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How much is enough? The role of R&D investment in the innovation process

Desmond Ng[1] | Leonardo Sánchez-Aragón[2]

[1]Texas A&M University, University College Station Texas, College Station, Texas, USA
[2]Escuela Superior Politécnica del Litoral, ESPOL, Facultad de Ciencias Sociales y Humanísticas, Guayaquil, Ecuador

Correspondence
Desmond Ng, Texas A&M University, College Station Texas, College Station, TX 77845, USA.
Email: dng@tamu.edu

Abstract

While both production function (PF) and Absorptive Capacity (AC) explanations have played an important role in explaining the relationship between a firm's Research and Development (R&D) and its innovation, each has developed independently of the contributions of the other. The purpose of this study is to theoretically and empirically develop a concept of AC that incorporates the role of diminishing returns and external spillovers (i.e., strategic alliances) into a biotechnology firm's R&D-innovation process. In using count estimations, this study finds that a firm's R&D-innovation process is subject to a nonlinear -U-shaped- learning process and that this process is moderated by its strategic partnerships. The contribution of this study is that it challenges the linearity assumptions and findings of AC research and that it offers a greater openness to PF explanations of the R&D-innovation process.

1 | INTRODUCTION

As a firm's ability to innovate has been widely attributed to its investments in Research and Development (R&D), the production function (PF) approach has played an important role in explaining this relationship (Boeing & Hunerman, 2020; Chatterjee et al., 2018; Hall et al., 2010; Hecht, 2018). The PF approach involves an input–output relationship where increasing investments in a firm's R&D result in declining returns to the firm's innovative outcomes (Griliches, 1979). For instance, Graves and Langowitzs' (1993, 1996) global manufacturing study found increasing investments in a firm's R&D had a diminishing effect on its number of patents. These findings were also observed with the number of product innovations (i.e., New Chemical Entities NCE) in the pharmaceutical industry. More recently, Hecht (2018) found similar diminishing returns in a variety of hi-technology industries (see also Chatterjee et al., 2018; Knott, 2002; Ravichandran et al., 2017). These diminishing returns are a significant concern for senior executives. This is because while senior executives recognize investments in their firm's R&D are pivotal to creating new firm's products and services, these diminishing returns significantly undermine the innovative returns on these investments (Knott, 2002; Leiponen & Helfat, 2010; Ravichandran et al., 2017). As Ravichandran et al. (2017) describe, the "pain from diminishing returns to R&D" (p. 812) has led executives to question their R&D commitment and thus ability to commercialize products/services from their R&D efforts.

To overcome such limits to a firm's R&D, management research suggest firms adopt a more open view of the R&D- innovation process (Akram et al., 2020; Denicolai et al., 2016; West & Bogers, 2014). This open view has been explained by Cohen and Levinthals' (1990) concept of absorptive capacity (AC). AC refers to a firm's ability to develop innovations by identifying, assimilating, and commercializing the experiences and technologies of others. This AC is commonly attributed to a firm's R&D because R&D offers scientific experiences that enable the firm to relate to and assimilate external technical advances (Volberda et al., 2010). Specifically, while AC exhibits many *dimensions* (Chaudhary & Batra, 2018; Zahra & George, 2002), a firm's R&D emphasizes an associative learning process that is central to the AC concept (Cohen & Levinthal, 1990; Volberda et al., 2010). This associative learning process finds that a firm's R&D assimilates external information that is related to its scientific experiences and that this association reinforces a firm's R&D to assimilate external information in future periods (Cohen & Levinthal, 1990). With this associative learning process, AC studies find R&D investments offer an assimilation of external experiences that increase the firm's ability to commercialize new products (e.g., Kostopoulos et al., 2011; Martínez-Sánchez et al., 2020; Moilanen et al., 2014; Rothaermel & Alexandre, 2009; Santoro et al., 2020).[1]

Yet, despite its contributions, the concept of AC has developed independently of PF research in which the law of diminishing returns has been virtually ignored in mainstream AC research (see possible exceptions, Brettel et al., 2011; Denicolai et al., 2016; Huang & Rice, 2012; Lichtenthaler, 2016). This omission occurs because the AC concept is based on a linearity assumption (Brettel et al., 2011) that the firm's associative learning process offers innovative benefits that outweigh its costs. This linearity assumption is problematic because it implies that as a firm invests in its R&D, it faces limited constraints in assimilating and commercializing external experiences. Hence, an important contribution of PF's law of diminishing returns is that it offers an important constraint to the linearity assumptions of AC research. The challenge, however, facing PF explanations is that it assumes a firm's R&D is "autarkic" (Hall et al., 2010) with respect to external technical advances. This autarkic view finds that the task of a firm's R&D is to create new knowledge and that this knowledge creation is separate from a firm's assimilation of external spillovers (see, e.g., Boeing & Hunerman, 2020; Chatterjee et al., 2018; Hecht, 2018). Yet, AC studies find strategic alliances offer an important source of external spillovers and that the assimilation of these external experiences is central to a firm's innovations (e.g., Akram et al., 2020; Santoro et al., 2018; West & Bogers, 2014). Hence, the challenge facing PF explanations is that because of its autarkic orientation, the role of these alliances on a firm's R&D assimilative function and their impact on a firm's innovations are excluded from PF explanations of the R&D-innovation process. These shortcomings motivate the following research questions: how do diminishing returns impact a firm's R&D-innovation process and how does the assimilation of alliance experiences influence this process?

To address these research questions, a concept of AC is developed that integrates PF's law of diminishing returns into the associative learning processes of a firm's R&D. This study argues that a firm's R&D is subject to an associative learning process in which the firm favors an assimilation that exploits its existing technical abilities. This exploitation exhibits a diminishing returns effect in which increasing R&D investments diminishes a firm's ability to innovate new products from its R&D expertise. This study also argues that these declines place increasing pressures on a firm's R&D to assimilate distant experiences. This assimilation involves exploring new products from the firm's R&D in which increasing R&D investments increases a firm's product innovations. Furthermore, by leveraging R&D's assimilative role, a firm's R&D increases its ability to identify alliances that complement its scientific knowledge. These complimentary relationships moderate a firm's AC to assimilate and commercialize those external experiences that can bring a firm's product to market. To examine these AC arguments, hypotheses were developed and empirically examined in the biotechnology industry. In using Poisson, Negative Binomial and Zero-Inflated Negative Binomial estimations, a biotechnology firm's R&D exhibit a robust U-shaped relationship to its product innovations and that this R&D-innovation process is positively moderated by its strategic alliances.

This study offers two key contributions to AC research. First, various AC studies have found that a firm's AC is linearly related to its innovative performance (see reviews Volberda et al., 2010; West & Bogers, 2014). By drawing on PF's diminishing returns, this study introduces an associative learning process that departs from the assimilation processes described in prevailing AC research (e.g., Aribi & Dupouet, 2016; Volberda et al., 2010; West & Bogers, 2014). This departure introduces nonlinear influences to the firm's R&D-innovation processes. This study's empirical findings not only confirm these nonlinear influences, but also that these influences offer opportunities to overcome myopic influences in a firm's innovation process. Second, this study argues that alliances offer opportunities to reveal new commercial uses to a firm's R&D. Specifically, while various internal mechanisms have explained a firm's commercialization of external experiences (Enkel et al., 2018; Xie, Zou, & Qi, 2018), this study argues and finds that this commercialization resides with a firm's alliance partners. As product innovations are increasingly driven by the feedback and experiences of supply chain members (Akram et al., 2020), this study supports this commercializing view in which a greater openness of a firm's R&D to its partner experiences is key to realizing its valued contributions.

2 | CONCEPTUAL/THEORETICAL DEVELOPMENTS

2.1 | Production function (PF) explanations of the R&D-innovation process

Having a long tradition in productivity research (Audretsch & Belitski, 2020; Bartelsman et al., 2019; Griliches, 1979), production function (PF) explanations have played an important role in explaining a firm's innovations (Boeing & Hunerman, 2020; Chatterjee et al., 2018; Hall et al., 2010; Hecht, 2018; Ravichandran et al., 2017). According to this PF approach, innovations involve an input–output relationship where a firm's output, Q, or total factor productivity, TFP, is related to its inputs. A firm's total factor productivity, TFP, is commonly calculated by its gross output, value-added, or sales (Boeing & Hunerman, 2020; Hall et al., 2010). A firm's TFP is then related to its inputs involving a firm's R&D expenditures, external knowledge spillovers, and other factor inputs, such as labor and physical capital stocks (Chatterjee et al., 2018; Hall et al., 2010; Hecht, 2018). With this input–output relationship, the principal task of a firm's R&D is to create new knowledge in a firm's production function in which new inventions or ideas are converted into products or processes that impact a firm's TFP (Audretsch & Belitski, 2020; Boeing & Hunerman, 2020; Chatterjee et al., 2018; Hall et al., 2010; Hecht, 2018; Ravichandran et al., 2017).

