Novelty and scope of innovation in manufacturing: The role of related and unrelated production experience

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In manufacturing, the accumulation of experience that occurs with production is likely to impact an organization's ability to innovate. However, how different types of experience may relate to the characteristics of an organization's innovation output is an open question. In this study we investigate how a firm's accumulated related and unrelated manufacturing experiences are associated with this firm's ability to innovate its production methods. We choose as our context the manufacturing of active pharmaceutical ingredients (APIs) for anti-cancer drugs that have lost product-patent protection. This allows us to examine our research question in a multi-product and multi-firm longitudinal setting. To characterize firms' innovation output we observe their portfolios of patented manufacturing inventions, which we qualitatively evaluate over time (through a unique collaboration with expert patent attorneys) along two critical dimensions: novelty and scope. We find that experience with manufacturing related products is associated with a decrease in the novelty and an increase in the scope of the manufacturing methods that a firm develops and patents for a focal product. Conversely, experience with manufacturing unrelated products is associated with an increase in a focal product's patents' novelty and a decrease in its patents' scope. This simultaneous consideration of both novelty and scope allows us to demonstrate how different types of experience may enhance one dimension of innovation while hurting another, and helps to reconcile conflicting conceptual arguments that have been presented in the literature. Our findings provide practical guidance regarding how managers might want to structure their firms' product portfolios and the longitudinal effect of their choices on their firm's intellectual property.

1. Introduction

Innovation, defined as "the production or emergence of a new idea" (Gupta et al. 2007), is critical to an organization's long term survival (Pisano 1997). For this reason, considerable research effort has been expended to understand the drivers of an organization's ability to innovate. While past literature suggests that an organization's experience is crucial for generating new ideas, i.e., innovating (Li et al. 2019), a more granular investigation into this relationship is needed (Argote and Miron-Spektor 2011). In particular, how different types of experience relate to an organization's innovative capability remains an open question (Cohen 2010) which motivates our study.

Experience is "what transpires in the organization as it performs its task" (Argote and Miron-Spektor 2011, p. 1024). Through experience, organizations gain knowledge, which becomes embed-

ded in various repositories such as an organization's members, tasks, and tools (Argote and Hora 2017). As a result, the type of experience that an organization accumulates plays an important role in shaping its ability to develop innovative solutions to its product and process development needs (Chari et al. 2007), allowing it to remain competitive. Specifically, when looking at a focal product or process, a distinction has often been made between related and unrelated experience (Cohen and Levinthal 1990, Fong Boh et al. 2007).

In manufacturing environments, technical knowledge is likely to be transferable across the production processes of related products, thus benefiting innovation (Garcia-Vega 2006). Indeed, when looking at the manufacturing of a focal product, experience with manufacturing related products, i.e., related experience, suggests an exposure to a variety of tasks and technical challenges which is likely to be very relevant when attempting to solve problems associated with the focal production process (Lawrence 2018). However, the accumulation of related experience can also, overtime, act as a deterrent to innovation as the firm becomes more likely to fall into a competency trap (Levitt and March 1988, Lawrence 2018) which may stifle its innovative capabilities (Reagans et al. 2005, Chari et al. 2007).

At the same time, experience with operating processes that produce unrelated products, i.e., unrelated experience, broadens the knowledge base of a firm (Leten et al. 2007) and allows the progressive development of a more diverse coalition of ideas and a proficiency at various technologies (Argote and Miron-Spektor 2011). As such, it can give rise to potentially greater innovation than if relying on related experience alone (Nelson 1959). Indeed, when firms diversify into unrelated fields, more learning opportunities are available through higher cross-fertilization between different technologies (Garcia-Vega 2006) and through learning from diverse errors (Egelman et al. 2017). Yet, even though unrelated experience may protect organizations from becoming locked into a particular set of technologies, it can also put a strain on a firm's limited financial and cognitive resources (Hitt et al. 1997), thereby hurting its innovative capabilities.

The above discussion suggests that, even when conceptually differentiating between related and unrelated experience, much uncertainty remains regarding their relationship with innovation. This is in line with Argote and Miron-Spektor (2011)'s observation that "a more fine-grained analysis of the experience-creativity link will help reveal underlying mechanisms and boundary conditions that explain how, when, and why prior experience affects knowledge creation in organizations". In this research we adopt such a "fine-grained" empirical investigation by not only distinguishing related and unrelated prior experience (relative to the production of a focal product) but also by simultaneously considering multiple qualitative dimensions of an organization's patent output,

which is a key indicator of its innovativeness. Thus, we contribute towards answering *how* prior experience might affect an organization's ability to generate new ideas and innovate.

We choose, as context for our study, the manufacturing of active pharmaceutical ingredients (APIs) for drugs that have lost product-patent protection. Product-patent expiration implies that the originating pharmaceutical firm faces competition from bio-equivalent versions, i.e., "generics", which contain the same API. We examine how a pharmaceutical firm's accumulated related and unrelated experiences in API manufacturing are associated with this firm's ability to innovate its production methods. We observe the latter through the firm's manufacturing process patents.

Our setting allows us to respond to recent calls in the literature for additional studies on how different types of experience affect learning and knowledge transfer in multi-product environments (Egelman et al. 2017). In fact, we take a step further and conduct our study not only in a multi-product but also in a multi-firm setting. This is a unique contribution made feasible because of our focus on the manufacturing of APIs for drugs open to competition from generics. Indeed, it allows us to compare the innovativeness of methods used by firms to manufacture essentially the same output, i.e., a given API, while taking into account their different product portfolios and manufacturing experience. Thus, by considering a variety of products and a variety of firms for each of these products, we are able to identify and measure more rigorously the effect of different types of experience on firms' innovativeness.

To qualitatively characterize firms' portfolios of patented manufacturing inventions, we collaborate with expert patent attorneys. This unique characteristic of our study allows us to simultaneously evaluate two critical dimensions of firms' portfolios: their novelty and their scope. By focusing our study on firms that all belong to a single industrial sector, i.e., the pharmaceutical industry, where the patent mechanism is widely considered as the preferred mechanism for protecting a firm's intellectual property (Mansfield 1986), we also reduce the need to control across firms "for fundamental differences in technological opportunity and propensity to patent" (Lieberman 1987, p. 258).

Among pharmaceutical products, we focus on APIs for antineoplastic drugs – the broad family of drugs which are used in the treatment of cancer – because these drugs are significant from both an economic and a political point of view. Antineoplastics "rank first in terms of global spending by therapeutic class" and "figure prominently in discussions over health reform, alternatively symbolizing wasteful spending and biomedical progress" (Howard et al. 2015, p.140). Moreover, compared to other families of drugs, anti-cancer drugs are complex, challenging-to-produce, and chemically diverse drugs that affect a variety of organs, tissues, and tumors (Chabner and Longo

2011). As such, to remain innovative, a firm must be capable of successfully integrating a complex technological skill set that relies on engineering, chemistry, and microbiology (Bennett and Cole 2003). Manufacturing experience is expected to play a crucial role in shaping this organizational skill set.

Our results suggest that related experience allows inventions of broader scope for the focal API's manufacturing process but limits their novelty. These findings reconcile the contradicting conceptual arguments presented earlier regarding the effect of related experience on innovation capability. Indeed, results demonstrate the value of related experience in enhancing one aspect of innovation, i.e., its scope, while also warning firms about the risk of falling into a competency trap, which would hinder their ability to radically innovate. On the other hand, we find that unrelated experience allows for inventions of higher novelty but narrower scope. This again helps reconcile previous assertions regarding the effect of unrelated experience. Indeed, results suggest that while unrelated experience can enhance a firm's absorptive capacity for the focal process, the associated diversion of resources could also prevent expanding inventions' scope.

Overall, our work makes the following significant contributions to the literature: First, we simultaneously measure two crucial dimensions of a firm's innovation output – its novelty and scope – by identifying and evaluating relevant patent portfolios. Moreover, we do so at the product level. This allows us to reconcile previous arguments about the effects of experience. Second, we construct a unique multi-product, multi-firm longitudinal panel dataset that includes, together with relevant controls, manufacturing experience measures that incorporate aspects of learning and forgetting. This empirical setup allows a more robust identification of experience effects because it allows us to control for product- and firm-specific characteristics. To the best of our knowledge, such an in-depth examination of the association between manufacturing experience and innovation is unique in the literature.

Our work also provides several guidelines that can aid practitioners in making innovation portfolio decisions. First, it may not always be beneficial to invest in the development of related products if the novelty of the manufacturing process for the focal product is crucial to its long-term success. Instead, firms might want to increase unrelated experience. On the other hand, if the main objective is to uniquely occupy a broad area on the technological landscape, i.e., the set of all possible process configurations (Mihm et al. 2015), the firm could benefit from accumulating related manufacturing experience, and might want to abstain from diverting much needed resources in the manufacturing of unrelated products. In addition, using insights from our paper and examining the composition of a firm's current product portfolio, both internal and external stakeholders may estimate the ability of the firm to generate high novelty and/or broad scope process inventions.

2. Literature review and hypothesis development

Past literature has extensively discussed some of the factors that affect a firm's ability to innovate. For instance, a firm's level of R&D spending and the extent of competition in the markets in which a firm operates have both been found to be important factors (Matraves 1999, Cohen 2010). Less well understood is the role of the firm's manufacturing experience. We begin our review by focusing on available evidence on the link between a firm's experience and its innovative capabilities. We then distinguish between related and unrelated manufacturing experience to offer a more nuanced discussion of this relationship.

