry (e.g., Teece et al., 1994; Helfat and Lieberman, 2002). However, most empirical research has focused on the complementary aspect of market-related resources that enables a firm to "derive maximum benefit from its technological achievements" (Nerkar and Roberts, 2004: 780) or sustains the incumbent's position despite disadvantages in technological resources (Klepper, 1996). We argue that market resources serve as a bottleneck based on the (relative) difficulty in trading and obtaining those resources.

In comparison with technological resources, market resources and knowledge about demand are typically tacit and difficult to codify (Fabrizio and Thomas, 2012) and suffer from imperfect factor markets. Studies in marketing (de Luca and Atuahene-Gima, 2007) and management (Lord and Ranft, 2000) argue that market-related knowledge is often the most difficult to transfer even within an organization. This is partly because market-related resources and knowledge are embedded across multiple functions, such as sales, marketing, and internal and external distribution (Day, 1994), and more systemic in nature compared to technological resources that are often contained more narrowly within specific functions, such as R&D. Some market resources are also embedded externally in relationships between the firm and its customers. In particular, customer relationships and brand value are built on "a complex collection of multi-point and multi-level contacts" (Zander and Zander, 2005: 1527). Their complex and distributed nature makes market resources much more challenging to disembody and monetize in the external market through alliances, joint ventures, licensing, and other collaborative arrangements (Ranft and Lord, 2002). In particular, the licensing of a valuable brand across organizational boundaries is often fraught with the risk of negative spillovers to the rest of the brand and product portfolio, especially compared to technological resources.[4] As a result, while brand licensing was once prevalent, the risks to brands and the difficulty in contracting for the protection of the brand name have sharply curtailed the practice over time (Laforet and Saunders, 2005; Colucci et al., 2008). Given the challenges to their external transfer and acquisition, firms in possession of valuable market resources may be forced to enter new product markets directly to capture their value. Conversely, the challenges in acquiring market resources discourage entry into product markets where the firm lacks market resources despite advantages in other (e.g., technological) resources.

In contrast, while earlier research emphasizes the inseparability of R&D and technological resources from the broader value chain (Teece, 1988), a burgeoning body of research documents the importance of markets for technology, ranging from patent transactions, R&D joint ventures, alliances, and licensing to contract R&D (Arora, Fosfuri, and Gambardella, 2001). In particular, Serrano (2010) finds that a significant portion of firm patents is traded during their lifetime, especially those that belong to failed startups (Serrano and Ziedonis, 2018). Few studies directly compare the strength of factor markets for technological and market resources, but Uzunka (2018) finds in the semiconductor industry that market-related resources are slower to converge relative to technological resources, consistent with our contention that market-related resources are stickier. Moreover, convergence in market resources has a much larger effect on increasing the risk of incumbent exit and decreasing a new entrant's exit, suggesting that market resources play a more critical role in entry dynamics. Similarly, Gambardella and Torrisi (1998) find that technological entry did not lead to business diversification among the thirty-two

[4] For example, Sony's OLED TVs and Apple's iPhones use display panels from affiliates of their key competitors, namely LG Display and Samsung Display, with limited customer awareness. In contrast, the sharing of customer data by Facebook to its developers has provoked severe reactions.

largest American and European electronics firms, noting the lack of product-specific downstream assets as the cause. Our propositions above theorize that firm growth centers on difficult-to-trade or -obtain bottleneck resources. Here, we argue that market resources are more likely to be the bottleneck resource than technological resources. We therefore predict that – on average – firms are more likely to develop new products around market-based resources than technological resources.

Hypothesis 1 (H1)*: Market relatedness has a larger positive effect on product market entry than technological relatedness.*

While the initial discussions by Penrose (1959) and Wernerfelt (1984) focused on the role of extant resources, a growing stream of research emphasizes firms' capability to acquire new resources that may diverge from their current resource portfolio (Helfat and Raubitschek, 2000; Karim and Mitchell, 2000; Moeen, 2017). This dynamic view is critical to examining firm growth and to our prediction that bottleneck resources that are difficult to acquire or sell determine the direction of product market entry. Returning to our model of product expansion, the predictive power of the bottleneck resource (*b*) for product market entry hinges on the relative accessibility of resource (*B*). In cases where obtaining or developing resource (*B*) is exceptionally easy, (*b*) becomes more central to firm expansion. Alternatively, when the firm's access to (*B*) in the open market is limited, we expect the relative dominance of (*b*) over (*a*) to decline. This suggests that the ability to assemble the rest of the bundle, in particular by accessing new technological resources that are competitive or at least on par with competitors, serves as an important contingency to the applicability of H1. As accessing technological resources externally becomes easier, this should increase the salience of market resources in driving product market entry. We explore four contingencies that are expected to affect a firm's ability to access and integrate new technological resources, and in turn, the relative severity of market resources as the bottleneck: firm size, public and private status, technological competence, and density of the product market.

Firm Size Pavitt (1998) posits that large firms will have little difficulty in mastering new technology, suggesting firm size as an important proxy that reduces the challenges to market entry based on technological barriers. This is consistent with the survey results from Arora, Cohen, and Walsh (2016) that with an increase in size, firms more actively acquire new technological resources in markets for technology. Moreover, organizational inertia and coordination costs tend to increase with firm size (Cohen and Klepper, 1996), further increasing the dominance of sticky market resources.

Public versus Private Firms Bernstein (2015) suggests that going public increases the external orientation of a firm's R&D activities by stimulating M&A and the hiring of external inventors. Public firms are also subject to scrutiny by various external stakeholders, including customers demanding that firms create new products that serve their needs as well as analysts and capital providers (Benner, 2010) that increase the salience of market-based resources.

Technological Competence Somewhat paradoxically, we expect market-relatedness to take on increased importance for technologically competent firms with a larger and more general stock of technological resources. Their ability to acquire new technological resources helps to lower the technological barriers to entry, increasing the relative severity of market resources as a bottleneck. In particular, some technological resources take on the form of general-purpose technology that can be applied to a wide range of product markets (Bresnahan and Trajtenberg, 1995). High technological competence also supports a model of relatively crude initial market-based entry followed by rapid technological refinement through subsequent investments.

Density of the Product Market Product markets with more firms will typically have fewer unmet consumer needs than those with fewer firms (Carroll, 1985). In this case, an industry or market segment with more firms will present fewer opportunities for firms to discover and exploit novel market-based niches in which to be competitive, thus devaluing the market-related resources that potential entrants may possess. This suggests that market relatedness is a weaker predictor of entry into crowded market segments as opposed to sparsely populated segments.

Hypothesis 2 (H2): *The positive effect of market relatedness on product market entry increases as access to external technological resources increases.*

2.2. Temporal Dynamics of Resource Assembly and New Market Entry

Finally, by distinguishing product market entry from technological diversification, our theory suggests temporal dynamics that relate the two perspectives; market relatedness provides the foundation for the strategic decision to enter new product markets, and this entry decision necessitates that the firm fills technological gaps in their resource portfolio to facilitate entry.

We expect that new technological resources may be gained through external sources, consistent with our argument about the importance of markets for technology. Incumbents often use various collaborative arrangements to access new technologies, spanning acquisitions, alliances, licensing, and contract R&D (Arora et al., 2001; Serrano, 2010; Bernstein, 2015; Keum, 2020). In particular, comparisons across entry modes suggest that alliances are typically the fastest way to gain access to new resources (Capron and Mitchell, 2012), and Rothaermel (2001) discusses how incumbents facing radical technological change leverage their complementary assets to negotiate alliance deals with new, technologically sophisticated entrants. We also observe increasing occurrences of external acquisitions aimed at obtaining technological resources to support an initial entry based on proximity to existing customers: Walmart's partnership with Accel Partners and the acquisition of Jet.com, Amazon's acquisition of Whole Foods, Google's acquisition of YouTube, Microsoft's purchase of Nokia, and the series of acquisitions by Facebook. We expect the increasing sophistication and maturity of markets for technology to further accelerate this trend.

Hypothesis 3a (H3a): *Market-driven entry will result in a significant increase in accessing technological resources through the external market.*

Firms will also engage in learning-by-doing (Brown and Eisenhardt, 1995) and build up relevant technological resources internally over time. For example, Moeen (2016) documents that firms actively develop related biotechnology prior to entering the transgenic crop market. In their case study, Adner and Levinthal (2001: 617) observe, "finding consumers who are willing to pay a high price for a relatively crude product may be critical to firms' ability to engage in the development effort," and it was "only after extensive further development that Xerox machines were able to satisfy the much higher functionality demands of the mainstream office market."

Hypothesis 3b (H3b): *Market-driven entry will result in a significant increase in internal R&D*

activities relevant to the entering market.

Firms likely differ systematically in their preferred mode of strengthening relevant technological resources (Speckbacher et al., 2015) based on contingencies discussed in H2. Large and public firms make more active use of external collaborative arrangements because they can better manage litigation costs and other hazards of accessing external markets for technology (Arora, Cohen, and Walsh, 2016). We also expect a firm's general technological competence to increase the reliance on external modes of sourcing over internal R&D. Technological competency allows firms to better manage external partners, absorb their knowledge, and integrate outside knowledge in an accelerated timeline (Cohen and Levinthal, 1990; Brusoni et al., 2003).

Taken together, H3 establishes a convergence between market resources and technological resources over time and accounts for why studies based on less granular measures of product market entry and its timing may find that organizational expansions are centered on technological resources; there is an active build-up of a firm's technological resources around the timing of entry. It is important to note that we are agnostic to whether firms develop relevant technological resources prior, during, or after a product market entry as long as the strategic decision to enter, anchored around market relatedness, motivates their development.

3. Data and Empirical Approach

To evaluate our theory on the importance of market relatedness in driving product market entry, we link two data sources – CorpTech and NBER's patent database. The CorpTech Directory of Technology Companies provides a listing of products for 77,100 high-tech firms in the United States across a wide variety of industries between 1997 and 2005.[5] The first three years are used to construct lagged measures used in the analysis (as described below). Additional information in CorpTech includes geographical location, sales, founding year, ownership structure, and the names of key executives, as well as the

[5] Unless otherwise noted, we exclude subsidiaries of non-US firms that constitute around 10% of the CorpTech data from our sample. These firms often do not file for patents in the US which can create downward bias in our measure of technological relatedness (described in detail below). Their inclusion has a negligible effect on all of the findings.

primary SIC code associated with the company and specific CorpTech product categories for each product. More than half the companies covered are not publicly traded. Due to the availability of detailed data and the coverage of small, private firms, CorpTech has been used in several previous studies related to new product introduction, such as R&D investment in complex new products (Ethiraj, 2007), entrepreneur boundary crossing (Wu and Dokko, 2007), external markets for technology (Arora and Nandkumar, 2012), optimal timing of organizational consolidation (Puranam et al., 2006), and IPOs (Stuart et al., 1999).

