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Technological Entry, Redeployability, and Firm Value

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ABSTRACT We provide a framework that enriches our understanding of resource redeployability, i.e., the value-generating option to withdraw resources from one use and reallocate them to another use. Existing works largely assume that the new uses of a resource are known ex ante and easily identifiable by managers. However, several cases from different industries suggest that new uses often emerge while a firm's technology base radiates into new domains. We analyse how a firm's technology base, by radiating into new domains that potentially reveal new uses and resource redeployment options, can spur firm value. We develop five hypotheses on the relationship between technological entry into new domains and firm value, and test them using a novel patent-based measure in a panel of US firms.

Keywords: New uses, Technological entry, Redeployability, Options, Patents

INTRODUCTION

An important stream of research in corporate strategy has adopted the lens of option theory to understand how firms redeploy resources into new domains (Folta et al., 2016; Sakhartov and Folta, 2014, 2015). The intuition behind this literature goes back to Chandler (1962) and Penrose (1959), but the idea has also been central in the work of other scholars such as Klepper and Simons (2000) and Cattani (2005, 2006), who examined Corning's entry into fibre optics via the redeployment of resources that were originally developed for glass manufacturing. The increasing attention on resource redeployment (Cattani and Mastrogiorgio, 2021) is part of an attempt to understand the different types of resources (Levinthal and Wu, 2010), their option-rich nature (Andriani and Cattani, 2019) and their role in enacting 'intertemporal economies of scope' (Helfat and Eisenhardt, 2004). Part of this research has started to concentrate on the inventive and technological antecedents of resource redeployment or, in the words of Dushnitsky

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and Klueter (2016), the process of 'linking inventive resources […] to commercial applications' (p. 286).

In this literature, it is often assumed that firms redeploy resources into new domains based on their expected growth, as if these new domains were known or easily identifiable ex ante (Dushnitsky and Klueter, 2016). In reality, as shown by the Corning example, new applications often *emerge* unexpectedly from firms' technological activities that had different original purposes (Cattani, 2005, 2006). This idea is at the centre of a recent literature that, building on evolutionary arguments (Cattani and Malerba, 2021), sheds light on the unexpected emergence of new uses of existing technologies, which reveal options to redeploy resources in new domains (Andriani and Cattani, 2016; Cattani and Mastrogiorgio, 2021). For instance, pharmaceutical firms often 'repurpose' (i.e., redeploy) their resources into new disease markets after stumbling upon unknown drug uses – as illustrated by Viagra, a drug originally developed for hypertension and then found to be effective against erectile dysfunction (Andriani et al., 2017). This view about resources and technologies was implicit in Penrose's claim that 'resources can be used in different ways and for different purposes' (1959, p. 76) as well as in the work of innovation scholars such as Basalla (1988), who pointed out that current applications 'are not always the ones for which the invention will become best known' (p. 141), meaning that they change over time, often in unexpected directions. Other scholars have recognized the inherent fungibility of certain types of technologies, and of their mapping with the new domains in which firms end up redeploying resources (Levinthal and Wu, 2010).

The approaches based on option theory have provided many insights to the strategy field, which has seen a growing interest on the economic mechanisms of resource redeployment (Sakhartov, 2017; Sakhartov and Folta, 2014, 2015). Despite these developments, there is still a limited understanding of the technological antecedents of resource redeployment, that is, of how firms' prior technological experience drives entry into new technological domains and of how this reveals new options to redeploy resources. The influential work of Cattani (2005, 2006) has investigated some of these aspects, but an option-based angle is still in the making (Cattani and Mastrogiorgio, 2021). To fill this gap, we ground our arguments on the resource redeployment literature (Sakhartov, 2017; Sakhartov and Folta, 2014, 2015), which models 'resource redeployability' (i.e., the option to redeploy resources) as 'growth options' (Kulatilaka and Perotti, 1998). According to this literature, the value of these options is a function of both 'inducements' (i.e., incentives to redeploy resources due to performance advantages in new domains, proxied by higher volatilities of financial returns) and 'redeployment costs' (i.e., costs to redeploy resources in new domains) (Sakhartov and Folta, 2014). Drawing on these insights, we investigate how firms can benefit from unexpectedly entering new technological domains. In so doing, we expand the research on resource redeployment (Folta et al., 2016) by modelling optionality as nested in the firm's technologies. Drawing inspiration from the evolutionary tradition (Cattani, 2005), we focus on 'technological entry' (Malerba and Orsenigo, 1999) in new technological domains via patenting. Such entry entails an option to redeploy resources in the new domains, which should be reflected in firm value (Bloom and Van Reenen, 2002; Oriani and Sobrero, 2008; Pakes, 1986; Schwartz, 2004). At the same time, patenting in new technological domains is peculiar from the perspective of optionality due to some inherent features that make it different from standard growth options (Andriani and Cattani, 2016; Adner and Levinthal, 2004; Leiblein et al., 2017).

We articulate our theory around five hypotheses. First, we posit that entry into a new technological domain (via patenting) would positively affect firm value through the value incorporated in redeployability options. Next, we hypothesize that return volatility in the firm's core industry increases the value of options, and thus positively moderates the first hypothesis. Moreover, conditional on entry into a new technological domain, the volatility in such domain increases the value of options, while its effect is lowered by redeployment costs. Finally, we hypothesize that, due to the inherent complexity of valuing technological entry, a firm's market value inefficiently reflects the financial gains of such entry (i.e., its value effect features some persistence). For the analysis, we employ a data set containing information on the patenting activities of US firms and a newly developed measure of technological entry. To capture entry outside the boundaries of a firm's existing technological knowledge, we count the number of patents applied by the firm in technological classes in which the firm did not (nor, arguably, anticipate to) patent before. Our measure is novel because it exploits both the primary *and* secondary classifications. Moreover, to assuage the concern that technological entry is fully anticipated by the firm, we use multiple validation approaches.

As Folta (2021) argues, much has been learned about resource redeployability since the early intuitions of Penrose (1959). A key assumption of this research pertains to the role of new uses of resources and, therefore, to the very definition of resource redeployability – the option to withdraw resources 'from one use and reallocate to another *use*' (Folta, 2021, p. 1). Here, the new uses of resources are often considered to be known ex ante and easily identifiable by managers. However, recent works suggest that new uses of resources are simply 'un-prestateable' (Felin et al., 2021), i.e., they are not known ex ante, because they emerge over time as a firm's technology base radiates into new domains (Cattani and Malerba, 2021). This raises the question of whether the radiation of a firm's technology base into new domains that reveal new uses of resources and redeployment options can spur firm value. Filling this gap, our contribution is to offer a conceptual and empirical framework to show how technological entry can affect firm value, and what are the boundary conditions that shape this relationship.

CURRENT LITERATURE

Resource Redeployment

The last few years have seen a renewed interest in corporate diversification. As Folta et al. (2016) put it, 'multi-business firms are alive and well' (p. 3), as is evident in the data patterns (Villalonga, 2004) and the growing research on the diversification-performance linkage and its multifaceted contingencies (Ahuja and Novelli, 2017; Santaló and Becerra, 2008). These matters have been approached from a variety of theoretical perspectives, such as the resource-based view (Barney, 1991), which suggests that resources play a role in diversification by having multiple uses that are activated when resources are in excess or they are subject to failures in strategic factor markets (Montgomery and Wernerfelt, 1988; Penrose, 1959; Peteraf, 1993). A stream of research into which resources are central is that on 'resource redeployment' from the viewpoint of options (Folta et al., 2016; Sakhartov and Folta, 2014, 2015), in which there is a growing interest (Dickler and Folta, 2020; Giarratana and Santaló, 2020; Giarratana et al., 2021; Morandi Stagni et al., 2020).

Resource redeployment has also been central to another stream of the strategy literature (Cattani, 2005, 2006), which has traced the origins of firms' performance heterogeneity (and of competitive advantage, broadly speaking) to differences in prior experience that spurs technological entry into new domains, placing emphasis on the idea that inventive efforts 'made in exploration of a new domain should be separated from those conducted without foreknowledge of any potential redeployment' (Cattani, 2005, p. 565). This perspective, in turn, has inspired a new literature that, building on evolutionary arguments, looks at resource redeployment processes from the perspective of multiple latent uses of technologies that often emerge *unexpectedly* and spur entry into new technological domains (Andriani and Cattani, 2016; Cattani and Mastrogiorgio, 2021; La Porta et al., 2020).

The Option-Based Approach

A tenet of the option literature is that corporate value derives, in part, from the discretion of firms to redeploy resources from one business to another, that is, from 'resource redeployability' (Sakhartov and Folta, 2014).[1] More specifically, resource redeployment consists in withdrawing resources from one business and reallocating them to another, rather than simply sharing them across businesses contemporaneously – what is known as 'synergy' (Sakhartov and Folta, 2014). From this perspective, resources can be seen as enactors of 'intertemporal economies of scope' beyond their role in intra-temporal ones, as in the case of their contemporaneous, synergistic uses (Helfat and Eisenhardt, 2004). This argument points to the idea that inter-temporal and intra-temporal economies of scope are respectively determined by different types of resources. In fact, as argued by Levinthal and Wu (2010), inter-temporal economies of scope imply a process of withdrawing *and* reallocating, which means that uses in one business preclude uses in another. In other words, inter-temporal economies of scope are underpinned by resources with capacity constraints that are known as 'non-scale free' (Levinthal and Wu, 2010).

This distinction is crucial, because it implies that the redeployment of non-scale free resources is driven by economic considerations about opportunity costs, such as those about the 'size, growth, and competitive conditions in alternative product markets' and businesses (Levinthal and Wu, 2010, p. 784). A well-known example is Du Pont's redeployment of resources from explosives to new types of businesses, when World War I ended and those resources initially used for explosives became unused (Chandler, 1962; Penrose, 1959, 1960).[2] Other examples, coming from various industries, can be found in a growing number of studies including Anand (2004), Anand and Singh (1997), Lieberman et al. (2017), O'Brien and Folta (2009), and Wu (2013).