To explain the impact of a firm's R&D on its TFP, the law of diminishing returns has played a central role in PF studies (Cohen & Harcourt, 2003). The law of diminishing returns originated from an empirical observation of agricultural production in the 1800s (Cannan, 1892). Put forth by Malthus, the law is stated as follows:

> "The improvement of the barren parts would be a work of time and labour; and it must be evident to those who have the slightest acquaintance with agricultural subjects, that in proportion as cultivation extended, the additions that could yearly be made to the former average produce must be gradually and regularly diminishes" (Cannan, 1892, p. 5).

For instance, when engaging in farm production, farm managers will deploy their workers to their most productive land first, and as the productive potential of the land is depleted, workers are deployed to increasingly less productive lands. Because of this observation, the law of diminishing returns finds that successive uses of labor -as well as other forms of capital, such as land- have lowered productive values or valued uses than their earlier uses.

While contemporary markets differ from these early agrarian observations, the law of diminishing returns remains an important feature of a firm's R&D-innovation process (Boeing & Hunerman, 2020; Chatterjee et al., 2018; Graves & Langowitz, 1993, 1996; Hall et al., 2010; Hecht, 2018; Leiponen & Helfat, 2010; Ravichandran et al., 2017). This is because the law of diminishing returns impacts the optimal amounts of R&D investments -as well as other capital inputs- in the firm's production function. Specifically, by drawing on this law, PF explanations argue that the rate of returns to a firm's capital stock -including R&D- is inversely related to the quantity of capital stock used in the production function (Cohen & Harcourt, 2003). This rate of return is determined by a capital stock's marginal value product. The marginal value product is computed by taking the product of the capital stock's marginal productivity and the per-unit output price of the product/service produced by this capital stock. When applied to a firm's R&D, the law of diminishing returns dictates that increases in the quantities in a firm's R&D capital stock reduces this factor's marginal productivity and thus reduces the rate of returns to this factor input (Cohen & Harcourt, 2003). Since this rate of returns is influenced by the innovative outcomes produced by a firm's R&D (Chatterjee et al., 2018; Hecht, 2018; Leiponen & Helfat, 2010; Ravichandran et al., 2017), this lower rate of return would be associated with reductions in a firm's ability to introduce new products to the markets. That is, by following the law of diminishing returns, higher levels of R&D expenditures are associated with lower product innovations than lower levels of R&D (Chatterjee et al., 2018; Graves & Langowitz, 1993; Martínez-Sánchez et al., 2020).

Several studies have shown support for such diminishing effects. For instance, as a firm's patents signal an intent to commercialize new product inventions, Graves and Langowitz (1996) drew on a Cobb–Douglas approach to find that increases in a firm's R&D exhibited diminishing returns to a firm's patent counts. In terms of a firm's product developments, Graves and Langowitz (1993) pharmaceutical study found increases in a biotechnology firm's R&D budget reduced the discovery of new chemical entities (NCE) (i.e., therapeutic compounds). These diminishing returns are consistent with Knott's (2002) study, who found that pharmaceutical firms, such as Pfizer, can improve their innovative outcomes by *reducing* their R&D budgets by \$3 billion/year. More recent developments by Hecht (2018) have supported similar diminishing returns to a firm's R&D, in which such diminishing effects were robust to a variety of hi-technology industries (see also Boeing & Hunerman, 2020; Chatterjee et al., 2018). By drawing on these observations, diminishing returns are defined by an R&D-innovation process in which increases in a firm's R&D are associated with a declining number of product innovations that can be commercialized by a firm's R&D expertise.

While such diminishing returns have been well established in R&D productivity research, the firm-level processes that contribute to such returns have largely escaped the attention of PF researchers. Penrose's (1959) theory of the growth of the firm offers insights into understanding this firm-level process. According to Penrose (1959), the firm's inputs consist of a bundle of assets/resources in which the task of the senior leader is to discover outputs or productive uses from these resource inputs. This discovery process is subject to a Penrose effect, where senior leaders are an "accelerator and brake" to the firm's growth. Senior engages in planning activities that discover new products from its resources to which "accelerate" a firm's rate of growth. Yet, since senior leaders also face operational demands to run their firm efficiently, these demands "brake" or constrain the senior leader's planning activities and thus reducing the firm's ability to discover new products. As R&D expenditures are an important resource/asset to generating new product opportunities, the Penrose effect suggests that senior leaders are engaged in planning activities to accelerate the discovery of commercial opportunities from its firm's R&D. These planning activities enable the leader to identify R&D projects with high internal rates of return (IRR) and thus accelerate the firm's rate of growth. However, as senior leaders also face pressures to manage the demands of their existing R&D-innovation pipeline, senior leaders face constraints in their time and effort to discover projects with high rates of IRR. These constraints introduce a "brake" that reduces the IRR from its R&D projects. This braking effect suggests that despite increases in a firm's R&D investment, firms will find it increasingly difficult to identify new product innovations from its R&D process (see also Rothaermel & Alexandre, 2009). These declines are consistent with PF explanations of diminishing returns.

While the Penrose effect offers firm-level insights to explaining the diminishing returns to a firm's R&D, both Penrose and PF approaches however do not recognize that a firm's R&D exhibits a dual function (e.g., Boeing & Hunerman, 2020; Chatterjee et al., 2018; Hall et al., 2010; Hecht, 2018). A firm's R&D exhibits a duality in which a firm's R&D involves not only the creation of new knowledge, but also the assimilation of external experiences. PF studies have long recognized that a firm's innovation is influenced by external knowledge spillovers. However, these external spillovers are often represented as an input that is separate from a firm's R&D (Boeing &

Hunerman, 2020; Chatterjee et al., 2018; Graves & Langowitz, 1993, 1996; Griliches, 1979; Hall et al., 2010; Hecht, 2018; Knott, 2002; Martínez-Sánchez et al., 2020; Tung & Binh, 2022). The challenge with this separability is that it removes consideration of an R&D's assimilative function and, with this removal, PF studies -as well as Penrosean explanations- do not consider the impact of this assimilation on a firm's innovation process.

2.2 | Firm's absorptive capacity (AC): Assimilation of external experiences

To address this shortcoming in both PF and Penrosean research, Cohen and Levinthals' (1990) concept of absorptive capacity (AC) has been a seminal influence in explaining a firm's assimilation of external experiences. Cohen and Levinthal (1990) argued that "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends is critical to its innovative capability" (p. 128). This ability refers to a firm's absorptive capacity (AC) where a firm's stock of prior knowledge is a central building block to a firm's AC (Cohen & Levinthal, 1990; Volberda et al., 2010; West & Bogers, 2014). This stock of prior knowledge has been commonly explained in terms of a firm's R&D because R&D offer scientific experiences that enable the firm to relate and assimilate external technical advances (Cohen & Levinthal, 1990; Denicolai et al., 2016; Kostopoulos et al., 2011; Moilanen et al., 2014; Ng et al., 2018). Specifically, this stock of scientific knowledge underscores an important associative learning process. A firm's associative learning involves storing external information events into a firm's memory or prior experiences and that these experiences enable the firm to form associations to other related information events (Cohen & Levinthal, 1990). A consequence of this associative learning process is that increases in a firm's R&D increase a firm's stock of scientific knowledge to which increases a firm's ability to relate and recognize the value of external technical advances. This recognition enables the firm to assimilate external advances into a firm's R&D experience and thus develops a firm's capacity to commercialize new products from a firm's R&D experience (Denicolai et al., 2016; Kostopoulos et al., 2011; Laursen & Salter, 2006; Moilanen et al., 2014; Rothaermel & Alexandre, 2009; Santoro et al., 2020).