2.1. Manufacturing experience and innovative output

Learning-by-doing has been shown to influence the innovativeness of a firm's manufacturing processes and enhance their productivity (Lieberman 1987). This occurs because, as firms accumulate experience manufacturing their products, they gain technological knowledge and skills (Xie and O'Neill 2013). These can then continuously be applied to follow-on research and problem solving and may contribute to the development of strong internal R&D capabilities (Yeoh and Roth 1999).

The importance of accumulated experience to a firm's innovative capabilities is particularly pronounced in pharmaceuticals, and other industries such as chemicals and medical equipment, where an intimate understanding of how complex scientific principles translate into manufacturing practice is essential for innovation to occur (Jain 2013). In these environments, technical knowledge may be codified in elements such as patents, production routines, computer models, etc., or remain tacit (Pisano 1997). For instance, a key component of this technical knowledge is an intuitive appreciation of the performance impact that different operational approaches might have (e.g., knowing which pharmaceutical excipients would perform best, and worst, under a particular set of process conditions). As such, an organization's existing technical knowledge provides a starting point for R&D efforts and guidance into the development of new production methods that take into account the characteristics of manufacturing equipment, employee skills, availability of standard operating procedures, and other more subtle idiosyncrasies of the production environment (Pisano 1997, Chaudhuri 2013, Cornelius 2017). This explains why pharmaceutical firms strive to streamline information flows between the lab and the shop floor, thereby supporting continuous collaboration between R&D and manufacturing (Cardinal et al. 2001).

To better highlight how an organization's accumulated manufacturing experience might inform its R&D efforts consider the following statement from the production and R&D head of a leading manufacturer of APIs[1]: *"Whenever production i) faces a technological or chemical problem (for*

[1] Additional details on this and other private communications with practitioners from the pharmaceutical industry that we have initiated in the context of this study can be provided upon request.

example, the manufacturing process is slow due to low temperature), ii) needs to increase or decrease the volume of production or iii) faces a quality issue, it informs R&D about the "challenge" and proposes a solution based on the production department's experience. R&D then proceeds to test the proposal of the production team in the lab and develops detailed instructions on how a possible change might be implemented. At the same time, R&D automatically checks the new solution for patentability. Production implements the solution at commercial scale and provides feedback to R&D about the achieved results. In our firm, production has no right to make any change in the manufacturing process without lab testing and approval from R&D."

The information flows described in the above statement are not unique to that firm. For example, as explained by Chaudhuri (2013), *"for problems observed in specific types of reactions and reagents for certain [pharmaceutical] products, analysis is done to determine which other products either in the same or different therapeutic category historically had same or similar processes and any specific solutions which were implemented for those. This requires collaboration among researchers within R&D who work on products of different therapeutic categories (p:236)*" so that available knowledge can be leveraged across products. If no prior knowledge on similar problems is available to the organization, then the *"product team brainstorms and tries to arrive at the best solution. The company also starts documenting lessons learnt while standardizing processes or using past experiences for solving specific problems, in electronic form in a "lessons learnt master"* (Chaudhuri 2013: p.236)".

This reliance on past experience also implies that different types of experience could affect differently a firm's ability to innovate. In particular, the extent to which past experience readily applies to the process at stake appears as an important differentiator.

2.2. Related and unrelated manufacturing experience

Experience in related technological domains may benefit a firm's innovative capabilities for the focal manufacturing process due to the possibility of internal knowledge transfers (Leten et al. 2007, Menon et al. 2020). As Egelman et al. (2017) suggest, the potential for knowledge transfers increases with the commonality between the items being produced. Essentially, as firms accumulate experience, they build core skills that are more likely to be applicable to innovation activities that take place in related (rather than unrelated) technological domains (Cohen and Levinthal 1990). This is especially the case in the pharmaceutical industry given the complexity and specificity of the underlying science.

2.2.1. Impact on inventions' novelty While the above discussion suggests that accumulation of related experience might enhance a firm's innovative capability, Cohen and Levinthal (1990) argue that as firms become more experienced in the manufacturing of related products, and therefore more capable at activities similar to the ones in which they are already engaged, accumulation of related experience does not contribute to the knowledge diversity that is critical to creating something substantially novel. Indeed, accumulation of related manufacturing experience leads to the development of organizational knowledge that is likely to become embedded in repositories such as production routines (Argote and Hora 2017). While such repositories might enable efficiency and productivity improvements, the accumulation of knowledge in technologically proximal repositories might also contribute to a firm's rigidity in dealing with novel situations and become a source of inertia or "competency trap" (Yeoh and Roth 1999). This is also reflected in the organizational learning literature (e.g., Gupta et al. 2007), which suggests that prior experience can constrain creative thinking as it can lead to drawing on familiar processes and heuristics when solving a problem. Along similar lines, Solheim et al. (2018) argue that accumulation of knowledge in related technological domains is more likely to promote incremental, as opposed to more radical, innovations. This is echoed in recent research. Using ten years of data from a single manufacturing facility of high-technology hardware components, Egelman et al. (2017) found that manufacturing experience with previous product generations helped develop and implement innovations in the production of newer generations.

On the other hand, acquiring manufacturing experience with unrelated products, which are produced through very distinct manufacturing processes, is likely to lead firms into a broader search that encompasses more distant regions of the technological landscape and has the potential to identify solutions that might otherwise remain unexploited for the focal process. Thus, developing experience in more distant areas of the landscape may provide firms with the potential to solve problems in radically different ways (Fleming and Sorenson 2004).

The above discussion suggests that, while a firm might be able to draw on its related experience to devise innovative solutions for the process at stake, the degree of novelty of these inventions, defined as the distance from the current state of the art, is likely to benefit from the firm's unrelated, rather than related, experience. This is reflected in the following hypotheses:

H1a: The magnitude of a firm's related experience is negatively associated with the novelty of manufacturing inventions for a focal product.

H1b: The magnitude of a firm's unrelated experience is positively associated with the novelty of manufacturing inventions for a focal product.

2.2.2. Impact on inventions' scope Despite its importance, novelty is not the only critical dimension along which the value of a firm's innovative output can be characterized. Another crucial dimension is "scope", which can be defined as the degree of difficulty for competitors to operate similar technological configurations without infringing on any of the patent-holding firm's patented manufacturing inventions (Lerner 1994). Thus, scope is a characteristic of a firm's portfolio of patents that is clearly distinct from novelty. As a result, patents' portfolios can be high in novelty but low in scope or vice-versa. To illustrate the former consider Mesna, a drug in our sample that is used in the treatment of chemotherapy-related cystitis (Vidal 2013). UCB Pharma developed a new manufacturing process for the Mesna API, that involves a hydrolysis step followed by an isolation step and results in an active ingredient of higher purity profile relative to prior art (Leveque et al. 2011). While the novelty of the process for the preparation of this API was high, the resulting patent was of narrow scope, as, according to our patent experts, competitors bypassed this invention in a relatively effortless manner. For example, Fresenius AG, Sagent Pharmaceuticals Inc, and Altan Pharma Ltd implemented minor changes to the invention disclosed by UCB Pharma and achieved production of the API with similar purity without violating UCB Pharma's patent (IMSHealth 2015). Conversely, an example of a low-novelty but broad-scope patent can be found with Bevacizumab, a drug mainly used to treat colorectal and lung cancers (Vidal 2013). F. Hoffmann–La Roche developed a new method for increasing the yield of antibodies in cell culture, which consists in substituting specific residues during the manufacturing process. The low novelty of the invention is explained by the existence, in prior art, of many techniques for producing antibodies using a variety of host cells. The high scope is justified because the invention encompasses a wide range of potential residues' substitutions and describes both which residues to substitute and the substitutes that could be used.

While scope has not received the same amount of attention as novelty in the literature, it represents an important dimension of innovation because it captures the breadth of a firm's innovative output. A patent portfolio with a broader scope allows the firm to maintain exclusive access to a broader set of technological configurations. However, building a broad portfolio of patented inventions requires higher R&D efforts, increased experimentation to achieve more extensive familiarity with feasible alternatives (Leonard-Barton 1988) and a deeper engagement with a wider range of associated production technologies and technological configurations (Mihm et al. 2015). Nevertheless, in industries with high propensity to patent, such as the pharmaceutical industry, having inventions of broad scope can be particularly critical for long-term profitability and survival (Yiannaka and Fulton 2001).

Related experience appears critical for mastering the wide set of alternative process choices that is implied by portfolios of broad scope. First, the accumulation of related manufacturing experience increases the likelihood that multiple associations between prior experience and current manufacturing challenges get recognized (Chen and Chang 2011). Indeed, such experience is more likely to closely relate to the specific manufacturing needs of the focal product and may facilitate the identification of alternative approaches to solving a given manufacturing problem or identifying valuable modifications to the focal product's production process (Nerkar and Roberts 2004). This more intimate understanding of the associated region of the technological landscape is likely to enable the firm to identify and patent solutions that will, over time, result in a portfolio that progressively captures and protects from competition a broader area (Leonard-Barton 1988). In addition, maybe as a result of the implied strategic focus, firms that accumulate more production experience related to the focal process tend to demonstrate more perseverance in their search for broad technological solutions when improving this process (Cohen and Levinthal 1990).

On the other hand, experience accumulated in unrelated technological domains is less likely to lead to the type of knowledge transfer that enables broad coverage of specific regions of the technological landscape. This can be due to manufacturing technologies being quite different and the ensuing difficulty for organizations to recognize broader parallels with the manufacturing technologies of the focal process (Fong Boh et al. 2007). Moreover, the accumulation of unrelated manufacturing experience might divert a firm's attention away from the focal product (Cohen and Levinthal 1990), leading to patent portfolios that are more likely to remain narrow in scope.

Overall, this discussion points towards the following hypotheses:

H2a: The magnitude of a firm's related experience is positively associated with the scope of manufacturing inventions for a focal product.