These considerations about opportunity costs can be understood in terms of options: the resources that are redeployable from business A (e.g., explosives) to a new business B embody a growth option in business B, which is more likely to be exercised when business A is declining while business B thrives. After its inception in financial economics (Black and Scholes, 1973), options theory began to expand in the strategy field building around the notion that a firm's resources often entail 'real options' that embed the discretion – but not the obligation – to undertake certain types of business initiatives, such as further expanding initial investments at a future date (Myers, 1977). It was this development that set the stage for the resource redeployment theory (Folta et al., 2016; Sakhartov and Folta, 2014, 2015), which indeed looks at the discretion to redeploy resources, which can be thought of as a real option (or, better, a growth option) when the firm can 'redeploy its resources to another business' (Sakhartov, 2017, p. 1062).

The applications of options theory in strategy research have ranged from acquisitions (Hurry, 1993) to global expansion (Kogut, 1983) and, relevantly for us, research and development (R&D) and patenting (Mitchell and Hamilton, 1987). From the lens of options theory, R&D consists in inventive activities leading to patents, which are also real options (Oriani and Sobrero, 2008; Pakes, 1986; Schwartz, 2004). In fact, the transformation of patents into cash-flow-generating technologies and products is realized only once the firm exercises the options embodied in patents through investment in further development and commercial activities (e.g., investment in further R&D, capital equipment, employees' training, or marketing) (Bloom and Van Reenen, 2002). Or, as Trigeorgis and Reuer (2017) put it, 'incremental cash flows [from innovation activities] are tied to the construction or scale up of a plant, the development of a product in an R&D program or the exploitation of a patent' (p. 44).

Unpacking the Technological Antecedents

A key underlying assumption of the literature cited is that the new uses of resources are known ex ante and easily identifiable by managers, as if they were part of a predefined mapping. In reality, the new uses of a resource often emerge while a firm's technology base radiates into new domains, and there is evidence showing how these uses often emerge unexpectedly from firms' technological activities that had different original purposes.[3] The examples abound in many industries, such as fibre optics (Cattani, 2005, 2006), aviation (Carignani et al., 2019), and chemical and pharma (Andriani and Kaminska, 2021), among others. In this regard, the pharmaceutical industry is particularly illustrative. The repositioning of pharmaceutical companies into new disease markets via resource redeployment is often a consequence of unexpected discoveries of previously unknown uses of drugs. A key example is offered by sildenafil, commonly known as Viagra. Originally conceived to treat hypertension and angina pectoris, the drug ended up being marketed in a very different disease class, after phase-I clinical trials revealed unexpected side effects against erectile dysfunction (Andriani et al., 2017; Meyers, 2007). This discovery was the technological antecedent of a massive redeployment of resources into the new market. In fact, as noted by Loe (2004), 'by the time Viagra was approved for the public, Pfizer was able to produce, maintain, and respond to extensive medical and commercial infrastructures that supported the blockbuster drug' (p. 18).

These processes are central to an emerging literature that, building on evolutionary arguments, describes technology as a container of multiple latent uses (Andriani and Cattani, 2016; Dew et al., 2004; La Porta et al., 2020) that, as they emerge from latency, incorporate growth options (to redeploy resources) in new domains (Cattani and Mastrogiorgio, 2021). This view raises two fundamental implications. First, not only a single technology but also a firm's accumulated technology base is potentially available for uses other than those for which it was originally developed, spurring the firm's technological entries into new domains that incorporate growth options in these. That is, as expressly said by Cattani (2005), 'each invention or innovation offers a spectrum of opportunities' and a firm 'might be endowed by its past history with skills and knowledge for reasons that are unrelated to their application in a new opportunity [domain]' (p. 566). Second, growth options are more peculiar than commonly assumed, because they progressively *emerge* from latent states of technology; as a result, technology itself can be seen as a bundle of 'shadow options' (Bowman and Hurry, 1993) that await recognition and progressively become (standard) growth options as new uses emerge and 'unveil opportunities to further invest in existing assets' (Andriani and Cattani, 2016, p. 12).

This perspective raises the following question: Does entry into a new technological domain incorporate a growth option that thus raises firm value? To answer this question, we provide a framework whose intuition is illustrated in Figure 1. In Figure 1(a), the firm's technology base is seen as a bundle of multiple *technological* uses in a latent state represented by dotted arrows behind a cloud, where this implies that new uses of resources and options of resource redeployment are also hidden, or 'shadow'; in Figure 1(b), new technological uses progressively come to light and the firm enters into new technological domains that reveal, thus bringing to light, new uses of resources and options of resource redeployment: therefore, shadow options progressively become standard growth options that spur firm value. The value-generating mechanisms are developed in the next section, through a formal framework leading to five testable hypotheses.

A FORMAL FRAMEWORK

The five hypotheses are illustrated in the conceptual model of Figure 2. In a nutshell, Hypothesis 1 will look at how technological entry, by revealing new uses of resources and options of resource redeployment, spurs firm value. Hypotheses 2, 3 and 4 will look at boundary conditions of the effect of technological entry on firm value: namely, 'inducements' (proxied by volatilities of financial returns) and 'redeployment costs'. Hypothesis 5 will look at how the market processes the effect of technological entry on firm value over time.

In order to characterize the studied processes, we focus on a firm's entry into a new domain from a technological point of view (Cattani, 2005), i.e., as a 'technological entry' (Malerba and Orsenigo, 1999; Leten et al., 2016). To be more specific, we conceptualize technological entry as patenting in technological classes that are new, and arguably unexpected, to the firm. We then associate patenting to real options of the growth type (Oriani and