By drawing on a firm's stock of R&D experience, a firm's R&D introduces an associative learning process that informs the linearity assumptions of AC research (Brettel et al., 2011). That is, AC operates on a linearity assumption that increases in a firm's AC increase its innovative performance (Todorova & Durisin, 2007; Zahra & George, 2002). This linearity assumption is influenced by the associative learning processes of a firm's R&D. This is because, as a firm increases its stock of scientific experiences or R&D, it not only offers efficiencies in assimilating external information, but that this assimilation reinforces a firm's R&D expertise to commercialize this external information. This associative learning process thereby introduces a positive or linear relationship in the firm's R&D-innovation process and is implicit in a variety of AC explanations (e.g., Akram et al., 2020; Laursen & Salter, 2006; Ng et al., 2018; Rothaermel & Alexandre, 2009). For instance, Laursen and Salters' (2006) U.K. manufacturing study found a firm's R&D intensity was positively and significantly related to a firm's number of radical and incremental product innovations. Furthermore, as product innovations are influenced by a firm's patent behaviors, Ng et al. (2018) and Rothaermel and Alexandres' (2009) studies respectively found a firm's R&D was positively and significantly related to a firm's patent claims and patents (see also Kostopoulos et al., 2011; Moilanen et al., 2014). These positive relationships have also been confirmed by dynamic capability (DC) explanations of the AC concept (Martínez-Sánchez et al., 2020; Todorova & Durisin, 2007; Zahra & George, 2002). According to this DC view, a firm's AC consists of a potential -acquisition and assimilation- and realized -transformation and exploitation–components in which various studies have reported a positive and linear relationship to a firm's innovative performance (Akram et al., 2020; Huang et al., 2018; Kang & Lee, 2017). For instance, in using survey responses from R&D employees, Kang and Lee (2017) found a firm's potential and realized AC were positively and linearly related to a firm's innovative behavior.

2.3 | Law of diminishing returns in the R&D innovation process

Due the linearity assumptions and findings of AC research, PF's law of diminishing returns has been largely ignored in mainstream AC research. This is because this linearity operates on an assumption that the associative learning processes of a firm's R&D offer innovative benefits that outweigh its costs (see also Brettel et al., 2011; Cohen & Levinthal, 1990; Denicolai et al., 2016; Lichtenthaler, 2016). Yet, this linearity assumption has been challenged by benefit–cost explanations of the AC concept. A small but growing body of AC research recognizes that a firm's R&D knowledge is subject to a variety of costs (Brettel et al., 2011; Denicolai et al., 2016; Lichtenthaler, 2016). For instance, as the valued uses of external knowledge are highly context specific, Lichtenthaler (2016) argued firms that lack the requisite scientific or R&D knowledge face costs in assessing these valued uses. In addition, Lichtenthaler (2016) argued a firm's R&D knowledge exhibits a tacit or non-codified dimension in which there is an assimilation cost to codifying this tacit knowledge to its R&D members (see also Kang & Lee, 2017; Laursen & Salter, 2006; Lichtenthaler, 2016). Last, a firm's R&D faces costs of exploiting or commercializing external experiences. These costs involve developing new learning processes, cultures, and decision structures that integrate this eternal knowledge into a firm's R&D expertise (e.g., Laursen & Salter, 2006; Xie, Zou, & Qi, 2018).

While these and other related costs can introduce diminishing returns to a firm's innovations, the influence of PF's law of diminishing returns on the associative learning processes of a firm's R&D has yet to be examined in any AC research (Brettel et al., 2011; Leiponen & Helfat, 2010; Lichtenthaler, 2016). Hence, this study argues that these diminishing returns can play an important influence on the associative learning processes in a firm's R&D. This study argues that increases in a firm's R&D favor an assimilation in which the exploitation of nearby experiences diminishes the valued uses of a firm's R&D's valued uses. While consistent with the law of diminishing returns, this study also argues that increasing R&D can introduce an associative learning process that overcomes such diminishing returns. This process involves an assimilation in which the exploration of distant experiences reveals valued uses from the firm's R&D. Thus, unlike the linearity assumption and findings of AC research, increasing R&D investments have a declining as well as an increasing effect on a firm's product innovations.

To elaborate on these associative learning processes, this study appeals to behavioral explanations. According to behavioral explanations (Levinthal & March, 1993), firms favor an exploitation of local or nearby experiences over the exploration of more distant experiences. This is because exploitation builds on the firm's existing competencies and offers more immediate and less uncertain returns than exploration (Levinthal & March, 1993). This exploitation is consistent with Cohen and Levinthal's (1990) associational learning process. Cohen and Levinthal (1990) argued that firms form associations to closely related external information because “learning performance is greatest when the object of learning is related to what is already known” (p. 131). A firm's R&D offers a stock of technical experiences that are not only key to realizing the benefits of this associative learning process, but as result of this learning process, it seeks to exploit closely related external experiences that reinforce a firm's stock of R&D experiences (Cohen & Levinthal, 1990;Lin et al., 2012; Schildt et al., 2012). By assimilating these proximate or nearby experiences, exploitation builds on a firm's existing technical knowledge because firms can learn from the closely related experience of others. A consequence of this exploitation is that it increases a firm's R&D stock of experiences to which increases a firm's efficiencies to exploit closely related experiences in future periods (see also Cohen & Levinthal, 1990; Ng et al., 2018).

While this exploitation affirms the associative learning processes of a firm's R&D, this study adds that this exploitation is subject to “diminishing return effects”. Namely, as an increasing investment in R&D favors an exploitation of nearby external experiences, this exploitation restricts the firm from exploring more distant knowledge experiences (see Rothaermel & Alexandre, 2009). For instance, Ravichandran et al. (2017) find that hi-technology firms, such as Pfizer, sought to exploit external developments in information technology to discover new ways to utilize their R&D capabilities in drug development. Yet, as investments in a firm's R&D favor an exploitation of nearby experiences, this exploitation drives out efforts to explore new valued added applications of a firm's R&D. This exploitation has been explained by myopic explanations of AC research. Cohen and Levinthal (1990) and others (Lin et al., 2012; Schildt et al., 2012) argue and find that an increasing exploitation of closely related external experiences can produce an “inward-looking absorptive capacity” (Cohen & Levinthal, 1990) that reduces a firm's innovation (see also Diaz-Diaz & Saa-Perez, 2014). This study argues that this inward-looking AC can be explained by an associative learning process in which increasing R&D expenditures yield an exploitation that diminishes a firm's ability to develop new product innovations (see also Rothaermel & Alexandre, 2009). This diminishing ability stems from the marginal value product explanations of PF research that find a R&D's marginal value product -involving its product innovations- is inversely related to its expenditure levels (Cohen & Harcourt, 2003; Graves & Langowitz, 1993; Knott, 2002). By drawing on this inverse relationship, PF explanations introduce a diminishing return effect to the associative learning process, where increasing investments in a firm's R&D yields an exploitation that diminishes the valued added uses of a firm's R&D.

While this exploitation introduces these diminishing effects to a firm's product innovations, these declines can, however, induce an associative learning process that explores experiences distant from a firm's R&D expertise. These declines have been described by AC's concept of “activation triggers” (Zahra & George, 2002). An activation trigger refers to a situation where declines in a firm's performance, such as a crisis or bankruptcy, causes firms to explore opportunities distant from the firm's existing technical expertise. This activation trigger is consistent with behavioral explanations that argue declines in a firm's performance induce an exploration of distant experiences because the exploration of nearby experiences cannot solve a firm's declining performance (Ng, 2020). Various innovation studies find that this exploration exposes a firm to new problems and experiences and that this exposure offers new opportunities to apply a firm's R&D expertise in ways not previously considered (Enkel & Heil, 2014; Laursen & Salter, 2006; Xie, Wang, & Zeng, 2018). For instance, a biotechnology firm's R&D expertise in gene mapping has multiple commercial applications ranging from the development of therapeutic products to drought and disease resistant agronomic crops. To reveal these new value-added applications, an exploration of distant experiences offers opportunities to apply a firm's R&D to addressing the problems of different product-market domains (see also Enkel & Heil, 2014). However, to explore these value-added uses, greater R&D investments are required. These investments involve developing an R&D culture of norms, routines, and decision processes that open the firm's R&D expertise to new external developments. Through these greater R&D investments, the firm develops a more complex knowledge structure to assimilate and integrate distant experiences (e.g., Enkel et al., 2018; Laursen & Salter, 2006; Vasudeva & Anand, 2011; Xie, Wang, & Zeng, 2018). Hence, unlike the diminishing returns of PF research that argue for a reduction in a firm's investments in R&D (Knott, 2002), the associative learning process of a firm's R&D favors a greater commitment of R&D because this commitment offers an exploration that can overcome the diminishing effects of exploitation. These associative learning processes suggest that in drawing on the R&D's assimilative function, a firm's R&D has a nonlinear or U-shaped relationship to its product innovations where there are initially diminishing returns to the firm's exploitation of its R&D followed by an increasing return from exploring opportunities not found by its exploration. This pattern of search is consistent with Levinthal and March (1993) explanations.