We organize our data in a firm-category-year panel, with one observation for each firm-year in product categories in which they had not previously been active. Thus, the empirical structure considers all possible new product markets the firm could enter into in any given year, and assesses which market(s) the firm chooses to enter. The two most significant empirical challenges are (1) identifying the resource requirements of a given product market and (2) assessing its relatedness to a firm's existing portfolio of resources. We first discuss our main construct of *market relatedness* in Section 3.1, and the corresponding measure of *technological relatedness* in Section 3.2. The broad, cross-industry coverage, while lacking in some fine-grained controls that can be found in detailed within-industry studies (e.g., Nerkar and Roberts, 2004; Sosa, 2009), allow us to look for patterns in firm entry behavior across a wider and more complete range of market relatedness.[6]

3.1. Market Relatedness

Analogous to previous research using the SIC system, we use proximity within the CorpTech product classification as a proxy for market relatedness. This measure of relatedness is uniquely applicable to market resources for two reasons. First, the CorpTech data was designed to be used in sales and marketing efforts. The goal was to facilitate the sales to customers by the sellers as well as the purchasing of a product by customers, and its classification reflects output characteristics rather than input characteristics. Products grouped in the same industry are often sold to the same customers or consumers,

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[6] For example, King and Tucci (2002) and Sosa (2009) look within a single industry and at generational shifts within an existing product market.

even if the inputs or underlying technologies are different. This focus on sales and marketing makes CorpTech uniquely suited for measuring market relatedness, particularly in terms of commonalities in consumers. Second, by directly controlling for technological relatedness, we eliminate the technological component that may be present in our measure of market relatedness.

CorpTech classifies products into three levels of hierarchy – 18 sectors, 256 industries, and 2,681 product segments. Sectors include software, medical devices, manufacturing equipment, and computer products. As an example of the most granular level, the product segments in the marketing software industry include different codes for sales reporting software, direct marketing software, sales force automation software, and market planning software among others. The product segments are much more fine-grained than "industries" based on SIC classifications and provide a valuable opportunity to observe the role of market relatedness in entry decisions.

We construct our specific measures of market relatedness in two different ways. First, corresponding to the three-level hierarchy that consists of sector, industry, and product, *market relatedness* is set to 1 for potential product market entries where the firm has experience (i.e., already offers at least one product) within the same industry (though not within the product category); to 0.5 if the firm has experience within the sector (though not within the same industry); and to zero if the firm has no experience within the sector at all. Second and as a robustness check, we use dummy variables capturing each level of market relatedness separately, which is insensitive to specific functional forms of how market relatedness affects entry.

3.2. Technological Relatedness

In order to demonstrate the importance of market resources as the independent and significant driver of product market entry (H1) and the development of relevant technological resources (H3), it is critical to accurately control for the relatedness between a firm's existing technological resources and those required for a given product category. We construct a firm's technological relatedness to a given product market in a two-step process. We first (i) identify the technological resources relevant for a given product category (i.e., “technological profile” of a product market), and (ii) assess the relatedness between the firm’s stock of technological resources and the profile before and after the entry. To address the first step, we start with all firms active in each product category and their patent portfolio based on the 421 USPTO patent classes (Hall et al., 2001). We consider a patent in a USPTO’s patent class *i* as providing a technological advantage for product *j* if two or more firms offer product *j* and have patented in class *i* in the previous three years. In identifying the technological profile of a product, we rely on “small, focused” firms – those active in 3 or fewer product categories – to eliminate noise from diversified firms such as Intel and Microsoft (Berger and Ofek, 1995; Chang, Kogut, Yang, 2016). There are important tradeoffs to imposing more or less stringent criteria for qualifying as a relevant patent class. Overly lenient criteria risk admitting too much noise and bias upwards (downwards) the support for H3 (H1). Overly stringent criteria risk overestimating the relevance of technological resources and bias upwards (downwards) the support for H1 (H3). We verify that our results are robust to varying the number of firms with a common patent class (e.g., shared by 1, 3, or 5 firms) and the definition of focused firms (e.g., having 1, 2, or 5 products). Our approach permits more than one patent class to be relevant, and indeed we find an average of 3.77 relevant patent classes per product category across a total of 2,681 product categories. Random spot-checking of relevant patent classes by product category shows strong face validity. For example, those relevant for immune system R&D include bio-affecting compounds (424), molecular biology (435), and synthetic materials (525).

We next measure the relatedness between the firm’s patent portfolio and the technological profile of a product. Specifically, we assume that patent classes A and B are more closely related if classes A and B cite each other more frequently (Jaffe, 1986; Breschi et al., 2003). Finally, we calculate the technological relatedness (TR_{ij}) between firm *i* and product category *j*. If firm *i* has a patent in any of the relevant patent classes of product *j*, TR_{ij} is set to 1 (maximal relatedness between the firm’s technological resources and those required in the product category). In case TR_{ij} is not 1, we find the best alternative technology class of firm *i* with the highest relatedness (S_{ij}) among the possible pairs of the patent portfolio of firm i (P_i) and technology profile of product category j (R_j).[7] While somewhat complex, our measurement approach closely follows Silverman (1999) and Breschi et al. (2003).

We find our measure to be well-behaved (discussed further in Table 2). Figure 2 shows the distribution of technological relatedness between a firm and product category (TR_{ij}). TR_{ij} is equal to 1 when a firm owns a patent in one or more technology classes relevant for the product category, and declines as the firm's most proximate technological resource becomes more distant. A TR_{ij} value of 1 shows a higher frequency than any other TR_{ij} values, indicating that there are quite a few firms with the potential to enter into product segments based on the proximity of technological relatedness. Except for when TR_{ij} equals one, the frequency of TR_{ij} decreases as TR_{ij} increases. To mitigate the concern that our findings may be driven by idiosyncratic measurement choices, we explore a series of alternative operationalization of technological relatedness. In particular, we find that our findings are robust to the alternative measure of technological relatedness proposed by Bryce and Winter (2009). Appendix A provides a more detailed description of the construction and the battery of robustness checks to potential pitfalls for this measure of technological relatedness.

-- Insert Figure 2 about here --

3.3. Control Variables

As proxies for available resources that may affect the likelihood of new market entry and the adoption of new technology, we include the logged value of sales (Agarwal and Audretsch, 2001) and the lagged number of product categories in which the firm was active in the previous year, both from CorpTech. We also control for the generality of a firm's technological resources (Hall et al., 2001), measured as the average generality of patents applied in the past three years, in order to address the concern that some patents contain general-purpose technologies and may facilitate entry into product markets with limited

[7] We focus on the maximum level of relatedness, as opposed to the mean or the median, to avoid penalizing diversified firms that are active in many patent classes. If, for example, Intel wanted to enter a new product category, it would not draw on its entire technological resources to enter, but would presumably focus on the most relevant technological knowledge that it had to facilitate entry.

direct technological relatedness.[8] In addition, we include a control for the competitive intensity of the market by including the number of firms in the product category and its square term. All specifications include firm fixed effects to address time-invariant characteristics, year fixed effects to control for the overall rate of entry based on macroeconomic conditions, and dummies at the level of the 18 sectors in the CorpTech data.

3.4. Dependent Variable and Empirical Methodology

Our dataset is structured at the firm-category-year level. We measure a new product entry based on the finest degree of characterization in the CorpTech data – 2,681 product categories – which is set to 1 if there is a listing in a new product category for the firm in a given year, and 0 otherwise. Thus, we have multiple observations per firm-year across 2,681 product categories. Since product entry is a binary outcome, we employ a logistic regression model. All standard errors are clustered at the firm level and adjusted for heteroskedasticity. We discuss the empirical approach for H3 in further detail below.

3.5. Overall Sample and Descriptive Statistics

CorpTech and the NBER patent database cover many more firms than we use in our sample, and our exclusion process is based solely on measurement. On the firm side, we exclude any firms that have not filed for any patents in the previous three years, as we cannot ascertain their technological resources, leaving us with 5,755 unique firms.[9] On the product side, we exclude any product categories with no entry during our sample period of 1997-2005. We also exclude product categories for which we are unable to identify any relevant patent classes. This arises when firms in the product category do not file any patents or when there are no focused firms active in the product category. We identify 341 unique categories for which we can measure technological profiles. The firm fixed effects also drop all firms that do not make any entries across the sample period, and our final sample consists of 1,851 entries across

[8] We add a missing dummy in cases where patents do not receive any citations and generality cannot be computed.
[9] We verify that in-sample firms do not systemically differ from out-of-sample firms in terms of observable characteristics, such as the number of products offered by the firm, the size of the firm based on the number of employees and sales, firm age, and the number of executives.

558,692 firm-category-year observations.[10]

Descriptive statistics are summarized in Table 1. While the overall entry rate is low due to a large number of potential product markets, there is a sufficient number of entries to test our hypotheses.[11] In Table 1, we find that the correlation between technological relatedness and market relatedness is only 0.002, suggesting that the two measures are capturing different aspects of relatedness in firm resources. The median firm is active in 12 product markets with approximately $250 million in annual sales, and the median product market has 10 active firms.

--- Insert Table 1 here ---

Figure 1, introduced earlier, visualizes the probability of product market entry across market and technological relatedness in a 3-by-3 heat map. The three levels of the *y*-axis capture each level of product relatedness (sectors, industries, and product segment), and the three levels of the *x*-axis capture each tercile of technological relatedness. A darker blue indicates a higher probability of entry. Three notable patterns emerge from the heat map. First, product market entry is a rare event across all cells. Second, there is a six to thirteen-fold increase in entry probability when moving from low to high market relatedness across the *y*-axis. Third, when moving from low to high technological relatedness across the *x*-axis, there is no increase in the high market relatedness row and only a twofold increase in entry probability in low and medium market relatedness rows. Possessing technological resources has little to no effect in the absence of market resources, providing preliminary support that market resources serve as the bottleneck to the entry process. We next use panel regression analysis to test our hypotheses.

4. RESULTS

4.1. Results of the Primary Models Testing (H1)

Table 2 reports the results of panel logit models with firm, year, and sector fixed effects. In Model 1, we

[10] Refer to Appendix B for the year-by-year and aggregated sample statistics.

[11] The maximum likelihood estimation suffers from a well-known small sample bias. However, the bias is dependent on the smaller of the numerator or the denominator, and the entry count of 1,851 provides sufficient variations. Our results are also robust to rare events logistics regressions (King and Zeng, 2001).

first start by replicating prior research showing that technological relatedness indeed leads to *technological* entry (Breschi et al., 2001). This model includes 421 technology-class fixed effects (Hall et al., 2001) as well as other control variables used in Breschi et al. (2001), including the patent share concentration index, the US specialization index, the number of firms in each technological class, and the number of patents and patent applications in each technological class *i*. The results confirm that technological relatedness increases the probability of technological entry; an increase in technological relatedness from the mean (0.004) to one standard deviation above the mean (0.024) increases the probability of technological entry by 1.77 times. The successful replication of Breschi et al. (2001) increases confidence in our measure of technological relatedness.