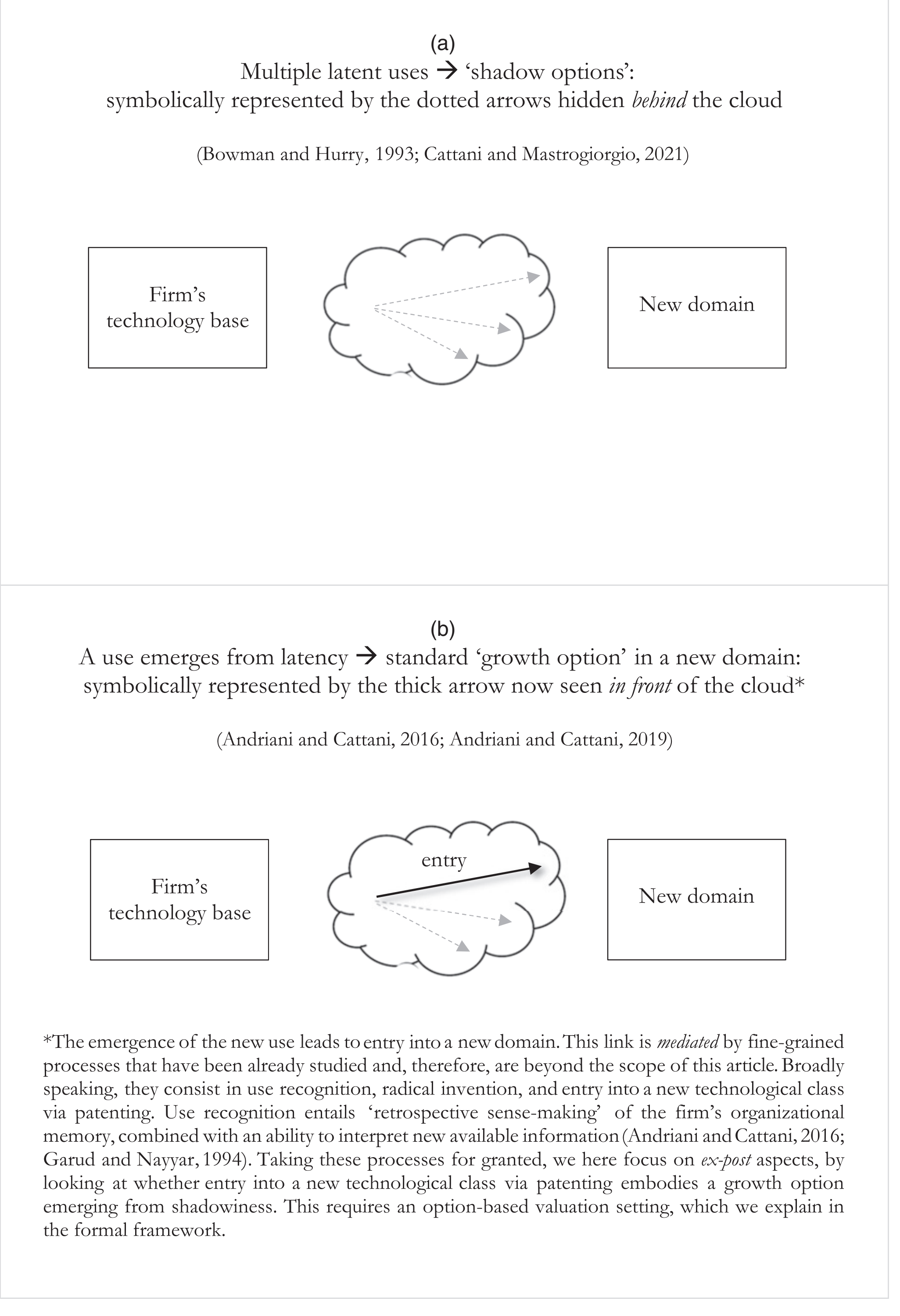

Figure 1. Illustration of the key intuition

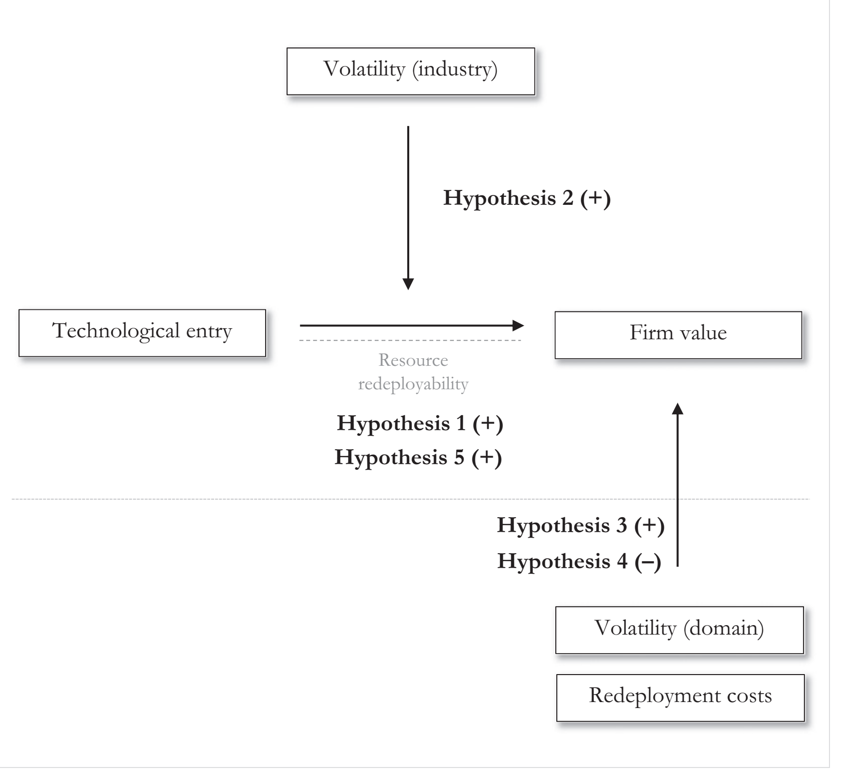

Figure 2. Conceptual model

Sobrero, 2008; Pakes, 1986; Schwartz, 2004), thus expanding the current work on resource redeployment (Folta et al., 2016; Sakhartov and Folta, 2014, 2015). A baseline condition to characterize patenting in a new technological class as a growth option is the 'disembodied' form of patenting. Following existing research, we posit that the value of a firm is a function, among other things, of its 'embodied' and 'disembodied' patents: that is, innovation that is already embodied in cash-flow-generating products *and* inventive knowledge that is legally protected but not yet embodied in cash-flow-generating products – being thus 'disembodied' (Bloom and Van Reenen, 2002). To embody patents into cash-flow-generating products, the firm would have to make scale-up investments in further R&D, capital equipment, employee training, marketing, and commercialization. Since a disembodied patent incorporates legal protection against future, eventual imitation from competitors that is conditional on the future, eventual existence of a cash-flow-generating product made with the scale-up investments, the patent also incorporates the discretion – but not the obligation – to make that investment. We thus associate it with a growth option, also residing in the fact that patenting takes place, via the unexpected route, in technological classes that are new to the firm, which in turn increases the likelihood of disembodiment.[4] [5] Therefore, as in Bloom and Van Reenen (2002), we posit that

$$V = f\left(\sum_{i=1}^{n_1} V_e\left(C_i\right) + \sum_{j=1}^{n_2} V_d\left(C_j\right)\right) \quad (1)$$

where V is the value of the firm, expressed as a function f of the sum of values V_e of n_1 embodied patents plus the sum of values V_d of n_2 disembodied patents in new technological classes, where the values of embodied and disembodied patents are a function of current and expected cash flows, respectively. More precisely, the value V_d is a function of expected cash flows whose activation is conditional on the redeployment of non-scale free resources in the new technological class – that is, on the exercise of the growth option via patent embodiment. Since the option is unexercised, V_d incorporates option value of resource redeployability. Based on standard options arguments (Folta et al., 2016; Sakhartov and Folta, 2014, 2015), the option to redeploy resources 'from the original business to the new use adds value [to the firm], regardless of its actual exercise' (Sakhartov, 2017, p. 1065), so we state the following baseline hypothesis:

Hypothesis 1: Entry into a new technology class positively affects firm value by incorporating option value of resource redeployability.

The next step is to understand how two option drivers – namely, 'inducements' (Hypotheses 2 and 3) and 'redeployment costs' (Hypothesis 4) – shape the hypothesized relationship, i.e., study the conditions under which technological entry is more valuable. In her influential work, Penrose (1959) introduced the idea of 'inducements', stressing the role of relative performances across businesses: 'If there are profitable opportunities for increased production anywhere in the economy, they will provide for some firm an external *inducement* to expand' (Penrose, 1959, p. 131, emphasis added), and 'the declining profitability of existing markets … is, of course, one aspect of the matter' (p. 170). Building on these early insights, the literature has defined inducements as the set of incentives to redeploy resources across businesses (Sakhartov, 2017; Sakhartov and Folta, 2014, 2015), putting emphasis on the role of volatilities in the current and new business (as well as on redeployment costs, defined as the efficiency lost when redeploying resources in new businesses due to unrelatedness [Montgomery and Wernerfelt, 1988]). Formally speaking, we express the option value of resource redeployability as in Sakhartov (2017):

$$V_d = \max_m E\left(\int_{t=0}^{t=T} e^{-rt} F_t dt\right) \tag{2}$$

where V_d specifically refers to the value of disembodied patents incorporating the option to redeploy resources, as in equation (1). That formula is here expanded, being V_d expressed as the maximum, with respect to a vector m of resource redeployment weights, of the expectation E of the cash flows F_t generated during the period [t = 0, t = T], where e^{-rt} is the discount factor. Cash flows F_t have a specific formulation that separates them into cash flows $C_{i,t}$ coming from the firm's *current industry* i, and cash flows $C_{j,t}$ coming from the *new class of technology* j in which the firm ends up patenting, which are activated through an increase of the portion $m_{j,t}$ of resources redeployed to j (withdrawing them from i, hence $m_{j,t} = 1 - m_{i,t}$). $C_{i,t}$ and $C_{j,t}$, in turn, are expressed in function of the volatility σ of the current industry and that of the new technological class – being both two fundamental drivers of V_d, thus influencing firm value, according to equation (1). In addition, cash flows F_t are expressed net of the costs S of redeploying resources to the new technological class. Equation (2) expresses the hypothetical 'true' (or fundamental) option value of resource redeployability that would occur in a situation of market efficiency (Sakhartov, 2017).

The specific effects of volatility on the previously stated hypothesis derive from the core assumptions of option valuation and, in a broad sense, they define optionality itself (Black and Scholes, 1973). For the sake of clarity, let us consider a simple call option, which gives the holder the discretion – but not the obligation – to buy a stock at a pre-specified future date at a strike price of 10. The holder exercises the right when the option is 'in the money', e.g., when the market price is 15. The holder can buy at 10 and immediately resell at 15, thus making a profit of 5. One of the assumptions of option valuation is that volatility, the dispersion of stock returns, would positively affect the value of the option: the higher the volatility, the higher the upside potential of the stock, i.e., the higher the value of exercising the 'call' right. In our setting, the key argument is that higher volatility σ_i in the current industry i leads to more option value, because the option can be eventually exercised via patent embodiment as a buffer against a higher *downside* potential in the current industry i; on the other hand, higher volatility σ_j in the new technological class j leads to more option value, because the option can be eventually exercised via patent embodiment to exploit the *upside* potential in the new technological class j. Therefore, more pronounced volatilities in the current industry and in the new technological class drive up the value of optionality in the presence of downside and upside movements, as reflected in firm value. These arguments are in line with the theoretical predictions of the literature (Sakhartov, 2017; Sakhartov and Folta, 2014, 2015). Using simulations that isolate the value of resource redeployability as a function of inducement variables, Sakhartov and Folta (2015) indeed show that the value of resource redeployability increases when the current business is more volatile, and that volatility in the new business also enhances it. These arguments lead to the following hypotheses:

Hypothesis 2: Volatility in the current industry positively moderates the effect of entry into a new technology class on firm value, by increasing the option value of resource redeployability.

Hypothesis 3: Conditional on entry into a new technology class, volatility in the new technology class positively affects firm value, by increasing the option value of resource redeployability.

Besides inducements, Penrose (1959) also referred to 'obstacles', like the costs of redeploying resources into different businesses: 'We should note in passing that it is important to discuss separately the nature of the inducements *and obstacles* to expansion instead of simply "net inducements to expand", because different kinds of inducements and difficulties influence differently both the direction and the method of expansion chosen'

(Penrose, 1959, p. 60, emphasis added). Defined as the efficiency lost when redeploying resources to new businesses, 'redeployment costs' are typically assumed to increase when the new businesses are un-similar and, vice versa, to decrease as a function of relatedness (Montgomery and Wernerfelt, 1988; Rumelt, 1974).[6] This explains their conceptualization, in the current research, in terms of un-similarity – or unrelatedness – between the current and new businesses (Sakhartov, 2017; Sakhartov and Folta, 2014, 2015). As noted by Sakhartov (2017), the loss of efficiency can be resource-specific or firm-specific, and redeployment costs can have a multifold nature (Sakhartov and Folta, 2015). When they take an economic nature, the loss of efficiency is exemplified by a hypothetical pharmaceutical firm that, ending up in a new profitable disease class, would have to retrain its specialized base of biochemists in a very different scientific field (and, relatedly, adapt its physical plants to different types of chemical reagents).

The key argument about redeployment costs as efficiency loss is grounded on the idea that resources are unique, idiosyncratic, and business-specific, meaning that, when the firm ends up in a new technological class, the exercise of the growth option via patent embodiment would be associated with a loss of efficiency.[7] This argument builds on the underlying notion of Ricardian rents (Montgomery and Wernerfelt, 1988), defined as rents accrued to a firm by means of unique resources, like a good manager or a complex production process. Due to their uniqueness, these resources are subject to imperfections in strategic factor markets (Denrell et al., 2003). Therefore, instead of selling or renting them, the firm is more likely to use them internally, for instance by redeploying them. Yet, their uniqueness also translates into lost efficiency during resource redeployment. Lost efficiency, in turn, lowers the option value of resource redeployability via equation (2): since future, expected cash flows are net of redeployment costs (Sakhartov, 2017), an increase of redeployment costs leads to a decrease of V_d, thus implying a decrease of the option value of resource redeployability. This leads to the following hypothesis:

> *Hypothesis 4*: Conditional on entry into a new technology class, redeployment costs negatively affect firm value, by decreasing the option value of resource redeployability.