Hypothesis 1. A firm's R&D has a U-shaped relationship with its product innovation.

2.4 | Strategic alliances

Since a firm's ability to assimilate external information is a central tenet of the AC concept, the sourcing of external knowledge is an important influence on a firm's R&D-innovation process. This external sourcing has been widely attributed to a firm's strategic alliances. Strategic alliances offer the firm access to external experiences/technologies/assets that extend the firm's internal technical expertise (Akram et al., 2020; Bogers et al., 2017; Kostopoulos et al., 2011; Santoro et al., 2018; Zobel, 2017). This external access is important to hi-technology firms because, as innovations have become increasingly complex, firms often lack the expertise to "go it alone" (Ng et al., 2018). As a result, various alliance, as well as AC studies, have argued and found that alliances are positively related to a firm's innovations (Akram et al., 2020; Bogers et al., 2017; Enkel & Heil, 2014; Kostopoulos et al., 2011; Laursen & Salter, 2006; Santoro et al., 2018; Zobel, 2017).

To elaborate, AC researchers argue that firms form alliances on the basis that they complement a firm's R&D (see also Denicolai et al., 2016; Kostopoulos et al., 2011; Moilanen et al., 2014). In particular, since a firm's R&D expenditure involves investments in basic scientific knowledge, this basic knowledge offers an AC that can identify the complementary relationships amongst its alliance members (Lane & Lubatkin, 1998). For instance, for a firm to recognize the value of genetic engineering and more recently Clustered Regularly Interspaced Short Palindromic Repeats (C.R.I.S.P.R.) technologies, a biotechnology firm must have at least some basic R&D expertise in subject areas, such as biochemistry, bio information, recombinant DNA technology, molecular biotechnology, and genetics (see also Lane & Lubatkin, 1998). Having such basic scientific knowledge enables the firm to identify how the technical advances of strategic alliance partners can fit or complement their internal R&D expertise. Furthermore, since investments in a firm's R&D are focused on commercializing new products and services (Cohen & Levinthal, 1990; Kostopoulos et al., 2011; Todorova & Durisin, 2007; Zahra & George, 2002), these R&D investments can promote the identification of those commercializing assets that can bring a firm's inventions to the market. For instance, a firm can form alliances with partners who possess commercializing assets, such as manufacturing, distribution, supplier, and marketing/brand development-related assets. Yet, since the identification of these complementary assets depends on a firm's R&D, a firm's R&D offers basic knowledge that not only enables the firm to identify these complementary relationships, but this identification increases a firm's R&D to commercialize on these external developments. With this R&D knowledge, a firm can engage in the sourcing of external alliances that complement the product innovations benefits of a firm's R&D. In that, as alliances can bridge a firm's internal R&D expertise to different external experiences, alliances offer an important bridging function where the firm's exploration of new external expertise complements the firm's exploitation of its internal R&D. Because of this bridging function, alliances reinforce the product innovation benefits of the firm's R&D.

> **Hypothesis 2.** A firm's strategic alliances positively moderate a firm's R&D.

3 | METHOD

3.1 | Data and sample

This study's hypotheses were empirically examined in the U.S. biotechnology industry. A sample of 519 public biotechnology firms was drawn from the 2005 "BioScan" database. The BioScan database consists of life science and pharmaceutical companies that span the four-digit standard industrial classification (SIC) codes of 2833, 2834, 2835, and 2836. This sample includes companies such as Monsanto, Dow Chemical, Genentech, and Pfizer, among others. The BioScan database contains various sources of firm-level data that include a firm's merger and acquisitions (M&As), number of employees, employees with advanced training (i.e., Ph.D.), and strategic alliances and is regarded as one of the most reliable database in the biotechnology industry (Ng et al., 2018; Rothaermel & Deeds, 2004). In addition to the BioScan data, this study draws on financial data from the Mergent online database. Data on the firm's revenues, R&D expenditures, and SIC code information was collected for the 2005 period and combined with our BioScan data. A resulting 310 observations for the 2005 sampling year were available to construct the variables used in this study's empirical examination.

3.2 | Measures: Dependent variable

3.2.1 | Innovative performance

A firm's innovative performance is measured by the number of its commercialized products, *Product_Mkt* (see also Huang & Rice, 2012; Kostopoulos et al., 2011; Leiponen & Helfat, 2010; Ng, 2011a, 2011b; Zahra & George, 2002; Zobel, 2017). The BioScan data includes a listing of products that the firm has completed clinical trials and/or has obtained FDA regulatory approval. A firm's product innovations, *Product_Mkt*, is a count of the products that have met these requirements (Ng, 2011a, 2011b).

3.3 | Measures: Independent variables

3.3.1 | Absorptive capacity

While AC has been measured along various dimensions, the focus of this study is on the R&D aspects of AC (e.g., Cohen & Levinthal, 1990; Kostopoulos et al., 2011; Leiponen & Helfat, 2010; Lin et al., 2012; Rothaermel & Alexandre, 2009; Volberda et al., 2010). This is because R&D expenditures reflect a firm's stock of scientific expertise that captures the firm's associative learning process and is a central measure in PF explanations (Boeing & Hunerman, 2020; Chatterjee et al., 2018; Hall et al., 2010; Hecht, 2018). To measure this stock of scientific expertise, the firm's annual R&D expenditures were used (see also Laursen & Salter, 2006; Santoro et al., 2020). This is because while a firm's AC reflects a stock of accumulated R&D experiences, the biotechnology industry faces rapid technological advances where senior managers place greater weight on recent experiences than their accumulated experiences. This is consistent with Bromiley and Harris (2014) behavioral studies of hi-technology industries where they find senior managers place greater weight on recent experiences because they are more relevant in relating to external technological advances (see also Tyler & Caner, 2016). Due to the skewness of the R&D expenditure variable, the log of a firm's R&D expenditures, *R&D*, was used (Leiponen & Helfat, 2010). To capture its nonlinear influences, the *R&D*^{2} variable was included.

3.3.2 | Strategic alliances

A firm's strategic alliances, *Alliances*, were constructed by aggregating the firm's Licensing, Research and Development (R&D), Marketing, Manufacturing, Commercializing, Supply, and Distribution agreements in the BioScan database. Biotechnology studies have drawn on this aggregation to measure a biotechnology firm's access to complementary experiences (e.g., Kostopoulos et al., 2011; Ng, 2011b; Rothaermel & Deeds, 2004). To examine the moderating influences of a firm's strategic alliances, an interaction term involving the product of a firm's *Alliances* and *R&D* variables were constructed, *R&D*Alliances* (see also Rothaermel & Alexandre, 2009; Santoro et al., 2020).

3.3.3 | Control measures

A firm's Mergers and Acquisitions (M&As) were used because M&As can broaden a biotechnology firm's technological base and can increase a firm's innovation (Jo et al., 2016). A firm's M&As variable, *M&As*, was measured by aggregating a firm's number of merger and acquisition activities. In addition, a firm's age can introduce myopic tendencies to a firm's innovation (Kostopoulos et al., 2011; Ng, 2011a), and thus a biotechnology firm's age, *Firm_Age*, was included. To control for scale effects, a firm's total assets, *Total_Assets*, and employees, *Employees*, were used (Kostopoulos et al., 2011; Ng, 2011a, 2011b). Specifically, employees were used because the number of employees can account for other AC found outside of a firm's R&D process (Santoro et al., 2020). A firm's market share was included because it can impact incentives to invest in a firm's R&D (Hecht, 2018). The firm's market share, *Market_Share*, was computed by taking the ratio of a firm's revenue to the total revenue across all four SIC codes. This is because, while a firm's market share by SIC was considered, prior studies have shown that biotechnology firms have diversified into various subsectors (Breschi et al., 2003; Leten et al., 2007). This study's market share variable was created to account for this diversification. Last, due to differences in the regulation of biotechnology products, a firm's SIC classification information was included (see also Hecht, 2018; Santoro et al., 2020). This included SIC codes 2833, 2834, 2835, and 2836 that have been associated with the biotechnology industry (see also Ng & Sanchez-Aragon, 2022; Rothaermel & Deeds, 2004).

