Paper to be presented at the DRUID Academy Conference 2016 in Bordeaux, France on January 13-15, 2016

Should I Stay or Should I Go Now? Organization-level Determinants of Novelty in Technology

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Abstract

Breakthroughs in Biotech Organization-level determinants of novelty and breakthrough impact Dennis Verhoeven - KULeuven, Department of Managerial Economics, Strategy and Innovation–November 2011–May 2016 (Dennis.Verhoeven@kuleuven.be) Joint work with Ashish Arora and Reinhilde Veugelers State-of-the-art Inventions introducing novel technological approaches to a problem are pivotal in the process of Schumpeterian creative destruction. While technological novelty is the ultimate source of breakthrough impact, pursuing novel inventive outcomes, on the one hand, is subject to more uncertainty (Fleming, 2001), and, on the other hand, requires distinctive capabilities (Rosenkopf & Nerkar, 2001; Shane, 2001). These distinct characteristics raise the question of which type of organizations have the right capabilities and economic motivation to aim at novel approaches rather than incrementally improving existing ones. Conventional wisdom views small entrants as being at an advantage when it comes to the generation of breakthrough innovation, while large, incumbent firms are better in generating follow-on incremental innovations. Empirical support of this conventional view is sparse and subject to debate among innovation scholars (Henderson, 1993; Methé et al., 1997; Chandy & Tellis, 2000; Baumol, 2003). Research gap These mixed empirical findings fail to unravel the mechanisms behind breakthrough invention. It is often claimed that large, incumbent firms are overly bureaucratic and myopic, which decreases their productivity in research that might lead to breakthrough inventions. Others argue that large incumbents have less incentives because of fear of cannibalization of their own profits. This paper aims at generating more insight in these mechanisms by zeroing in on the role of technological novelty and its effect on breakthrough invention. We develop a simple model to explain both investment in novel vs incremental R&D, and the rate of breakthrough invention for these types of R&D. Theory We develop a simple model to explain novelty rates of inventive activity as well as breakthrough outcomes. In our model, R&D projects are either novel or incremental. For both types of projects, actors make a ranking based on their expected return and invest in those projects for which this expected return is higher than a constant marginal cost. For both novel and incremental projects, firms can differ in terms of their ability to detect profitable projects, as well as in their constant marginal costs. Breakthroughs are those projects that are outliers in terms of impact, and we assume that, on average, these are the projects with higher expected returns. This model links breakthrough outcomes to investment choices in different types of projects and is able to explain differences in novelty and breakthrough rates without relying on conventional assumptions of differing capabilities in breakthrough invention. Method We use all US biotech patents from 1995-2005 to track inventive activity of different organizations. We distinguish between universities, large firms and small firms, and use patent-based indicators of technological novelty (Verhoeven et al., 2015) and breakthrough impact (Arts et al., 2013). We estimate the relative novelty rate of different actors, as well as the breakthrough rate from both novel and incremental projects, controlling for technology fields as well as for a variety invention-level characteristics. Results Preliminary results show, controlling for technological opportunity, science-intensity and broadness of the invention, that both universities and small firms are relatively more active than large firms in generating novel inventive outcomes. Interestingly, all actor-types generate a higher rate of breakthrough impact for their novel inventions. This raises the question of why – while all actors generate breakthroughs through novelty – large firms pursue relatively less novel outcomes. Our model explains this tension by raising the argument that large firms have lower costs for incremental projects than small firms and universities. This will provide them with incentives to 'accept' incremental projects that are further down the marginal return curve, which decreases novelty rates, but does not change the fraction of novel projects resulting in breakthroughs. Moreover, while novelty increases breakthrough rates for all actors, the type of novelty through which breakthroughs arise are different between the actors. Large firms benefit from making new connections between technological fields, universities from linking scientific fields to hitherto technological fields, and small firms benefit from both types of novelty. In conclusion, our preliminary results suggest that all actors are capable of generating high-impact novelty (but different types), but large firms have a relative advantage in generating incremental inventions, decreasing their relative novelty rate. References Arts, S., Appio, F.P., Looy, B.V. (2013): Inventions shaping technological trajectories: do existing patent indicators provide a comprehensive picture? Scientometrics 97, 397–419. Baumol, W.J. (2004): Entrepreneurial Enterprises, Large Established Firms and Other Components of the Free-Market Growth Machine. Small Business Economics 23, 9–21. Chandy, R.K., Tellis, G.J. 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Jelcodes:O31,O32

Should I Stay or Should I Go Now?

Organization-level Determinants of Novelty in Technology

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January 2015

PRELIMINARY AND INCOMPLETE WORK

Abstract

This paper sets out to explain novelty creation by different types of organizations. We establish a number of empirical patterns using a large sample of biotechnology patents applied for between 1995 and 2005. The results show that novelty is strongly associated to breakthrough impact for all different organization types – small firms, large firms and universities. Yet, while all types of organizations seem to benefit from their novel inventions, we observe vast differences in the rate at which they produce novelty. These observations motive us to develop a model that can explain when organizations stay in their existing fields and when they go and explore new technological approaches. Rather than relying on traditional assumptions of differences in costs, capabilities and search strategies, the model explains differences in novelty rates through experience built up in technological fields and limited information on the value of new fields. This model yields a number of testable implications that can explain novelty creation beyond a mere distinction on size.

1. Introduction

Inventions introducing novel technological approaches to a problem are pivotal in the process of Schumpeterian creative destruction. For instance, the Polymerase Chain Reaction was a novel invention introducing the capacity to multiply DNA sequences in vitro. As such, this invention paved the way for the rise of biotechnology and associated technological and economic progress. Given this association between technological novelty and breakthrough (and economic) performance, it is critical for policy makers to understand how novel inventions come about. This paper aims to contribute to this understanding by zeroing in on the conditions under which economic actors produce technological novelty.

Students of the evolution of technology emphasize how technologies evolve steadily along trajectories, which are only rarely interrupted by a paradigm shift introduced by a novel invention (Dosi, 1982; Arthur, 2007, 2009). Although these novel inventions are the ultimate source of breakthrough impact, they are typically also surrounded by more uncertainty in terms of performance (Fleming, 2001; Verhoeven et al., 2015). Indeed, many novel approaches prove to be dead-ends or only live up to their potential after much follow-on inventive effort. Such uncertainty raises the concern that market failures for innovations are more pronounced for the novel inventions at the source of breakthrough performance. The high-risk-high-reward nature of inventive activity targeting novel approaches, leads to the question of what are the determinants of an organization's decision to invest in further developing familiar technologies resulting in incremental improvements versus moving towards novel, high-potential approaches.

A stream of literature has focused on size and incumbency of firms to explain radical innovation[1] outcomes. Conventional wisdom views small entrants as being at an advantage when it comes to the generation of breakthrough innovation, while large, incumbent firms are better in generating follow-on incremental innovations. Empirical support of this conventional view is sparse and subject to debate among innovation scholars (Henderson,

[1] We loosely adopt the term 'radical innovation' in its broad meaning here. It is to be noted that this term covers a wide range of different constructs, including novelty and impact, as well as technological and economic characteristics of technologies.

1993; Methé et al., 1997; Chandy & Tellis, 2000; Baumol, 2003). The lack of consensus on how to conceptualize and operationalize the different concepts related to 'radical innovation' further attenuates the difficulties in better understanding the issue. Moreover, it proves difficult to unravel the mechanisms behind breakthrough invention (Henderson, 1993). It is often claimed that large, incumbent firms are overly bureaucratic and myopic, which decreases their productivity in research that might lead to breakthrough inventions. This view assumes large firms are less efficient at R&D targeting breakthroughs as they lack the 'right' capabilities. Some studies suggest remediation of this problem by implementing strategies that include searching beyond what the firm already knows (Rosenkopf & Nerkar, 2001; Ahuja & Lampert, 2001). Others argue that large incumbents have less incentives because of fear of cannibalization of their own profits (Reinganum, 1983; Chandy & Tellis, 1998).