Despite the broad appeal of the option-based logic, technologies are peculiar from the point of view of options, due to their inherent fungibility, as well as the unprestateability of all possible uses and their 'shadow-like' features (Andriani and Cattani, 2016, 2019). This complicates option valuation (Cattani and Mastrogiorgio, 2021; Felin et al., 2016) and makes a theory of 'realistic real options' more necessary (Leiblein et al., 2017; see also Adner and Levinthal, 2004). Problems of valuation – of technologies and resources, and of the options incorporated in them – are central to the strategy literature, which has long debated whether strategic factor markets are efficient (Barney, 1986) or, as claimed by Denrell et al. (2003), they are not, due to the complex, non-commoditized nature of technologies and resources, which complicates the imputation of value via market incompleteness. Yet, as noted by Sakhartov (2017), there is room for identifying the different situations in which misvaluation happens, particularly when new uses emerge unexpectedly and resources are redeployable into new domains – an aspect on which there is, still, little understanding.

This analysis is particularly compelling in our setting. As Bernstein (1996) notes, economic agents 'can calculate probabilities from real-life situations only when similar experiences have occurred often enough. But when events are [*new* and] unique, ambiguity takes over' (p. 302, emphasis added). Put differently, learning asymmetries (Leiblein et al., 2017), combined with the inherent fungibility and 'unprestateability' of technology, may prevent the calculation of distributions (Felin et al., 2014), hindering the valuation of option returns (Andriani and Cattani, 2016): or, in Bowman and Hurry's (1993) terms, shadow options 'awaiting *recognition*' (p. 763) may – in a certain sense – never stop waiting. From a formal point of view, this amounts to assessing the misvaluation of the option value of redeployability, conditional on entry into a new technological class, which means assessing if there is a deviation from the hypothetical 'true' value $\mathbf{V}_{\mathbf{d}}$ that would occur in a situation of efficiency. Considering that, under market efficiency, information would immediately be reflected in firm value (Fama, 1965, 1970; Malkiel, 2003), the lack of efficiency means that information is reflected in firm value with some time persistence, implying a misvaluation in the option value of redeployability (conditional on entry into a new technological class). This leads to the following hypothesis:

Hypothesis 5: Entry into a new technology class positively affects firm value with time persistence.

EMPIRICAL SETTING

Data Sources

To test our hypotheses, we gathered data from several sources. Patent information comes from the National Bureau of Economic Research (NBER) patent data set, which contains all patents filed at the US Patent and Trademark Office (USPTO) and represents the main data source in the innovation literature (e.g., Hall et al., 2001). Financial data at the firm level comes from the Compustat data set, which contains comprehensive information on US listed companies. Stock return data comes from the Center for Research in Security Prices (CRSP). We matched these data sources using the procedure described in Bessen (2009) to get a panel data set containing 3,296 unique firms for a total of 24,889 observations (net of missing values in the variables discussed next) from 1985 to 2006.

Dependent Variables

To test Hypotheses 1 through 4, we needed a measure of firm performance. To this end, we employed a forward-looking measure of firm performance which hinges on the firm's market value. Specifically, we employed the market to book ratio (MTB), computed as the ratio between the market value of a firm's equity divided by the book value of equity. This is a common measure of market-based performance, which is also easier to compute than the Tobin's Q since it does not require an estimate of the replacement value of assets. Alternatively, we followed suggestions in the existing literature (Sakhartov and Folta, 2014) and adopted the return on assets (ROA), computed as the ratio of earnings before interest, taxes, depreciation, and amortization divided by the one-year lagged book value of total assets. A key feature of the ROA is that it captures current operating performance by measuring the ability of the firm to generate operating profits out of the asset base.

We also used MTB to test Hypothesis 5. Sakhartov (2017) hints at more direct measures of misvaluation, such as the difference between the price paid by a bidder during an acquisition and what is disclosed in the due diligence process. We believe that both acquisition-based and MTB measures are useful to capture the same underlying phenomenon: market inefficiency due to the misvaluation of resource redeployability. While acquisition-based measures may capture more directly what happens in strategic factor markets, MTB captures the firm's stock market value more broadly.

Explanatory Variables

Technological entry. Central to our study is a measure of entry into a new class of technology, which we involve in the testing of Hypotheses 1, 2, and 5. The approach we follow is inspired by the evolutionary literature (Cattani, 2005; Mastrogiorgio and Gilsing, 2016). Specifically, we build the variable *Technological entry* as the logarithm of one plus the instances of entry into technological classes which are entirely new to the firm's patent portfolio. To measure the *novelty* of a technological class, we look at both main *and* secondary three-digit technological classifications where a firm has patented in the past: if the patent's main classification differs from both the main and secondary classifications of all the patents granted to firm i (during the years preceding t), we classify it as novel to the firm's existing technological knowledge base. If instead the patent's main classification belongs to the set of main and secondary classifications of all the patents granted to firm i, we classify it as non-novel or belonging to a firm's existing technological knowledge base. This measure, which is the output of a computationally intensive algorithm, has the following logic: the USPTO assigns the focal patent to a main technological classification that identifies the main type as well as the 'function' (or 'use', here used interchangeably) of the underlying technology. Indeed, the USPTO uses the 'fundamental, direct, or necessary function as the principal basis of classification', where the function is the result achieved by 'similar processes or structures … by the application of similar natural laws to similar substances' (USPTO, 2012). The idea of the measure is to compare the main use of the focal patent with the universe of uses implied by the portfolio of patents granted to the firm previously. If the main use of the focal patent differs from this universe, this may indicate an unexpected inventive process whereby 'investigators were searching in one problem space but made their discovery in another' (Yaqub, 2018, p. 171).

In our setting, the problem space of search is the domain of a firm's previous experience (as proxied by its patent portfolio). Operationally, we compare the main use of the focal patent with a universe containing both the main uses of previous patents *and* other uses eventually envisioned but not claimed as principal invention. For this purpose, we exploit a peculiarity of the US patent system: the assignment of patents to both Original Reference and Cross Reference technological classifications, OR and XR, respectively. The OR class is mandatory, as it reflects the controlling claim of the patent. In other words, it reflects the main use of the underlying technology, and it appears in bold font in the first position of a patent document: we can think about the OR class as the 'main idea' behind the technology. The XR class, instead, is required or not depending on whether it is based on claimed or unclaimed inventor information or on other types of information. Although the XR class is not mandatory and thus potentially undisclosed for strategic reasons, the percentage of patents with undisclosed XR classes in our database is extremely small, given the peculiarities of the US patent claiming system (Fromer, 2009). Therefore, the XR class may reflect other eventual uses envisioned when the patent was being drafted and it appears in plain font after the first position of a patent document: we can think about the XR class as 'other ideas' about the technology (USPTO, 2012). Overall, the idea of the measure is to compare the OR class of the focal patent with the universe of OR and XR classes contained in the portfolio of patents granted to the firm previously. If the OR class of the focal patent differs from this universe, this indicates novelty. Formally speaking, a new technological entry can be expressed as follows:

$$d_{i,t} = \begin{cases} 1 \text{ if } \exists j \ s.t. \ c^{OR}_{j,i,t} \notin U = \{ c^{OR}_{h,i,(t-1\_t-5)}, c^{XR}_{h,i,(t-1\_t-5)} \} \\ 0 \qquad\qquad\qquad\qquad\qquad \text{otherwise} \end{cases}$$

where $d_{i,t}$ is a dummy equal to 1 if there exists at least one applied patent j such that the OR class c of patent j applied by firm i at time t does not belong to the set given by the non-repeated list of OR and XR classes c included in all the h = 1, 2, … N patents granted to firm i in the time interval between t−1 and t−5. Otherwise $d_{i,t}$ is 0. For the empirical analysis, we sum all instances of new technological entry by a firm at a given point in time (so as to have a continuous measure, indicated by $s_{i,t}$ in the models). Then, we take the logarithm of one plus the resulting measure (where one is added to avoid losing firms without new entry).

A simple example is provided in Figure A1 of this article's online Appendix, which contains the front page of a patent P1 protecting a molecular system designed to operate in the realm of quantum superposition before collapsing on classical states. The OR class, 506, appears in bold font in the first position on the patent document (see [a] in the figure), and it refers to a set of uses of the technology in the domain of 'combinatorial chemistry technology: method, library, apparatus'. The first XR class, 706, appears in plain font after the first position (see [b] in the figure), and it refers to a set of uses of the technology in the domain of 'data processing: artificial intelligence'. If the firm owning P1 specializes in chemistry and later on applies for another patent P2 protecting a quantum molecular system specifically designed for artificial intelligence, this new use would be already envisioned in patent P1 (as also evident in the abstract of P1), and thus the firm's entry into the artificial intelligence class would not be classified as unexpected. Hence, a key question regarding our measure is the extent to which it captures unexpectedness – and, broadly speaking, *serendipity* – in inventive processes that spur entry into new technological classes.

Establishing that a given inventive process, as proxied by patenting in the new technological class, had some element of unexpectedness is challenging and requires a combination of approaches (Cattani and Mastrogiorgio, 2021). We propose several validation tests (reported in the article's online Appendix) to offer glimpses into this issue.