3.4 | Econometric estimation

Since a biotechnology firm's product innovations, *Product_Mkt*, involve count data, a Poisson count estimation procedure is appropriate (Blevins et al., 2015). However, Poisson estimations assume the count data have a mean–variance equivalence or equi-disperson (Blevins et al., 2015). A Likelihood-ratio (LR) test was computed to examine violations of this mean–variance assumption. The LR test of alpha rejects the null hypothesis of a mean–variance equivalence (the LR test varies from 758 to 1240 for all six models estimated, see Table 3). This rejection favors a Negative Binomial estimation procedure because it includes a parameter value that controls for over dispersion. Yet, the challenge with Negative Binomial estimations is that problems of over-dispersion can still arise, especially when there are excessive zeros counts in the data (Antonakis et al., 2014). In our data, 26% of our biotechnology firms have 0 product innovations, *Product_Mkt* (see Table 4). A Zero-Inflated Negative Binomial estimation (ZINB) can account for these excessive zeros. A ZINB estimation consists of a two-step procedure in which a logit model includes an inflated variable(s) to predict the excessive zeros in the count data. The second step takes the results from this zero-inflated model and combines it with a Negative Binomial count model (for further description Blevins et al., 2015). The challenge with ZINB models is that few studies offer a theoretical rationale for their choice of inflated variable(s) (Blevins et al., 2015). In identifying this study's inflated variable, a biotechnology firm's age, *Firm_Age*, was chosen. The reasoning is that younger or inexperienced biotechnology firms lack the experience or knowledge to assimilate and commercialize their R&D experiences and thus face greater challenges in commercializing their products. These firms are thereby likely to explain the excessive zeros in our data. In Table 4, the coefficient estimates for the inflated age variable, *Firm_Age*, were significant ($p < .05$) in all six model specifications. A biotechnology firm's age, *Firm_Age*, thereby appears to be appropriate for modeling the excessive zero counts in the ZINB estimations. Yet, as AC studies have used Poisson and Negative Binomial estimation approaches (e.g., Graves & Langowitz, 1993; Ng, 2011a, 2011b), this study reports the results for the Poisson, Negative Binomial, and Zero-Inflated Negative binomial (ZINB) estimations. All estimations are reported using the Stata 16 software package.

4 | RESULTS

The descriptive statistics and correlations are shown in Table 1. Table 1 shows some moderate to high correlations. As these correlations can raise potential multicollinearity problems, a Variance Inflation Factor (VIF) Test[2] shows a mean value of 3.39. This mean value is less than the critical value of 10 and thus multicollinearity is not an issue. The coefficient estimates for each variable in the Poisson, Negative Binomial, and ZINB estimators are shown in the respective Tables 2–4.

TABLE 1 Summary statistics and Correlations.

Variables	Mean	Std. dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) (Product_Mkt)	4.84	9.15											
(2) (Total_Assets)	18.94	2.54	0.3653										
(3) (Employee)	4301.16	16897.08	0.3712	0.5709									
(4) (Firm_Age)	29.00	34.08	0.2309	0.5430	0.5453								
(5) (M&As)	1.66	3.31	0.5613	0.4670	0.3498	0.2795							
(6) (Market_Share)	0.00	0.02	0.3869	0.6199	0.9309	0.5552	0.3771						
(7) (sic_2833)	0.01	0.12	−0.0185	−0.0650	−0.0328	−0.0226	−0.0542	−0.0354					
(8) (sic_2834)	0.36	0.48	0.0052	0.1665	0.1270	0.0426	0.0124	0.1324	−0.1026				
(9) (sic_2835)	0.09	0.29	0.1627	−0.1767	−0.0865	−0.0739	0.0835	−0.0934	−0.0427	−0.2794			
(10) (sic_2836)	0.18	0.38	−0.1078	−0.0924	−0.1261	−0.1165	−0.0819	−0.1219	−0.0673	−0.4400	−0.1833		
(11) (R&D)	16.91	2.14	0.2802	0.8686	0.5275	0.4152	0.3776	0.5673	−0.0850	0.2722	−0.2304	−0.0500	
(12) (Alliances)	129.37	226.77	0.5460	0.5317	0.5482	0.3098	0.4271	0.5940	0.0182	0.1846	−0.0641	−0.0385	0.5534

In explaining the coefficient estimates for this study's control variables, a firm's *M&As*, was positive and significant at the 1% level in all count estimations and are consistent with our expectations (see also Jo et al., 2016). A biotechnology firm's age, *Firm_Age*, was generally negative and significant in the Poisson estimations. For instance, Table 2 estimations vary from $\beta_2 = -.00184$ (p < .05) in model 2 to $\beta_6 = -.00310$ (p < .01) in model 6; but was not significant in the Negative Binomial (Table 3) and ZINB estimations (Table 4). In controlling for a firm's scale effects, a firm's total assets, *Total_Assets*, were positive and significant for all count estimations, while the employee variable, *Employee*, was positive and significant for a subset of these estimations. The SIC dummies, especially SIC codes 2834 and 2836 were significant in all estimations.[3]

In examining the main variables of interest, *R&D*, and *R&D²*, all count estimations show the coefficient estimates on both these variables were respectively negative and positive and were significant. For instance, in Table 2, the Poisson estimates for *R&D* and *R&D²* variables in model 3 were $\beta_3 = -2.002$, (p < .01) and $\beta_3 = .0582$ (p < .01), respectively. The Negative Binomial estimations in Table 3 and model 3 were $\beta_3 = -2.416$ (p < .01) and $\beta_3 = .0652$ (p < .01). Similarly, the ZINB estimations in Table 4 in model 3 were $\beta_3 = -2.253$(p < .01) and $\beta_3 = .0613$ (p < .01). The negative and significant count estimates on the R&D variable indicate that increases in a firm's R&D variable, *R&D*, were associated with a declining number of product innovations. These negative findings are consistent with this study's diminishing return effect explanations. In addition to these diminishing effects, the positive and significant effects of the R&D², *R&D²*, variable indicate increasing R&D investments lead to increasing product innovations. Hypothesis 1 cannot be rejected.

To examine the moderating influences of a firm's strategic alliances on a firm's R&D, model 4 in Tables 2–4 show the estimates of the moderating variable, *R&D*Alliances*. In model 4, the strategic alliance moderating variable, *R&D*Alliances*, was positive and significant in the Poisson ($\beta_4 = .00129$, p < .01, Table 2), Negative Binomial ($\beta_4 = .00176$, p < .01, Table 3) and ZINB ($\beta_4 = .00175$, p < .01, Table 4) estimations. These positive moderating results suggest alliances exhibit a complementary effect on a firm's R&D-innovation process. Yet, since alliances have also been widely associated with a firm's innovation, these complementary effects are also examined jointly with the *Alliances* variable. This variable was entered in model 5 and the joint effects of the *Alliances* variable and its moderating influence, *R&D* Alliances*, were included in model 6. With model 5, Poisson ($\beta_5 = .0256$, p < .01, Table 2), Negative Binomial ($\beta_5 = .0345$, p < .01, Table 3) and ZINB ($\beta_5 = .346$, p < .01, Table 4) show that *Alliances* have a positive and significant effect on a firm's product innovations, *Product_Mkt*. This finding is consistent with alliance studies that emphasize the importance of external relations on a firm's innovations (see also e.g., Akram et al., 2020; Kostopoulos et al., 2011; Ng, 2011a, 2011b; Santoro et al., 2018; Zobel, 2017).

However, when examining both the Alliances and moderating alliance, R&D*Alliance, variables, model 6 shows that these variables were significant in the Poisson (*Alliances*: $\beta_6 = -.101$, p < .01; *R&D*Alliances:* $\beta_6 = .00613$, p < .01, see Table 2), but not in the Negative