In this paper, we take a step back and analyze breakthrough performance at its source – novelty creation. The rationale behind this approach is that the association between breakthrough performance and novelty is a one-way-street only. Most breakthrough inventions introduce (or closely build upon) a novel technological approach. Indeed, many studies on breakthrough innovations implicitly or explicitly assume that breakthroughs come about through the introduction of a novel technological approach. Then, mechanisms behind novelty creation – such as distant search – are argued to be at the source of breakthrough performance. However, it is important to see that most novel approaches to a problem are of little use and might not even show up in the data because there is no (patent) record of them. Moreover, even if a new approach displays a lot of potential, the actual outcome is highly uncertain. Hence, in order to understand the few cases that make it to success, we need to understand the decision process behind investing in such novel approaches. Disregarding these underlying mechanisms behind technology strategies can lead to an incomplete view on organization-level drivers of breakthrough performance.

In a first stage, this paper documents novelty and breakthrough patterns in biotechnology. We use new indicators to measure technological novelty (Verhoeven et al., 2015) separately from breakthrough impact and make a distinction between 3 actor types – Universities, Small Firms, and Large Firms. Confirming previous studies, findings show that novelty in general is related to outlier impact. Furthermore, our preliminary results show, controlling for technological opportunity, science-intensity and broadness of the invention, that both universities and small firms are relatively more active than large firms in generating novel inventive outcomes. Interestingly, all actor-types generate a higher rate of breakthrough impact for their novel inventions. This raises the question of why – while all actors generate breakthroughs through novelty – large firms pursue relatively less novel outcomes.

In the second stage, we develop a model to explain novelty rates of inventive activity. In the model, investing in a technological field ('approach') new to the actor results with some random probability in a novel technology. Nature defines the set of all possible technological approaches (fields). Each field consists of a number of projects actors can invest in. The value of each project is determined by nature, and projects in the same field correlate in terms of value. Actors only observe (the value of) a subset of all possible projects and are able to rank them based on their value. They make a decision to invest in a field based on the expected profits in that field, and select the project with the highest value. For each field, they face a downward sloping marginal cost behaving like an experience curve. Breakthroughs are those projects that are outliers in terms of value and follow simply from novelty because firms can invest in the most valuable project in a field first. We analyze how, in this model, expected field value evolves with increasing experience in the field and increasing information on a field's value. The model is able to explain differences in novelty and breakthrough rates without relying on conventional assumptions of differing capabilities in breakthrough invention.

2. Motivating Empirical Patterns

2.1 Methodology

Sample

We use all US biotech patents from 1995-2005 to track inventive activity of different organizations (Arts et al., 2014). Biotechnology is an interesting field to study in our context because of at least 3 reasons. First, since patenting is effective in biotechnology, we have a relatively comprehensive account of inventive activity using patent information. Second, both incremental and novel inventive activity is prevalent in our time frame because the biotechnology sector between 1995 and 2005 was still heavily growing, yet it had enough maturing technologies resulting in first applications. Third, we have enough heterogeneity in organization types as both small companies, universities and large incumbent firms were investing in biotechnology.

Data

To distinguish between universities, large firms and small firms, we collect all applicant names present on the patents using the algorithm developed in Du Plessis et al. (2010). Since this algorithm is more reliable for larger firms, we performed further cleaning in order to harmonize applicant names using string similarity algorithms and manual verification in different iterations. We distinguish between universities and companies using the sector allocation developed in Du Plessis et al. (2010). We group hospitals and other governmental institutions in the 'others' group. Within companies, we distinguish between small and large firms using previous patenting intensity and mark a company as large when it has a 5 year patent stock of 25 or above. Results are robust to varying the threshold used between 10 and 50. When calculating the patent measures, we use information on the family members in other offices as well (DOCDB definition, see Martinez, 2011 for more details on patent families). We end up with 40 797 patent families belonging to 5107 different actors.

Variables

To measure technological novelty, we use the indicators developed in Verhoeven et al. (2015). We distinguish between two types of novelty. Novelty in Recombination (NR) takes value 1 if at least one patent in the family makes a combination between two IPC groups that were previously never combined. NR captures novelty residing from making a novel connection between two fields of technological knowledge. Novelty in Scientific Origins (NSO) takes a value of 1 when at least one patent in the family cites a scientific paper from a Web of Science (WOS) category that was previously never cited by a patent with the focal patent's IPC groups, zero otherwise. NSO captures whether an invention connects a field of technological knowledge to a previously unconnected scientific field of knowledge.

To capture whether an invention entails breakthrough impact, we use forward patent citations, correcting for patent families (Bakker et al., 2015). To construct our breakthrough measure we estimate the first and second moment of the distribution of forward citations for each IPC subclass – year combination. The measure takes value 1 if the patent family is among the 2 standard deviation outliers in the distribution of at least one of its IPC subclass – year combinations (Arts et al., 2014; Verhoeven et al., 2015).

We estimate the relative novelty rate of different actors, as well as the breakthrough rate from both novel and incremental projects, controlling for technology fields as well as for a variety invention-level characteristics. To control for technology field fixed effects, we include IPC class dummies. Moreover, we control for family size and presence in different patent jurisdictions (dummies indicating whether at least one family member was filed at the EPO or through the PCT route). Furthermore, since our novelty measures are sensitive to the number of class combinations made, we control for the number of IPC subgroup combinations made, as well as the number of IPC subgroup – WOS category combinations. Moreover, since the IPC scheme is subject to changes and new IPC codes can be added (artificially creating new combinations), we control for whether the patent family belongs to an IPC code that was added to the IPC classification scheme after 1980. To control for the extent to which an invention relies on many previous sources, we control for the number of backward patent references.

2.2 Results

Out of our sample of 40 797 biotech patent families, applied for between 1995 and 2005, 17 296 (about 42%) belong to large firms, 12 220 (about 30%) belong to small firms, 7 168 (about 18%) belong to universities, and the remaining 4 113 (about 10%) belong to other institutions. Table 1 presents the summary statistics of and correlations between the different variables that will be used in the analyses. Both Novelty and Breakthrough are skewed phenomena (about 5% of patent families are classified as breakthrough, while less than 11% displayed either novelty in recombination (NR) or novelty in scientific origins (NSO)). In the remainder of the analyses Novelty will indicate scoring on either NR or NSO, and we will also use the exclusive categories (NR only, NSO only, both NR and NSO) to distinguish between different types of novelty. When looking at the correlations between the variables used in the multivariate analyses, we see that all variables are positively correlated, but the correlations are generally small, decreasing concerns about multicollinearity. The highest correlations observed are in the range of 0.5-0.6 and occur between the EPO/PCT-member and family size variables on the one hand, and between the number of IPC subgroup and IPC subgroup – WOS category combinations made. The results are robust to only including any one of the highly correlated variables.

	Variable	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Breakthrough	5.40%	22.61%	1.0000								
(2)	Novelty	10.65%	30.85%	0.1498*	1.0000							
(3)	Family Size	6.66	6.58	0.2483*	0.1219*	1.0000						
(4)	EPO member	.55	.50	0.0907*	0.0946*	0.5825*	1.0000					
(5)	PCT member	.60	.49	0.0718*	0.0693*	0.4793*	0.6333*	1.0000				
(6)	Backward Ref.	15.26	21.82	0.2592*	0.1595*	0.1580*	0.0496*	0.0321*	1.0000			
(7)	New IPC	.11	.32	0.0216*	0.0181*	0.0938*	0.1141*	0.1066*	0.0139*	1.0000		
(8)	Nr Comb NR	20.47	42.09	0.1642*	0.1784*	0.3208*	0.2717*	0.2013*	0.1105*	0.2706*	1.0000	
(9)	Nr Comb NSO	31.33	43.96	0.1859*	0.2358*	0.2478*	0.1402*	0.1349*	0.2871*	0.2535*	0.4882*	1.0000

Table 1: Descriptive statistics of and correlation between variables in the model. * indicates p-value<0.01

Table 2 displays the coefficients from a linear probability model, explaining different types of novelty by the type of applicant (models 1, 4, 7 and 10) where the reference category is large firms, controlling for the number of combinations made (models 2, 5, 8 and 11) and other control variables (models 3, 6, 9 and 12). The conditional descriptive statistics (models 1, 4, 7 and 10) show that there are important differences between the actors in performing any type of novelty. The probability of a patent to be novel (NR or NSO, model 1) when it belongs to a large firm (intercept) is about 8.7%, while this probability is about 14.5% for small firms, 10.4% for universities and 7.9% for other institutions. Hence, small firms perform two thirds more novelty than large firms, universities perform 20% more novelty than large firms. When distinguishing between different types of novelty (models 4, 7 and 10), we see the difference between small and large firms remains present for all types of