- *Fine-tuning the measure*. Even if our measure is based on technological classes that are new to the firm (that is, no patents were granted to the firm in this class in the past), the patents filed in such class may have built on the firm's existing technological knowledge base. To reduce this concern, we reclassified $d_{i,t}=1$ as 0 if the patent leading to entry into a new technological class made any citation to other patents filed by the same firm in the past (see Cattani, 2005). A related concern is that the patent's technology class is new to the firm, but inventors were already active in this class in the past. To avoid this concern, the novelty and unexpectedness of the class should also be established by leveraging inventors' data. Hence, we reclassified again $d_{i,t}=1$ as 0 if inventors were already experienced in the class of the patent that we used to capture technological entry. This restriction is implemented by using disambiguated patent data from the Patent Network Database (Li et al., 2014) and has been applied solely within the period 1980–95 due to data constraints. Tables A1 and A2 in this article's online Appendix, in which both restrictions are applied, show that our results are largely robust.
- *Text mining of patent corpus*. Based on the Text Analytics Toolbox of Matlab, we built an algorithm to analyse the textual properties of patent documents (from Google Patents and the USPTO website). Leveraging on recent advancements in natural language processing (Arts et al., 2021), we mined a predefined 'dictionary of unexpectedness'[8] in the abstract, background, summary, and description sections of a random sample of 3,000 patents drawn from our data set. As Table A3 in this article's online Appendix shows, the number of unexpectedness-related words in a patent's corpus is positively associated with the probability that our main patent measure identifies a technological entry.
- *Tests of power-law distribution*. We will show that entries in new technological classes are rare, in line with previous evidence on similar unexpected phenomena (Andriani et al., 2017). As further validation, we tested whether the number of words related to unexpectedness in a patent corpus (see the previous point) follow a skewed distribution known as 'power-law'. Relying on the statistical test proposed by Clauset et al. (2009), we found significant evidence of a power-law distribution.[9]
- *A qualitative approach*. We analysed news articles obtained from Factiva to qualitatively assess whether some of our patents (for which we found reference in media articles) were indeed the result of unexpectedness during the inventive process. This article's online Appendix explains the details of the analysis and reports the findings, which also validate our measure.

Volatilities. We now discuss the construction of the other explanatory variables. To test Hypothesis 2, we need a measure of volatility of stock returns in the firm's main industry (*Industry-level volatility*), which we compute by taking the average (logged) standard deviation of monthly firms' stock returns by each three-digit SIC industry and year (from CRSP). The higher the value, the higher the dispersion of stock returns in that industry and year.[10] The testing of Hypothesis 3 involves a measure of return volatility in the technological class of entry. To operationalize such a measure (*Technology-level volatility*), we start by taking the patent-level data set and identify the stock return of each patentee at the patent's application year.[11] Using this data, we compute the average standard deviation of stock returns across each three-digit technological class and year. Then, we compute the ratio of a firm's patents in the new technological class scaled by all patents in that year; this ratio gives us the relative importance of a given technological entry as compared with the firm's entire patent portfolio. Finally, for firms entering a new technological class, we multiply the average standard deviation of stock returns of that class by the above ratio and compute the (logged) average standard deviation of returns across all technological classes and year.

Redeployment costs. To measure redeployment costs, which are used to test Hypothesis 4, we rely on the approach developed in Kim and Kung (2017). This approach aims at measuring asset redeployability from the Bureau of Economic Analysis (BEA) capital flow table, which breaks down capital expenditures into a variety of asset categories for a broad cross-section of industries. Building on the notions of asset specificity (Williamson, 1988) and asset market thickness (Gavazza, 2011), the asset-level redeployability score is computed as the proportion of firms that use a given asset: the redeployability score would be higher when more firms in the economy use a given asset, i.e., when those assets feature a greater 'saleability' and can thus be redeployed across a wider array of activities.[12] From Kim and Kung (2017), we derive a firm-level redeployability measure (*Redeployability*) spanning from 1985 to 2006. As a robustness check, we follow the suggestion in Sakhartov and Folta (2014) and employ a measure of relatedness between the class of technological entry and the firm's main industry by using Brian Silverman's concordance table between international patent classes and SIC codes. The underlying idea is that it would be cheaper for a firm to redeploy its current assets in the technological class of entry when such class is more closely related to the firm's current activities.

Control variables. We compute several variables used to control for factors that may relate to both technological entry and firm performance, thus generating an omitted factor bias.

Technological entry will be more likely at firms that are generally more active in patenting. To account for this factor, we control for the count of a firm's i patent at time t scaled by one-year lagged R&D expenditures (*Innovation efficiency*). We further control for the degree of originality and generality of a firm's patent portfolio by using two measures (*Patent originality* and *Patent generality*) based on the distribution of forward and backward citations across technological fields, which are common to the patent literature (Hall et al., 2001); these measures are useful to account for the fact that entry into new technological classes can be more likely among firms with more radical patent portfolios (e.g., due to their superior recombination ability or access to more heterogeneous knowledge sources), which at the same time can exhibit higher performance.

Next, we include a set of accounting characteristics. We control for firm size by using the logarithm of the book value of total assets (*Ln assets*). To control for a firm's internal and external development activities, we compute the ratio of capital expenditures scaled by the one-year lagged value of total assets (*Capital expenditures*), the ratio of R&D expenditures again scaled by lagged total assets (*R&D expenditures*), and the logarithm of (one plus) the number of completed acquisitions (*Ln acquisitions*), drawn from the SDC Platinum data set. Growth in the top line of the balance sheet is controlled for via the annual growth of a firm's revenues (*Revenue growth*). Moving to the financial structure, we control for the ratio of the book value of debt scaled by the book value of total liabilities (*Leverage*). Using data from Compustat Segment, we also control for industry diversification by computing the Herfindahl-Hirschman index of concentration of firms' revenues across three-digit SIC industries (*Industry diversification*). Together with our control on a firm's acquisitions, this variable accounts for the fact that firms may enter unrelated domains by acquiring target firms whose patents are also novel to the firm's technological domain.

Finally, depending on the specification, we control for firm fixed effects to remove constant heterogeneity at the company level, year dummies to remove common temporal effects, and industry×year and state×year dummies to remove time varying geographic and industry heterogeneity.

Regression Models

To test our hypotheses, we rely on an empirical framework similar to that proposed by Sakhartov (2017), where measurable manifestations of a firm's performance and stock market misvaluation are modelled as a function of technological entry. The models to test the first hypothesis take the following form:

$$y_{i,t} = \beta_0 + \beta_1 s_{i,t} + \beta_2 Z_{i,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ is the MTB or ROA of firm i in year t and $s_{i,t}$ is our technological entry measure as defined in the previous section. Consistent with our first hypothesis, we expect the coefficient β_1 to be positive and statistically significant. $Z_{i,t}$ is a vector containing the firm-level controls discussed earlier, which remove the effect of observable firm characteristics on performance. This model is estimated using the full sample. In this and all subsequent models, standard errors are clustered by firm to account for serial correlation and heteroskedasticity in the residuals.

The models to test the second hypothesis take the following form:

$$y_{i,t} = \beta_0 + \beta_1 s_{i,t} + \beta_2 \sigma_{i,t} + \beta_3 s_{i,t}\sigma_{i,t} + \beta_4 Z_{i,t} + \varepsilon_{i,t}$$

where $y_{i,t}$, $s_{i,t}$, and $Z_{i,t}$ are the same as before, while $\sigma_{i,t}$ is the industry-level return volatility – expressed by the corresponding three-digit SIC code – of firm i in year t, followed by the interaction $s_{i,t}\sigma_{i,t}$ between technological entry and industry-level return volatility. Our hypothesis suggests that β_3, the coefficient of the interaction term, will be positive and statistically significant. This model, too, is estimated using the full sample.

The models to test the third and fourth hypotheses take the following form:

$$y_{i,t} = \beta_0 + \beta_1 \overline{\sigma}_{i,t} + \beta_2 c_{i,t} + \beta_3 Z_{i,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ and $Z_{i,t}$ are again the same as before, whereas $\overline{\sigma}_{i,t}$ and $c_{i,t}$ represent, respectively, the (log of) technology-level return volatility and the measure of redeployment costs (proxied by the redeployability variable). This model is only estimated for the subsample of firms experiencing technological entry and considers the years following the entry event. Again, we augment these models with firm fixed effects.

Finally, the model for the fifth hypothesis, in part based on Hirshleifer et al. (2013), takes the following form:

$$y_{i,t} = \beta_0 + \beta_1 s_{i,t} + \beta_2 s_{i,t-1} + \beta_3 s_{i,t-2} + \beta_4 s_{i,t-3} + \beta_5 Z_{i,t} + \varepsilon_{i,t}$$

where $s_{i,t}$ and $Z_{i,t}$ are the same as before, while $s_{i,t-i}$ are the technological entry lags in year t−1, t−2, and t−3 that aim to capture delayed reflection of information in market valuation.

FINDINGS

Table I, Panel A, shows the mean, median, and standard deviation for the key variables, whereas Panel B reports the correlations. Figure 3 illustrates the instances of technological entry in each firm's patent portfolio. As shown, the distribution is clearly skewed: a large fraction of firms does not experience any technological entry at all, and a small fraction of firms experiences multiple entries.

Before moving to the testing of our hypotheses, we describe the association between technological entry and firm characteristics. We do so in Table II, which shows the results of a t-test comparison of the firm-level variables described previously. As shown, most of these variables are unbalanced between firms with and without technological entry. For instance, the former appear to file more patents per R&D expenditure, and file patents that are more general and original. They are also larger, more engaged in acquisitions and capital expenditures, but less on R&D spending. These differences point to the importance of controlling for a comprehensive vector of firm characteristics and, as we do, also remove constant heterogeneity via firm fixed effects.