H2b: The magnitude of a firm's unrelated experience is negatively associated with the scope of manufacturing inventions for a focal product.

3. Dataset and variables

3.1. Dataset

To test our hypotheses we construct a large-scale dataset using both primary and secondary data sources. We focus on antineoplastic (or anti-cancer) drugs, i.e., drugs identified as belonging to the class L1 of the European Pharmaceutical Marketing Research Association's (EphMRA) drug classification system (EphMRA 2015). Our initial sample consists of quarterly observations, for the ten-year period starting in January 2005 and ending in December 2014, for all 208 antineoplastic APIs that exist during that timeframe.

To measure our dependent variables of novelty and scope, we focus on U.S. manufacturing process patents to control for differences among country-level regulations that govern competition and innovation. The U.S. market represents 33.7% of global generics' sales (*Source:* Marketline Industry Profile). Among the 208 APIs considered, 148 are no longer covered by a product patent, and 121 of these have at least one manufacturing process patent in the U.S.

To measure our independent variables related to experience, we account for experience gained globally across all APIs included in our initial sample (i.e., 208 APIs). In particular, we record quarterly API sales across the U.S. and three major European countries[2], namely France (9.8% of the European generics market), Spain (6.5% of the European generics market) and Italy (2.5% of the European generics market). We choose these specific markets because while the U.S. is the largest pharmaceutical market worldwide, France, Italy, and Spain are all within the top five European pharmaceutical markets and among the most important markets globally for the sale of anti-cancer drugs specifically (Aitken et al. 2018)[3]. Among the 208 APIs included in our initial sample, 136 show sales in at least one of the four countries considered during our ten-year timeframe.

After narrowing down our sample to APIs that have observations for both dependent and independent measures, our final sample consists of 50 APIs with manufacturing patents by 105 firms, for which we evaluate novelty and scope (i.e., dependent variables), and 89 APIs, that are produced by those same firms, used to measure our experience (independent) variables. We provide a list of the 89 APIs used to construct our firm experience measures and highlight the 50 APIs for which we construct patents' portfolio novelty and scope measures in Table A.1 of Online Appendix A.

3.2. Variable definitions and sources

Table 1 provides summary statistics for all variables presented next. Pairwise correlations are reported in Table 2.

3.2.1. Performance: Firm's innovative output We measure pharmaceutical firms' innovative output for the APIs in our sample by observing their respective U.S. patent portfolios. We rely on the Thomson Reuters Newport database, which is recognized in the pharmaceutical industry as the reference database for patents and other intellectual-property information (Grimaldi et al. 2015). Patents are frequently used in the operations management (e.g., Chan et al. 2018) and organizational learning (e.g., Jain 2013) literatures as a valid indicator of a firm's innovative output

[2]The European generics market accounts for 20.1% of the global generics market (*Source:* Marketline Industry Profile).

[3]We could not use data from the other two top European countries (i.e., Germany and the UK) because pharmaceutical firms' names may not legally be disclosed for sales in the UK, and Germany has a very fragmented market for pharmaceuticals, owing to its federal structure and complex procurement systems.

(Griliches 1990). For any given API, since the end product is virtually identical across firms (Babar 2019), all patents contained in our sample introduce innovative manufacturing methods, and are thus referred to as "process patents" (Lieberman 1987). As an illustrative example, consider the API for Idarubicin – an anti-leukemia drug produced and sold by 5 firms in our sample. In Q4 of 2004, Synbias Pharma developed and patented a manufacturing method that reduced the number of required chemical steps from 12 to 4. As a result, the production yield increased from 5% to 30% and enabled Synbias Pharma to become the market leader for this drug.

Variable	Mean	Std. Dev.	Min	Max
NOV	3.13	0.68	1	4
SCP	2.99	0.64	1	4
FExp	9.85	5.86	0	20.40
RExp	16.98	20.59	0	123.29
UExp	84.34	79.99	0	296.68
HHI	0.69	0.37	0	1
InnovInt	4.18	2.63	1	12
R&D	6.18	1.69	0.10	8.80
InitFam	5.77	22.12	0	131

n=978

Table 1 Summary Statistics

	NOV	*SCP*	*FExp*	*RExp*	*UExp*	*HHI*	*InnovInt*	*R&D*	*InitFam*
NOV	1								
SCP	0.17^{***}	1							
FExp	-0.07^{**}	0.09^{***}	1						
RExp	0.12^{***}	0.03	0.09^{***}	1					
UExp	0.12^{***}	-0.13^{***}	0.01	0.23^{***}	1				
HHI	-0.02	-0.01	0.012^{***}	-0.04	-0.11^{***}	1			
InnovInt	0.17^{***}	-0.02	0.17^{***}	0.09^{***}	0.13^{***}	0.13^{***}	1		
R&D	-0.08^{**}	0.19^{***}	0.57^{***}	0.08^{**}	0.08^{**}	0.12^{***}	0.02	1	
InitFam	-0.07^{**}	-0.17^{***}	0.07^{**}	0.13^{***}	0.011^{***}	-0.13^{***}	0.05	0.02	1

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 2 Pairwise correlations

For each patent portfolio, we evaluate two distinct dimensions, namely novelty and scope. To achieve this, we first developed survey questions based on the formal constructs' definition provided below. We then asked three expert patent attorneys, all of whom have extensive chemical and biotechnological backgrounds[4], to rate the individual patents within each portfolio. We provide a

[4]Details are available from the authors upon request.

detailed description of this evaluation process in Online Appendix B, along with inter-rater reliability statistics. Overall, the patent experts evaluated 234 individual patents, which are technical documents that range in our sample from 9 to 165 pages.

For each API-firm-quarter combination, the variable *NOV* reflects the technological distance between the portfolio of active patented inventions (that are owned by the focal firm for the focal API during the focal quarter) and the prior art (Reitzig 2003). To construct *NOV*, which is a portfolio-level measure, we rely on within-portfolio individual patents' levels of novelty. These are based on patent experts' answer to the question: "How would you evaluate the overall novelty of the process patent with respect to the state of the art at the time of the patent filing?". Evaluations were collected on an ordinal scale ranging from 1 (very low) to 5 (very high). We construct the *NOV* measure by averaging the novelty evaluations of the patents within the portfolio and update it every time that the portfolio changes, i.e., a patent expires or a new patent is added.

The variable *SCP* reflects the breadth of the portfolio, i.e., the difficulty to bypass the active patented inventions without infringing on the patent-holding firm's rights. To construct *SCP*, which is also a portfolio-level measure, we rely on within-portfolio individual patents' levels of scope. These are based on patent experts' answer to the question: "How broad are the claims of the process patent with respect to the state of the art at the time of the latest patent filing?". Evaluations were collected on an ordinal scale ranging from 1 (very low) to 5 (very high). We construct the *SCP* measure by averaging the scope evaluations of the patents within the portfolio and update it every time that the portfolio changes.

3.2.2. Predictors: Firms' manufacturing experience Our experience measures are based on quarterly sales data for the APIs in our sample from the Intercontinental Medical Statistics (IMS) Health's MIDAS pharmaceutical sales proprietary database. This database tracks quarterly sales for almost every pharmaceutical product sold by every pharmaceutical firm worldwide and is considered to be the most reliable source of sales information in the pharmaceutical industry (Kanavos 2014). Given that several final dosage forms may exist for the same API, we measure sales for a focal API as the total number of kgs of the focal API sold by a firm in a quarter (Caves et al. 1991). In our ten-year study horizon, we observe sales from 105 distinct corporate groups[5]– hereafter referred to as "firms". In Table A.2 of Online Appendix A we provide a list of the 105 firms appearing in our sample.

[5]In the Newport database, a corporate group is the parent company to which the marketer (i.e., the company responsible for sales of a drug product in a specific market) and the patent holder (i.e., the company that holds the rights granted by a patent) belong (Newport 2018).

In line with the organizational learning literature (e.g., King and Tucci 2002), we measure a firm's accumulated experience for a focal API in a given quarter using adjusted cumulative sales. Specifically, let $k_{(ij,q)}$ be the total sales (in kgs) of API i sold by firm j in quarter q. We follow the approach described by Benkard (2000) and define the experience accumulated by firm j for API i in quarter q, $E_{(ij,q)}$, as:

$$E_{(ij,q)} = \delta \times E_{(ij,q-1)} + k_{(ij,q-1)} \tag{1}$$

where δ is the experience's quarterly retention rate, which allows accounting for organizational forgetting (Benkard 2000). This implies that more recent production is more valuable in determining a firm's current ability to innovate. Specifically, we set the quarterly experience retention rate to $\delta = 0.975$, which suggests an annual experience depreciation rate of 10% [6]. This is a reasonable choice for this setting based on earlier literature on organizational learning and forgetting (cf., Argote et al. 1990). Nonetheless, we test the sensitivity of our results for alternative depreciation rates in Section 4.4. To initialize our experience measures we set $E_{(ij,0)} = 0$ for all i and j and use the first four quarters of sales for a given API-firm combination as the calibration period. This is also in line with typical approaches in earlier literature (cf., Fader et al. 2010). We also test the sensitivity of our results to the duration of the calibration period in Section 4.4.

To distinguish between related and unrelated experience we rely on the EphMRA classification. Within the broad L1 class of anti-cancer drugs, nine sub-classes exist (specifically, the L1AB, L1C, L1D, L1F, L1G, L1H, L1X1, L1X3 and L1X9 sub-classes). APIs that are part of the same sub-class have similar molecular structures and, consequently, similar manufacturing technologies (Anderson 2012). For instance, sub-class L1D contains, among others, Doxorubicin and Epirubicin which can both be produced through similar production steps (i.e., halogenation, hydrolysis, chromatographic purification and crystallization) and may even share production equipment. This is possible due to the similarity of their chemical structures, despite important differences in the starting materials and in the execution of each production step (e.g., volume and concentration, type of solvents, etc.). Thus, accumulation of experience for one drug is likely to apply when dealing with production challenges for the other drug.