-- Insert Table 2 here --

Models 2 to 5 test H1 with product-market entry as the dependent variable. In Model 2 which only includes control variables, technological relatedness is negatively related to entry but statistically insignificant ($p = 0.570$).[12] In Model 3, market relatedness is positively related to product-market entry. This also holds true in Model 4 where we use indicator variables to split market relatedness into three categories. Entry is 7.3 times more likely when market relatedness is 1 (i.e., same industry), and 3.1 times more likely when market relatedness is 0.5 (i.e., same sector). The inclusion of market relatedness also improves McFadden's (or pseudo) R^2 value by 2.7 percentage points. In Model 5, we add an interaction term between technological and market relatedness and find the coefficient to be negative in both nominal and marginal effects and lack statistical significance.[13] The null interaction was unexpected but consistent with our theory. Entering a new product market is a rare event, so when a firm discovers a productive market opportunity, it is willing to enter with or without pre-possessing technological resources (Danneels, 2011).

[12] Some studies document a significant negative effect of technological relatedness on entry due to the risk of cannibalization (de Figueiredo and Silverman, 2007) and disruptions to existing organizational routines (Henderson, 1993; Eggers, 2012). Sakhartov (2017) uses a computational model to show that inter-temporal economies of scope can generate a curvilinear relationship where firms maintain a portfolio of moderately related products rather than most closely related products.

[13] Interpreting the interaction term in a non-linear model requires much caution as the coefficient does not represent the marginal effect (Ai and Norton, 2003). We obtain a consistent null result in a linear probability model.

These results provide uniform support that market resources act as a bottleneck and in turn, constrain entry decisions to center on market relatedness (H1). Contrary to prior characterizations of market resources as playing a secondary role to technological resources, the importance of market relatedness is independent of technological relatedness. While we hypothesize on the greater importance of market relatedness, the finding of a null effect on technological relatedness is unexpected. We explore this "non-effect" more carefully in Section 4.3.

4.2. Contingencies around the Significance of Market Relatedness (H2)

Next, we conduct a series of cross-sectional analyses and explore potential contingencies that affect the relative severity of market resources as the bottleneck to the entry process. The statistical differences in the coefficients for market relatedness are based on *z*-statistics and noted in parentheses. In Table 3, Models 1 and 2 divide the sample into the top and bottom half by firm sales and confirm that the relevance of market relatedness increases for larger firms (2.163 vs. 1.836; $p<0.10$). Models 3 and 4 examine whether a firm's public or private status influences the importance of market relatedness. Market relatedness is indeed more important for public firms than for private firms (2.359 vs. 1.532, $p<0.01$). As public firms tend to be larger, we verify that the results are robust when we restrict the sample to firms with sales above the sample median. We next examine a firm's technological competency. We divide the sample into high and low competency firms based on the total number of patents in Models 5 and 6 and the maximum value of a firm's patent generality in Models 7 and 8. We expect high generality firms to possess a higher capacity to learn and absorb new technological resources, increasing the relative severity of market resources as the bottleneck.[14] We find that market relatedness is more important for firms with a large number of patents (2.431 vs. 1.750; $p<0.01$) and more general patents (2.252 vs. 1.841; $p<0.10$). As a notable exception to the general null effect of technological relatedness, we find that it has a positive and significant effect on low generality firms and a negative and significant effect on high generality firms. While we did not expect the negative effect for high generality firms, the contrast provides nuanced

[14] Using the maximum value helps to reduce potential biases arising from large differences in the number of patents. We obtain similar but slightly less sharp results using the mean value.

support for the role of bottleneck resources; firms with a narrow technological focus are constrained in their ability to access missing technological resources and experience technological resources to be another bottleneck, leading to the positive and significant effect on entry.

--- Insert Table 3 here --

Looking at the industry-level characteristics, Models 9 and 10 split the sample by the median number of active firms and find the importance of market relatedness to decrease in magnitude by 22 percent in crowded markets (2.408 vs. 1.870; $p<0.01$). This is consistent with the argument that a larger number of active firms in a given market segment decrease the potential to create a competitive advantage based solely on market-based resources (Carroll, 1985). To further explore the industry-level dynamic, Table 4 repeats our main analysis for each sector.[15] We would expect the effect of market resources on product market entry to be greater in sectors with more developed markets for technology. We only report the technological and market relatedness coefficients, but all controls are included in the models.

While lacking strong priors, the ranking is largely consistent with the commonly perceived strength of the external markets for technology and the Carnegie Mellon Survey (Cohen, Nelson and Walsh, 2000). The survey distinguishes between discrete and complex sectors based on the intuition that accessing and integrating external technological resources are easier in discrete categories (e.g., drugs, chemicals, and metals) relative to complex categories (machinery, computers, electrical equipment, instruments, and transportation equipment). While we do not have concordance between CorpTech categorization system and SIC codes used in Cohen et al. (2000), there is a notable overlap – with the single exception of *Transportation*. The high coefficient for market relatedness for pharmaceutical, chemical, and medical sectors is consistent with the outsourcing of R&D to small, specialized firms documented in these sectors as well as active markets for licensing and patent transfers (Higgins and Rodriguez, 2006; Serrano, 2008). Meanwhile, industries where technological know-how may be exceptionally difficult to transfer – including computer software, the Internet, and manufacturing – show

[15] We use random-effects specification instead of fixed-effects because the industry subsampling substantially reduces variation in market-relatedness and makes fixed effects specifications problematic (Greene, 2003).

the lowest coefficients. It is also assuring to see that the coefficient for market relatedness is the highest in the pharmaceutical sector where we know with strong confidence that there are well-functioning markets for technology.

-- Insert Table 4 here --

In addition to providing more nuanced support for our theory of bottleneck resources centered on access to factor markets, these inter-firm and inter-industry differences address the concern that market resources may drive entry not because they act as a bottleneck but because they are simply more valuable. Even *within* a given industry where technological resources should carry similar value, the relative importance of market relatedness varies based on a firm's ability to access markets for technology. In addition, our sample consists of high-tech firms from the directory of technology firms, of which a significant share operates in pharmaceutical, biotechnology, and chemical industries. There is robust empirical evidence that technological resources are highly valuable in these settings, especially patents (Cohen, Nelson, and Walsh, 2000).

4.3. The Temporal Dynamics of Resource Development (H3)

Finally, we test H3 that proposes temporal dynamics in resource development. We first examine whether the strategic decision to enter a new product market indeed triggers firms to access external technological resources (H3a). In Table 5, we match CorpTech to the SDC platinum database and examine the number of alliances and JV formed around the new product market entry in a linear probability model. We restrict the sample to firms that make at least one entry but find consistent results based on the full sample. Firms on average form 0.12 additional joint ventures and alliances at the year of new market entry (t+0). We do not detect any significant increase prior to the entry. Table 6 examines whether the increase differs by the conditions examined in H2. The increase is significant only for large, public, and technologically competent firms at year t and t+1, consistent with their ability to better manage the hazards of accessing intangible, technological resources in the open market. While providing support for our theory, the analysis is at the firm-year level (*versus* firm-category-year), and there is some risk that the increase relates to firm activities unrelated to product market entry. However, the temporal pattern whereby the increase peaks at the year *t* and *t*+1 is unlikely to be driven by random noise.

-- Insert Table 5 & 6 here --

In Table 7, we next look at a firm's internal R&D activities (H3b) and compare changes in technological relatedness to the entering product category with changes to non-entering product categories within a firm. Unlike the previous analyses on joint ventures and alliances at the firm-year level, we can link patents to the technological requirements for each product market and conduct a much more granular analysis at the firm-category-year level. The increasingly positive and significant coefficients of entry at *t*+1 and *t*+2 and insignificant coefficients for preceding years indicate that the decision to enter drives firms to build technological resources associated with the product category and do so in a relatively short time frame. In Appendix C, we repeat the analysis in a logit specification with technological relatedness of 1 as the binary dependent variable. The results show that the post-entry increase in technological relatedness is driven by firms directly filing for patents in the relevant technology classes following an entry.

In Table 8, we again explore whether the intensity and pace of the internal development of technological resources differ by the conditions examined in H2. The magnitude of response is in fact four times larger for small firms compared to large firms and two times larger for private firms than public firms. The increase in internal patenting is also larger for firms with a low and less general stock of technological resources, consistent with the earlier discussion that they are more limited in their ability to access and utilize markets for technology and hence constrained to internal development. We also find the increase is larger for sparsely populated markets. We suspect this is because product markets with few firms do not have active markets for technology. The overall pattern of building technological resources through internal R&D activities around entry provides a clear mirror image to that observed for external acquisitions of technological resources in Table 6 and supports the idea that firms systematically differ in their preference for internal or external development of technological resources. The significant increase in technological relatedness also helps to validate our measure and addresses the concern that the null result on technological relatedness arises from measurement issues, especially as the noise around technological relatedness is likely to be greater for testing H3b than H1.

--- Insert Tables 7 & 8 here ---

Taken together, the results in Table 5 through 8 provide robust and nuanced support for the hypothesized temporal dynamics that link market resources, product market entry, and the acquisition of relevant technological resources.[16] The post-entry buildup of relevant technological resources also reinforces the proposed distinction between the most valuable resource and the bottleneck resource and their effects on entry: while technological resources do not drive entry, they are still valuable and critical to post-entry performance, requiring firms to actively acquire them through multiple channels.

5. Discussion and Conclusion

In this study, we argue that bottleneck resources determine the direction of new product market entry. We develop our theory based on a core tenet of the RBV; firms and products are a bundle of resources and activities (Teece, 1986; Henderson and Clark, 1990; Helfat and Raubitschek, 2000; Keum, 2020; Chang 2020). Because missing a single resource can foil the entire entry effort, the process of assembling the resource bundle necessary to enter a new product market centers on bottleneck market resources that are difficult to obtain and sell, as opposed to technological resources which may be easier to obtain through markets for technology.

Our theory and findings have important implications across four research streams. First, this study contributes to the strategy literature on the nature of "corporate coherence" in multiproduct firms (Teece et al., 1994). Firms organize new product entries around market resources. While consistent with the theoretical idea of coherence, our findings represent a significant departure from the typical view that

[16] The results are also consistent with the qualitative analysis discussed in Appendix D, noting that firms pursuing market-driven entry employ both internal and external development opportunities to facilitate entry. While we find the buildup of technological resources to occur during or after product market entry, we do not claim the dynamics to be sequential, as this would require data on all possible ways to leverage the markets for technology, including licensing, hiring, and patent-level transactions, in addition to establishing precise timelines of when firms make use of them.

coherence emerges around the reuse of proprietary technological resources. This provides a theoretical foundation for technological convergence among firms that share important market assets and the blurring of traditional industry boundaries. The convergence of online and off-line channels provides a case in point, where, in efforts to capture a larger share of customers' wallets, traditional retailers are going online (e.g., Walmart) while online retailers are acquiring physical stores (e.g., Amazon) even though such expansion requires building a vastly different set of technological capabilities.

Second, Arora et al. (2001) discuss the organizational and strategic implications of burgeoning markets for technology, such as the increased viability of a focused business model. Our theory and findings suggest that markets for technology also shift the direction of firm growth by increasing the "acquirability" of technological resources and, in turn, increasing the relative importance of bottleneck market resources. Our results do not reject the significance of technological resources in enhancing post-entry performance. The post-entry buildup of relevant technological resources in fact indicates the opposite. Our findings, however, point to more nuanced resource dynamics that differentiate technological entry from product entry, and product entry from the post-entry performance. Given the increasing sophistication of markets for technology where firms can both buy and sell (or license) technological resources, it is unclear whether technological resources always pass Barney's (1991) criteria for strategic resources to be rare. Our discussions of resource fungibility (the flexibility of moving resources *within* firm boundaries) and resource bottlenecks (the flexibility of moving resources *across* firm boundaries) join existing conversations around resource value (Barney, 1991) and the existence of excess capacity (Penrose, 1959) to further explicate the nuanced relationship between resources and organizational evolution. Given the centrality of resources to discussions of organizational scope and diversification, our articulation of the importance of bottleneck resources provides novel insights into the complex way in which resources affect firm growth and entry dynamics.