The results for the first hypothesis are reported in Table III. Column 1 shows the results obtained using MTB as the dependent variable, the continuous measure of technological entry as the explanatory variable, and controlling for firm and year fixed effects. Columns 2 through 5 sequentially include the patent and accounting controls, together with a set of dummies to control for industry- and region-specific time effects. Finally, column 6 validates the results using ROA as the dependent variable. In line with the first hypothesis, the coefficient of technological entry always has a positive and statistically significant effect on firm performance. In an additional analysis, we have estimated the effect of entry on subsequent firm performance (i.e., one or two years after). The estimated effects (untabulated) are generally in line with our theory, and – as expected – slightly stronger in magnitude.[13]

The results for the second hypothesis are reported in Table IV. Column 1 reports the model estimated on the full sample. The key coefficient of interest is that of the interaction term between technological entry and industry-level return volatility. Since the model controls for industry×year intercepts, we exclude the direct effect of industry volatility.[14] As shown, the coefficient of the interaction term is positive and significant at the 1 per cent level. This finding is illustrated in Figure 4, which – in line with our second hypothesis – shows how the effect of technological entry on the MTB is more pronounced in regimes of high industry-level return volatility as compared with regimes of low volatility.

The results for our third and fourth hypotheses are reported in Table V. As shown, there is a positive and 5 per cent significant association between a technological class's stock return volatility and firm performance, when measured via ROA. That is, our third hypothesis received mixed support. The model shows that the coefficient of asset redeployability is not statistically different from zero, i.e., our fourth hypothesis is not

Table I. Descriptive statistics

Panel A. Summary statistics

	Obs.	Mean	Median	s.d.
Technological entry [0/1]	24,889	0.3089	0	0.4621
Technological entry [cont.]	24,889	0.4208	0	0.7598
Innovation efficiency	24,889	0.5157	0	4.2481
Patent originality	24,889	0.1077	0	0.2073
Patent generality	24,889	0.06195	0	0.1525
Return on assets	24,889	−0.0127	0.1048	0.4763
Market to book	24,889	3.2005	1.6305	3.4743
Ln assets	24,889	4.6798	4.5606	2.3561
Revenue growth	24,889	0.2003	0.0767	0.7986
Ln acquisitions	24,889	0.2958	0	0.4940
Leverage	24,889	0.1893	0.1062	0.2775
Capital expenditures	24,889	0.0604	0.0411	0.0781
R&D expenditures	24,889	0.1269	0.0665	0.1984
Industry diversification	24,889	0.5932	0.5	0.3384
Industry-level volatility	24,889	−1.9834	−1.9619	0.2100

Panel B. Correlations

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. Technological entry [0/1]	1.0000													
2. Technological entry [cont.]	0.8283*	1.0000												
3. Return on assets	0.1866*	0.1735*	1.0000											

(Continues)

Table I. (Continued)

Panel B. Correlations

4. Market to book	0.0306*	0.0541*	−0.0082	1.0000											
5. Ln assets	0.4433*	0.4946*	0.4098*	0.1472*	1.0000										
6. Revenue growth	−0.0645*	−0.0531*	−0.1850*	0.1566*	−0.0600*	1.0000									
7. Ln acquisitions	0.2256*	0.2773*	0.1704*	0.1234*	0.4345*	0.0032	1.0000								
8. Leverage	0.0138*	0.0205*	−0.1449*	−0.0951*	0.0456*	0.1045*	0.0138*	1.0000							
9. Capital expenditures	0.0692*	0.0789*	−0.1350*	0.1005*	0.0512*	0.2152*	0.0248*	0.1279*	1.0000						
10. R&D expenditures	−0.1295*	−0.1117*	−0.6546*	0.1945*	−0.3165*	0.2342*	−0.1060*	0.0788*	0.1866*	1.0000					
11. Industry diversification	−0.0165*	−0.0485*	0.0490*	−0.1086*	−0.2564*	0.0068	−0.1267*	−0.0434*	0.1326*	0.0003	1.0000				
12. Innovation efficiency	0.0959*	0.0771*	0.0108	−0.0190*	−0.0376*	−0.0098	−0.0045	0.0290*	0.0149*	−0.0340*	0.0284*	1.0000			
13. Patent originality	0.4967*	0.4198*	0.1604*	−0.1113*	0.2456*	−0.0507*	0.0869*	0.0106	0.0917*	−0.1272*	0.2828*	0.0948*	1.0000		
14. Patent generality	0.3915*	0.3427*	0.1268*	−0.1174*	0.1735*	−0.0465*	0.0251*	0.0100	0.0848*	−0.1023*	0.2279*	0.0738*	0.6712*	1.0000	
15. Industry-level volatility	−0.0756*	−0.0645*	−0.1449*	0.1966*	−0.2590*	0.0674*	−0.0569*	−0.0748*	0.0155*	0.2365*	0.0050	−0.0226*	−0.2019*	−0.1610*	

*Denotes significance at 5%.

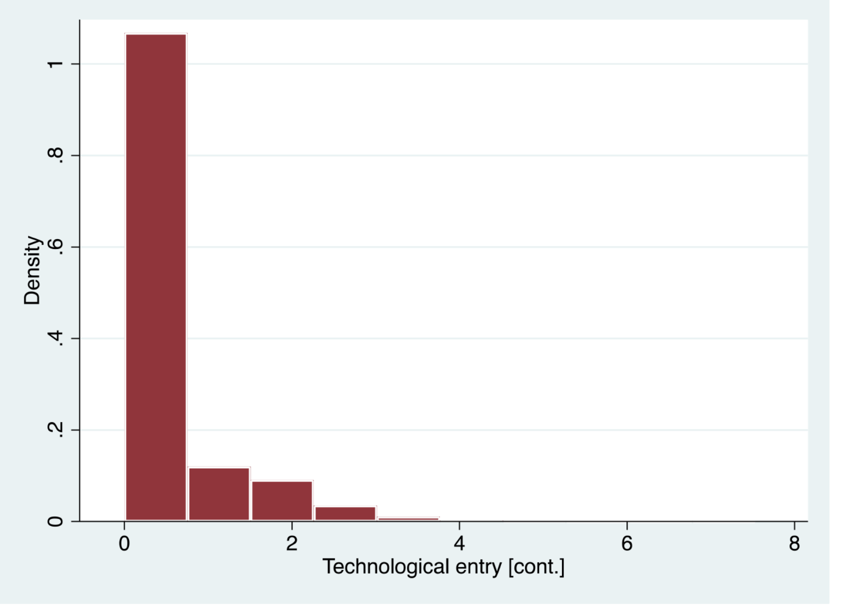

Figure 3. Frequency of technological entry [Colour figure can be viewed at wileyonlinelibrary.com]

confirmed. We derive similar (insignificant) results if we adopt the relatedness measure between the technological class of entry and a firm's SIC, as discussed in the previous section.

The results for the fifth hypothesis are reported in Table VI, which shows the model estimated using as explanatory variables the measure of technological entry in the year t, its lagged values in the years t−1, t−2, and t−3, and the usual set of controls and fixed effects. As already shown in our testing of Hypothesis 1, the coefficient of time-t entry has a positive effect on the MTB, which is significant at the 5 per cent level. Yet, lagged entry at t−1, t−2, and t−3 are not statistically significant, suggesting that current market values tend to incorporate the information provided by the occurrence of technological entry, and thus providing puzzling results for Hypothesis 5, which are discussed in the next section.

Besides the validation analyses mentioned previously, this article's online Appendix reports some additional findings. First, one concern for the causal interpretation of our results arises from reverse causality, according to which firm performance may drive the ability to enter new technological classes (and not vice versa). To alleviate this concern, we conduct a specific test in which we analyse the effect of past performance on technological entry. To this end, we exploit the longitudinal dimension of our data and analyse whether the MTB or ROA at time t −1 have a significant effect on technological entry at time t (for the subset of firms without technological entry from t−3 to t−1, to discern the direction of causality). Our results in Table A4 in online Appendix show that this is not the case.

Another concern is about the assumption that entries in new technological classes embody valuable growth options. To probe into this assumption, we tested if entry patents

Table II. Firm characteristics and technological entry

	Entry = 0	*Entry = 1*	*Difference (2) − (1)*
	(1)	*(2)*	*(3)*
Innovation efficiency	0.243	1.125	0.882***
			(0.059)
Patent originality	0.039	0.262	0.223***
			(0.002)
Patent generality	0.022	0.151	0.129***
			(0.002)
Ln assets	3.981	6.242	2.261***
			(0.029)
Revenue growth	0.235	0.123	−0.112***
			(0.011)
Ln acquisitions	0.221	0.463	0.242***
			(0.006)
Leverage	0.187	0.195	0.008**
			(0.004)
Capital expenditures	0.057	0.068	0.011***
			(0.001)
R&D expenditures	0.144	0.088	−0.066***
			(0.003)
Industry diversification	0.597	0.584	−0.013***
			(0.004)

Note: Standard errors in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

are impactful also from a technological point of view. Based on a random sample, we conducted a patent-level analysis that compared the forward citations received by an entry patent with those received by other patents. The results are reported in Table A5 in online Appendix, in which forward citations are regressed on the entry dummy, controlling for patent generality, originality, technological class, and grant year dummies. In column 4 we show the results based on a negative binomial specification, whereas the other columns show the OLS results. As we can see, the entry dummy has a positive and statistically significant effect on forward citations. The finding is robust to using propensity score matching.