On the other hand, as an example of how production technologies may change across sub-classes, consider L1H and L1D. While production of APIs in the L1H sub-class is characterized by the use of an enzymatic process (Guengerich et al. 2004), production of APIs in the L1D sub-class relies on semi-synthetic molecules, which require radically different manufacturing technologies (Madduri

[6] A quarterly retention rate of 0.975 implies an annual retention rate of $0.975^4 = 0.9$ or, equivalently, an annual depreciation rate of 0.1.

et al. 1998). Despite these differences, experience with drugs in one sub-class can nevertheless benefit manufacturing innovation for drugs in another sub-class. For instance, experience producing Doxorubicin (an L1D API) through a one-pot process was key in inspiring and informing the development of a new, much shortened, process for Everolimus (an L1H API) that bypassed separate preparation of an intermediate product[7]. In Table A.3 of Online Appendix A we present how the 89 APIs that we use to construct our experience measures are grouped across the nine sub-classes of L1 APIs.

Let $A_{R,ij}$ denote the set of APIs in the same sub-class as API i (i.e., related) that are manufactured by firm j, and $A_{U,ij}$ denote the set of all APIs in sub-classes other than the sub-class of API i (i.e., unrelated) that are manufactured by firm j. We define the accumulated manufacturing experience "related" to API i for firm j in quarter q as:

$$RExp_{(ij,q)} = \sum_{a \in A_{R,ij}, a \neq i} ln(E_{(aj,q)}) \tag{2}$$

Note that we log-transform API-level experience measures $E_{(aj,q)}$ prior to adding them to account for the orders-of-magnitude difference that might characterize the production volume of different APIs and yet not translate into such differences in knowledge accumulation. For example, for the same firm in a given quarter, output for a given API might be in the order of hundreds of kgs whereas output for another related API might be in the order of tens of tons. Thus, not controlling for the vast difference in scale may underestimate the relative contribution to a firm's experience that APIs with lower output volumes might provide (Acemoglu and Linn 2004). Such transformation is consistent with the literature (Clark and Huckman 2012).

Similarly, we define the accumulated manufacturing experience "unrelated" to API i for firm j in quarter q as:

$$UExp_{(ij,q)} = \sum_{a \in A_{U,ij}} ln(E_{(aj,q)}) \tag{3}$$

3.2.3. Control variables

Market Concentration. Past research has found that market concentration, a measure of a market's competitiveness, influences firms' innovation efforts. For example, Schumpeter (1942) argues that higher market concentration may increase firms' innovation efforts as firms might enjoy profits due to market power that they can invest in R&D, whereas Arrow (1972) asserts that higher market concentration eliminates or diminishes competition and may reduce the urgency to innovate. In the pharmaceutical industry Matraves (1999) finds a positive relationship between

[7]The API manufacturer that communicated to us this example asked us not to publicly disclose its name.

market concentration and innovation. In line with previous research (Rego et al. 2013), we measure market concentration for API i in quarter q using the following HHI index:

$$HHI_{(i,q)} = \sum_{j} Share^2_{(ij,q)} \tag{4}$$

where $Share_{(ij,q)}$ is firm j's share of total U.S. sales for API i in quarter q, as reported in the IMS Health database. Thus a value of 1 for this index would mean a monopoly. In our sample, $HHI_{(i,q)}$ has a mean of 0.69.

Innovation Intensity. To control for heterogeneous opportunities for innovation among APIs, we consider the overall level of innovation intensity for API i in quarter q across all firms. In particular, we define $InnovInt_{(i,q)}$ as the total number of active U.S. patents owned by all firms in quarter q for API i. We interpret higher values of $InnovInt_{(i,q)}$ as indicative of the presence of more extensive innovation activities around the focal API (Lieberman 1987).

R&D Expenses. The magnitude of a firm's R&D expenses has been found to be associated with the quality and quantity of a firm's innovation output (Bhaskaran and Ramachandran 2011). Thus, we log-transform and include $R\&D_{(j,q)}$–firm j's R&D expenses in quarter q as reported on Standard & Poor's Compustat– as a control in our analyses.

Focal Experience. We control for firm's direct experience with manufacturing the focal product. Similar to our measures of related and unrelated experience, we define the experience "focal" to API i for firm j in quarter q as:

$$FExp_{(ij,q)} = ln(E_{(ij,q)}) \tag{5}$$

Initial Familiarity. To control for the familiarity that firm j has with API i at the start of our observation time window (Lawrence 2018), we introduce $InitFam_{(i,j)}$ which we measure as the number of quarters from the date of the first market authorization that firm j receives for producing API i until the first quarter of 2005 (i.e., the start of our timeframe). We construct this measure using the Thomson Reuters Newport database.

4. Analyses and Results

4.1. Model specification

To test the association between a firm's related and unrelated experience and the qualitative characteristics of its manufacturing inventions, we employ a hierarchical linear modeling (HLM) approach (Raudenbush et al. 2002). This approach allows us to accommodate and exploit the multi-level structure of our data, specifically the fact that APIs are cross-nested within pharmaceutical firms. Effectively, even though characteristics such as market concentration and innovation intensity

may differ across APIs, a firm's production experience is relevant for all APIs produced by it–as reflected in our experience measures. As a result, the observations across APIs and across firms are likely to be correlated, which violates classical OLS assumptions (DeHoratius and Raman 2008). Moreover, HLM estimation can accommodate the unbalanced nature of our panel as each firm has a different number of observations due to the different number of APIs in its product portfolio (Valentine et al. 2019).

In particular, we perform maximum likelihood estimation for the following model using the xtmixed command in STATA:

$$\begin{aligned} ln(DepVar)_{(ij,q)} = {} & (\beta_0 + \zeta_{0j}) + (\beta_1 + \zeta_{1j}) \cdot FExp_{(ij,q-t)} + (\beta_2 + \zeta_{2j}) \cdot RExp_{(ij,q-t)} + (\beta_3 + \zeta_{3j}) \cdot UExp_{(ij,q-t)} \\ & + \beta_4 \cdot HHI_{(i,q)} + \beta_5 \cdot InnovInt_{(i,q)} + \beta_6 \cdot ln(R\&D_{(j,q)}) + \beta_7 \cdot InitFam_{(i,j)} \\ & + \lambda_q + \epsilon_{(ij,q)} \end{aligned} \tag{6}$$

We set $DepVar = NOV$ to test hypotheses H1a & H1b and $DepVar = SCP$ to test hypotheses H2a & H2b; λ_q represents year fixed effects.

A noticeable feature of our model is that it allows not only for a firm-level random intercept ζ_{0j}, but also for firm-level random slopes, ζ_{1j}, ζ_{2j}, and ζ_{3j}. While the random intercept accounts for unobserved firm-level characteristics that might influence firms' ability to innovate, firm-specific random slopes for focal, related, and unrelated experience account for potential heterogeneity in firms' ability to derive practical value from their experience. Such a model structure is supported by the literature. For example, Ang et al. (2002) model differences in learning rates across IT institutions by estimating random slopes for each institution.

We control for API-level variables (i.e., *HHI* and *InnovInt*), firm-level variables (i.e., *R&D*) and API-firm-level variables (i.e., *FExp* and *InitFam*). To account for potential simultaneity bias and buttress causality interpretations, we lag our experience measures by $t = 4$ quarters (Rothaermel and Hess 2007). We choose such a lag based on prior literature which suggests that the typical time that is necessary from the inception of an invention until its patenting, when it would appear in our dataset, is approximately a year (e.g., King and Tucci 2002). This suggests that a firm's experience up to one year prior would be most relevant for the patent portfolio characteristics we observe in the focal quarter. In Section 4.4 we conduct sensitivity analyses with alternative lags and find consistent results.

We also note that in using a log-level model, we implicitly assume an exponential relation between firm experience and the firm's patent novelty and scope. Such an approach is common in the literature on learning curves (e.g., Lapré and Tsikriktsis 2006, Clark et al. 2013) because it minimizes

any biases that might be introduced in the analysis from the omission of experience that a firm may have accumulated prior to a study's observation time window.