TABLE 2 Poisson estimations (Product_Mkt).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Total_Assets	0.151***	0.262***	0.200***	0.216***	0.214***	0.220***
	(0.0150)	(0.0281)	(0.0308)	(0.0307)	(0.0307)	(0.0309)
Employee	5.63e-06***	6.30e-06***	2.88e-06	9.12e-08	7.50e-07	−1.60e-06
	(1.07e-06)	(2.07e-06)	(2.39e-06)	(3.06e-06)	(2.93e-06)	(3.43e-06)
Firm_Age	0.000431	−0.00184**	−0.00282***	−0.00247***	−0.00231***	−0.00310***
	(0.000745)	(0.000931)	(0.000879)	(0.000898)	(0.000895)	(0.000914)
M&As	0.103***	0.102***	0.0917***	0.0895***	0.0888***	0.0926***
	(0.00503)	(0.00547)	(0.00559)	(0.00567)	(0.00566)	(0.00573)
Market_Share	−4.549**	3.200	−29.71***	−21.75**	−20.89**	−28.10***
	(1.821)	(6.339)	(7.673)	(9.076)	(8.796)	(10.00)
s2833	0.263	0.303	−0.0464	−0.292	−0.319	−0.157
	(0.230)	(0.250)	(0.251)	(0.251)	(0.252)	(0.252)
s2834	−0.115*	−0.0256	−0.344***	−0.524***	−0.509***	−0.538***
	(0.0593)	(0.0728)	(0.0775)	(0.0804)	(0.0800)	(0.0811)
s2835	0.879***	0.870***	0.807***	0.681***	0.687***	0.683***
	(0.0820)	(0.0867)	(0.0841)	(0.0830)	(0.0831)	(0.0829)
s2836	−0.205**	−0.158*	−0.408***	−0.547***	−0.529***	−0.583***
	(0.0830)	(0.0912)	(0.0931)	(0.0937)	(0.0935)	(0.0946)
R&D		−0.147***	−2.002***	−1.350***	−1.402***	−1.294***
		(0.0280)	(0.133)	(0.148)	(0.147)	(0.150)
R&D^2			0.0582***	0.0358***	0.0376***	0.0339***
			(0.00421)	(0.00473)	(0.00470)	(0.00478)
R&D*Alliances				0.00129***		0.00613***
				(0.000103)		(0.00102)
Alliances					0.0256***	−0.101***
					(0.00213)	(0.0213)
Constant	−1.635***	−1.237***	14.63***	9.723***	10.09***	9.381***
	(0.287)	(0.327)	(1.168)	(1.280)	(1.272)	(1.290)
Observations	310	259	259	259	259	259
Number of Obs	310	259	259	259	259	259
LR-χ^2	1348	1348	1529	1681	1666	1705
Pseudo-R^2	0.324	0.362	0.410	0.451	0.447	0.458
LogLikelihood	−1408	−1188	−1098	−1022	−1029	−1010

Note: Standard errors in parentheses.
***$p < .01$; **$p < .05$; *$p < .1$.

Binomial and ZINB estimations (see Tables 3 and 4, respectively). These latter findings suggest that alliances and their moderating influences cannot be used jointly in developing a firm's product innovations. One explanation for this finding is that since a reliance on external partnerships can hollow out a firm's technical abilities (e.g., Denicolai et al., 2016; Rothaermel & Alexandre, 2009), these alliances can reduce a firm's R&D. This reduction in a firm's R&D reduces its ability to discover the complementary relationships with its alliance members. The lack of significance found in the joint effects of a firm's alliances, *Alliances*, and its moderating influence on a firm's R&D, *R&D*Alliance*, in model 6 of Tables 3 and 4 are consistent with this explanation. However, since the focus of moderation effects is on the significance of interaction effects and not the significance of the main effects, the estimates for the *R&D*Alliance* variable in model 4 in Tables 2–4, show robust support for these moderation effects. Hypothesis 2 cannot be rejected.

4.1 | Ex-post analysis

To examine the robustness of this study's main findings, alternative specifications of the firm's R&D were used. Specifically, as firm's AC

TABLE 3 Negative Binomial estimations (Product_Mkt).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Total_Assets	0.0975***	0.393***	0.308***	0.357***	0.361***	0.356***
	(0.0360)	(0.0862)	(0.0818)	(0.0800)	(0.0806)	(0.0805)
Employee	1.13e-05**	−1.74e−06	3.70e−06	4.73e−07	1.88e−07	5.07e−-07
	(5.49e−06)	(2.02e-05)	(1.78e-05)	(1.22e-05)	(1.25e-05)	(1.22e-05)
Firm_Age	0.00326	0.000762	−0.000636	−0.00127	−0.00113	−0.00129
	(0.00274)	(0.00381)	(0.00359)	(0.00325)	(0.00326)	(0.00325)
M&As	0.116***	0.111***	0.107***	0.0983***	0.0986***	0.0983***
	(0.0261)	(0.0259)	(0.0249)	(0.0236)	(0.0236)	(0.0236)
Market_Share	−5.697	52.42	−30.79	−41.96	−38.41	−42.35
	(4.983)	(59.43)	(53.76)	(39.04)	(39.96)	(39.38)
s2833	−0.0108	−0.244	−0.207	−0.800	−0.872	−0.790
	(0.585)	(0.646)	(0.623)	(0.634)	(0.644)	(0.651)
s2834	−0.493***	−0.442**	−0.543***	−0.575***	−0.562***	−0.576***
	(0.182)	(0.208)	(0.199)	(0.191)	(0.192)	(0.192)
s2835	0.501*	0.279	0.258	0.219	0.219	0.219
	(0.275)	(0.285)	(0.272)	(0.263)	(0.264)	(0.263)
s2836	−0.395*	−0.538**	−0.721***	−0.761***	−0.752***	−0.761***
	(0.215)	(0.230)	(0.224)	(0.217)	(0.217)	(0.218)
R&D		−0.362***	−2.416***	−1.855***	−1.925***	−1.847***
		(0.0883)	(0.518)	(0.484)	(0.482)	(0.496)
R&D^2			0.0652***	0.0451***	0.0472***	0.0448***
			(0.0157)	(0.0150)	(0.0149)	(0.0154)
R&D*Alliances				0.00176***		0.00197
				(0.000449)		(0.00322)
Alliances					0.0345***	−0.00418
					(0.00884)	(0.0637)
Constant	−0.558	0.0683	17.66***	12.91***	13.36***	12.86***
	(0.656)	(0.753)	(4.394)	(4.102)	(4.096)	(4.156)
Lnalpha	0.315***	0.251**	0.138	0.0427	0.0463	0.0424
	(0.103)	(0.113)	(0.118)	(0.122)	(0.122)	(0.122)
Observations	310	259	259	259	259	259
LR-χ^2	102.1	112.8	132.1	148.4	148	148.4
Pseudo-R^2	0.0608	0.0800	0.0937	0.105	0.105	0.105
LogLikelihood	−787.9	−648.3	−638.7	−630.5	−630.7	−630.5
LR test	1240	1080	918.5	782.2	796.8	758

Note: Standard errors in parentheses.
***$p < .01$; **$p < .05$; *$p < .1$.

involves drawing on a stock of past R&D experiences, an aggregate measure of R&D expenditures covering multiple sampling periods (i.e., 3) was used. The firm's *R&D Stock* variable was constructed by aggregating the last three years of a firm's R&D expenditures. The *R&D* and *R&D^2* variables were then replaced and reestimated by the log form of the *R&D Stock* variable and its squared counterpart, *R&D Stock^2*. Furthermore, biotechnology studies find that R&D expenditure can be subject to a depreciation where annual depreciation rates have been reported between 10 and 20% (Ahmed & Cozzarin, 2009; Bosse & Alvarez, 2010; Deeds et al., 1997). To account for this depreciation, an annual depreciation rate of 15% (Bosse & Alvarez, 2010) for each of the three years was applied to the *R&D Stock* variable to creating the *R&D Stock Dep.* and *R&D Stock Dep.^{2}* variables (see Bosse & Alvarez, 2010). To examine the moderating influences of the firm's alliance variable on the *R&D stock* and *R&D Stock Dep.* variables, the product of the alliance variable, *Alliance*, and the *R&D stock—Alliance*R&D Stock-* and the *R&D Stock Dep.* variables *-Alliance*R&D Stock Dep.-* were created. Last, as a firm's AC can be influenced by the educational training of its employees (see Santoro et al., 2020 review), the number of employees with Ph.D. training,