	Novel			NR only			NSO only			NR and NSO		
	(1)	(2)	(3)	(5)	(7)	(4)	(6)	(8)	(10)	(11)	(12)	(13)
small	5.841***	5.954***	3.140***	2.088***	2.331***	1.181***	2.154***	1.995***	1.226***	1.599***	1.627***	0.734***
	(0.384)	(0.372)	(0.337)	(0.259)	(0.257)	(0.240)	(0.239)	(0.232)	(0.233)	(0.193)	(0.189)	(0.177)
university	1.695***	1.637***	2.725***	-1.055***	-0.234	0.247	2.116***	1.320***	1.747***	0.634**	0.551**	0.730***
	(0.419)	(0.405)	(0.374)	(0.243)	(0.241)	(0.233)	(0.291)	(0.282)	(0.289)	(0.209)	(0.207)	(0.189)
others	-0.807	-0.148	1.601***	-1.170***	-0.507	0.238	0.434	0.211	0.718*	-0.0707	0.148	0.645**
	(0.471)	(0.460)	(0.416)	(0.291)	(0.288)	(0.273)	(0.313)	(0.307)	(0.307)	(0.228)	(0.227)	(0.210)
Family Size			0.109**			0.0931***			-0.0298			0.0455*
			(0.0386)			(0.0244)			(0.0228)			(0.0212)
EPO member			1.228**			0.347			1.116***			-0.235
			(0.402)			(0.267)			(0.274)			(0.211)
PCT member			-0.0649			0.0461			-0.228			0.117
			(0.343)			(0.235)			(0.243)			(0.173)
Backward Ref.			0.0487***			0.00323			0.0382***			0.00725
			(0.00817)			(0.00548)			(0.00625)			(0.00467)
New IPC			-2.518***			0.167			-1.432***			-1.253***
			(0.521)			(0.363)			(0.365)			(0.283)
Nr Comb NR		0.0616***	0.0355***		0.0827***	0.0580***		-0.0401***	-0.0351***		0.0190***	0.0126***
		(0.00631)	(0.00612)		(0.00504)	(0.00486)		(0.00301)	(0.00326)		(0.00350)	(0.00378)
Nr Comb NSO		0.136***	0.133***		-0.0353***	-0.0397***		0.114***	0.117***		0.0578***	0.0559***
		(0.00586)	(0.00594)		(0.00337)	(0.00373)		(0.00463)	(0.00508)		(0.00382)	(0.00376)
IPC3 dummies	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Intercept	8.684***	3.057***	0.000398	3.845***	2.975***	-0.768**	3.018***	0.478**	1.896***	1.821***	-0.395**	-1.128***
	(0.214)	(0.241)	(0.405)	(0.146)	(0.166)	(0.278)	(0.130)	(0.151)	(0.292)	(0.102)	(0.133)	(0.218)
N	40797	40797	40797	40797	40797	40797	40797	40797	40797	40797	40797	40797
R-squared	0.00728	0.0681	0.255	0.00385	0.0267	0.152	0.00274	0.0528	0.0743	0.00212	0.0408	0.172

Table 2: Results Linear Probability model (OLS) explaining different types of novelty (Novel: scoring on either NR or NSO, NR only: scoring only on NR, NSO only: scoring only on NSO, NR and NSO: scoring on both NR and NSO). Robust standard errors between brackets.

*** p-value<0.05, ** p-value<0.01, *** p-value<0.001**

novelty, while the difference between universities and large firms are driven by differences in novelty including novelty in scientific sources. The coefficients of interest barely change when controlling for the number of combinations made. This indicates differences cannot be explained by heterogeneity in terms of IPC classifications (for instance level of aggregation) between areas where different actors patent in. Controlling for other patent characteristics reflecting specificities in technology field and application procedures, decreases the differences slightly, but the variables of interest remain highly significant and the differences important.

Table 3 presents the coefficients from a linear probability model explaining breakthrough performance. Models 1, 2 and 3 provide conditional descriptive statistics of breakthrough probability by actor (model 1), and by actor and (different types of) novelty (models 2 and 3). Models 4, 5 and 6 shows these results when controlling for other patent characteristics reflecting specificities in technology field and application procedures. When looking at model 1, we see that about 5.5% of patents applied for by large firms are breakthroughs, while 7.2% of patents applied for by small firms and 3.5% of patents applied for by universities are breakthroughs. These results seem to indicate a relative advantage for small firms, and a relative disadvantage for university (and other institutions) at generating breakthrough inventions. However, when distinguishing between novel and non-novel patents, we see that small firms, large firms and universities equally generate breakthroughs with their novel patents. The relationship between novelty and breakthrough is strong, with differences in breakthrough probabilities around 10% between novel and non-novel patents (for small firms, large firms and universities). For other institutions, the difference is smaller (about 3.6%), but still statistically significant. These differences are accounted for by all types of novelty, but most strongly for patents combining novelty in scientific sourcing (NSO) and novelty in recombination (NR) (between 14% and 20%). When controlling for other patent characteristics, general differences between actors disappear, but the differences between novel and non-novel patents remain (but decrease in size). These differences are accounted for mainly by patents that include novelty in scientific sourcing (NSO).

Breakthrough	(1)	(5)	(6)	(2)	(7)	(8)
Small	1.579***	0.892**	0.892**	0.368	0.0993	0.102
	(0.291)	(0.278)	(0.278)	(0.269)	(0.264)	(0.264)
University	-1.918***	-2.062***	-2.062***	0.463	0.269	0.290
	(0.282)	(0.257)	(0.257)	(0.275)	(0.261)	(0.261)
Others	-3.045***	-2.341***	-2.341***	0.202	0.511	0.521
	(0.301)	(0.293)	(0.293)	(0.290)	(0.283)	(0.283)
Large X Novel		11.39***			2.340**	
		(0.960)			(0.905)	
Small X Novel		11.54***			3.793***	
		(0.919)			(0.868)	
University X Novel		10.92***			3.574**	
		(1.266)			(1.157)	
Others X Novel		3.621**			-2.331	
		(1.327)			(1.349)	
Large X NR only			7.897***			-0.700
			(1.293)			(1.224)
Small X NR only			8.593***			2.329
			(1.311)			(1.232)
University X NR only			6.978***			-0.229
			(2.083)			(1.946)
Others X NR only			5.029*			-1.656
			(2.488)			(2.564)
Large X NSO only			11.51***			4.313**
			(1.617)			(1.522)
Small X NSO only			9.714***			3.646**
			(1.445)			(1.381)
University X NSO only			11.61***			5.778***
			(1.827)			(1.639)
Others X NSO only			2.686			-0.891
			(1.833)			(1.846)
Large X NR and NSO			18.59***			5.475*
			(2.384)			(2.179)
Small X NR and NSO			19.40***			6.667***
			(2.127)			(1.895)
University X NR and NSO			13.96***			3.424
			(2.804)			(2.558)
Others X NR and NSO			3.312			-6.225*
			(2.711)			(2.600)

Family Size				0.796^{***}	0.794^{***}	0.796^{***}
				(0.0508)	(0.0504)	(0.0503)
EPO member				-3.106^{***}	-3.142^{***}	-3.131^{***}
				(0.361)	(0.359)	(0.358)
PCT member				-1.080^{***}	-1.073^{***}	-1.071^{***}
				(0.257)	(0.256)	(0.255)
Backward Ref.				0.190^{***}	0.188^{***}	0.187^{***}
				(0.00855)	(0.00855)	(0.00854)
New IPC				-1.312^{**}	-1.250^{**}	-1.194^{**}
				(0.401)	(0.402)	(0.401)
Nr Comb NR				0.0325^{***}	0.0316^{***}	0.0329^{***}
				(0.00518)	(0.00519)	(0.00522)
Nr Comb NSO				0.0304^{***}	0.0266^{***}	0.0233^{***}
				(0.00496)	(0.00501)	(0.00509)
IPC3 dummies	No	No	No	Yes	Yes	Yes
Intercept	5.574^{***}	4.584^{***}	4.584^{***}	-2.950^{***}	-2.919^{***}	-2.955^{***}
	(0.174)	(0.166)	(0.166)	(0.328)	(0.326)	(0.326)
N	40797	40797	40797	40797	40797	40797
R-squared	0.00450	0.0267	0.0298	0.146	0.148	0.149

Table 3: Results Linear Probability model (OLS) explaining breakthrough rates by actor type and (different types of) novelty by actor. Robust standard errors between brackets. * p-value<0.05, ** p-value<0.01, *** p-value<0.001

2.3 Interpretation

From these analyses, two clear patterns emerge. First, novelty indeed seems to be the main driver of breakthrough performance in biotechnology. While some non-novel patents result in breakthrough performance, the probability to induce breakthrough performance strongly increases when the invention incorporates (different types of) technological novelty. This result confirms previous studies (Fleming, 2001; Verhoeven et al., 2015) in explaining high impact by the introduction of novel technological approaches. While the breakthrough rate of 'incremental' inventions is about 5%, novel inventions have a rate of about 15%. Moreover, all types of actors display these increased rates for their novel inventions with negligible differences in size. Moreover, when controlling for other patent characteristics, differences between the actors disappear, but the increased rates of breakthroughs for novel inventions remains present.