Third, our perspective that firms acquire and strengthen relevant technological resources to support entry through markets for technology highlights temporal dynamics in firm resource development that have received little attention (Helfat and Raubitschek, 2000). Notably, we expect a decoupling between a firm's technological and product portfolio at the timing of the entry but also their convergence within a relatively short amount of time. This raises an important methodological caution. Without careful attention to the precise timing of product market entry and development of technological resources, it becomes unclear whether (technological) relatedness causes entry or entry causes relatedness. The possibility of market resources serving as a locus of this process and an antecedent of technological resources represents an important area for future research (Wu et al., 2014).

Lastly, the null effect of technological relatedness on product market entry emphasizes the importance of taking a more balanced approach that incorporates both consumers and product-market contexts into resource-based research (Adner and Levinthal, 2001; Ethiraj et al., 2005; Priem, 2007). Product market entry is "often initiated by signals received in the course of production or from customers and markets, and are based on fairly tedious and (from a scientific viewpoint) mundane activities" (Arora and Gambardella, 1994: 524).[17] The role of customers in the discovery of market opportunities relates to a growing body of research that emphasizes the role of demand factors in shaping the direction of firm growth (Priem and Butler, 2001; Manral and Harrigan, 2017) and likely further reinforces the proposed importance of market resources.

While we find our results to be robust to a battery of robustness tests (discussed more in detail in Appendix A), there are fundamental limitations to measuring the presence and depth of a firm's technological resources based on patents. Patents contain the most codifiable and transferrable component of firms' technological resources, and a clear separation from the broader organizational know-how may not be possible. An ideal dataset would also include a full range of access to external resources, including patent transactions, licensing, contract R&D, and the hiring of inventors. There are also important boundary conditions to the null finding on technological relatedness, including limitations to high tech sectors with relatively well-developed markets for technology as well as the inability to capture "new-to-

[17] In their survey of American manufacturing firms, Arora, Cohen, and Walsh (2016) report that 49% of the most important product innovations originated externally with customers as the most frequent source, followed by suppliers.

the-world" product categories. It is entirely possible that truly radical entries or entries into more nascent industries are determined more by technological resources than market resources.

We conclude with the flipside of the research question at hand, namely why firms fail to enter certain markets (Christensen, 1997; Tripsas, 2009). Previous research on why incumbent firms have difficulty adapting to disruptive change has focused primarily on technological aspects, such as the architectural nature of the change or managerial and organizational rigidity with regards to the adoption of radical technology. Our findings suggest that the market-based component of the disruption may be an even more important consideration than its technological component in understanding firm response or the lack thereof.

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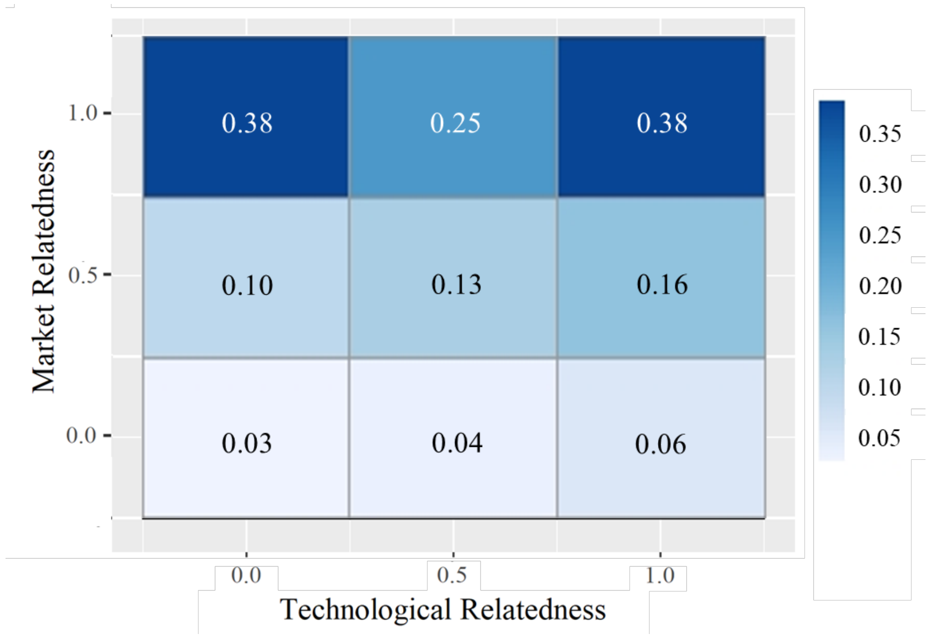
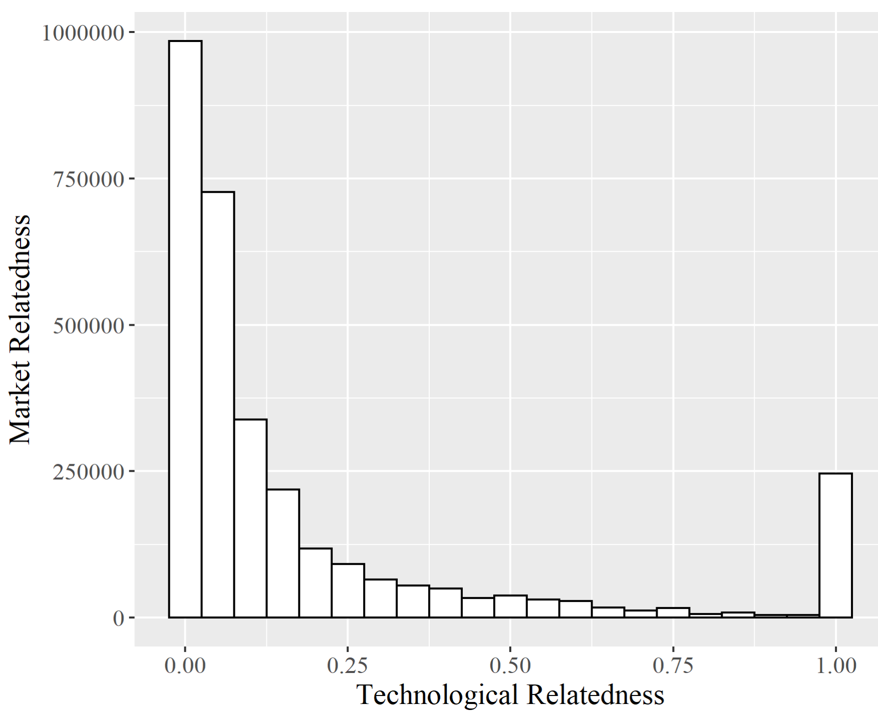
Figure 1. Entry Probability Across Market and Technological Relatedness



Note. The number in each cell indicates the percentage likelihood of entry, calculated as the number of realized entries divided by the total number of product segments.

Figure 2. Histogram of Technological Relatedness between Firms and Product Categories



Note. A bin size is 0.05. There are 2,084 observations which have 0 technological relatedness.

Table 1. Correlations and Summary Statistics

	1	2	3	4	5	6	7
1. (DV) Product Entry	-						
2. Technology Relatedness	0.004	-					
3. Market Relatedness	0.019	0.002	-				
4. (Firm) *log* (Sales)	-0.003	0.022	0.017	-			
5. Technology Generality	0.002	0.003	0.009	-0.039	-		
5. (Firm) No. of Products	0.019	0.003	0.094	0.113	0.008	-	
6. (Product) No. of Firms in Category	0.022	0.333	0.010	-0.002	0.0003	0.024	-
Average	0.001	0.187	0.072	17.505	0.587	14.612	13.414
SD	0.024	0.286	0.203	5.977	0.208	16.757	11.946
Min	0	0	0	0	0	1	2
Max	1.0	1.0	1.0	28.6	1.0	288.0	121.0

Note. The correlation between technology relatedness and product relatedness is only 0.002, suggesting that the two measures are clearly capturing different aspects of relatedness.

Table 2. Market Relatedness and Product Market Entry

	Tech. Entry	Product Market Entry			
	(1)	(2)	(3)	(4)	(5)
Market relatedness			2.017***		2.107***
			(0.109)		(0.120)
Market relatedness = 0.5 (dummy)				1.120***	
				(0.091)	
Market relatedness = 1.0 (dummy)				1.968***	
				(0.113)	
Market relatedness × Tech. rel.					-0.370
					(0.249)
Tech. relatedness	0.640***	-0.057	-0.056	-0.055	0.033
	(0.139)	(0.101)	(0.102)	(0.102)	(0.113)
log (Sales)	-0.163	0.055	0.052	0.054	0.052
	(0.175)	(0.081)	(0.087)	(0.088)	(0.087)
Tech. generality		0.244	0.289	0.289	0.287
		(0.412)	(0.443)	(0.444)	(0.442)
No. of products		0.014**	0.014**	0.014**	0.014**
		(0.004)	(0.005)	(0.005)	(0.005)
No. of firms in category		0.062***	0.061***	0.062***	0.061***
		(0.004)	(0.004)	(0.004)	(0.004)
No. of firms in category (sq)		-0.0003***	-0.0003***	-0.0003***	-0.0003***
		(0.000)	(0.000)	(0.000)	(0.000)
Tech. entry controls	*yes*	*n/a*	*n/a*	*n/a*	*n/a*
Tech generality missing dummy	*yes*	*yes*	*yes*	*yes*	*yes*
Sector fixed effect	*n/a*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*n/a*	*yes*	*yes*	*yes*	*yes*
Firm fixed effect	*n/a*	*yes*	*yes*	*yes*	*yes*
Pseudo R2	0.063	0.077	0.104	0.104	0.104
Log Likelihood	-63,811	-8,536	-8,289	-8,287	-8,287
Chi-square	6,395	1,162	2,021	1,995	2,056
N	1,734,047	558,692	558,692	558,692	558,692

*Note. +p<0.1; *p<0.05; **p<0.01; ***p<0.001.*

Table 3. Main Regression Results by Subsample

	DV: Product Market Entry									
	Small firms	Big firms	Private	Public	Low tech. capability	High tech. capability	Low generality	High generality	Crowded market	Sparse market
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Market relatedness	1.836***	2.163***	1.532***	2.359***	1.750***	2.431***	1.841***	2.253***	1.870***	2.408***
	(0.167)	(0.147)	(0.161)	(0.144)	(0.166)	(0.143)	(0.161)	(0.154)	(0.123)	(0.183)
Subsample differences	*z*: 1.469, *p*=0.071		*z*: 3.82, *p*<0.01		*z*: 3.10, *p*<0.01		*z: 1.85, p=0.03*		*z: 2.43, p<0.01*	
Tech. relatedness	-0.038	-0.031	0.047	-0.122	-0.010	-0.073	0.312*	-0.343*	0.044	-0.334
	(0.154)	(0.136)	(0.143)	(0.146)	(0.145)	(0.152)	(0.138)	(0.155)	(0.106)	(0.285)
Controls	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Tech generality missing dummy	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Sector fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Pseudo R2	0.115	0.112	0.127	0.127	0.127	0.105	0.119	0.103	0.100	0.072
Log Likelihood	-3,489	-4,628	-3,991	-4,164	-4,051	-3,905	-3,799	-4,179	-5,900	-1,728
Chi-square	1,064	55,318	1,053	47,561	46,331	1,040	48,752	960	1,387	343
N	233,464	295,716	261,451	286,503	212,286	275,741	209,752	284,696	258,216	85,620

*Note. +p<0.1; *p<0.05; **p<0.01; ***p<0.001;* subsample differences are based on *z*-statistics.