VARIABLES	ln(*NOV*) (Model 1)	ln(*NOV*) (Model 2)	ln(*NOV*) (Model 3)	ln(*NOV*) (Model 4)	ln(*NOV*) (Model 5)	ln(*NOV*) (Model 6)
RExp		-0.002**	-0.002		-0.008***	-0.008***
		(0.001)	(0.001)		(0.003)	(0.003)
UExp			0.001			0.001***
			(0.001)			(0.001)
Intercept	1.154***	1.154***	1.151***	1.105***	1.113***	1.092***
	(0.097)	(0.095)	(0.098)	(0.112)	(0.111)	(0.111)
Controls						
HHI	-0.010	-0.018	-0.019	-0.021	-0.021	-0.022
	(0.033)	(0.034)	(0.035)	(0.039)	(0.039)	(0.038)
InnovInt	0.013	0.013	0.013	0.012	0.011	0.012
	(0.010)	(0.011)	(0.011)	(0.017)	(0.017)	(0.016)
ln(*R&D*)	-0.009	-0.008	-0.009	-0.001	-0.001	0.001
	(0.012)	(0.011)	(0.010)	(0.008)	(0.008)	(0.009)
FExp	0.002	0.002	0.002	0.002	0.002	0.001
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
InitFam	-0.001	-0.001	-0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Random coefficients	no	no	no	yes	yes	yes
Observations	978	978	978	978	978	978
Log likelihood	434.38	449.32	451.36	623.38	626.12	628.36
AIC	-836.77	-864.63	-866.73	-1208.76.	-1212.25	-1214.72
Prob > χ^2	0.001	0.001	0.001	0.001	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables. *** p<0.01, ** p<0.05, * p<0.1

Table 3 H1a & H1b results

4.2. Firm experience and novelty

In Table 3, we present our results for hypotheses H1a & H1b. Specifically, we build towards our main model, i.e., Model 6, as follows: First, we consider a model with only the controls included (cf., Model 1). Next, we introduce the dependent variables in a stepwise manner (DeHoratius and Raman 2008). In particular, Model 2 includes *RExp* and Model 3 includes both *RExp* and *UExp*. Models 4, 5, and 6 mirror our three first models but with the inclusion of firm-level random coefficient for the experience variables (i.e., *RExp*, *UExp*, and *FExp*) in addition to the firm-level random intercepts. From comparing models 1, 2, 3 and 4, 5, 6, we observe that the introduction of the two key independent experience variables both maximizes log-likelihood and minimizes the Akaike Information Criterion (AIC) thereby suggesting that the best model fit is provided from

the models that include both *RExp* and *UExp* as predictors of a portfolio's novelty. In addition, the relatively better fit of the models that include firm-specific random slopes for the experience measures (Models 4, 5, and 6), formally tested using likelihood-ratio tests ($p < 0.001$ for all three pairs of models), supports our modeling approach, i.e., the inclusion of firm-level random slopes.

Hypothesis H1a posits that the magnitude of a firm's related experience is negatively associated with the novelty of its portfolio of patented manufacturing inventions for a focal product. The coefficient for *RExp* in Model 6 is negative and statistically significant (-0.008, $p < 0.01$), which provides support for H1a. Hypothesis H1b posits that the magnitude of a firm's unrelated experience is positively associated with the novelty of its portfolio of patented manufacturing inventions for a focal product and is also supported by our results, i.e., the coefficient of unrelated experience in Model 6 is positive and statistically significant (0.001, $p < 0.01$).

VARIABLES	ln(*SCP*) (Model 7)	ln(*SCP*) (Model 8)	ln(*SCP*) (Model 9)	ln(*SCP*) (Model 10)	ln(*SCP*) (Model 11)	ln(*SCP*) (Model 12)
RExp		0.003	0.003		0.007**	0.008**
		(0.003)	(0.002)		(0.004)	(0.004)
UExp			-0.001			-0.002**
			(0.001)			(0.001)
Intercept	1.101***	1.103***	1.103***	1.121***	1.121***	1.129***
	(0.108)	(0.106)	(0.109)	(0.077)	(0.077)	(0.076)
Controls						
HHI	-0.055	-0.044	-0.045	0.001	0.001	0.001
	(0.047)	(0.046)	(0.045)	(0.020)	(0.019)	(0.020)
InnovInt	0.003	0.003	0.003	-0.002	-0.002	-0.002
	(0.011)	(0.010)	(0.011)	(0.004)	(0.004)	(0.004)
ln(*R&D*)	0.003	0.001	0.001	-0.009	-0.009	-0.009
	(0.014)	(0.014)	(0.013)	(0.009)	(0.009)	(0.009)
FExp	-0.005	-0.006	-0.006	0.001	0.001	0.001
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
InitFam	-0.002***	-0.002***	-0.002***	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Random coefficients	no	no	no	yes	yes	yes
Observations	978	978	978	978	978	978
Log likelihood	344.09	367.81	367.86	716.45	718.24	720.09
AIC	-656.18	-701.62	-699.72	-1394.89	-1396.48	-1398.18
Prob > χ^2	0.001	0.001	0.001	0.001	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables. *** p<0.01, ** p<0.05, * p<0.1

Table 4 H2a & H2b results

4.3. Firm experience and scope

In Table 4 we present our results for hypotheses H2a & 2b. The structure of Table 4 is identical to the structure of Table 3 that we discussed in Section 4.2 and we can make similar observations: the best model fit is provided from the models that include both *RExp* and *UExp* as predictors of portfolio's scope, and the inclusion of firm-specific random slopes for the experience measures (Models 10, 11, and 12), is warranted–here also formal comparison of the models' fit via likelihood-ratio test shows $p < 0.001$ for all three pairs of models.

Hypothesis H2a posits that the magnitude of a firm's related experience is positively associated with the scope of its portfolio of patented manufacturing inventions for a focal product. The coefficient for *RExp* in Model 12 is positive and statistically significant (0.008, $p < 0.05$), which supports H2a. Hypothesis H2b posits that the magnitude of a firm's unrelated experience is negatively associated with the scope of its portfolio of patented manufacturing inventions for a focal product. This is also supported by our results: the coefficient for *UExp* in Model 12 is negative and statistically significant (-0.002, $p < 0.05$).

4.4. Robustness checks

We assess the robustness of the results for Models 6 and 12 (i.e., full models for H1 and H2 hypotheses sets) through several checks. First, we consider alternative values for the quarterly experience retention rate δ (cf., eq. (1)). Specifically, we set δ to 1.000, 0.987, 0.960 and 0.946, which (respectively) correspond to annual experience depreciation rates of 0%, 5%, 15% and 20% (our baseline value is $\delta = 0.974$, which corresponds to an annual depreciation rate of 10%). Overall, results remain consistent (cf., Tables C.1 and C.2 in Online Appendix C)[8].

Second, we tested the sensitivity of our results to the choice of lags for our experience measures. Specifically, we re-estimate Models 6 and 12 by setting t equal to 1, 2 and 3 quarters (our baseline value is $t = 4$). Results for these alternative lags are consistent with the main results (cf., Table C.3 in Online Appendix C).

Third, we tested the sensitivity of our results to the duration of the experience measures' calibration period. While in our main analysis we rely on the four initial quarters of our time window to calibrate our experience measures, we also tested Models 6 and 12 by initializing our experience measures using two, six and eight quarters and found that results continue to hold (cf., Table C.4 in Online Appendix C).

Fourth, to more precisely account for unobserved time-varying factors and unobserved product characteristics we also test Models 6 and 12 by introducing half-year fixed effects (Reagans et al.

[8] All results which are discussed but not presented in the paper are available in Online Appendix C.

VARIABLES	ln(*NOV*) (Model 13)	ln(*SCP*) (Model 14)
ln(*RExp*)	-0.055**	0.058**
	(0.023)	0.028)
ln(*UExp*)	0.022*	-0.037**
	(0.011)	(0.015)
Intercept	1.032***	1.175***
	(0.097)	(0.093)
Controls		
HHI	-0.009	-0.021
	(0.037)	(0.030)
InnovInt	0.013	0.001
	(0.013)	(0.008)
ln(*R&D*)	0.003	-0.001
	(0.010)	(0.009)
ln(*FExp*)	0.015	0.009
	(0.018)	(0.035)
IXP	0.002	-0.004**
	(0.001)	(0.001)
Random coefficients	yes	yes
Observations	978	978
Log likelihood	590.85	675.80
AIC	-1139.71	-1309.60
Prob > χ^2	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables. *** p<0.01, ** p<0.05, * p<0.1

Table 5 Log-log model results

2005) and API sub-class fixed effects (Henderson and Cockburn 1996). In our baseline analysis we included full-year fixed effects. Overall, our results remain consistent (cf., Table C.5 in Online Appendix C).

Fifth, we note that some of the production that we attribute to the firms in our sample is being outsourced to third-party manufacturers (Gray et al. 2015). As such, the experience is not generated in-house, which suggests that, with respect to a firm's learning, one unit of outsourced production may not be as valuable as one unit of in-house production (Sting and Loch 2016). However, we also note that given the stringent regulations that govern pharmaceutical manufacturing, third-party manufacturers are in very close collaboration with the outsourcing firm regarding process design and execution, how to handle production issues, etc. and typically have limited freedom in terms of executing changes on their own (Bruccoleri et al. 2019). As such, any learning opportunity that arises in the environment of a third-party manufacturer is likely to also benefit the outsourcing firm. Nevertheless, to account for the potentially different learning benefits from in-house versus

outsourced production we discount outsourced production quantities. Thus, we change equation (1) as follows:

$$K_{(ij,q)} = \delta \times K_{(ij,q-1)} + d \times k_{(ij,q-1)} \tag{7}$$

and update our experience measures as defined in equations (2), (3), and (5). Here, d corresponds to the discount coefficient for outsourced production. We estimate Models 6 and 12 using $d = 0.8$, 0.7, and 0.5 when production is outsourced, while setting $d = 1$ when production occurs in-house. To distinguish between in-house and outsourced production we check whether firm j has an active drug master file for API i registered with the US FDA (USFDA 2020) or the European Directorate for the Quality of Medicine and Healthcare (EDQM 2020) in quarter q. We assume that production occurs in-house if this is the case and is outsourced otherwise (Chaudhuri 2013). Our main results persist (cf., Table C.6 in Online Appendix C).

Sixth, we re-estimate Models 6 and 12 while allowing for the firms' random intercepts and slopes to be correlated, i.e., a less onerous assumption. This suggests that firms' relative ability to use previous experience in their innovation efforts is somewhat independent from their relative overall ability to innovate. Our results continue to hold (cf., Table C.7 in Online Appendix C).

Seventh, the literature suggests that firm size is a key determinant of innovation output. However, this relationship rests on the fact that larger firms tend to have more R&D spending (Cohen 2010). This is supported by the high correlation between firm size and R&D expenses in our dataset ($\rho = 0.86$, $p < 0.01$). This is why we have only included *R&D* as a control in our primary analysis. However, in this robustness check, we substitute *R&D* with *SIZE*, which we also log-transform. We obtain *SIZE* through firms' assets as reported in Standard & Poor's Compustat database. Again, the main results remain consistent (cf., Table C.8 in Online Appendix C).