Second, there are important differences between different organization types in their novelty rates. Large firms perform significantly less inventions displaying novelty compared to small firms and universities. Moreover, universities mainly create inventions which display novelty in scientific knowledge origins, a result which should not surprise. The difference between small firms and large firms is present for all types of novelty. Controlling for a variety of patent characteristics does not qualitatively change these conclusions.

Tying these two facts together, raises the intriguing question of why, if all actors are able to create breakthroughs through novelty, there remain differences in rates of performing novelty. To be able to explain this, we need a theory that is able to explain why novelty leads to breakthrough performance for all actors, while not all actors engage to the same extent in creating novel inventions. In the next section we develop a model that can explain these patterns without relying on the assumption of systematic differences in capabilities to develop certain types of inventions. Instead, it assumes downward sloping marginal costs at a decreasing rate to model learning about a certain technological approach. Moreover, it models how increasing information (or knowledge) on an approach increases its attractiveness. These two mechanisms increase the threshold of expected value necessary to move towards developing a new approach. Furthermore, it predicts more abstract technological knowledge leads to information on a broader range of technological approaches, increasing the relative likelihood to engage in developing novel technologies.

3. The Model

3.1 Rationale

The model starts off with the assumption that nature defines each and every possible combination between components and principles to serve some purpose (=technology). Moreover, the value of each technology is predetermined (one can look at this as being the usefulness of the technology). Note that most technologies will have very limited value (they do not 'work'). Then, technologies group naturally into 'approaches' or fields. The idea is that technologies cluster according to the knowledge that connects them. For instance, a chair is a different technology than a stool, but having knowledge about the how and why a chair functions, might lead one to the concept of a stool, whereas it will not likely lead to the concept of a knife. So stools and chairs are in the same field (approach), while knifes are in a different one. Then, it is easy to see that values of different technologies within one field are correlated. This notion of 'distance' according to knowledge connecting technologies and different fields, also makes it easier to distinguish between specific and more abstract knowledge. Indeed, specific knowledge can then be defined as leading to closely related technologies (or ideas for technologies), while more abstract knowledge can be defined as leading to more distant technologies. Specific knowledge on the components and principles of the working of a chair, might quite easily lead to the idea of a stool, while more abstract knowledge about its functioning such as an understanding of the mechanics and materials behind its functioning, might lead to the conception of a table or even a knife. In short, nature pre-defines each and every technology and its usefulness (value). The fact that knowledge on one technology might lead to the conception of the other defines distances between technologies. Close technologies correlate in value and group into fields, while also between fields, nature defines distances.

All actors are intrinsically the same. They do not fundamentally differ in terms of costs they face or the profits they can make from a certain technology. They only differ from each other in a (1) the experience they built up by investing in projects a certain field and (2) in the information they have on the value of certain projects in certain fields. Indeed, they only observe the value of a limited number of technologies (which are the projects they could pursue). Furthermore, the marginal costs of performing a project (=developing the technology) in a field are decreasing with the number of projects they already performed in that field because of learning.

Based on the information on projects in a field, the actor derives the expected value of investing in a field. Since they do not have information on all projects in the field, they assume the value of the unknown projects is equal to the average value of the projects it has information on. It then orders all prospective projects (including the unknown ones) according to their (expected) value to calculate the prospective (discounted) profits in the field by subtracting the marginal costs from the marginal revenues (equal to the (expected) values of projects). It takes into account that it will not have to invest in all projects in the field and calculates the optimal stopping point (where prospective marginal revenues are equal to marginal costs). It does so for all fields for which it has information and chooses the most profitable field by investing in the project with the highest expected value.

Then, the decision to move to a new field is dependent on the relative expected field values. These can change over time as more information on the value of projects is gathered. Two basic mechanisms are at the basis of changing expected field value over time. First is the experience effect. As the actor invests in projects in a certain field, its marginal costs decrease through learning. This decreases the average costs for a field with increasing experience (learning effect). However, since the best projects are chosen first, the average prospective revenues of a field decline (depletion effect). The total effect on the evolution of the field value with increasing experience depends on total value of the field, as well as on the marginal cost curve specificities. Second is the information effect. Given a positive actual field value, as more information on the value of projects in a field is available, the expected value of the field increases on average. The reason for this is that actors are able to rank projects and select the best ones. Hence, as more information becomes available, the optimal stopping point with limited information moves closer to the optimal stopping point under full information (which is the best one). Moreover, because future profits are discounted, ordering projects with decreasing value increases expected field value because low-value projects are relatively more heavily discounted than high-value projects.

It is reasonable to assume that information on projects is gathered with each project performed in a field and that this information will be local to the projects performed. Then, the model can explain why actors are generally 'path-dependent'. Moving to a new field will only occur when another field's expected value is higher than the expected value of the field active in. Given exactly the same value of and information on another field, the probability of moving with more experience in the field active in first decreases as marginal costs go down and more information is gathered on the field active in, then increases when learning and information effects decrease and the depletion effect increases. Moreover, when an actor has the ability to develop more abstract knowledge as their experience grows, its probability to move to a new field increases. This theoretical framework can explain higher novelty rates of small firms (less experience) and universities (more abstract knowledge generation) without relying on the traditional assumptions of differing costs to develop more novel technologies. We propose two testable implications that follow from the model. First, the likelihood to develop technologies new to the firm (thus with some probability, which we assume randomly distributed over actors, new to the world) depends on experience built up *within* *a certain field (approach)* rather than on the overall size of the organization. Second, firms with a higher ability to generate abstract knowledge from their experience are, ceteris paribus, more likely to engage in developing novel approaches.

3.2 Building blocks

Nature defines C fields with P projects each. A project is denoted by (i, p) where $i \in \{1, 2, \ldots, C\}$ *and* $p \in \{1, 2, \ldots, P\}$. Furthermore nature defines a value $V_{i,p}$ for each project. For each field i, the actor calculates its expected profits at each time period. For notational simplicity, we omit a time subscript, but ask the reader to recall the calculation of expected profits in a field i is updated each period.

Actors only have information on the value of a subset of projects defined by nature. N_i denotes the number of projects in i for which the actor knows the value. For all other $P - N_i$ projects, the actor forms expectations based on the values it knows.

For each i, the actor defines its Information Set $\boldsymbol{IS_i}$:

$$\boldsymbol{IS_i} = [\, v_{i,1} \quad \cdots \; v_{i,q_i} \quad E(v_i) \; \cdots \; E(v_i) \quad v_{i,w_i} \;\; \cdots \quad v_{i,N_i} \,]$$

$$where \;\; v_{i,1} \geq \; v_{i,2} \geq \;\; \cdots \geq E(v_i) = \cdots = \; E(v_i) \geq \; \cdots \geq \quad v_{i,N_i} \,]$$

where

$$E(v_i) = \sum_{j=1}^{N_i} \frac{v_{i,j}}{N_i}$$

And q_i denotes the number of projects for which the value is greater or equal than $E(v_i)$, while w_i the number of projects for which the value is smaller than $E(v_i)$.

These values will be used to calculate the total expected value of a field. To this end, the actor defines $\widetilde{\boldsymbol{IS}}_{\boldsymbol{i}}$ which differs from $\boldsymbol{IS_i}$ in that $\widetilde{\boldsymbol{IS}}_{\boldsymbol{i}}$ does not contain already executed projects.