DISCUSSION

Several strategy scholars have adopted the formalism of option theory to examine how firms redeploy their resources. Existing undertakings in this literature typically assume

Table III. Effect of technological entry on firm value (Hypothesis 1)

	Market to book					*Return on assets*
Dependent variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Technological entry	0.1261***	0.1679***	0.0930**	0.0952**	0.0991**	0.0131***
	(0.0433)	(0.0442)	(0.0422)	(0.0440)	(0.0451)	(0.0035)
Innovation efficiency		−0.0001	0.0028	0.0042	0.0047	−0.0002
		(0.0043)	(0.0043)	(0.0034)	(0.0036)	(0.0005)
Patent originality		−0.4207***	−0.4365***	−0.2054	−0.1945	0.0073
		(0.1411)	(0.1363)	(0.1454)	(0.1450)	(0.0120)
Patent generality		−0.5136**	−0.1852	−0.2585	−0.1893	0.0132
		(0.2002)	(0.1937)	(0.1994)	(0.1995)	(0.0136)
Ln assets			0.6866***	0.7013***	0.7125***	0.0418***
			(0.0527)	(0.0548)	(0.0577)	(0.0079)
Revenue growth			0.2400***	0.2305***	0.2196***	0.0259***
			(0.0330)	(0.0335)	(0.0340)	(0.0057)
Ln acquisitions			0.1755***	0.1669***	0.1658***	0.0147***
			(0.0449)	(0.0461)	(0.0461)	(0.0045)
Leverage			−0.9107***	−0.9041***	−0.8732***	−0.0651***
			(0.1126)	(0.1193)	(0.1210)	(0.0229)
Capital expenditures			3.6627***	3.2628***	3.2295***	−0.4529***
			(0.3885)	(0.4068)	(0.4180)	(0.0938)
R&D expenditures			0.5235**	0.3272	0.2836	−1.2116***
			(0.2119)	(0.2190)	(0.2216)	(0.0604)
Industry diversification			0.1941	0.1683	0.1875	0.0370**
			(0.1309)	(0.1356)	(0.1358)	(0.0155)

(Continues)

Table III. (Continued)

Dependent variable	*Market to book*					*Return on assets*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year dummies				Yes	Yes	Yes
State × Year dummies					Yes	Yes
Observations	24,889	24,889	24,889	24,889	24,889	24,889

Note: Standard errors clustered by firm are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table IV. Moderating effect of industry-level volatility (Hypothesis 2)

Dependent variable	*Market to book* (1)	*Return on assets* (2)
Technological entry [cont.]×Industry-level volatility	0.8019***	0.0454***
	(0.1511)	(0.0134)
Technological entry [cont.]	1.6467***	0.1006***
	(0.3124)	(0.0278)
Innovation efficiency	0.0052	−0.0002
	(0.0036)	(0.0005)
Patent originality	−0.1350	0.0107
	(0.1447)	(0.0120)
Patent generality	−0.1297	0.0165
	(0.1975)	(0.0135)
Ln assets	0.7089***	0.0416***
	(0.0576)	(0.0079)
Revenue growth	0.2203***	0.0260***
	(0.0340)	(0.0057)
Ln acquisitions	0.1620***	0.0145***
	(0.0458)	(0.0045)
Leverage	−0.8720***	−0.0650***
	(0.1208)	(0.0229)
Capital expenditures	3.2291***	−0.4529***
	(0.4178)	(0.0938)
R&D expenditures	0.2739	−1.2121***
	(0.2219)	(0.0604)
Industry diversification	0.1668	0.0358**
	(0.1354)	(0.0156)
Firm fixed effects	Yes	Yes
Industry×Year dummies	Yes	Yes
State×Year dummies	Yes	Yes
Observations	24,889	24,889

Note: Standard errors clustered by firm are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

that the domains in which firms redeploy resources are known, or easily identifiable, ex ante (Dushnitsky and Klueter, 2016; Sakhartov and Folta, 2014, 2015). In reality, many examples across different industries suggest that the new domains of an application often emerge unexpectedly from firm's technological activities that accumulate without anticipation of subsequent uses. This evidence calls for further examinations of the

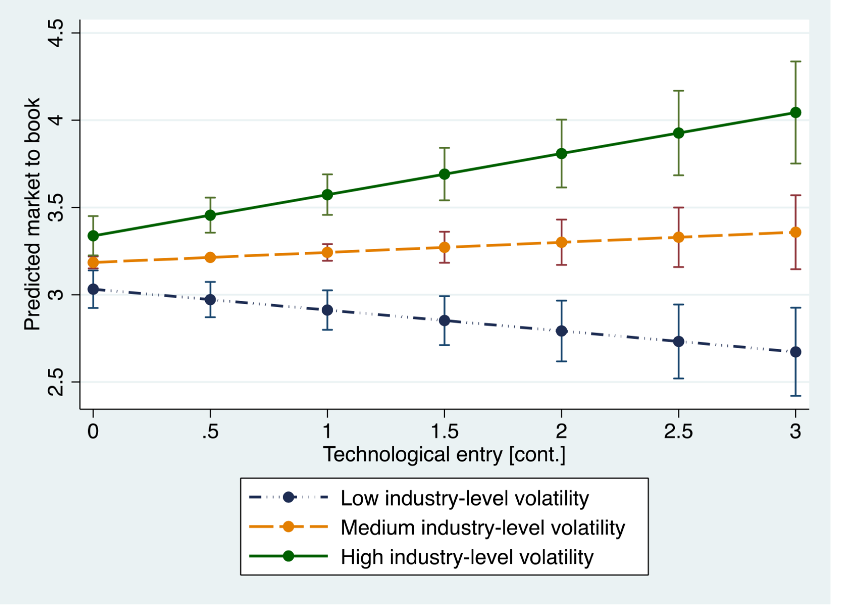

Figure 4. Effect of technological entry on market to book by industry-level volatility (Hypothesis 2) [Colour figure can be viewed at wileyonlinelibrary.com]

notion that inventive efforts 'made in exploration of a new domain should be separated from those conducted *without foreknowledge* of any potential *redeployment*' (Cattani, 2005, p. 565, emphasis added), an idea that takes central stage in a recent evolutionary literature that sheds light on the unexpected uses of technologies (Andriani and Cattani, 2016; Andriani et al., 2017; Cattani and Mastrogiorgio, 2021). By bridging these literatures, we examined firms' entries into new technological classes via patenting and proposed a framework according to which technological entry produces option value as a function of return volatilities and redeployment costs.

The empirical findings confirmed that technological entry spurs firm value, especially in volatile industry settings. Yet, contrary to our expectation, redeployment costs did not play a significant role. This result is puzzling but, at the same time, interesting, because it suggests that the unrelatedness of new technological domains does not necessarily preclude the potential of firms to efficiently redeploy. It thus talks to some established assumptions, like those about the value pitfalls of a firm's pre-entry experience (Christensen et al., 1998) and, more specifically, the notion that value increases only with higher relatedness between a firm's pre-entry experience and the new domains of entry (Helfat and Lieberman, 2002). While unpacking such complex issues is outside the scope of this article, our findings appear to suggest that firms' technological bases are inherently *option-rich*, i.e., they drive unexpected entries in new technological areas that in turn raise firm value. Is this, perhaps, another *contingency* that invalidates the inverted U-shaped linkage (Ahuja and Novelli, 2017) between the degree of relatedness and the value of firms? We do not have an answer to this question, but further work in this direction may prove valuable.

Table V. Effects of technology-level return volatility and redeployability (Hypotheses 3 and 4)

Dependent variable	*Market to book* (1)	*Return on assets* (2)
Technology-level volatility	−0.0140	0.0079**
	(0.0635)	(0.0035)
Redeployability	−0.5263	0.1422
	(5.8584)	(0.3345)
Innovation efficiency	0.0254	0.0027*
	(0.0177)	(0.0014)
Patent originality	−0.0023	−0.0204
	(0.2531)	(0.0151)
Patent generality	1.1176***	0.0343**
	(0.3334)	(0.0148)
Ln assets	0.7056***	0.0140
	(0.1546)	(0.0108)
Revenue growth	0.3600***	0.1033***
	(0.1361)	(0.0183)
Ln acquisitions	0.1496**	0.0099***
	(0.0732)	(0.0036)
Leverage	−0.6778**	−0.0027
	(0.3187)	(0.0207)
Capital expenditures	4.5871***	0.2953***
	(0.9243)	(0.0799)
R&D expenditures	0.9962	−0.4472***
	(0.9279)	(0.1223)
Industry diversification	0.6769**	0.0447***
	(0.2885)	(0.0162)
Firm fixed effects	Yes	Yes
Industry×Year dummies	Yes	Yes
State×Year dummies	Yes	Yes
Observations	6,639	6,639

Note: Standard errors clustered by firm are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Overall, we contribute to the growing literature on resource-based diversification (Folta, 2021). As recently noted by Cattani and Malerba (2021), firms grow not only by expanding within their current businesses but also by entering new businesses, as shown by the Corning example. In this regard, a firm's resources provide a platform for growth because, as Penrose argued decades ago, these 'can be used in different ways and for

Table VI. Persistence of technological entry on market value (Hypothesis 5)

	Market to book			
Dependent variable	*(1)*	*(2)*	*(3)*	*(4)*
Technological entry $_{t}$	0.0991**			
	(0.0451)			
Technological entry $_{t=-1}$		0.0486		
		(0.0430)		
Technological entry $_{t=-2}$			0.0005	
			(0.0429)	
Technological entry $_{t=-3}$				−0.0664
				(0.0404)
Innovation efficiency	0.0047	0.0059	0.0057	0.0059
	(0.0036)	(0.0037)	(0.0037)	(0.0037)
Patent originality	−0.1945	−0.1544	−0.1476	−0.1573
	(0.1450)	(0.1511)	(0.1556)	(0.1589)
Patent generality	−0.1893	−0.1993	−0.2340	−0.1518
	(0.1995)	(0.2032)	(0.2205)	(0.2360)
Ln assets	0.7125***	0.7238***	0.7386***	0.7911***
	(0.0577)	(0.0590)	(0.0614)	(0.0646)
Revenue growth	0.2196***	0.2193***	0.2075***	0.2295***
	(0.0340)	(0.0343)	(0.0354)	(0.0371)
Ln acquisitions	0.1658***	0.1682***	0.1704***	0.1600***
	(0.0461)	(0.0469)	(0.0478)	(0.0484)
Leverage	−0.8732***	−0.8927***	−0.9841***	−1.0422***
	(0.1210)	(0.1224)	(0.1259)	(0.1286)
Capital expenditures	3.2295***	3.2708***	3.5576***	4.0201***
	(0.4180)	(0.4332)	(0.4772)	(0.4915)
R&D expenditures	0.2836	0.2666	0.3758	0.6011**
	(0.2216)	(0.2212)	(0.2310)	(0.2415)
Industry diversification	0.1875	0.1883	0.1920	0.2314
	(0.1358)	(0.1366)	(0.1390)	(0.1417)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry×Year dummies	Yes	Yes	Yes	Yes
State×Year dummies	Yes	Yes	Yes	Yes
Observations	24,889	24,022	22,979	21,780

Note: Standard errors clustered by firm are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

different purposes' (1959, p. 76). A key implication of conceptualizing resources as bundles of possible uses is that all the uses of a resource *cannot* be possibly known or identified ex ante (Felin et al., 2021). Resources, in other words, represent what Bowman and Hurry (1993) called 'shadow options' of redeployment that await recognition. How are new uses uncovered, and how do shadow options *emerge*, thus becoming standard growth options that spur firm value? We elaborated a conceptual and empirical framework that shows how a firm's technology base, by *progressively* radiating into new domains that potentially reveal new uses and options of resource redeployment, spurs firm value.