Eighth, we test a log-log model to examine the robustness of our results to the introduction of a power-form learning curve. Thus, we log-transform *RExp*, *UExp*, and *FExp* and re-estimate Models 6 and 12. The results are presented in Models 13 and 14 of Table 5 for *NOV* and *SCP* respectively and are consistent with our main results. Despite the fact that these models do not achieve as good of a fit as our main log-level models, we choose to include the results from their estimation in the paper as they allow for a more managerially-relevant interpretation of the effect of related and unrelated experience measures. For example, Model 13 in Table 5 suggests that for a 1% increase in *RExp*, portfolio novelty decreases by 5.5% ($p < 0.1$). From the same model, we further observe that a 1% increase in *UExp* results in a 2.2% increase in portfolio novelty. Similarly, Model 14 in Table 5 suggests that for a 1% increase in *RExp*, portfolio scope increases by 5.8% ($p < 0.05$) whereas a 1% increase in *UExp* results in a 3.7% decrease in portfolio scope.

5. Discussion and concluding remarks

Our study combines elements from the operations, innovation, and organizational learning literatures and allows us to reconcile several contradicting arguments. Specifically, we find that experience with manufacturing related products is associated with a decrease in the novelty and an increase in the scope of the manufacturing methods that a pharmaceutical firm develops and patents for a focal product over time. Thus, while the drop in novelty points towards a risk of falling into a competency trap, the increase in scope indicates that the accumulation of related experience enables firms to better understand the structure of a focal product's technological landscape and develop a broad set of applicable innovative production methods.

We also find that experience with manufacturing unrelated products is associated with an increase in a focal product's patents' novelty and a decrease in its patents' scope. Hence, our analysis suggests that engagement with a diverse set of products and, as a result, manufacturing technologies, permits firms to identify and patent more novel methods that apply to the production of a focal product. However, it also highlights that the strain on firms' cognitive and financial resources that comes with engaging in the manufacturing of a diverse set of products, could prevent firms from broadly mastering the focal product's technological landscape.

As such, our study provides specific guidance in terms of how managers might want to structure their firms' product portfolios and the longitudinal effect of their choices on their firms' intellectual property. Such guidance is important because developing a firm's product portfolio around more related or more diverse products carries very different practical implications for the design and execution of both R&D and manufacturing-related activities (Wiersema and Beck 2017). Moreover, even though we conduct our study in the pharmaceutical setting, our findings are likely to carry implications for other high-technology industries as well. This is because the development of innovative pharmaceutical manufacturing methods requires pharmaceutical firms, like other firms in high-tech industries, to "couple the worlds of leading-edge science with the realities of plant operations" (Pisano 1997, p.21).

Specifically, our results suggest that, for firms where sales are more concentrated in a set of related products, the intellectual property that firms build for these products over time is likely to be characterized by broad scope but may lack in terms of novelty. Whether such an outcome is desirable depends on firms' strategic priorities. For example, practitioners from a generics-focused manufacturer that we communicated within the context of this project stated that their key priority is developing and patenting inventions that are as broad in scope as possible whereas novelty is secondary in importance. In the context of API manufacturing this translates into promoting

the identification and patenting of a broad number of different routes of synthesis through which a given API might be produced, and this even if all of these routes may not necessarily be implemented in practice. This would be important from a competitive standpoint because it would prevent competitors from taking advantage of production methods that are proximal to these of the innovating firm and, presumably, of comparable efficiency. Our analysis suggests that, for firms with such a strategic priority, building and maintaining a portfolio of related products might be an effective way to achieve this objective.

Conversely, our results imply that when a firm's priority is to develop a portfolio of novel manufacturing inventions, maintaining a diverse product portfolio over time is likely to be invaluable. One reason why firms might promote novelty over scope is that innovations of higher novelty typically have a higher economic value and the potential to more profoundly impact the competitive environment by disrupting existing competencies or even eliminating existing players from the market (Bessen 2009). Teva pharmaceuticals, a large generics manufacturer with a diverse product portfolio, provides a relevant example. Teva developed and patented a very novel process for producing Letrozole, a drug used in the treatment of breast cancer, that substantially increased yield relative to the state of the art at the time (Vogel 1995). While implementation required Teva to build a new manufacturing facility, the new process allowed Teva to achieve a level of productivity that permitted it to double its market share and eliminate major competitors such as Bristol-Myers Squibb and Hikma Pharmaceuticals from the U.S. market (IMSHealth 2015).

As is inevitable with studies of this kind, our work has some limitations. First, not all patentable inventions are patented (Griliches 1990). Nevertheless, the pharmaceutical industry is characterized by a very high propensity to patent. Pharmaceutical firms generally prefer patenting relative to other forms of intellectual property protection (e.g., trade secrecy) and this results in more than 80% of patentable inventions being patented (Mansfield 1986). This is particularly true for the case of new manufacturing methods which is the form of inventions that we study. Infringement of a corresponding patent may be identified from the "chemical fingerprint" that a manufacturing process leaves on the final product (Deconinck et al. 2008) or through on-site inspections of suspected infringing competitors (Blakeney 2005). Moreover, as a pharmaceutical firm must disclose in detail the characteristics of its manufacturing process when applying to public health authorities for a legal license to sell a product (Cartwright 2016), such details could potentially be obtained by competitors through future court orders. Also, protection via trade secrecy is inherently risky because competition may succeed in independently discovering a firm's invention, reverse engineer it, or hire away from the inventing firm key personnel with the necessary technical knowledge

(Arundel and Kabla 1998). Second, our study is focused on the pharmaceutical industry and more specifically on the production of APIs that are no longer patent-protected. Future studies that test our findings in other settings would be especially valuable. Third, additional insight into firms' learning could be obtained from the analysis of data that provides visibility into which facilities manufacture which products (Egelman et al. 2017). Nevertheless, identifying such data at the scale of our study is challenging.

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Online Supplement

Novelty and scope of innovation in manufacturing: The role of related and unrelated production experience

Appendix A: Sample construction

ALITRETINOIN	**CELECOXIB**	**EVEROLIMUS**	**IRINOTECAN**	**TOPOTECAN**
ANAGRELIDE	**CISPLATIN**	**FINASTERIDE**	**LETROZOLE**	**TRASTUZUMAB**
AZACITIDINE	**CLOTRIMAZOLE**	**FLUDARABINE**	**MESNA**	**TRETINOIN**
BEVACIZUMAB	**COLCHICINE**	**FLUOROURACIL**	**METHOTREXATE**	**VERTEPORFIN**
CABAZITAXEL	**DECITABINE**	**GEFITINIB**	**METOCLOPRAMIDE**	**VINCRISTINE**
CALCITRIOL	**DOCETAXEL**	**GEMCITABINE**	**MITOMYCIN**	**VINORELBINE**
CALCIUM FOLINATE	**DOCOSANOL**	**IDARUBICIN**	**OXALIPLATIN**	**BESIFLOXACIN**
CALCIUM LEVOFOLINATE	**DOXORUBICIN**	**IFOSFAMIDE**	**PEMETREXED**	**ROMIDEPSIN**
CAPECITABINE	**EPIRUBICIN**	**IMATINIB**	**RITUXIMAB**	**VALRUBICIN**
CARBOPLATIN	**ETOPOSIDE**	**IPILIMUMAB**	**TEMOZOLOMIDE**	**VORINOSTAT**
BEXAROTENE	CIDOFOVIR	GLUCARPIDASE	PACLITAXEL	CERITINIB
BLINATUMOMAB	CLOFARABINE	HYDROXYCARBAMIDE	PALIFERMIN	DABRAFENIB
BORTEZOMIB	CYCLOPHOSPHAMIDE	LEFLUNOMIDE	PYRIDOXINE	DASATINIB
BOSUTINIB	CYTARABINE	MAGNESIUM	RAMUCIRUMAB	LAPATINIB
BUSULFAN	DACTINOMYCIN	MERCAPTOPURINE	TACROLIMUS	PAZOPANIB
CARMUSTINE	DEXRAZOXANE	METHOXSALEN	TEMSIROLIMUS	PEMBROLIZUMAB
CHLORAMBUCIL	DOXERCALCIFEROL	MITOTANE	AFLIBERCEPT	TRAMETINIB
CHORIOGONADOTROPIN	EFLORNITHINE	NELARABINE	AXITINIB	

Table A.1 List of the 89 drugs used to construct experience measures. NOV and SCP are constructed based on the 50 drugs (in bold font) in the upper part of the table.