Table 4. Results by Sector

Sector	Market relatedness		Tech. Relatedness		N
Pharmaceuticals	4.716***	(0.916)	-2.425	(1.751)	68,990
Transportation	4.176***	(1.085)	0.327	(1.832)	20,456
Biotechnology	2.807***	(0.362)	0.037	(0.364)	165,627
Chemicals	2.212**	(0.705)	-0.848	(0.991)	94,260
Photonics and Optics	2.202*	(0.895)	-0.562	(1.207)	48,278
Energy	2.197**	(0.736)	-0.358	(0.675)	88,587
Medical Equipment	2.033***	(0.457)	-0.759*	(0.432)	311,377
Subassemblies and Components	1.585***	(0.456)	-0.159	(0.299)	472,161
Computer Hardware	1.085*	(0.471)	0.496	(0.370)	167,964
Factory Automation	1.017+	(0.596)	0.375	(0.346)	264,718
Telecommunications and Internet	1.008**	(0.331)	-0.458**	(0.228)	262,127
Test and Measurement	1.002	(0.649)	-0.465	(0.438)	167,866
Computer Software	0.783**	(0.288)	-0.233	(0.183)	291,941
Environmental	0.729	(1.594)	-5.023***	(1.890)	122,266
Manufacturing	-2.114	(1.349)	0.192	(0.348)	116,413
Advanced Materials	-2.476	(2.774)	0.740	(0.641)	120,596

*Note. +p<0.1; *p<0.05; **p<0.01; ***p<0.001.*
Refer to Appendix B for detailed descriptions of each industry sector.

Table 5. Joint Venture and Alliance Activities Pre- and Post-Entry

	DV: JV & Alliances				
	Year: -2	Year: -1	Year: 0	Year: 1	Year: 2
Entry	-0.003	0.052	0.122*	0.064	0.014
	(0.042)	(0.069)	(0.062)	(0.040)	(0.025)
log (Sales)	-0.014	-0.045*	-0.030*	-0.012	-0.018*
	(0.017)	(0.019)	(0.012)	(0.009)	(0.009)
Tech. generality	0.042	0.002	0.039	-0.008	-0.001
	(0.036)	(0.054)	(0.033)	(0.025)	(0.022)
No. of products	-0.011**	-0.012+	-0.011+	-0.012*	-0.012**
	(0.004)	(0.006)	(0.006)	(0.005)	(0.004)
No. of firms in category	0.001	-0.001	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No. of firms in category (sq)	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech generality missing dummy	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
Firm fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
R2 / Log Likelihood	0.034	0.034	0.046	0.066	0.088
N	17,261	17,261	17,261	17,261	17,261

*Note. +p<0.1; *p<0.05; **p<0.01; ***p<0.001.*

Table 6. Joint Venture and Alliance Activities by Subsample Pre- and Post-Entry

	DV: JV & Alliances				
	Year: -2	Year: -1	Year: 0	Year: 1	Year: 2
Small firms	0.002	-0.014	0.000	-0.019*	0.010
	(0.017)	(0.015)	(0.017)	(0.009)	(0.009)
Big firms	-0.001	0.127	0.201+	0.128+	0.025
	(0.074)	(0.127)	(0.111)	(0.072)	(0.045)
Private	0.001	0.007	-0.004	-0.013+	0.008
	(0.010)	(0.009)	(0.013)	(0.007)	(0.007)
Public	0.004	0.102	0.221+	0.132+	0.036
	(0.080)	(0.133)	(0.115)	(0.075)	(0.048)
Low tech. competency	-0.035	0.050	-0.012	-0.002	-0.012
	(0.048)	(0.063)	(0.027)	(0.026)	(0.017)
High tech. competency	0.043	0.135	0.270*	0.104	0.002
	(0.067)	(0.093)	(0.111)	(0.070)	(0.039)
Low generality	-0.013	-0.036	0.014	-0.020	-0.014
	(0.033)	(0.027)	(0.026)	(0.023)	(0.016)
High generality	0.025	0.071	0.216+	0.104	0.026
	(0.073)	(0.124)	(0.116)	(0.070)	(0.044)
Crowded	0.012	0.026	0.103+	0.053	0.024
	(0.048)	(0.052)	(0.058)	(0.054)	(0.040)
Sparse	0.034	0.189+	0.213*	0.057	-0.005
	(0.101)	(0.112)	(0.103)	(0.068)	(0.055)

Note. +p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Table 7. Changes in Technological Relatedness Pre- and Post-Entry

	Tech. Relatedness				
	Year: -2	Year: -1	Year: 0	Year: 1	Year: 2
Entry	-0.008	0.013	0.003	0.057***	0.092***
	(0.016)	(0.014)	(0.007)	(0.012)	(0.017)
log (Sales)	0.005	-0.004	-0.006	0.004	0.006
	(0.012)	(0.008)	(0.005)	(0.007)	(0.007)
Tech. generality	0.018	0.008	-0.017	-0.017	-0.048
	(0.069)	(0.043)	(0.028)	(0.046)	(0.057)
No. of products	-0.001	0.000**	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
No. of firms in category	0.002***	-0.001*	0.010***	0.007***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
No. of firms in category (sq)	-0.000***	0.000	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech generality missing dummy	*yes*	*yes*	*yes*	*yes*	*yes*
Sector fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
Firm fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
R2 / Log Likelihood	0.211	0.206	0.171	0.183	0.218
N	163,801	274,401	586,050	271,727	161,942

*Note. +p<0.1; *p<0.05; **p<0.01; ***p<0.001.*

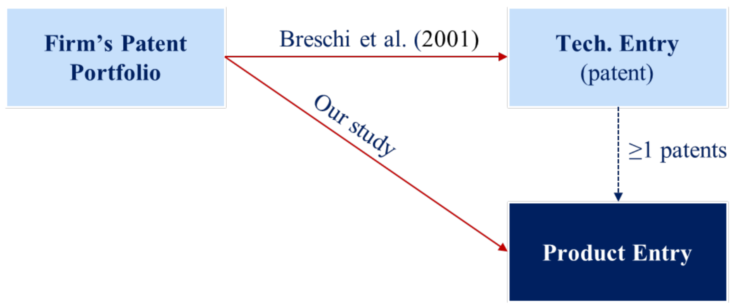
Table 8. Changes in Technological Relatedness by Subsample Pre- and Post-Entry

	Tech. Relatedness				
	Year: -2	Year: -1	Year: 0	Year: 1	Year: 2
Small firms	-0.026	-0.011	-0.001	0.090***	0.137***
	(0.026)	(0.019)	(0.009)	(0.018)	(0.024)
Big firms	0.007	0.027	0.010	0.021	0.044*
	(0.019)	(0.019)	(0.011)	(0.016)	(0.022)
Private	-0.037	-0.006	0.008	0.101***	0.126***
	(0.029)	(0.021)	(0.010)	(0.018)	(0.025)
Public	0.002	0.021	-0.001	0.013	0.060**
	(0.019)	(0.018)	(0.011)	(0.015)	(0.022)
Low tech. competency	-0.005	0.011	0.010	0.093***	0.138***
	(0.031)	(0.019)	(0.009)	(0.018)	(0.025)
High tech. competency	-0.005	0.018	-0.001	0.024	0.049*
	(0.018)	(0.019)	(0.011)	(0.016)	(0.021)
Low generality	-0.019	-0.014	0.029**	0.088***	0.145***
	(0.028)	(0.020)	(0.010)	(0.019)	(0.025)
High generality	0.000	0.028	-0.018+	0.038*	0.048*
	(0.018)	(0.018)	(0.010)	(0.016)	(0.022)
Crowded market	-0.007	0.018	0.011	0.051***	0.083***
	(0.017)	(0.015)	(0.009)	(0.013)	(0.018)
Sparse market	-0.014	-0.015	-0.011	0.114***	0.167***
	(0.040)	(0.025)	(0.010)	(0.034)	(0.046)

*Note. +p<0.1; *p<0.05; **p<0.01; ***p<0.001.*

Appendix A: *Capturing Technological Relatedness*

Appendix A describes the measurement of technological relatedness. In its operationalization, we follow as closely as possible prior studies that find significant effects of technological relatedness on technological entry (e.g., Breschi *et al*., 2001). The key difference is that testing our theory requires us to measure the distance to a product (rather than another technological class) that embeds multiple technologies and patents.



For example, smartphones embed hundreds of patents, and identifying the breadth and depth of related technological resources presents a significant challenge. Other studies have addressed the issue in part by focusing on sectors whose technological profiles are narrowly defined and relatively straightforward to identify (e.g., pharmaceutical, disk-drive, or crop market), but our theory requires examination across a wide spectrum of products.

There are three key issues:

1. Identification of technological profile for each product
2. Measurement of distance (or technological relatedness) between a firm's patent portfolio and technological profile for the product
3. Identification of a firm's patent portfolio based on matching CorpTech and NBER patent DB

A.1. *Identification of technological profile*

We start with all firms active in each product category and their patent portfolio. We identify the relevant technologies for a given product category by looking for commonalities in the recent patenting behavior of focused firms that are active in relatively few product categories. To reduce noise from holding companies or large firms that maintain a broad patent and product portfolio (as suggested by our theory and Brusoni et al. 2001), we base our identification of a technological profile using "focused" firms which are active in 3 or fewer product categories. We also check robustness by applying more stringent and lenient thresholds for focused firms (firms active in only 1 product category and up to 5 product categories). All results remain qualitatively consistent, and we report results based on the threshold of three.