Then $\widetilde{\boldsymbol{IS}}_{\boldsymbol{i}}$ is defined as:

$$\widetilde{\boldsymbol{IS}}_{\boldsymbol{i}} = [\ V_{i,1}\ \dots\ V_{i,Q_i} \quad E(v_i)\ \dots\ E(v_i) \quad V_{P-S_i-W_i+1}\ \dots \quad V_{i,P-S_i}\ ]$$

$$where\ V_{i,1}\ \geq \cdots \geq V_{i,Q} \geq\ E(v_i) = \cdots = E(v_i)\ \geq V_{P-S_i-W_i+1} \geq \cdots\ \geq\ V_{i,P-S_i}$$

$\widetilde{\boldsymbol{IS}}_{\boldsymbol{i}}$ contains all (expected) values of projects not executed yet for field i, in decreasing order of (expected) value. Q_i denotes the number of projects in $\widetilde{\boldsymbol{IS}}_{\boldsymbol{i}}$ for which the value is greater or equal than $E(v_i)$, while W_i denotes the number of projects in $\widetilde{\boldsymbol{IS}}_{\boldsymbol{i}}$ for which the value is smaller than $E(v_i)$. S_i is the number of projects already executed in field i.

Then, the expected profit for each field i reads

$$EP_i = \sum_{j=1}^{P-S_i} (\widetilde{IS}_{i,j} -\ MC_{i,j+S_i})$$

Where $MC_{i,1+S_i}$ is the marginal cost of the first project performed given S_i already executed projects.

If d is the discount rate for future profits

$$EP_i = \sum_{j=1}^{P-S_i} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}}$$

We can split up this sum into three sums according to whether the projects' values are known to the firm. For the first Q_i projects, the actor knows the value and it is higher than the expected value of the unknown projects. For the next $P - S_i - W_i - Q_i$ projects, the value is unknown, while for the last W_i projects the value is known and below the expected value of the unknown projects.

$$EP_i = \sum_{j=1}^{Q_i} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}} + \sum_{j=Q_i+1}^{P-S_i-W_i} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}} + \sum_{j=P-S_i-W_i+1}^{P-S_i} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}}$$

The firm has the opportunity to stop investing in a field after T periods. The expected profit if the firm stops investing in the field after T periods is expressed as[2]:

$$EP_{i,T} = \sum_{j=1}^{\min(Q_i,T)} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}} + \sum_{j=Q_i+1}^{\min(P-S_i-W_i,T)} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}} + \sum_{j=P-S_i-W_i+1}^{\min(P-S_i,T)} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}}$$

Then, the optimal stopping point T* is calculated and the expected profit of field i is expressed as

$$EP^*{}_i = \max_T(EP_{i,T})$$

For each field i the actor calculates $EP^*{}_i$ and chooses to invest in field o if $EP^*{}_o > EP^*{}_i$ for each $i \neq o$, and $EP^*{}_o > 0$.

$\boldsymbol{\widetilde{IS}_i}$ is the result of a stochastic process. Hence, in order to illustrate how $EP^*{}_i$ depends on the information available to the actor later on in this section, we calculate the expected value of each of the ranks for the projects in $\boldsymbol{\widetilde{IS}_i}$. If, for simplicity, we assume the projects are drawn from a standard uniform distribution $unif(0,1)$, the mean of the k^{th} order statistic (in descending order) of a sample of n is given by:

$$\frac{(n+1)-k}{(n+1)}$$

This gives us following expression for $IS_{i,j}$ in function of j :

$$\begin{cases} IS_{i,j} = \dfrac{(n+1)-j}{(n+1)} & if\ j \leq q_i \\ IS_{i,j} = E(v_i) & if\ q_i < j \leq P - w_i \\ IS_{i,j} = \dfrac{(n+1)-(j-(P-w_i-q_i))}{(n+1)} & if\ P - w_i < j \leq P \end{cases}$$

[2] If $\min(Q_i, T)$, $\min(P - S_i - W_i)$, $\min(P - S_i)$ is smaller than respectively $1, Q_i + 1, P - S_i - W_i + 1$, the respective summation is defined as zero.

3.3 Effect of Decreasing Marginal Costs on Field Value

In this model, the expected value of a field depends on both the marginal costs of prospective projects and the number of prospective projects in the information set. First, we show how growing experience in the field affects $EP^*{}_i$ discarding the effect of the number of prospective projects available. Two opposite forces are at work in this respect. First is the learning effect. With increasing experience in the field (S_i in the model), the marginal cost of prospective projects decreases. This positive effect on the expected value of a field decreases in size as long as $MC''{}_i(p) > 0$. Second is the depletion effect. As the actor picks the best projects in a field first and the number of projects in a field is finite, the value of a field decreases with the number of projects performed.

3.3.1 General Mechanism

To show this, consider a situation in which the actor has information on all projects at all times. This gives us the expression for EP_i for any number of already executed projects S_i :

$$EP_i = \sum_{j=S_i+1}^{P} \frac{(MR_{i,j} - MC_{i,j})}{(1+d)^{j-1-S_i}}$$

Note that nor $MR_{i,j}$, nor $MC_{i,j}$ have to be updated over time. The reason for this is that we assume full information at any time. EP_i changes over time as less projects become available (S_i increases). Then, if T_i^* is the optimal stopping point:

$$EP_i^* = \sum_{j=S_i+1}^{T_i^*} \frac{(MR_{i,j} - MC_{i,j})}{(1+d)^{j-1-S_i}}$$

T_i^* is the rank number of the last profitable project. Note that T_i^* does not vary over time because of our full information assumption (and the denominator is positive for every j, S_i). We now derive an expression of the evolution of EP_i^* with increasing S_i.

Let $S_i + 1 = X$, then $EP^*_{i,X}$ can be expressed as

$$EP^*_{i,X} = MR_{i,X} - MC_{i,X} + \frac{MR_{i,X+1} - MC_{i,X+1}}{(1+d)} + \cdots + \frac{MR_{i,T_i^*} - MC_{i,T_i^*}}{(1+d)^{T_i^*-X}}$$

Now, let $S_i + 1 = X + 1$, then

$$EP^*_{i,X+1} = MR_{i,X+1} - MC_{i,X+1} + \frac{MR_{i,X+2} - MC_{i,X+2}}{(1+d)} + \cdots + \frac{MR_{i,T_i^*} - MC_{i,T_i^*}}{(1+d)^{T_i^*-X-1}}$$

Then

$$EP^*_{i,X} = MR_{i,X} - MC_{i,X} + EP^*_{i,X+1} * (1+d)$$

Then,

$$EP^*_{i,X+1} = (EP^*_{i,X} - (MR_{i,X} - MC_{i,X})) * \frac{1}{(1+d)}$$

Let $\Delta EP^*_i = EP^*_{i,X+1} - EP^*_{i,X}$, then

$$\Delta EP^*_i = (EP^*_{i,X} - (MR_{i,X} - MC_{i,X})) * \frac{1}{(1+d)} - EP^*_{i,X}$$

Which can be rewritten as

$$\Delta EP^*_i = \left(\frac{1}{(1+d)} - 1\right) * EP^*_{i,X} - \frac{MR_{i,X} - MC_{i,X}}{(1+d)}$$

For every $X \epsilon \{ 1,2, \dots , T_i^* - 1\}$.

This gives us an expression for the change in field value from any period to the next one in function of the number of projects already performed. The intuition is the following. In the next period, the first project available now, will not be available anymore (depletion), which decreases the field value (second part of the expression). Moreover, the field value is discounted as it is transferred to the next period, so the difference between the discounted value of $EP^*_{i,X}$ and the current value is taken into account (first part of the expression).

Then we can derive the condition under which the expected profit increases:

$$\left(\frac{1}{(1+d)} - 1\right) * EP^*_{i,X} - \frac{1}{(1+d)} * \left(MR_{i,X} - MC_{i,X}\right) > 0$$

Or, by rearranging and multiplying by $(1 + d)$

$$MR_{i,X} - MC_{i,X} < -d * EP^*_{i,X}$$

Given $d * EP^*_{i,X} > 0$ as long as the actor invests in field i, this expression shows that the value of a field increases as long as profits are smaller than $-d * EP^*_{i,X}$. This condition can be interpreted intuitively as follows: because for every X some profit in the field is to be made in the future (otherwise $X = T_i^*$), the loss incurred at time X can be seen as an investment necessary to gain profits in the future. Hence, at $X + 1$, this necessary investment is made already, increasing the total expected value of the field compared to time X. Then, $d * EP^*_{i,X}$ represents the part of the expected field value that is lost between X and $X + 1$ because of discounting. Hence, for the expected field value to increase, the investment made at time X should outweigh the effect of discounting future profits over the next period.