ABBOTT LABORATORIES	ABBVIE INC	ACETO CORPORATION
AKORN INC	ALIGEN INDEPENDENT LABORATORIES	ALLERGAN PLC
ALLSCRIPTS HEALTHCARE SOLUTIONS INC	ALPHAGEN LABORATORIES INC	ALVA-AMCO PHARMACAL COMPANIES
AMERICAN HEALTH PACKAGING	AMNEAL PHARMACEUTICALS COMPANY	ANI PHARMACEUTICALS INC
ANTARES PHARMA INC	APOTEX INC	AREVA PHARMACEUTICALS INC
ASTRAZENECA PHARMACEUTICALS LP	AUROBINDO PHARMA LTD	AVION PHARMACEUTICALS
AVKARE INC	BAXTER INTERNATIONAL INC	BAY PHARMA INC
BAYER AG	BD RX INC.	BEACH PRODUCTS INC
BLAINE LABS INC	BOEHRINGER INGELHEIM KG	BRISTOL-MYERS SQUIBB
CAPITAL PHARM	CELGENE CORPORATION	CENTURION INC
CIPLA LTD	CONCORDIA HEALTHCARE CORP	CURA PHARMACEUTICALS INC
DAIICHI SANKYO CO LTD	DAKOTA LABORATORIES LLC	DR REDDY'S GROUP
EISAI CO LTD	ELI LILLY AND COMPANY	EMCURE HOUSE
ENDO INTERNATIONAL PLC	ESTEVE GROUP	FRESENIUS AG
GANEDEN BIOTECH INC	GENERAMEDIX INC	GENSCO LABS
GLAXOSMITHKLINE PLC	GLENMARK PHARMACEUTICALS LTD	H L MOORE DRUG EXCHANGE
HETERO GROUP	HIKMA PHARMACEUTICALS PLC	HOFFMANN-LA ROCHE AG
IMPAX LABORATORIES INC	INGENUS PHARMACEUTICALS	INTAS PHARMACEUTICALS LTD
JAYMAC PHARMACEUTICALS LLC	JOHNSON & JOHNSON	KADMON PHARMACEUTICALS
LABORATOIRES BOIRON	LABORATORIOS ALMIRALL SA	LANNETT COMPANY INC
LEADING PHARMA	LEGACY PHARMACEUTICALS INTERNATIONAL	LIBERTY PHARMACEUTICALS
LUPIN LTD	MALLINCKRODT INC	MCKESSON CORPORATION
MEDA AB	MEDAC GMBH	MEDISCA INC
MERCK AND CO INC	MOBIUS THERAPEUTICS	MYLAN LABORATORIES INC
NESTLE SA	NOVARTIS AG	ONSET DERMATOLOGIC
OTSUKA PHARMACEUTICAL CO LTD	PALMETTO PHARMACEUTICALS INC	PD-RX PHARMACEUTICALS
PERRIGO COMPANY	PFIZER INC	PIERRE FABRE GROUP
PRASCO LABORATORIES	PRECISION DOSE INC	PRODIGY GENERICS
PROPHARMA INC	REPACKAGER	ROUSES POINT PHARMACEUTICALS
SAGENT PHARMACEUTICALS INC	SANOFI	SHEFFIELD LABORATORIES
SHIRE PHARMACEUTICALS GROUP PLC	SPEAR PHARMACEUTICALS INC	SPECTRUM PHARMACEUTICALS
SUN PHARMACEUTICAL INDUSTRIES LTD	SUNEVA MEDICAL INC	TAKEDA PHARMACEUTICAL COMPANY
TEVA PHARMACEUTICAL INDUSTRIES LTD	THE HARVARD DRUG GROUP	THE LETCO COMPANIES
VALEANT PHARMACEUTICALS	VALIDUS PHARMACEUTICALS	VISTAPHARM INC
WG CRITICAL CARE LLC	WOCKHARDT LTD	XANODYNE PHARMACEUTICALS INC

Table A.2 List of firms

GROUP	APIs
L1AB	AZACITIDINE, CARMUSTINE, DECITABINE, MERCAPTOPURINE, TEMOZOLOMIDE BUSULFAN, CHLORAMBUCIL, FLUDARABINE, MESNA, TRETINOIN CALCIUM FOLINATE, CLOFARABINE, FLUOROURACIL, METHOTREXATE, VERTEPORFIN CALCIUM LEVOFOLINATE, CYCLOPHOSPHAMIDE, GEMCITABINE, NELARABINE CAPECITABINE, CYTARABINE, IFOSFAMIDE, PEMETREXED
L1C	CABAZITAXEL, ETOPOSIDE, METHOXSALEN, TOPOTECAN, VINORELBINE DOCETAXEL, IRINOTECAN, PACLITAXEL, VINCRISTINE
L1D	DACTINOMYCIN, EPIRUBICIN, IDARUBICIN, MITOMYCIN, VALRUBICIN DOXORUBICIN
L1F	CARBOPLATIN, CISPLATIN, OXALIPLATIN
L1G	BEVACIZUMAB, IPILIMUMAB, RITUXIMAB, TRASTUZUMAB, PEMBROLIZUMAB BLINATUMOMAB, RAMUCIRUMAB
L1H	ANAGRELIDE, FINASTERIDE, LEFLUNOMIDE, TACROLIMUS, CERITINIB BORTEZOMIB, GEFITINIB, LETROZOLE, TEMSIROLIMUS, DASATINIB BOSUTINIB, HYDROXYCARBAMIDE, PALIFERMIN, VORINOSTAT, PAZOPANIB EVEROLIMUS, IMATINIB, ROMIDEPSIN, AXITINIB
L1X1	ALITRETINOIN, COLCHICINE
L1X3	AFLIBERCEPT
L1X9	BESIFLOXACIN, CHORIOGONADOTROPIN, DOCOSANOL, MAGNESIUM, DABRAFENIB BEXAROTENE, CIDOFOVIR, DOXERCALCIFEROL, METOCLOPRAMIDE, LAPATINIB CALCITRIOL, CLOTRIMAZOLE, EFLORNITHINE, MITOTANE, TRAMETINIB CELECOXIB, DEXRAZOXANE, GLUCARPIDASE, PYRIDOXINE

Table A.3 L1 APIs grouped across the nine sub-classes

Appendix B: The patent evaluation process

We administer a questionnaire to obtain data for our *NOV* and *SCP* variables to three expert patent attorneys (one primary and two secondary), who combine expertise in law, chemistry and biotechnology (their contact information is available upon request). We first tested with our primary attorney (hereafter referred to as "Expert 1") the acceptability of the questions and corrected the wording for ambiguities. Expert 1 then evaluated all 234 individual patents.

With respect to novelty, Expert 1 was asked to assess the distance (i.e., the degree of "newness") between the active patented process innovations and the prior art. Specifically, the expert was asked "How would you evaluate the overall novelty of the process patent with respect to the state of the art at the time of the patent filing?". Evaluations were collected on an ordinal scale ranging from 1 (very low) to 5 (very high).

With respect to scope, Expert 1 was asked to evaluate the breadth, i.e., the complexity to bypass the patented process innovations without infringing on the patent-holding firm's rights. Specifically, the expert was asked "How broad are the claims of the process patent with respect to the state of the art at the time of the patent filing?". Evaluations were again collected on an ordinal scale ranging from 1 (very low) to 5 (very high).

In order to check the reliability of the evaluations provided by Expert 1 for novelty and scope, we selected a random sub-sample of 11 drugs (22% of the total number of drugs for which we construct *NOV* and *SCP* measures), which corresponds to 28 individual patents (12% of the total number of patents in our final sample). We then asked Expert 2 and Expert 3 to independently evaluate the novelty and scope of each patent in this sub-sample. We used their responses to check inter-rater reliability, i.e., the level of agreement among experts.

Inter-rater reliability quantifies the degree of agreement between different experts' independent ratings that have been provided on a scale (e.g., a Likert scale). We follow earlier studies in operations management (e.g., French and Laforge 2006, Hsieh et al. 2011), which have used an inter-rater reliability coefficient that estimates the proportion of true variance in the experts' judgments relative to true variance plus error variance (James et al. 1984). The resulting index of inter-rater reliability takes a maximum value of 1 (perfect reliability) and a minimum value of 0 (no reliability). Using this technique, the inter-rater reliability coefficients between Expert 1's and Expert 2's responses (on the five-point Likert scale) are 0.951 and 0.949 (0.9068 and 0.9437 between Expert 1's and Expert 3's responses) for individual-patent novelty and scope respectively. The results suggest substantial agreement among experts' evaluations (James et al. 1984, Hsieh et al. 2011).

Appendix C: Robustness checks

C.1. Alternative values for the quarterly experience retention rate

VARIABLES	ln(*NOV*) (Model 15)	ln(*NOV*) (Model 16)	ln(*NOV*) (Model 17)	ln(*NOV*) (Model 18)
RExp	-0.009***	-0.008**	-0.009***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
UExp	0.001**	0.001**	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	1.095***	1.100***	1.093***	1.088***
	(0.112)	(0.112)	(0.107)	(0.106)
Controls				
HHI	-0.021	-0.023	-0.023	-0.021
	(0.035)	(0.035)	(0.034)	(0.033)
InnovInt	0.010	0.011	0.011	0.012
	(0.017)	(0.016)	(0.016)	(0.016)
ln(*R&D*)	0.001	-0.001	0.002	0.002
	(0.009)	(0.009)	(0.009)	(0.009)
FExp	0.002	0.002	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
InitFam	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Random coefficients	yes	yes	yes	yes
Observations	978	978	978	978
δ	1.000	0.987	0.960	0.946
Log Likelihood	629.83	633.33	628.02	626.18
AIC	-1217.67	-1224.67	-1213.05	-1210.36
Prob > χ^2	0.001	0.001	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables.
*** p<0.01, ** p<0.05, * p<0.1

Table C.1 H1a & H1b results

VARIABLES	ln(*SCP*) (Model 19)	ln(*SCP*) (Model 20)	ln(*SCP*) (Model 21)	ln(*SCP*) (Model 22)
RExp	0.008**	0.009**	0.008**	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
UExp	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	1.112***	1.124***	1.126***	1.127***
	(0.074)	(0.077)	(0.075)	(0.075)
Controls				
HHI	0.005	0.002	0.011	0.011
	(0.019)	(0.018)	(0.021)	(0.021)
InnovInt	-0.001	-0.002	-0.002	-0.003
	(0.004)	(0.004)	(0.005)	(0.005)
ln(*R&D*)	-0.008	-0.009	-0.009	-0.008
	(0.009)	(0.009)	(0.008)	(0.008)
FExp	0.001	0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
InitFam	-0.001**	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Random coefficients	yes	yes	yes	yes
Observations	978	978	978	978
δ	1.000	0.987	0.960	0.946
Log Likelihood	727.40	723.34	718.01	713.53
AIC	-1412.81	-1404.69	-1392.02	-1385.06
Prob > χ^2	0.001	0.001	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables.
*** p<0.01, ** p<0.05, * p<0.1