Table A1.1: Average number of relevant patent classes for sectors over time

(Sector ID) Sector	2000	2001	2002	2003	2004	2005	Average over time
(AUT) Factory Automation	6.65	11.69	9.07	12.14	8.00	6.50	9.01
(BIO) Biotechnology	4.70	3.38	9.13	6.82	4.18	7.13	5.89
(CHE) Chemicals	1.25	1.60	3.86	2.11	2.29	8.50	3.27
(COM) Computer Hardware	1.64	2.25	1.42	1.63	1.56	1.70	1.70
(DEF) Defense	- [a]	-	-	-	-	-	-
(ENR) Energy	5.50	7.00	4.00	3.67	2.75	2.33	4.21
(ENV) Environmental	2.00	2.13	1.25	3.57	1.30	2.33	2.10
(MAN) Manufacturing	6.71	6.78	8.86	5.44	9.20	7.17	7.36
(MAT) Advanced Materials	2.00	1.71	4.43	1.83	2.25	1.89	2.35
(MED) Medical Equipment	3.75	4.95	3.44	3.04	4.57	2.74	3.75
(PHA) Pharmaceuticals	2.50	1.00	2.38	1.33	1.75	1.50	1.74
(PHO) Photonics and Optics	1.00	1.80	1.00	1.29	1.00	1.00	1.18
(SOF) Computer Software	1.54	2.47	1.71	3.33	3.33	2.55	2.49
(SUB) Subassemblies and Components	2.45	2.55	6.52	2.92	3.46	3.59	3.58
(TAM) Test and Measurement	1.57	2.58	1.92	2.00	5.00	2.00	2.51
(TEL) Telecommunications and Internet	1.00	2.31	2.30	2.09	5.23	4.05	2.83
(TRN) Transportation	-	-	1.00	2.00	1.00	1.00	1.25
(ZZZ)[a] Holding Companies	-	-	-	-	-	-	-
Average over sector	3.27	3.73	4.37	3.79	3.97	3.51	3.77

Note: [a] There is no product category with a requisite technological class.

Table A1.2: Examples of Relevant Patent Classes by Product Category

In verifying our measure, we also have checked whether the concordance between identified patent classes and product categories is reasonable. We provide five illustrative cases below. While these are sampled categories, the concordance built through our approach produces links between patent classes and product categories that have high face validity.

Sector	Industry	Product	Sample product description	Identified USPTO patent class	Class description
BIO (Biotech.)	IM	M	Immune system treatment research and development	424	Drug, bio-affecting and body treating compositions
				435	Chemistry: molecular biology and microbiology
				525	Synthetic resins or natural rubbers - part of the class 520 series
SOF (Computer Software)	OA	GD	Interactive entertainment software	74	Machine element or mechanism
				370	Multiplex communications
	UT	C	Error checking software	706	Data processing: artificial intelligence
MED (Medial Equipment)	DG	TI	Microbiological diagnostic products	29	Metal working
				174	Electricity: conductors and insulators
				248	Supports
				362	Illumination
				524	Synthetic resins or natural rubbers - part of the class 520 series
				606	Surgery
MAT (Advanced Materials)	FR	F	Industrial fillers / nano powders	424	Drug, bio-affecting and body treating compositions
				427	Coating processes
				536	Organic compounds - part of the class 532-570 series
TAM (Test and Measurement)	SS	A	Data acquisition/alarm and control systems	705	Data processing: financial, business practice, management, or cost/price determinatio
				710	Electrical computers and digital data processing systems: input/output
				714	Error detection/correction and fault detection/recovery
				715	Data processing: presentation processing of document

A.2. *Calculating Technological Relatedness*

In our baseline specification, if firm i has a patent in any of the relevant technology classes of product j, TR_{ij} is set to 1 (maximal relatedness between the firm's technological resources and those required in the product category). In case TR_{ij} is not 1, we find the best alternative technology class of firm i with the highest relatedness (S_{ij}) among the possible pairs of the patent portfolio of firm i (P_i) and the technology profiles of product category j (R_j):[18]

$$TR_{ij} = \max_{p \in \{k | P_{ik}=1\}, r \in \{t | R_{jt}=1\}} (S_{pr})$$

A potential concern is that we ignore the potential for resource "intensity" by transforming a continuous measure into a dichotomous measure (e.g., by treating having one vs. one hundred patents in a particular technological class to be the same). This potentially overstates technological relatedness and the role of technological resources. To alleviate this concern, we test the robustness of our main results to employing three alternative approaches. We find that these new measures produce qualitatively consistent results to our main measure.

(I) Instead of using the maximal relatedness between a firm's technological resources and that required in the product category (which could lead to artificially high levels of relatedness if firms need to master all relevant patent classes to enter), we take the average technological relatedness to each of the required technology classes of product j as follows:

$$TRA1_{ij} = \frac{1}{n_j} \cdot \sum_{r \in \{t | R_{jt}=1\}} TR_{ijr} = \frac{1}{n_j} \cdot \sum_{r \in \{t | R_{jt}=1\}} \left(\max_{p \in \{k | P_{it}=1\}} S_{pr} \right)$$

where n_j is the number of required technology classes of product j; thus, n_j is the number of elements in the set, $\{t \mid R_{jt} = 1\}$ (i.e., $n = \left| \{t \mid R_{jt} = 1\} \right|$). If firm i has a patent in required technology class r of product j, TR_{ijr} is set to 1. If TR_{ijr} is not 1, we find the best alternative technology class of firm i with the highest relatedness (S_{ij}) among the possible pairs of firm i and the required technology class r of the product category j.

(II) We use the average number of required technology classes in which firm i has a patent as follows:

$$TRA2_{ij} = \frac{1}{n_j} \cdot \sum_{r \in \{t | R_{jt}=1\}} TR_{ijr} = \frac{1}{n_j} \cdot \sum_{r \in \{t | R_{jt}=1\}} \left(\max_{p \in \{k | P_{it}=1\}} \lfloor S_{pr} \rfloor \right)$$

where $\lfloor S_{pr} \rfloor$ is the greatest integer which is smaller than or equal to S_{pr}. Given that S_{pr} has a value between 0 and 1, S_{pr} is either 0 or 1. $\lfloor S_{pr} \rfloor$ is 1 if S_{pr} is 1, and

[18] In our baseline specification, we focus on the maximum level of relatedness, as opposed to the mean or the median, to avoid penalizing diversified firms that are active in many patent classes. If, for example, Intel wanted to enter a new product category it would not draw on its entire technological knowledge portfolio to enter, but would presumably focus on the most relevant technological knowledge that it had to facilitate entry.

$\lfloor S_{pr} \rfloor$ is 0 otherwise. If firm *i* has a patent in required technology class *r* of product *j*, TR_{ijr} is set to 1. Unlike the original measure in the manuscript and the first alternative measure, in cases where TR_{ijr} is not 1, we do not find the best alternative technology class of firm *i*, and simply set TR_{ijr} to 0.

(III) We were concerned that our original measure may overstate technological relatedness because we did not incorporate resource depth in one or more technological classes. To incorporate knowledge depth, we add a weight term w_{ip} (= number of patents of firm *i* in technology class *p* / total number of patents of firm *i*) to the second alternative measure as follows:

$$TRA3_{ij} = \sum_{r \in \{t | R_{jt}=1\}} \left(w_{ip} \cdot \max_{p \in \{k | P_{it}=1\}} S_{pr} \right)$$

We illustrate how to calculate these measures by comparing the original measure and the above three alternative measures with an example. The main measure we used in the manuscript, TR_{ij}, is calculated as follows.

$$\begin{aligned} TR_{ij} &= \max(S_{AA}, S_{BA}, S_{CA}, S_{AD}, S_{BD}, S_{CD}) \\ &= \max(1, 0.1, 0.2, 0.3, 0.4, 0.5) = 1 \end{aligned}$$

The first alternative measure $TRA1_{ij}$ is calculated as follows:

$$\begin{aligned} TRA1_{ij} &= 0.5 \cdot (TR_{ijA} + TR_{ijD}) \\ &= 0.5 \cdot (\max(S_{AA}, S_{BA}, S_{CA}) + \max(S_{AD}, S_{BD}, S_{CD})) \\ &= 0.5 \cdot (\max(1, 0.1, 0.2) + \max(0.3, 0.4, 0.5)) \\ &= 0.5 \cdot (1 + 0.5) = 0.75 \end{aligned}$$

The second alternative measure $TRA2_{ij}$ is calculated as follows:

$$\begin{aligned} TRA2_{ij} &= 0.5 \cdot (TR_{ijA} + TR_{ijD}) \\ &= 0.5 \cdot (\max(\lfloor S_{AA} \rfloor, \lfloor S_{BA} \rfloor, \lfloor S_{CA} \rfloor) + \max(\lfloor S_{AD} \rfloor, \lfloor S_{BD} \rfloor, \lfloor S_{CD} \rfloor)) \\ &= 0.5 \cdot (\max(1, 0, 0) + \max(0, 0, 0)) \\ &= 0.5 \cdot (1 + 0) = 0.5 \end{aligned}$$

The third alternative measure $TRA3_{ij}$ is calculated as follows:

$$\begin{aligned} TRA3_{ij} &= (w_{iA} \cdot \max(S_{AA}, S_{AD})) + (w_{iB} \cdot \max(S_{BA}, S_{BD})) + (w_{iC} \cdot \max(S_{CA}, S_{CD})) \\ &= 0.2 \cdot \max(1, 0.3) + 0.5 \cdot \max(0.1, 0.4) + 0.3 \cdot \max(0.2, 0.5) \\ &= 0.2 \cdot 1 + 0.5 \cdot 0.4 + 0.3 \cdot 0.5 = 0.37 \\ &= 0.5 \cdot (1 + 0) = 0.5 \end{aligned}$$

When we compare the size of these measures, TR_{ij} is the largest among all these measures with the following relationships: (1) $TR_{ij} > TRA1_{ij} > TRA2_{ij}$ and (2) $TR_{ij} > TRA3_{ij}$. $TRA3_{ij}$ can be larger than $TRA1_{ij}$ or $TRA2_{ij}$ depending on the value of w_{ip}. Thus, our alternative measures are less likely to overstate the technological relatedness.

Across all three new measures, we find that technological relatedness does not drive a product market entry. As a variation of our third new technological measure ($TRA3_{ij}$), we have also applied different weighting schemes (w_f), for example applying logs to the number of patents in calculating intensity and find consistent results (untabulated).