The main takeaway here is that field value can only increase if some loss now has to be incurred to secure profits in the future. This means that the marginal cost curve should be higher than the marginal revenue curve for some X for which $EP^*_{i,X}$ is still positive. A necessary (but not sufficient) condition for this to happen is that $MC'_X < 0$ for some X (there is a 'learning' effect). Moreover, this learning effect should be larger than the depletion effect ($MC'_X < MR'_X$) for some X.

3.3.2 Dependence on Parameter Values

To show how the field value evolves with increasing values of X and depends on the marginal cost/revenue curve parameters, consider following functional forms for the marginal revenues and marginal costs.

$$MR_{i,S_i} = Z * \frac{(P+1) - (S_i + 1)}{(P+1)}$$

This marginal revenue curve is the result of P projects sampled from a uniform distribution with minimum value 0 and maximum value Z. Note that for full information (the value of all P projects is known at all times), $\widetilde{IS}_{i,j} = MR_{i,S_i}$

Now consider following Marginal Cost curve:

$$\begin{cases} MC_{i,S_i} = K - a(S_i + 1) & if\ S_i + 1 < \dfrac{(K-L)}{a} \\ MC_{i,S_i} = L & if\ S_i + 1 \geq \dfrac{(K-L)}{a} \end{cases}$$

Where K is the cost of the first project, a is the rate at which the Marginal Costs decrease, and L is the minimum cost that can be observed. Then $\frac{(K-L)}{a}$ is the value of X for which marginal costs become L. We use this linear form as a simple case for a situation where learning occurs for the first projects performed, but disappears for projects above some threshold. Again, under the full information assumption $MC_{i,j+S_i} = MC_{i,S_i}$

Let $S_i + 1 = X$. We now look at the evolution of the condition under which field value increases dependent on X.

$$(MR_{i,X} - MC_{i,X}) < -d * (EP^*_{i,X})$$

Consider the case in which $X < \frac{(K-L)}{a}$, then the expression becomes

$$Z - Z * \frac{X}{1+P} - (K - aX) < -d * (EP^*_{i,X})$$

Or

$$\left(\frac{-Z}{1+P} + a\right) * X + Z - K < -d * (EP^*_{i,X})$$

While if $X \geq \frac{(K-L)}{a}$:

$$Z - \frac{Z * X}{1+P} - L < -d * (EP^*_{i,X})$$

In the case where $d = 0$, the expression reads

$$\left(\frac{-Z}{1+P} + a\right) * X + Z - K < 0 \qquad \text{for } X < \frac{(K-L)}{a}$$

and

$$Z - \frac{Z * X}{1+P} - L < 0 \qquad\qquad \text{for } X \geq \frac{(K-L)}{a}$$

Then we can derive under which parameter values the expected field value in/decreases with increasing values of X.

If $X < \frac{(K-L)}{a}$, the condition can be rewritten as

$$\left(\frac{-Z}{1+P} + a\right) * X < K - Z$$

if $\frac{-Z}{1+P} + a = 0$, the change in field value is not dependent on X, and increases when $K < Z$ and decreases when $K > Z$. However, in the latter situation the actor would never invest in the field to begin with ($T_i^* = 0$). Now, when $\frac{-Z}{1+P} + a < 0$ (this is the case in which the marginal revenue curve is steeper than the marginal cost curve), the condition for increasing field profits becomes

$$X > (K - Z) * \left(\frac{-Z}{1+P} + a\right)^{-1}$$

The right hand side represents the value of X for which $MR_{i,X} = MC_{i,X}$. So, the field value decreases up until $X = (K - Z) * \left(\frac{-Z}{1+P} + a\right)^{-1}$, after which the actor stops investing as profits become negative for all larger X. However, this situation would only occur if $K < Z$ (otherwise $T_i^* = 0$).

When $\frac{-Z}{1+P} + a > 0$ (the case for which the marginal costs decrease faster than the marginal revenues up until some point), the condition for increasing field profits becomes

$$X < (K - Z) * \left(\frac{-Z}{1+P} + a\right)^{-1}$$

Again, the right hand side represents the X for which $MR_{i,X} = MC_{i,X}$. So, the field value increases up until $X = (K - Z) * \left(\frac{-Z}{1+P} + a\right)^{-1}$, the intersection between marginal costs and marginal revenues. For larger values of X, the field profit starts decreasing up until point T_i^*.

Now consider the case of $X \geq \frac{(K-L)}{a}$ and $T_i^* > \frac{(K-L)}{a}$. This means there exists some $X \geq \frac{(K-L)}{a}$ for which $MR_{i,X} > MC_{i,X}$ and these curves intersect at $X = T_i^*$.

The condition for increasing field profits can be rewritten as

$$X > \frac{(L-Z)(1+P)}{Z}$$

The expression on the right hand side is the intersection between the marginal cost and marginal revenue curve. Consequently, no X exists such that $\frac{(K-L)}{a} \leq X \leq T_i^*$ for which field value is increasing.

If $d > 0$, the expected field profit from any period to another shifts downwards with $d * (EP^*_{i,X})$. Since $EP^*_{i,X}$ is positive as long as the actor invests in the field, the condition for increasing expected field value over time becomes more stringent when the actor uses discounting of future profit streams. The rate at which $EP^*_{i,X}$ changes $(EP^*_{i,X+1} - EP^*_{i,X})$, cannot be easily expressed directly in terms of X. However, we know that for values of X for which $MR_{i,X} - MC_{i,X} > 0$, $EP^*_{i,X}$ is decreasing, making the condition relatively less stringent for higher values of X. For values of X for which $MR_{i,X} - MC_{i,X} < 0$, $EP^*_{i,X}$ is increasing, making the condition more stringent. In conclusion, with higher values of d, the value of X with which the expected field profit starts decreasing becomes lower.

In general, the model can explain a situation in which the value of a particular field increases with the experience in that field. For this situation to occur, two conditions should be met. First, the cost of the first project should be higher than its revenue. Second, the rate at which costs of subsequent projects decrease should be higher than the decrease in revenues from these projects. The likelihood of and the extent to which fields become more attractive with higher experience increases with higher costs of initial projects (K), lower minimum costs of projects (L), lower values of initial projects (Z), higher rates at which costs decrease (a) and lower rates at which revenues decrease $(\frac{-Z}{(1+P)})$.

3.4 Effect of Additional Information on Field Value

In the previous section, we assumed the actor had all information on all projects. In that situation, the actor could simply choose the field with the highest profit, and it would switch to a new field simply when the value of the field it was active in became lower than the value of any other field. Since full information is a very unrealistic assumption, we model limited information by introducing the information set, which is a subset of all projects defined by nature. In this section, we examine how the *expected* field value evolves when more information enters the information set, discarding the learning and depletion effect discussed in previous section.

3.4.1 General Mechanism

First consider a situation without discounting ($d = 0$), and where the firm performs every single project in the field ($T_i^* = P$). Moreover, the firm always has some projects in $\boldsymbol{IS_i}$ not yet executed. In this scenario, the expected sample mean is equal to the population mean, regardless of the sample size[3]. Hence, with $d = 0$ and $T_i^* = P$, the expected field value does not vary with N_i. Hence, expected field value is only influenced by the number of projects in the information set through the mechanism of discounting of future profits and the ability to select profitable projects in a field.

Now we show that the expected field value increases with increasing N_i when the actor does not perform all projects in a field ($T_i^* < P - S_i$). Define $\Delta EP_i^* = EP_{i,N_i+1}^* - EP_{i,N_i}^*$, then

$$\Delta EP_i^* = EP_{i,N_i+1} - \sum_{j=T_{i,N_i+1}^*+1}^{P-S_i} \left(\widetilde{IS}_{i,j} - MC_{i,j+S_i}\right) - EP_{i,N_i} + \sum_{j=T_{i,N_i}^*+1}^{P-S_i} (\widetilde{IS}_{i,j} - MC_{i,j+S_i})$$

From the argument above, we know $\Delta EP_i = EP_{i,N_i+1} - EP_{i,N_i} = 0$. Then

$$\Delta EP_i^* = -\sum_{j=T_{i,N_i+1}^*+1}^{P-S_i} \left(\widetilde{IS}_{i,j} - MC_{i,j+S_i}\right) + \sum_{j=T_{i,N_i}^*+1}^{P-S_i} (\widetilde{IS}_{i,j} - MC_{i,j+S_i})$$

[3] We proof this in the extended version of the paper, available upon request.