Table C.2 H2a & H2b results

C.2. Choice of lags for the experience measures

VARIABLES	ln(*NOV*) (Model 23)	ln(*NOV*) (Model 24)	ln(*NOV*) (Model 25)	ln(*SCP*) (Model 26)	ln(*SCP*) (Model 27)	ln(*SCP*) (Model 28)
RExp	-0.010***	-0.010***	-0.010***	0.007**	0.007**	0.008**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
UExp	0.001**	0.001***	0.001**	-0.003*	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Intercept	1.110***	1.104***	1.101***	1.100***	1.099***	1.105***
	(0.105)	(0.108)	(0.110)	(0.070)	(0.068)	(0.065)
Controls						
HHI	-0.038	-0.034	-0.029	0.038	0.032	0.027
	(0.035)	(0.034)	(0.034)	(0.025)	(0.024)	(0.022)
InnovInt	0.010	0.011	0.011	-0.004	-0.004	-0.003
	(0.016)	(0.017)	(0.017)	(0.004)	(0.004)	(0.004)
ln(*R&D*)	0.006	0.006	0.005	-0.007	-0.007	-0.007
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
FExp	-0.001	-0.001	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
InitFam	0.001	0.001	0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Random coefficients	yes	yes	yes	yes	yes	yes
Observations	978	978	978	978	978	978
Lag (quarters)	1	2	3	1	2	3
Log Likelihood	650.68	646.74	643.43	768.79	760.52	753.48
AIC	-1259.37	-1251.48	-1244.86	-1495.59	-1479.04	-1464.96
Prob > χ^2	0.001	0.001	0.001	0.001	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables. *** p<0.01, ** p<0.05, * p<0.1

Table C.3 H1 & H2 results

C.3. Duration of the experience measures' calibration period

VARIABLES	ln(*NOV*) (Model 29)	ln(*NOV*) (Model 30)	ln(*NOV*) (Model 31)	ln(*SCP*) (Model 32)	ln(*SCP*) (Model 33)	ln(*SCP*) (Model 34)
RExp	-0.007***	-0.010***	-0.010***	0.002	0.008**	0.009**
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
UExp	0.001***	0.001**	0.001*	-0.001	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Intercept	1.081***	1.113***	1.117***	1.108***	1.112***	1.083***
	(0.105)	(0.124)	(0.131)	(0.077)	(0.070)	(0.079)
Controls						
HHI	-0.011	-0.026	-0.032	-0.018	0.019	0.025
	(0.040)	(0.035)	(0.035)	(0.025)	(0.024)	(0.028)
InnovInt	0.012	0.011	0.012	-0.007**	-0.001	0.005
	(0.013)	(0.019)	(0.020)	(0.003)	(0.005)	(0.009)
ln(*R&D*)	0.001	0.006	0.005	-0.004	-0.007	-0.009
	(0.010)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
FExp	0.004	-0.001	-0.002	-0.001	0.001	-0.001
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)
InitFam	0.001	0.001	0.001***	-0.001***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Random coefficients	yes	yes	yes	yes	yes	yes
Observations	1,032	920	860	1,032	920	860
Calibration period (quarters)	2	6	8	2	6	8
Log Likelihood	639.69	595.65	557.59	697.21	717.16	689.03
AIC	-1235.39	-1149.31	-1075.19	-1350.42	-1392.32	-1338.06
Prob > χ^2	0.001	0.001	0.001	0.001	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables.
*** p<0.01, ** p<0.05, * p<0.1

Table C.4 H1 & H2 results

C.4. Half-year fixed effects and API sub-class fixed effects

VARIABLES	ln(*NOV*) (Model 35)	ln(*NOV*) (Model 36)	ln(*NOV*) (Model 37)	ln(*SCP*) (Model 38)	ln(*SCP*) (Model 39)	ln(*SCP*) (Model 40)
RExp	-0.008***	-0.004*	-0.004*	0.008**	0.005*	0.005*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
UExp	0.001***	0.002*	0.002*	-0.002**	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	1.080***	0.985***	0.979***	1.129***	0.929***	0.926***
	(0.112)	(0.135)	(0.131)	(0.073)	(0.116)	(0.114)
Controls						
HHI	-0.022	0.010	0.010	0.001	0.009	0.009
	(0.038)	(0.020)	(0.020)	(0.019)	(0.036)	(0.036)
InnovInt	0.012	0.028***	0.028***	-0.002	-0.001	-0.001
	(0.016)	(0.006)	(0.006)	(0.004)	(0.008)	(0.008)
ln(*R&D*)	0.003	0.002	0.003	-0.009	-0.003	-0.002
	(0.009)	(0.006)	(0.006)	(0.009)	(0.005)	(0.005)
FExp	0.001	-0.004**	-0.004**	0.001	-0.001	-0.001
	(0.003)	(0.002)	(0.002)	(0.005)	(0.004)	(0.004)
InitFam	0.001	-0.001	-0.001	-0.001**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	978	978	978	978	978	978
Random coefficients	yes	yes	yes	yes	yes	yes
Time fixed effects	half-year	year	half-year	half-year	year	half-year
Sub-class fixed effects	no	yes	yes	no	yes	yes
Log Likelihood	629.74	1202.59	1204.67	721.33	982.86	984.07
AIC	-1199.48	-2351.19	-2337.35	-1382.67	-1911.72	-1896.15
Prob > χ^2	0.001	0.001	0.001	0.001	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables. *** p<0.01, ** p<0.05, * p<0.1

Table C.5 H1 & H2 results

C.5. Discounting of outsourced production experience

VARIABLES	ln(*NOV*) (Model 41)	ln(*NOV*) (Model 42)	ln(*NOV*) (Model 43)	ln(*SCP*) (Model 44)	ln(*SCP*) (Model 45)	ln(*SCP*) (Model 46)
RExp	-0.007***	-0.007***	-0.007***	0.006*	0.006*	0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
UExp	0.001**	0.001**	0.001**	-0.001*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	1.091***	1.090***	1.088***	1.102***	1.101***	1.100***
	(0.105)	(0.104)	(0.104)	(0.076)	(0.076)	(0.076)
Controls						
HHI	-0.011	-0.012	-0.014	0.004	0.005	0.006
	(0.025)	(0.025)	(0.024)	(0.014)	(0.014)	(0.014)
InnovInt	0.007	0.007	0.007	-0.001	-0.001	-0.001
	(0.013)	(0.013)	(0.012)	(0.003)	(0.003)	(0.003)
R&D	0.001	0.001	0.001	-0.006	-0.006	-0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
FExp	0.002	0.001	0.001	0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
InnovInt	0.001	0.001	0.001	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	978	978	978	978	978	978
Random coefficients	yes	yes	yes	yes	yes	yes
Discount rate	0.8	0.7	0.5	0.8	0.7	0.5
Log Likelihood	593.66	593.96	594.24	683.06	681.55	679.51
AIC	-1145.33	-1145.93	-1146.48	-1324.13	-1321.11	-1317.03
Prob > χ^2	0.001	0.001	0.001	0.001	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables. *** p<0.01, ** p<0.05, * p<0.1

Table C.6 H1 & H2 results

C.6. Allowing for the firms' random intercepts and slopes to be correlated

VARIABLES	ln(*NOV*) (Model 47)	ln(*SCP*) (Model 48)
RExp	-0.007***	0.005*
	(0.002)	(0.003)
UExp	0.001***	-0.002**
	(0.001)	(0.001)
Intercept	1.094***	1.118***
	(0.112)	(0.077)
Controls		
HHI	-0.007	-0.023
	(0.033)	(0.025)
InnovInt	0.010	0.001
	(0.018)	(0.004)
ln(*R&D*)	0.001	-0.005
	(0.011)	(0.009)
FExp	0.001	0.002
	(0.002)	(0.005)
InitFam	0.001	-0.001*
	(0.001)	(0.001)
Observations	978	978
Random coefficients	yes	yes
Covariance	unstructured	unstructured
Log Likelihood	639.39	733.34
AIC	-1246.79	-1434.68
Prob > χ^2	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables. *** p<0.01, ** p<0.05, * p<0.1

Table C.7 H1 & H2 results

C.7. Controlling for firm size

VARIABLES	ln(*NOV*) (Model 49)	ln(*SCP*) (Model 50)
RExp	-0.008***	0.007*
	(0.003)	(0.004)
UExp	0.001***	-0.002**
	(0.001)	(0.001)
Intercept	1.004***	1.127***
	(0.188)	(0.167)
Controls		
HHI	-0.023	0.001
	(0.038)	(0.019)
InnovInt	0.012	-0.002
	(0.016)	(0.004)
ln(*SIZE*)	0.010	-0.005
	(0.015)	(0.015)
FExp	0.001	0.001
	(0.003)	(0.005)
InitFam	0.001	-0.001**
	(0.001)	(0.001)
Observations	978	978
Random coefficients	yes	yes
Log Likelihood	628.58	719.77
AIC	-1215.16	-1397.55
Prob > χ^2	0.001	0.001

Notes. Robust standard errors in parentheses. All models include year fixed effects and firm random effects. Random coefficients refer to firm-level random slopes for the experience variables. *** p<0.01, ** p<0.05, * p<0.1

Table C.8 H1 & H2 results

References

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