TABLE 4 Zero-Inflated Negative Binomial Estimation (Product_Mkt).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Total_Assets	0.0976***	0.364***	0.282***	0.333***	0.338***	0.331***
	(0.0351)	(0.0862)	(0.0816)	(0.0791)	(0.0797)	(0.0797)
Employee	1.13e-05**	2.22e-06	5.91e-06	1.36e-06	1.18e-06	1.41e-06
	(5.09e-06)	(1.92e-05)	(1.68e-05)	(1.14e-05)	(1.17e-05)	(1.13e-05)
Firm_Age	0.00170	−0.000902	−0.00205	−0.00266	−0.00251	−0.00270
	(0.00259)	(0.00361)	(0.00342)	(0.00306)	(0.00308)	(0.00307)
M&As	0.106***	0.104***	0.101***	0.0912***	0.0915***	0.0912***
	(0.0244)	(0.0246)	(0.0237)	(0.0222)	(0.0223)	(0.0222)
Market_Share	−5.788	39.86	−33.78	−40.89	−37.78	−41.69
	(4.660)	(55.90)	(50.14)	(35.97)	(36.84)	(36.10)
s2833	−0.0335	−0.244	−0.224	−0.817	−0.892	−0.792
	(0.565)	(0.624)	(0.603)	(0.601)	(0.611)	(0.619)
s2834	−0.429**	−0.401*	−0.511***	−0.548***	−0.537***	−0.551***
	(0.180)	(0.207)	(0.198)	(0.188)	(0.188)	(0.188)
s2835	0.526**	0.323	0.309	0.273	0.273	0.273
	(0.268)	(0.279)	(0.268)	(0.257)	(0.258)	(0.257)
s2836	−0.354*	−0.510**	−0.698***	−0.741***	−0.733***	−0.743***
	(0.213)	(0.227)	(0.220)	(0.212)	(0.213)	(0.213)
R&D		−0.323***	−2.253***	−1.674***	−1.748***	−1.656***
		(0.0887)	(0.489)	(0.453)	(0.452)	(0.466)
R&D^2			0.0613***	0.0406***	0.0429***	0.0401***
			(0.0148)	(0.0140)	(0.0140)	(0.0144)
R&D*Alliances				0.00175***		0.00225
				(0.000423)		(0.00308)
Alliances					0.0346***	−0.00998
					(0.00841)	(0.0612)
Constant	−0.444	0.0497	16.57***	11.69***	12.16***	11.58***
	(0.642)	(0.731)	(4.130)	(3.821)	(3.821)	(3.874)
Inflate						
Firm_Age	−0.221***	−0.253**	−0.261**	−0.249**	−0.252**	−0.248**
	(0.0852)	(0.116)	(0.117)	(0.107)	(0.108)	(0.106)
Constant	0.923	1.015	1.052	1.062	1.065	1.061
	(0.960)	(1.188)	(1.199)	(1.124)	(1.135)	(1.121)
Lnalpha	0.152	0.118	0.00806	−0.122	−0.114	−0.123
	(0.125)	(0.135)	(0.138)	(0.145)	(0.143)	(0.145)
Observations	310	259	259	259	259	259
Zero-Obs	81	68	68	68	68	68
LR-χ^2	97.72	106.4	125.6	143.6	143.1	143.6
LogLikelihood	−784.1	−645.8	−636.3	−627.2	−627.5	−627.2

Note: Standard errors in parentheses.
***$p < .01$; **$p < .05$; *$p < .1$.

PhD Employees, was included in our models. Through these modifications, models 1–6 were then reestimated using the Poisson, Negative Binary, and Zero-inflated estimations.

In examining the nonlinear effects, the nonlinear estimates for the *R&D Stock* and *R&D Stock Dep*. variables were robust in all count estimations.[4] The estimate on the *R&D Stock* variable was negative and significant ($\beta_{\text{Poisson}} = -1.643$ ($p < .01$), $\beta_{\text{Negbin}} = -2.108$ ($p < .01$), $\beta_{\text{ZeroInf}} = -1.908$ ($p < .01$)), while the estimate on the *R&D stock variable*^{2} was positive and significant ($\beta_{\text{Poisson}} = .0403$ ($p < .01$), $\beta_{\text{Negbin}} = .0499$ ($p < .01$), $\beta_{\text{ZeroInf}} = .0455$ ($p < .01$)). Similarly, the *R&D Stock Dep*. and *R&D Stock Dep*.^{2} estimates remained significant and were respectively negative ($\beta_{\text{Poisson}} = -7.34$ ($p < .01$), $\beta_{\text{Negbin}} = -2.108$

($p < .01$), $\beta_{\text{ZeroInf}} = -7.053$ ($p < .01$)) and positive ($\beta_{\text{Poisson}} = .203$ ($p < .01$), $\beta_{\text{Negbin}} = .0499$ ($p < .01$), $\beta_{\text{ZeroInf}} = .193$ ($p < .01$)). Hypothesis 1 is robust to these different specifications of R&D. When examining the moderating influences of the *R&D*Alliance Stock* variable, it was positive and significant in the Poison estimation ($\beta_{\text{Poison}} = .00391$ ($p < .01$)) but not in the remaining count estimations. The moderating influences of *R&D Stock Dep.* Alliance* variable were not significant in any of the count estimation models ($\beta_{\text{Poisson}} = -.00143$ ($p > .1$), $\beta_{\text{Negbin}} = .00195$ ($p > .1$), $\beta_{\text{ZeroInf}} = -.00383$ ($p > .1$)). However, when replacing the *R&D Stock* Alliance** and *R&D Stock Dep.*Alliance* variables with the *R&D*Alliance* variable, the *R&D*Alliance* variable remained positive and significant ($\beta_{\text{Poisson}} = .00162$ ($p < .01$), $\beta_{\text{Negbin}} = .00160$ ($p < .01$), $\beta_{\text{ZeroInf}} = .00155$ ($p < .01$)). Hypothesis 2 is largely rejected for *R&D*Alliance Stock* and *R&D Stock Dept*Alliance Stock*. variables but not for the moderating influences of the *R&D*Alliance* variable. This suggests that the moderating influences of a firm's alliance may be influenced by more contemporary forms of R&D experiences than a firm's stock of accumulated R&D experiences. Future research is called for to examine this temporal distinction. Lastly, when examining the addition of the *PhD Employees* variable, it was not significant in the majority of the models. While this may suggest that the advanced training of employees (i.e., Ph.D.) does not have an impact on the firm's product innovation, such conclusions need to be tempered by the cross-sectional limitations of this study's data.

5 | DISCUSSIONS AND CONTRIBUTIONS TO THEORY

This study's findings advance understanding of AC research in three ways. First, by drawing on the diminishing returns to a firm's R&D, this study's associative learning process introduces an R&D-innovation process that differs from prevailing AC explanations. Despite their differences, most AC models follow a sequential assimilation process involving exploration, transformation, and exploitation (Aribi & Dupouet, 2016; Todorova & Durisin, 2007; Volberda et al., 2010; Zahra & George, 2002). This study's associative learning process reverses the explorative-transformation-exploitation sequence of AC research, in which a firm's exploitation precedes a firm's exploration. This study's associative learning process thereby not only offers an alternative to the explorative-transformation-exploitation sequence of AC research, but that this study's assimilation sequence also introduces nonlinearities to the AC-performance relationship. These nonlinearities have been confirmed with this study's empirical findings and thus offer insights into understanding the AC-performance relationship. In that, since AC is widely associated with a firm's innovative performance, a contribution of this study is that the "sequence" in which a firm assimilates external knowledge can impact this nonlinear performance relationship. This has direct implications for AC research because, while a firm's search for external knowledge has been widely associated with a firm's innovative performance (Akram et al., 2020; West & Bogers, 2014), the sequence in which a firm assimilates this external knowledge can also impact this performance.

Second, as risk preferences are an important influence on a firm's innovation, a firm's risk preference is implicit in this study's associative learning process. This risk preference involves an "uncertainty or risk" avoidance, in which a firm favors the exploitation of local experiences over the exploration of more distant experiences. Organizational learning (Levinthal & March, 1993; Ng, 2020) and AC research (Cohen & Levinthal, 1990; Volberda et al., 2010) have argued that this risk preference can generate myopic tendencies in which the benefits of AC cannot be assured (Cohen & Levinthal, 1990; Diaz-Diaz & Saa-Perez, 2014; Volberda et al., 2010). Yet, since diminishing returns to a firm's R&D results in a reduction in their performance, this reduction triggers greater risk-taking. Consistent with organizational learning research (Bromiley & Harris, 2014; Ng, 2020), this risk-taking behavior involves an exploration of distant experiences. Hence, a contribution of this study's associative learning process is that this risk preference has not been examined in the firm's assimilation process (see e.g., Akram et al., 2020; Chaudhary & Batra, 2018; Enkel et al., 2018; Xie, Wang, et al., 2018; Xie, Zou, et al., 2018). This risk preference implies that this study's associative learning process offers an assimilation in which a firm's exploitation can "drive in" the exploration of distance experiences. This assimilation is importance because it can overcome the myopic problems in organizational learning and AC research (see Diaz-Diaz & Saa-Perez, 2014; Levinthal & March, 1993; Volberda et al., 2010) and thus enable firms to more fully realize the innovative benefits of its AC.