Hence, the condition under which $\Delta EP_i^* > 0$ is

$$\sum_{j=T^*_{i,N_i+1}+1}^{P-S_i} (\widetilde{IS}_{i,j} - MC_{i,j+S_i}) < \sum_{j=T^*_{i,N_i}+1}^{P-S_i} \left(\widetilde{IS}_{i,j} - MC_{i,j+S_i}\right)$$

Note that both terms of this inequality are negative, because it refers to the projects the actor will not pursue (negative profits). Now, consider following expression

$$EP_{i,T_i^*} = \sum_{j=1}^{\min(Q_i,T_i^*)} (\widetilde{IS}_{i,j} - MC_{i,j+S_i}) + \sum_{j=Q_i+1}^{\min(P-S_i-W_i,T_i^*)} (\widetilde{IS}_{i,j} - MC_{i,j+S_i})$$
$$+ \sum_{j=P-S_i-W_i+1}^{\min(P-S_i,T_i^*)} (\widetilde{IS}_{i,j} - MC_{i,j+S_i}) + \sum_{j=T_i^*+1}^{P-S_i} (\widetilde{IS}_{i,j} - MC_{i,j+S_i})$$

With N_i projects available in the information set (subscripts are omitted). The expression gives us the total expected field value if the optimal stopping point T_i^*, provided the actor would not stop investing. The value of the opportunity to stop is equal to $-\sum_{j=T^*_{i,N_i+1}+1}^{P-S_i}(\widetilde{IS}_{i,j} - MC_{i,j+S_i})$.

Consider the case in which $T_i^* \geq P - S_i - W_i + 1$. Now, when $N_i + 1$ projects would be available, one project is removed from the second term, and dependent on its value $V_{i,p}$, enter one of the other terms. Because there is a strictly positive probability that $V_{i,p} < V_{i,T_i^*}$, thus an additional negative profit enters the last term, the expected value of the last term decreases which fulfills the condition posited above.

When $Q_i + 1 \leq T_i^* \leq P - S_i - W_i$, we can state, without loss of generality, that with $N_i + 1$ projects available, again a project is removed from the second term. With some strictly positive probability, $V_{i,p} < V_{i,T_i^*}$, so again the expected value of the last term decreases, fulfilling the condition posited above.

When $T_i^* \leq Q_i$, the second and third term of the expression are equal to zero. Hence, when $N_i + 1$ projects would be available, a project is removed from the last term. With some strictly positive probability, $V_{i,p} > V_{i,T_i^*}$, and a positive term is removed. Hence the expected value of the last term decreases, fulfilling the condition posited above.

Intuitively, we can interpret this argument as follows. Under full information, the ability to stop after a number of projects has a positive value, and this positive value is maximized at T_i^*. Now, as extra information on the field arrives, the observed distribution will be more similar to the actual distribution, which shifts the optimal stopping point determined based on the subsample of the population towards the optimal stopping point of the population distribution, moving the value of the ability to stop towards its maximum.

Now we turn to showing how d increases expected field value with increasing information. To show this, consider the expression for EP_i, when N_i projects are known (subscript omitted).

$$EP_i = \sum_{j=1}^{Q_i} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}} + \sum_{j=Q_i+1}^{P-S_i-W_i} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}} + \sum_{j=P-S_i-W_i+1}^{P-S_i} \frac{(\widetilde{IS}_{i,j} - MC_{i,j+S_i})}{(1+d)^{j-1}}$$

Now, one project enters the information set and is removed from the second term (without loss of generality we can assume it is $\widetilde{IS}_{i,Q_i+1}$). This project will have a value higher or lower than $E(v_i)$. The mechanism behind this argument, is that when the value of the newly entered project is higher, it will be discounted relatively less than when it is lower. However, the rank of multiple projects might change, changing their discount factor. To show that the expected field value always increases with extra information, we will define a lower bound of ΔEP_i when the value of a new project is higher than $E(v_i)$, and an upper bound of ΔEP_i when the value of the new project is lower, and show that the lower bound is still always greater than the upper bound.

First we write the expression when N_i projects are available, and omit the marginal cost terms as it will not change with increasing information.

$$EP_i = \sum_{j=1}^{Q_i} \frac{\widetilde{IS}_{i,j}}{(1+d)^{j-1}} + \sum_{j=Q_i+1}^{P-S_i-W_i} \frac{\widetilde{IS}_{i,j}}{(1+d)^{j-1}} + \sum_{j=P-S_i-W_i+1}^{P-S_i} \frac{\widetilde{IS}_{i,j}}{(1+d)^{j-1}}$$

Now consider a project entering the information set. Let V^+ be the expected value of a project, given it is higher than $E(v_i)$, and let V^- be the expected value of a project, given it is lower than $E(v_i)$. We denote the probability a project enters with value higher than $E(v_i)$ as $Pr^+$and the probability a project enters with value lower than $E(v_i)$ as Pr^-. Note that because of the definition of the expected value: $Pr^+ * \left(V^+ - E(v_i)\right) = Pr^- * \left(V^- - E(v_i)\right)$. Now consider the difference in expected field value when a project with V^+ enters the set. Let R^+ be the rank of the new project. Then all other projects with value higher than $E(v_i)$ and with rank larger or equal than R^+ are 'shifted' one place to the future. This means only projects with rank larger or equal R^+ and lower or equal $Q_i + 1$ are affected by the project entering. We get this expression for the difference in expected field value:

$$\Delta EP_{i,V^+} = \frac{(V^+ - \widetilde{IS}_{i,R^+})}{(1+d)^{R^+-1}} + \frac{(\widetilde{IS}_{i,R^+} - \widetilde{IS}_{i,R^++1})}{(1+d)^{R^+}} + \frac{(\widetilde{IS}_{i,R^++1} - \widetilde{IS}_{i,R^++2})}{(1+d)^{R^++1}} + \cdots + \frac{(\widetilde{IS}_{i,Q_i-1} - \widetilde{IS}_{i,Q_i})}{(1+d)^{Q_i-1}} + \frac{(\widetilde{IS}_{i,Q_i} - E(v_i))}{(1+d)^{Q_i}}$$

Very similarly, we derive an expression for the change when a project with value V^- enters the information set. Let R^- be the rank of the new project. Then all other projects with value lower than $E(v_i)$ and with rank lower or equal than R^- are 'shifted' one place to the present. This means only projects with rank higher or equal $P - S_i - W_i$ and lower or equal R^- are affected by the project entering. This gives us following expression:

$$\Delta EP_{i,V^-} = \frac{(\widetilde{IS}_{i,P-S_i-W_i+1} - E(v_i))}{(1+d)^{P-S_i-W_i-1}} + \frac{(\widetilde{IS}_{i,P-S_i-W_i+2} - \widetilde{IS}_{i,P-S_i-W_i+1})}{(1+d)^{P-S_i-W_i}} + \cdots + \frac{(\widetilde{IS}_{i,R^-} - \widetilde{IS}_{i,R^--1})}{(1+d)^{R^--1}} + \frac{(V^- - \widetilde{IS}_{i,R^-})}{(1+d)^{R^-}}$$