What organizational policies could companies adopt to foster technological unexpectedness leading to firm value via option effects? We refer to the evolutionary-inspired literature, which has examined a variety of possible arrangements (Cattani and Mastrogiorgio, 2021). Worth mentioning are the different types of de-structured organizational arrangements, like bottom-up rather than hierarchical power, boundary spanning, cross-functional teamwork, deadline removal, and the opportunity to play, freely, with ideas (Cunha et al., 2010). The success of these arrangements explains their wide use in companies such as Google, Pixar, and 3M, among others. 3M, for instance, is well-known for a human-resource policy that allows its engineers and inventors to spend up to 15 per cent of their time to pursue whatever project they like. This policy has been credited for the invention of many breakthrough technologies some of which, like the Post-It, were originally unintended (Cattani, 2019). Other examples are Google's inventions of SkyMap, StreetView, and Gmail, which resulted from similar policies.

Limitations and Future Research Directions

Our study has some limitations that are worth acknowledging. The first is of a methodological nature and is related to the classification of technological entry based on patents. Notoriously, patent data suffer from two shortcomings: (1) firms do not patent all their inventions; and (2) the technological classifications of patents may not always coincide with the underlying pieces of knowledge. While we have provided a battery of tests to reinforce the validity of our findings, patent-based measures remain imperfect. Future studies could employ more fine-grained data (for instance, based on primary sources coming from surveys to inventors) with the aim of shedding light on the cognitive processes that underlie the activities leading to unexpected entries in new technological classes. Another fruitful area of investigation concerns the factors that mediate the relationship between technological entry and firm value. In untabulated analyses, we found some evidence that firms which enter new technological classes *invest more* and *diversify* their revenues following entry. This evidence may point to how firms exercise the implicit options granted by the technological entry, and thus to the mechanisms of value creation in the aftermath of technological entry. An ideal test of these mechanisms would require investment or revenue data by product or technological class.

A second limitation of our study is that the positive effects of volatilities on option value could be an artefact of the absence of 'contemporaneous uncertainty'. As argued by Posen et al. (2018), strategy scholars conventionally think that the value of a real option increases with higher levels of volatility, which serves as a proxy for 'future' uncertainty about the value of the underlying asset. Yet, due to market incompleteness (Denrell et al., 2003), the illiquid nature of real assets limits the availability of information and fundamentally complicates valuation (Bowman and Moskowitz, 2001), thus generating 'contemporaneous uncertainty' that may lead to managerial 'value-destroying errors' that decrease – rather than increase – option value (Posen et al., 2018, p. 1132). Although our models include proxies for contemporaneous uncertainty that should, in principle, control for it (e.g., the industry's stage of technology development, captured by fixed effects, or common temporal shocks, captured by year dummies and their interaction with industry dummies), future work could engage with these issues by further exploring the behavioural deviations from efficiency.

A third limitation, related to the second, is that our study does not take fully into account the mechanisms of inefficient valuation implied by some of our key arguments – in particular, in the fifth hypothesis, for which we indeed found puzzling results. We believe that addressing these issues is of fundamental importance for the development of a comprehensive theory that aims to link unexpected entry into new technological classes to a firm's market value via the option value of redeployability. In this regard, the financial literature on market inefficiency (Fama, 1965, 1970; Samuelson, 1965; Shiller, 2000) could be the starting point of a fine-grained empirical detection of inefficiency, perhaps in the time-series of stock returns rather than in raw performance variables. The link between technology and stock returns has received increasing attention (Cohen et al., 2013; Hall, 2001; Hobijn and Jovanovic, 2001; Nicholas, 2008; Pastor and Veronesi, 2005) as part of a broader debate on the idea that inefficiency – and economic disequilibrium, broadly speaking – is endogenously generated by technology (Arthur, 2014). This type of analysis, therefore, could help to further clarify and shed light on the problematic nature of optionality when applied to technologies and resources (Adner and Levinthal, 2004; Leiblein et al., 2017).

CONCLUSION

Resource redeployability is receiving increasing attention in the strategy field. Much has been learned about resource redeployability, but more work has been urged to challenge assumptions that are fundamental to theory. 'Resource redeployability' has been defined as the value-generating option to withdraw resources 'from one use and reallocate to another *use*' (Folta, 2021), where a key assumption is that new uses of resources are known ex ante, and thus easily identifiable by managers. However, many real cases from different industries show that new uses often have technological origins, meaning that they emerge over time while a firm's technology base radiates into new domains. We have proposed a conceptual and empirical framework to identify how a firm's technology base, by radiating into new domains that potentially reveal new uses and options of resource redeployment, spurs option value. We articulated five hypotheses and proposed a new measure, finding that technological entry into new domains increases firm valuation. Our work provides useful guidance for future inquiries on the origin and implications of resource redeployability.

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NOTES

[1] For the sake of clarity, 'businesses' are here broadly defined, being assumed that the firm is already operative in them. In our specific setting, instead, redeployment refers to the current industry of the firm and the new technological class into which it enters (and in which its business presence is absent or very limited).

[2] Yet, as recounted by Penrose (1960), neither Du Pont nor Hercules (its former subsidiary) really knew *where* they were going to redeploy their resources after World War I: 'at the end of the First World War the plant, organization, and accumulated funds of the firm were much greater than could be used in explosives in view of the drastic decline in demand after the war. In the immediate postwar period numerous opportunities for profitable investment were open on all sides in the expanding, changing economy. But which of them would furnish opportunities …?' (Penrose, 1960, p. 6).

[3] Dushnitsky and Klueter (2016) provided the first study that, *within* the redeployment stream (Folta et al., 2016), has begun to unpack the idea that the uses of technology aren't easily identifiable. This idea is at the centre of an established evolutionary literature, on which we build, and to which we bring an option-valuation angle that is still missing.

[4] This formal framework also provides a clean setting for testing the hypothesis that patents are options. Several studies have associated patents with options, but a key challenge has been that of separating the pure value of optionality from other confounding factors that also drive value but are not due to optionality. Patenting in technological classes that are new to the firm and unexpected allows, at least in part, this type of separation.

[5] As noted by Cattani (2006), there are fine-grained 'watershed events' that separate unexpectedness from intentionality, which are intrinsically difficult to capture in a large sample study like ours. To be more specific, both patenting and the inventive process that immediately precedes it may involve some significant degrees of intentionality. Unexpectedness, therefore, would lie in the discovery phase that precedes invention. 'Patenting via the *unexpected* route', therefore, is here meant as unexpectedness at the origin of the discovery-invention-patenting chain, not in patenting (or technological entry) per se.

[6] '[We can] think of the distance to that market as larger to the extent that the critical factors in the market differ from those in the firm's current scope. […] The farther from its current scope that it must go, ceteris paribus, the larger will be the loss in efficiency and the lower will be the competitive advantage conferred by the factor' (Montgomery and Wernerfelt, 1988, p. 625).

[7] In reality, as our results will show, entry into new technological classes does not seem to preclude the ability of firms to scale up efficiently, as illustrated by Corning's entry into fibre optics from glass manufacturing (Cattani, 2005), or by the entry of pharmaceutical firms into new disease markets via the *off-label* route (Andriani et al., 2017).

[8] After searching for the synonyms of 'unexpected' on the Oxford Languages website, we defined the following dictionary: serendipitous, serendipity, chanceful, chance, accidental, accident, lucky, luck, fortuitous, fortune, unexpected, unanticipated, unforeseen, coincidental, fluky, exaptive, exaptation.

[9] The test gave a p-value of 0.898. This means that a power-law cannot be excluded (see Clauset et al., 2009).

[10] The three industries with the lowest value (in 2006) are Cigarettes (SIC 211), Paints, Varnishes, Lacquers, and Allied Products (SIC 285), and Miscellaneous Transportation Equipment (SIC 379); the three industries with the highest value (in 2006) are Household Audio and Video Equipment (SIC 365), Communication Services (SIC 489), and Miscellaneous Electrical Machinery (SIC 369).

[11] When the patentee applies for multiple patents in the same year, the stock return is the same.

[12] Assets with high redeployability are, for example, those related to 'industrial trucks, trailers and stackers', which are used in a broad array of industries, whereas assets with low redeployability are 'drilling oil and gas wells', which are mostly used in the oil and gas industry (Kim and Kung, 2017).

[13] It could be argued that a simpler explanation of our findings is that there is firm value in experimenting with new technologies, as the relevant technology base of industries changes over time. This argument has been made in the literature on exploration, which has demonstrated a positive association between technological exploration and performance and the role of environmental factors (Jansen et al., 2006; Uotila et al., 2009). Technological exploration activities, though, are intentional, while our focus is entirely on unexpected technological outcomes and their value implications mediated by optionality, as both our theory and the empirical validations seek to show. In addition, our models include controls for R&D, patent characteristics, and industry dummies, which indirectly account for exploration. We thank one reviewer for raising this point.

[14] Results are robust to excluding industry×year intercepts and including industry volatility.

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