Table A2.1: Alternative Measures of Technological Relatedness

	Product Entry			
	Baseline Tech. measure	Alternative Tech. measure 1	Alternative Tech. measure 2	Alternative Tech. measure 3
	(1)	(2)	(3)	(4)
Tech. relatedness	-0.056	0.154	0.284	0.173
	(0.102)	(0.163)	(0.177)	(0.239)
Market relatedness	2.017***	2.017***	2.017***	2.016***
	(0.109)	(0.109)	(0.109)	(0.109)
log (Sales)	0.052	0.053	0.052	0.054
	(0.087)	(0.087)	(0.087)	(0.087)
Tech. generality	0.289	0.291	0.289	0.294
	(0.443)	(0.444)	(0.445)	(0.444)
No. of Products	0.014**	0.014**	0.014**	0.014**
	(0.005)	(0.005)	(0.005)	(0.005)
No. of firms in Category	0.061***	0.060***	0.060***	0.060***
	(0.004)	(0.004)	(0.004)	(0.004)
No. of firms in Category (sq)	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tech generality missing dummy	*yes*	*yes*	*yes*	*yes*
Sector fixed effect	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*
Firm fixed effect	*yes*	*yes*	*yes*	*yes*
(Pseudo) R2	0.104	0.104	0.104	0.104
Log Likelihood	-8,289	-8,288	-8,288	-8,289
Chi-square	2,021	1,995	1,997	2,003
N	558,692	558,692	558,692	558,692

Table A2.2: Alternative Measures of Technological Relatedness based on Bryce and Winter (2009)

	Product Entry			
	Baseline Tech. measure	Bryce-Winter Tech. measure 1	Bryce-Winter Tech. measure 2	Bryce-Winter Tech. measure 3
	(1)	(2)	(3)	(4)
Market relatedness	2.017***	2.337***	2.357***	2.327***
	(0.120)	(0.106)	(0.108)	(0.104)
Tech. relatedness	0.033	0.154	-0.076	-0.056
	(0.113)	(0.163)	(0.068)	(0.048)
Market. rel x Tech. rel	-0.370	-0.095	-0.146	-0.095
	(0.249)	(0.066)	(0.093)	(0.067)
log (Sales)	0.052	0.109	0.110	0.108
	(0.087)	(0.106)	(0.106)	(0.106)
Tech. generality	0.287	-0.711*	-0.717*	-0.711*
	-0.442	-0.319	(0.319)	(0.319)
No. of Products	0.014**	-0.003	-0.003+	-0.003
	(0.005)	(0.002)	(0.002)	(0.002)
No. of firms in Category	0.061***	0.076***	0.076***	0.076***
	(0.004)	(0.004)	(0.004)	(0.004)
No. of firms in Category (sq)	-0.003***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Tech generality missing dummy	*yes*	*yes*	*yes*	*yes*
Sector fixed effect	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*
Firm fixed effect	*yes*	*yes*	*yes*	*yes*
(Pseudo) R2	0.104	0.102	0.102	0.102
Log Likelihood	-8,289	-18,831	-18,832	-18831
Chi-square	2,021	2,203	2,222	2,202
N	558,692	649,999	649,999	649,999

Note. Standard errors are in parentheses.

In replicating Bryce and Winter's (2009) measurement of industry relatedness, we need to adjust some weighting schemes to accommodate differences (detailed below). As we modify the weighting scheme (specifically in Step 2 of Bryce and Winter's procedure), we test whether our Bryce and Winter approach-based measure is robust to changes in our weighting scheme. We made three different versions of the Bryce and Winter approach-based technological relatedness measures by following procedures.

Bryce and Winter (2009) developed their industry relatedness measure by using the Longitudinal Research Database (LRD) at the Center for Economic Studies (CES) at the U.S. Census Bureau. As we need to measure technological relatedness between different products from different datasets (i.e., Corptech and NBER Patent database), we need to modify the original Bryce and Winter to accommodate such differences. Specifically, we calculate Bryce-Winter approach-based technological relatedness measure by the following procedures (from Steps 1, 2, and 3). Our procedure is almost identical to Bryce and Winter's measure in Steps 1 and 3. We need to modify Step 2 due to the difference between the LRD database and the NBER Patent database. Specifically, the LRD database has the sales data for each business unit (by SIC code), and Bryce and Winter use this business unit sales to give a weight between different business units. When we apply this Bryce and Winter type of measure, an ideal patent dataset needs to have a contribution (e.g., in terms of the impact or novelty) of each patent class for each multiclass paten. However, no patent datasets have such data; we need to have a modified version of the weighting scheme in Step 2. The details are below.

Step 1 – First, we make a roster of all possible dyads of patent classes. Then, for all dyads, we count the number of patents in both classes. Precisely, let $C_{ik} = 1$ if patent k is with class i, and 0 otherwise. The number of patents with class i is $n_i = \Sigma_k C_{ik}$, and the number of patents with class i and j is $J_{ij} = k\ \Sigma C_{ik} \cdot C_{jk}$.

Second, although J_{ij} increases with the technological relatedness of patent classes i and j, it also increases with the technological prominence (i.e., size; the number of patents) of patent classes n_i and n_j. Therefore, J_{ij} must be adjusted for the number of patents in the dyad if patents were allocated to patent classes at random. To do this, we define a random draw from this distribution J_{ij} as a random variable X_{ij}. We calculate the probability that x out of K patents receive a random assignment to patent classes i and j. First, we calculate the number of ways of selecting x from a total of n_i patents, that is, $\binom{n_i}{x}$. Second, there are $(n_j - x)$ positions in the n_j list to be added with patents that do not have class i. The number of ways of adding patents without patent class i is the number of ways of choosing $(n_j - x)$ from a possible $(K - n_i)$ patents, that is, $\binom{K-n_i}{n_j-x}$. Thus, the number of unique ways of selecting a list for patent class j is $\binom{n_i}{x}\binom{K-n_i}{n_j-x}$.

Third, we transform this count variable into a probability. We divide it by the number of possible ways of the co-occurrence of patent class j in total, which is $\binom{K}{n_j}$. The probability of random co-occurrences X_{ij} of two patent classes of size n_i and n_j follows a hypergeometric random variable, $P[x = X_{ij}] = \binom{n_i}{x}\binom{K-n_i}{n_j-x} / \binom{K}{n_j}$. The average of X_{ij} is μ_{ij} $(= E(X_{ij}) = \frac{n_i n_j}{K})$, and the variance of X_{ij}

is σ_{ij}^2 $(= \mu_{ij}(1 - \frac{n_i}{K})(\frac{K-n_j}{K-1})$.. The difference between J_{ij} and the expected value of X_{ij} is normalized as $\tau_{ij} = (J_{ij} - \mu_{ij})/\sigma_{ij}$.

Step 2 – Because we calculate τ_{ij} with raw co-occurrence counts, it is a rough measure of the extent to which dyad ij is technologically prominent. This measure does not reflect the dyad's technological prominence to the average patent with the dyad. The dyad of two patent classes could be only weakly related in a patent with many patent classes than in a patent with two patent classes only. If this tendency is consistent across all patents with two focal patent classes, then relatively lower or higher weights need to be allocated to the dyad's relatedness score. We compute these weights by comparing the proportions of the focal patent classes to all the patent classes. The lower value of these two proportions (for the two focal patent classes) is chosen for each patent. This lower value is an upper bound of how closely related the two patent classes are when they show up together. When patent class A has a proportion of 0.5, and patent class B has a proportion of 0.1, the 0.1 will be chosen. Then, these lower proportions are averaged across all patents with the dyad to create the dyad weight S_{ij} as follows.

$$S_j^{min} = \frac{\Sigma_k min_k[s_i, s_j]C_{ik}C_{jk}}{\Sigma_k C_{ik}C_{jk}}$$

Then, scores of τ_{ij} in Step 1 are normalized by the weights in S_{ij} in Step 2. Before normalizing, we change the scores of τ_{ij} to a distance measure (i.e., transforming a relatedness matrix into a distance matrix). First, we identify the largest τ_{ij} among the scores. Then, we subtract all scores τ_{ij} from this largest value. In the distance matrix, smaller values represent high relatedness. Also, the value of zero means the most related pair. All other cells have positive values. Also, we divide cell values in the distance matrix by S_{ij}. The final distance matrix represents a network in which matrix cells' values are the distances between patent classes i and j. The network comprises patent class vertices linked by arcs having weights (inversed with technological relatedness). We used this version of the Bryce-and-Winter-style technological relatedness measure in Column 2.

As we mentioned above, because of the difference in data (LRD vs. NBER Patent database), we create two different versions to check the robustness of our procedure. Precisely, the second version of Bryce and Winter technological relatedness measure (which is used in Column 3) is calculated with the following weight S_{ij}:

$$S_j^{mean} = \frac{\Sigma_k mean_k[s_i, s_j]C_{ik}C_{jk}}{\Sigma_k C_{ik}C_{jk}}$$

Finally, the third version of Bryce and Winter technological relatedness measure (which is used in Column 4) is calculated with the following weight S_{ij}:

$$S_j^{median} = \frac{\Sigma_k median_k[s_i, s_j]C_{ik}C_{jk}}{\Sigma_k C_{ik}C_{jk}}$$

Step 3 – First, to determine relatedness for any possible dyads, the measure should provide values for all possible class combinations. We address this issue by using the shortest path distance between every pair of patent classes in the final distance matrix in Step 2. The method creates a distance measure for all dyads.

Second, the weighted distance matrix, where cell values are replaced with shortest distance scores, is converted to a similarity matrix. We subtract each computed path length score from the largest distance value. Then, we calculate the similarities score by subtracting the mean of the distribution from each value and dividing by the standard deviation.

A.3. *Identification of a Firm's Patent Portfolio*

In order to identify a firm's patent portfolio and its evolution over time, we need to match the CorpTech DB with the NBER patent DB. Because the two databases do not share a common company identifier, firm entries are matched based on firm name, state, and city locations to identify each firm's patent portfolio. There are also multiple ids (*pdpass*) for some firms in the NBER patent database while CorpTech maintains one id for each firm even as firms go through name changes, mergers, and acquisitions. We experimented with several methods to find a compromise between too many "false positives" (different companies being incorrectly classified as the same) and too many "false negatives" (the same company misclassified as different companies). In Table A.1, we list matching algorithms and their performances from the most stringent one (matching algorithm 1) to the most lenient one (matching algorithm 8). Stem name (algorithm 5 and 8) removes "Inc.", "Corp.", "Corporation", "Com.", and other appendices from full firm names using algorithms used by Hall et al. (2001) available from their website. Next, we randomly selected matches and checked for their integrity. Since we found that there are too many false positives with the matching algorithm 8, the stem-name-only criteria, we regard two companies as the same if one of the first seven conditions holds. Irrespective of the algorithm used, there will be some errors in any matching process. However, there is no reason to believe that the matching is producing systematic errors.

Table A3.1: Matching Algorithm and No. of Matches

	Matching algorithm	**No. of additional matches (unit: NBER pdpass - CorpTech id)**	**No. of cumulative matches [a] (unit: NBER pdpass - CorpTech id)**
1	Full name, State, City	48,980	48,980
2	Stem name, State, City	5,780	54,760
3	Full name, City	301	55,061
4	Full name, State	7,108	62,169
5	Stem name, City	48	62,217
6	Stem name, State	1,224	63,441
7	Full name only	7,468	70,909
8	Stem name only	9,960	80,869

Note: [a] sum of number of additional matches. For example, the number of cumulative matches of algorithm 2 (54,670) is the sum of the no. of additional matches of algorithm 1 (48,980) and 2 (5,780).