Now we define a lower bound for $\Delta EP_{i,V^+}$, and an upper bound for $\Delta EP_{i,V^-}$:

$$l(\Delta EP_{i,V^+}) = \frac{(V^+ - \widetilde{IS}_{i,R^+})}{(1+d)^{Q_i}} + \frac{(\widetilde{IS}_{i,R^+} - \widetilde{IS}_{i,R^++1})}{(1+d)^{Q_i}} + \frac{(\widetilde{IS}_{i,R^++1} - \widetilde{IS}_{i,R^++2})}{(1+d)^{Q_i}} + \cdots + \frac{(\widetilde{IS}_{i,Q_i-1} - \widetilde{IS}_{i,Q_i})}{(1+d)^{Q_i}} + \frac{(\widetilde{IS}_{i,Q_i} - E(v_i))}{(1+d)^{Q_i}}$$

$$u(\Delta EP_{i,V^-}) = \frac{(\widetilde{IS}_{i,P-S_i-W_i+1} - E(v_i))}{(1+d)^{P-S_i-W_i-1}} + \frac{(\widetilde{IS}_{i,P-S_i-W_i+2} - \widetilde{IS}_{i,P-S_i-W_i+1})}{(1+d)^{P-S_i-W_i-1}} + \cdots + \frac{(\widetilde{IS}_{i,R^-} - \widetilde{IS}_{i,R^--1})}{(1+d)^{P-S_i-W_i-1}} + \frac{(V^- - \widetilde{IS}_{i,R^-})}{(1+d)^{P-S_i-W_i-1}}$$

Or

$$l(\Delta EP_{i,V^+}) = \frac{(V^+ - E(v_i))}{(1+d)^{Q_i}}$$

$$u(\Delta EP_{i,V^-}) = \frac{(V^- - E(v_i))}{(1+d)^{P-S_i-W_i-1}}$$

Since Pr^+ and Pr^- are the probabilities a project with higher, respectively lower value than $E(v_i)$ enters, we can express the expected field value change with one extra project arriving in the information set as

$$\Delta EP_i = Pr^+ * \Delta EP_{i,V^+} + Pr^- * \Delta EP_{i,V^-}$$

The condition under which the expected field value increases is

$$\Delta EP_i > 0$$

Thus

$$Pr^+ * \Delta EP_{i,V^+} > -Pr^- * \Delta EP_{i,V^-}$$

This is always true when

$$Pr^+ * l(\Delta EP_{i,V^+}) > -Pr^- * u(\Delta EP_{i,V^-})$$

Or

$$Pr^+ * \frac{(V^+ - E(v_i))}{(1+d)^{Q_i}} > -Pr^- * \frac{(V^- - E(v_i))}{(1+d)^{P-S_i-W_i-1}})$$

Now, since $Pr^+ * \left(V^+ - E(v_i)\right) = Pr^- * \left(V^- - E(v_i)\right)$, and $(1+d)^{Q_i}$<$(1+d)^{P-S_i-W_i-1}$ this is true for each distribution of project values.

3.4.2 Dependence on Parameter Values

To show how this mechanism depends on parameter values, let us turn back to our expression for the marginal revenues (we assume, without loss of generality that the number of projects performed is zero). Moreover, because we assume a uniform distribution from which projects are drawn, $E(v_i) = \frac{Z}{2}$ and $w_i + q_i = n$. Then we get

$$\begin{cases} IS_{i,j} = Z * \dfrac{(n+1) - j}{(n+1)} & if\ j \leq q_i \\ IS_{i,j} = \dfrac{Z}{2} & if\ q_i < j \leq P - w_i \\ IS_{i,j} = Z * \dfrac{(n+1) - (j - (P - n))}{(n+1)} & if\ P - w_i < j \leq P \end{cases}$$

The marginal cost curve is again given by

$$\begin{cases} MC_{i,j} = K - aj & if\ j < \dfrac{(K-L)}{a} \\ MC_{i,j} = L & if\ j \geq \dfrac{(K-L)}{a} \end{cases}$$

If the field is profitable, there exists some optimal stopping point T_i^* at a given number of projects known n at the intersection between $IS_{i,j}$ and $MC_{i,j}$. Since the slope of $IS_{i,j}$ is the same for projects with higher and lower value than $\frac{Z}{2}$, the optimal stopping point (and expected field value) will change with the same value with increasing n. This means we only need to analyze the case in which the intersection is at a value of $j \leq q_i$. Now consider the case where the intersection is at a value of $j < \frac{(K-L)}{a}$. Then the optimal stopping point with n projects available is at j for which

$$Z * \frac{(n+1) - j}{(n+1)} = K - aj$$

Solving for j gives

$$j = (K - Z) * \left(\frac{-Z}{1+n} + a\right)^{-1}$$

At $n + 1$ projects available this becomes

$$j = (K - Z) * \left(\frac{-Z}{2+n} + a\right)^{-1}$$

Then the change in the optimal stopping point is

$$\Delta T_i^* = (K - Z) * \left(\frac{-Z}{2+n} + a\right)^{-1} - (K - Z) * \left(\frac{-Z}{1+n} + a\right)^{-1}$$

Since $\frac{-Z}{1+P} + a < 0$ for this case (otherwise the optimal stopping point would not be in this range), ΔT_i^* is positive and profits will increase with

$$Z * \frac{(n+1) - T_i^*}{(n+1)} - Z * \frac{(n+1) - (T_i^* + \Delta T_i^*)}{(n+1)}$$

Or

$$\frac{Z * \Delta T_i^*}{(n+1)}$$

ΔT_i^* (and hence the profit increase from extra information) decreases with higher values of n as $\frac{-Z}{2+n} - \frac{-Z}{1+n}$ goes to zero with higher values of n. Moreover, the gain from extra information is higher with higher total field value, lower costs of the first project and steeper marginal cost curves.

Now consider the case where the intersection is at a value of $j \geq \frac{(K-L)}{a}$. Then

$$\Delta T_i^* = \frac{Z - L}{Z}$$

And the increase in profits is

$$\frac{Z - L}{(n+1)}$$

Again, we see that as the number of projects increases, the value of one extra project in the information set decreases. Moreover, the higher the total value of the field and the lower the lowest marginal cost the more extra information increases expected field value.

4. Implications

If we assume actors face the same cost parameters, whether an actor will move to a new field depends on its experience built up in their existing fields on the one hand, and how its information set changes on the other. We have not modelled yet how the information set changes, or which is the underlying process of new projects entering. It is reasonable to assume that as experience is built up in a field, the projects entering an actor's information set are 'local' to the fields they are active in. Indeed, by our definition of distance, knowledge built up in a field will shed light on more similar technologies. Now, assume a number of projects of a certain field enters the information set at each time. Let the probability that projects from some field enter the information set decrease with the distance from that field to the field the actor was last active in. This mimics a situation in which an actor generates information on new projects through the knowledge built up in the field it is working in. Note that although the new projects most often will be projects in the same field working in, but with some likelihood, projects from neighboring fields enter. Because for a given actual value of a field, more information increases the expected value, this mechanism will further increase path-dependency of the actors.

The model can explain the observed patterns from the analyses above and suggests a number of testable implications. Compared to small firms, large firms face low marginal costs and have a lot of projects in their information set in the fields they are active in. Hence, the threshold in terms of expected value necessary to move them into a new field is higher than for small firms. Universities are different from firms in that they generally possess a great deal of abstract, scientific knowledge about the fields they are active in. This increases the average distance of the new projects entering their information set to the fields already active in. Hence, for any level of experience in a field, they gain information on a larger number of other (more distant) fields, which increases their information for those fields, increasing the probability to move to new, more distant fields.

A first implication of the model is that experience in a field is an important determinant of moving to a new field. This leads us to argue that, rather than overall size of the organization, experience in specific fields drives the decision to engage in developing new approaches. Second, organizations with more abstract knowledge (or the ability to create such knowledge) are more likely to engage in new fields at any level of experience in existing fields. Moreover, the new fields they enter, are more distant from their existing fields, compared to novel approaches introduced by organizations without abstract knowledge.

5. Conclusion

This paper sets out to explain novelty decisions by organizations. Motivated by a number of empirical patterns in novelty and breakthrough innovation in biotechnology, we develop a model that explains novelty decisions through the mechanisms of learning, depletion and limited information, rather than relying on traditional assumptions on differences in capabilities and search strategies. As this is very preliminary work, a lot of improvements suggest themselves. First, we do not take into account competition in technology development. Introducing competitive interactions might complicate the model, but might also lead to a number of interesting extensions. Furthermore, the model explains decisions with respect to novelty to the organization, and does not yield specific predictions for novelty to the world (the concept measured in the empirics, and of main interest to policy makers). Hence, the conclusions of the model only extend to novelty to the world if we assume that approaches that are novel to the organization result randomly (not correlated with organization type, experience or the arrival of new information) in inventions novel to the world. Yet, we hope this version of the paper will already incite useful and lively discussion resulting in vast improvements.