Third and subsequently, while studies have shown that alliances can moderate various dimensions of a firm's AC (e.g., Santoro et al., 2018, 2020), this study's moderating effects are supported by a firm's R&D. This moderating effect is important for two reasons. First, open innovation research has shown that the growth of intellectual assets, involving a firm's R&D, has grown significantly amongst OECD countries (Grimaldi et al., 2017). Since R&D plays an important assimilative function, a firm's ability to leverage this assimilation function with a firm's alliance partners will be important to explaining a firm's innovations. Specifically, a contribution of this study is that by appealing to R&D's assimilative function, it introduces a non-separation to PF explanations. This non-separation argues that the marginal value product of a firm's R&D cannot be readily separated from the innovative contributions of a firm's alliances. This non-separation is important to AC research because a failure to recognize this non-separation can lead to an underinvestment in a firm's R&D and thus reduce a firm's AC to leverage the benefits of its alliance or supply chain partners. Second and relatedly, a firm's R&D often entails a significant "basic" research component in which the goal is to commercial R&D's valued uses. By forming partnerships with a firm's supply chain members, this study's moderating findings suggest alliances can introduce new valued or commercial uses to a firm's R&D. Hence, while various internal mechanisms have explained a firm's commercialization of external experiences (Xie, Zou, & Qi, 2018), this study's empirical findings suggest that a firm's AC to transform and apply external knowledge can also be influenced by those of its partners. Thus, unlike PF explanations, this study argues for a greater openness to explaining the commercializing aspects of a firm's R&D.

6 | MANAGERIAL IMPLICATIONS

This study's associative learning process emphasizes the importance of a manager's long-term commitment to its firm's R&D-innovation process. This commitment does not mean that managers should blindly make continual investments in their R&D (i.e., based on a fixed percentage of sales). But managers should develop a commitment to see through the pains of the diminishing returns in their R&D-innovation process. In particular, a manager's response to declining returns is not to reduce their commitments to a firm's R&D (Boeing & Hunerman, 2020; Chatterjee et al., 2018; Hall et al., 2010; Hecht, 2018; Knott, 2002; Ravichandran et al., 2017). Instead, managers should seek a commitment that applies its R&D to problems not previously considered. Such a commitment requires developing a greater collaboration with industry partners to identify technical or marketing problems that can be solved by a firm's R&D expertise. For instance, managers can institute data integration strategies that directly internalize customer-supplier feedback into the firm's R&D process (e.g., Chaudhary & Batra, 2018). With such commitments, managers can overcome the diminishing returns in their firm's associative learning process and thus more fully realize the innovative potential of their firm's R&D expertise.

In light of this study's findings and implications, it is important to outline this study's limitations. The firm's R&D-innovation process assumes that it is subject to an associative learning process (Cohen & Levinthal, 1990; Volberda et al., 2010). From an econometric standpoint, this associative process is unique to a firm's experience and thus should be estimated through a fixed effect panel estimation. Yet, due to the cross-sectional limitations of this study, such an approach is not possible with our data. Furthermore, even if such data were available, there are no estimation procedures available for a fixed effect panel estimation of count models, especially ZINB models. Future research is thus called for in developing this dynamic panel estimated approach. Last, while 2005 year has been noted for major breakthroughs in the biotechnology industry (AAAS, 2005; Bhattacharya, 2005), a limitation is that this study's findings should be reconfirmed with more current data. At the same, it should be noted that empirical examinations of the U-shaped relationship in AC research are rare. This study's data limitations should therefore be considered in light of its findings. In addition, while this study's estimation procedures provide robust support for its hypotheses, a more direct examination of the underlying associative learning process is called for in future research. Nevertheless, this study's empirical findings should be interpreted as offering tentative support for the proposed associative learning process and thus offer a starting basis to advance future work on the firm's R&D-innovation process. Last, an important boundary condition of this study is that it does not consider other forms of innovation, such as process innovations in the manufacturing sector and thus future research is called for to examine these alternative forms of innovation.

7 | FUTURE DIRECTIONS

In outlining some directions for future research, AC researchers have called for a greater need to develop a greater precision in understanding the AC concept (Song et al., 2018), Specifically, while a firm's capacity, competence, and capabilities have been associated with the firm's AC, they are often used interchangeably where researchers have called for greater need to understand their distinctions (Cegarra-Navarro et al., 2021; Cegarra-Sánchez et al., 2022; Nagarajan & Prabhu, 2015; Vincent, 2008). In developing these distinctions,[5] capacity emphasizes a potential to acquire and assimilate knowledge, competence involves reasoning skills to interpret different information phenomena and capabilities involve routines that exploit a unit's competence in solving novel problems (e.g. Cegarra-Navarro et al., 2021). These concepts of capacity, competence, and capability offer important parallels to better understand not only the recognition, assimilation, and exploitation dimensions of the AC concept, but also this study's R&D-innovation process.

For instance, with respect to the recognition dimension, a firm's capacity appeals to the firm's potential to recognize external experiences where this potential rests on developing the firm's stock of prior knowledge experiences (see also Cegarra-Sánchez et al., 2022). In this study's R&D-innovation process, this capacity involves increasing the firm's stock of R&D expertise where increases in the firm's R&D expenditures increases the firm's potential to recognize the external expertise of its alliance partners. By developing this capacity, it impacts the firm's ability to assimilate where this assimilation involves a competence or skill to interpret and integrate these alliance experiences into the firm's internal expertise. This competence involves developing efficiencies in the firm's R&D-innovation process to not only recognize the value of its external information, but to relate these external experiences in ways that could be understood by a firm's R&D expertise. Last, the firm's exploitation involves a capability where it exploits the firm competence to solve commercially valued problems. This exploitation involves developing learning routines that combine the assimilated information with the firm's internal expertise to reveal novel solutions to these problems. As this study R&D-innovation process involves recombining a firm's internal/external experiences (i.e., alliance), this capability is central to developing this innovation process. Hence, by drawing on the capacity, competence, and capabilities distinctions raised by innovation researchers (Cegarra-Navarro et al., 2021; Cegarra-Sánchez et al., 2022; Nagarajan & Prabhu, 2015; Vincent, 2008), they offer a greater understanding of the recognition, assimilation, and exploitation aspects of the R&D-innovation process. A future direction for this study is to empirically examine their diminishing effects.

8 | CONCLUSIONS

In both PF and AC approaches, a firm's R&D has played a central role in explaining a firm's innovation. Yet, PF and AC approaches have developed independently of the advances of the other. This study develops a theoretical and empirical examination of the

R&D-innovation process that draws on each of their insights. This R&D-innovation process involves an associative learning process that introduces PF's law of diminishing returns to a firm's AC. With these diminishing returns, a firm's AC faces pressures to exploit and explore external opportunities in which a nonlinear relationship to a firm's product innovations was supported by a sample of biotechnology firms. Furthermore, a firm's alliances were also argued and shown to play an important role in complimenting this R&D-innovation process. This complementarity develops a greater openness to the R&D-innovation process in which a firm's exposure to alliance partners offers opportunities to reveal new valued or commercial uses to a firm's R&D. By drawing on these insights, this study's associative learning process offers new directions for AC research to explain the assimilation and commercialization of a firm's R&D.

DATA AVAILABILITY STATEMENT

Data subject to third party restrictions.

ORCID

Desmond Ng https://orcid.org/0000-0003-4558-951X

ENDNOTES

[1] While R&D investments have also been related to process innovations, AC focusses on thus commercialization aspect of R&D and thus tends to focus on product related innovations (see Cohen & Levinthal, 1990; Zahra & George, 2002).

[2] Because the nonlinear effects of R&D^2 variable is a product of itself, there is naturally a high degree of collinearity between this non-linear term and the R&D variable. Including this non-linear term would artificially inflate the VIF test and was therefore excluded from this test.

[3] It is important to recognize that in Table 1, the sum of these SIC classes in Table 1 is less than 1. This is because while this study sampled biotechnology firms from the BioScan database, it not only included firms that belonged in the SIC classes 2833, 2834, 2835 and 2836, but also in other related SIC classes. Yet as SIC classes (2833, 2934, 2835 and 2836) have been used in prior biotechnology studies (Ng & Sanchez-Aragon, 2022; Rothaermel & Deeds, 2004), the study's sample was restricted to only these classes to which yielded an aggregation of SIC dummies that was less than 1.

[4] Due to space limitations, the full results are not reported but are available on request.

[5] In Cegaarra-Navarro et al.s' higher educational study (Cegarra-Navarro et al., 2021), they define "capacity is [as] the potential for people in general… to (re)learn or unlearn something and achieve lasting outcomes; competence refers to the state of being ready to do something; capability is the art of performing a core competence over time (i.e. preserving competitiveness)" (p. 1304).

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