Appendix B: ***Sample Selection***

Year	Entry Year	Total Firms	Sample Firms	Total Categories	Sample Categories	No. of Entries	No. of Observations
1997-1999	2000	41,339	2,734	2,063	178	194	71,875
1998-2000	2001	40,412	2,878	2,084	188	251	99,097
1999-2001	2002	43,274	2,963	2,190	188	325	117,147
2000-2002	2003	45,151	2,859	2,172	199	372	126,528
2001-2003	2004	52,264	2,883	2,115	199	362	125,829
2002-2004	2005	58,118	2,944	2,104	34	69	18,216
Total	-	-	-	-	-	1,851	3,090,189
Unique	-	77,100	5,755	2,681	341	-	-

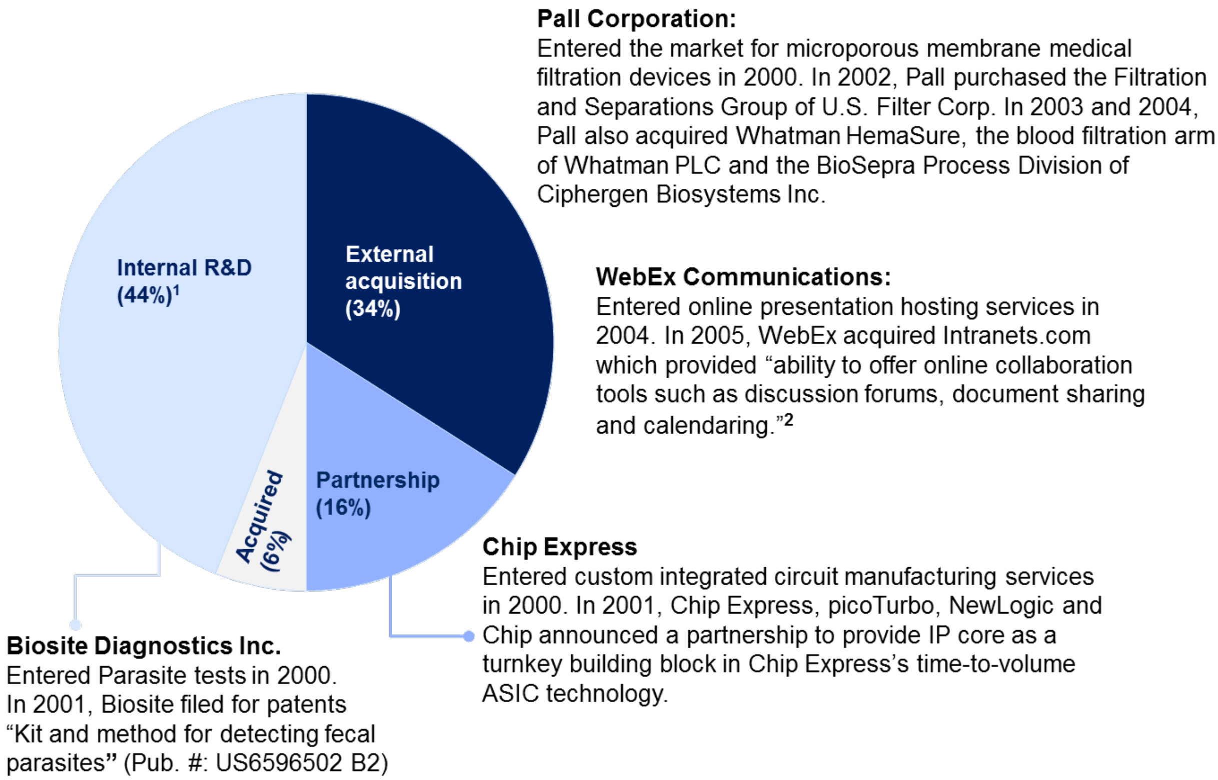
Note.[a] The table provides the total number of firms and product categories in CorpTech and our sample numbers. We use data from the three years prior to each entry year to construct measures of technological resources, technological relatedness, market resources, and market relatedness. The drop in the number of sample categories for 2005 is due to right censoring of the NBER patent data at 2006.

Appendix C: Post-Entry Changes in Technological Relatedness in Logit Specification

	Tech. Relatedness=1				
	Year: -2	Year: -1	Year: 0	Year: 1	Year: 2
Entry	-0.001	0.079	-0.005	0.821***	1.207***
	[0.166]	[0.142]	[0.095]	[0.109]	[0.142]
log (Sales)	0.026	-0.011	-0.035	0.026	0.038
	[0.109]	[0.078]	[0.054]	[0.072]	[0.073]
Tech. generality	0.531	0.238	-0.405	-0.446	-0.463
	[0.715]	[0.473]	[0.350]	[0.502]	[0.647]
No. of products	-0.005	0.003*	-0.001	-0.001	-0.003
	[0.004]	[0.002]	[0.002]	[0.003]	[0.004]
No. of firms in category	0.094***	0.091***	0.087***	0.092***	0.096***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]
No. of firms in category (sq)	-0.001***	-0.001***	-0.000***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tech generality missing dummy	*yes*	*yes*	*yes*	*yes*	*yes*
Sector fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
Firm fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*
R2 / Log Likelihood	-42119	-69592	-124727	-68347	-40884
N	160,145	270,535	579,584	266,280	156,744

Note. +p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Appendix D: ***Case Studies of 50 Market-driven Entries***



1. Includes 4 cases with limited information on both external and internal related activities
2. https://en.wikipedia.org/wiki/WebEx

Appendix E: *Additional Robustness Tests*

	Product Entry						
	Random effects	Tech. rel. range: [0, 1)	Tech rel range: [0.5, 1]	Market-Year with 2+ entry	Expanded Product FE	Matching on Tech rel.	Matching on Market rel.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tech. relatedness	-0.146	-0.177	-0.275	-0.037	0.051		-0.088
	(0.093)	(0.176)	(0.397)	(0.104)	(0.104)		(0.153)
Market relatedness	1.876***	1.989***	2.140***	1.986***	2.082***	2.501***	
	(0.078)	(0.116)	(0.245)	(0.111)	(0.111)	(0.223)	
log (Sales)	0.035*	0.030	0.070	0.048	0.056		
	(0.017)	(0.087)	(0.223)	(0.087)	(0.087)		
Tech. generality	0.224	0.366	-0.203	0.324	0.298		
	(0.178)	(0.449)	(0.937)	(0.443)	(0.444)		
No. of products	0.016***	0.016***	0.007	0.016***	0.015***		
	(0.001)	(0.005)	(0.006)	(0.004)	(0.005)		
No. of firms in category	0.062***	0.063***	0.059***	0.050***	0.002	0.052***	0.066***
	(0.004)	(0.004)	(0.009)	(0.004)	(0.010)	(0.007)	(0.005)
No. of firms in category (sq)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech generality missing dummy	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Sector fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Firm fixed effect	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Log Likelihood	-11,760	-7,304	-957	-7,657	-7,961	-1,038	-3,106
Chi-square	2,313	1,939	38,833	1,603	4.59e+09	554	30,371
N	2,809,340	475,909	22,285	411,062	558,692	6,548	89,256

*Note. +p<0.1; *p<0.05; **p<0.01; ***p<0.001.*

Models (6) and (7) employ a matching approach. In Model (6) we include firm-year fixed effects and focus on observations from the same firm-year as an observed entry with a nearly identical (within 0.001) level of technological relatedness to the observed entry. This allows us to test the effect of market relatedness and eliminates technological relatedness (since this is nearly identical across observations) and variables with no variation at the firm-year level, such as firm size. Model (7) takes the opposite approach – matching on market relatedness within the same firm-year and assessing the effect of technological relatedness.

Additional Analyses: Counterfactuals in the Data

To further explore the data, we wanted to see if any firms seemed to follow a "technology leading" approach to product market entry, as opposed to the "market leading" approach that is apparent in the regression results. To do this, we split the levels of both market relatedness and technological relatedness into thirds. We considered a given product market entry decision to be "technology leading" if the technological relatedness variable was in the highest third of the data and the market relatedness variable was in the middle or lowest third, or if the technological relatedness variable was in the middle third while the market relatedness variable was in the bottom third. For these entries, the level of technological relatedness is significantly higher than that of market relatedness, making the entry behavior consistent with a logic favoring technology. We then looked at the firm level to find firms that had multiple technology-driven entries and no market-driven entries (determined through the inverse of the approach discussed above). These are firms that show consistency in their reliance on technology (having used made technology-leading entries at least twice) and have ignored the role of market resources.

This analysis shows that there are 57 firms with multiple technology-driven entries and no market-driven entries in the data. This includes 53 entries by 23 companies where technology relatedness is in the top 10% (generally equal to one) and market relatedness is zero (they are not present anywhere in the same sector). The set of firms includes Guidant (medical devices), Motorola (telecommunications), Planar (displays), and Tektronix (software), all firms that would generally be considered to be technology-focused companies with a strong history of patenting. The existence of these technology-leading companies raises the question of whether the observed results are driven by (a) fewer technology-leading companies than market-leading companies, or (b) fewer entries by technology-leading companies, even though the technology-leading companies may be as plentiful in number in the data. The data show that technology-leading companies make as many entries across the range of our data as market-leading companies (3.2 entries versus 3.3 entries, respectively), but that there are more market-leading firms in the data overall. This suggests that some firms make entry decisions based on technological relatedness and that these companies appear on the surface to be the types of firms that make heavy investments in technology, but just that there are relatively few such companies in the data.

Appendix F: *Boundary Conditions and Limitations*

From both an empirical and theoretical perspective, we highlight three important boundary conditions. First, our empirical approach does not allow us to consider "new-to-the-world" product categories, only existing categories. As such, we study entry decisions that may be organizationally radical but are not necessarily technologically radical (Henderson, 1993). Many of the entries that we study represent significantly novel entries, but only from the perspective of being "new-to-the-firm." We recognize that it is entirely possible that truly radical entries are determined more by technological resources than market resources. Second, our focus on comparisons between technological and market resources means that firm must have an established track record to be included in our data. Thus, the entries that we consider are not the first products offered by new firms, but are at least the second product launched by the firm.

Third, we focus on industries where intellectual property (patents) is especially relevant, in part to measure the firm's relevant technological resources. This is an especially important boundary condition, because our theory about the results showing the importance of downstream resources derives in part because of assumptions about the availability of technological (or operational) resources in the factor market. If industries have little codifiable intellectual property, then such markets are likely to function quite poorly, which should increase the importance of tacit operational resources. Thus, we would predict that our theory would only really hold in industries where transferrable intellectual property exists – a theory that is consistent with the results that we show in Table 6, but the testing of which is beyond the scope of this paper and our data. Given our medium range panel (1997-2005) that includes the dot-com bubble, there is a distinct possibility that we may be observing specific phases of economic development where the diffusion of information communication technology and the increasing availability of other general purpose technologies (Bresnahan and Trajtenberg, 1995) enabled a relatively crude initial market-based entry followed by technological refinement through subsequent investments. Our theory also highlights how technological resources can be less important in high technology sectors, and it would be interesting to verify whether our finding generalizes to low technology sectors.

There are several other important limitations to our empirical approach. Most notably, we rely on patents to proxy for technological resources of firms as well as to identify technological profiles of each product market. Small firms are less likely to patent their technological resources, which may contribute to the null finding on technological relatedness. However, we find a limited difference in the effects of technological relatedness across subsamples based on firm size. As another partial redress, we have also varied the threshold for each patent technology class to be associated with a product category. Lowering or increasing the threshold for a technological class to be counted as a technological profile has minimal effects on our findings on technological relatedness. As noted earlier, another issue is that NBER patent database does not track changes in the ownership of patents through acquisition or licensing, limiting our ability to directly test for the role of external markets for technology that serve as an important underlying mechanism in the development of our hypotheses. An in-depth study similar to Sosa (2009) or Nerkar and Roberts (2004) has the potential to provide more detailed measure of firm resources and resource profiles of a product market. However, one of the primary goals of the present paper is to test patterns in firm entry behavior across a wide range of market relatedness in a cross-industry study.