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Sourcing Applied and Basic Knowledge for Innovation and Commercialization Success

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Abstract

We study how sourcing of applied and basic knowledge is related to the likelihood and speed at which inventions become innovations as well as their profitability. By using a patent database with unique commercialization information, we reveal that inventions strongly based on applied knowledge lead to innovations more quickly, while inventions embedding basic knowledge lead to more profitable innovations. Sourcing both applied and basic knowledge (i.e., their combination effect) is negatively related to innovation speed. Explanations include the notion that inventions based on applied knowledge follow more established technological trajectories. Hence, such inventions relatively easily turn into innovations, but due to hard competitive pressure, profits are modest. Conversely, inventions embedding basic knowledge likely depart from conventional technological trajectories and market logic and are more difficult and/or riskier to transform into innovations. However, if such innovations are launched, the gains could be significant because of their improved performance and distinctiveness. Finally, recombining applied and basic knowledge may become too complex to handle, thus hampering innovation speed. From a managerial perspective, managers who seek to innovate quickly should exploit inventions embodying applied knowledge; however, those who seek increased profitability should exploit inventions embodying basic knowledge even if this may be more difficult and riskier. From a policy perspective, actions aiming to lessen the risks associated with commercializing inventions based on basic knowledge should be implemented.

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1. Introduction

This paper contends that the conversion of inventions into innovations can be explained by the types of knowledge sourced for developing the inventions. Indeed, such knowledge characterizes them by shaping inventions' knowledge base (Fleming, 2001).

A key distinction in the inventions' knowledge base refers to its representation in terms of applied or basic knowledge (Martin & Scott, 2000)[1], reflecting how innovation may follow diverse cumulative paths (Dosi, 1982; Dosi & Nelson, 2010). Sourcing applied knowledge entails developing technologies by creatively combining existing technologies, each with a given purpose, to meet novel market needs (e.g., Adner & Snow, 2010; Arthur, 2007). Sourcing basic knowledge entails developing new technologies embedding knowledge that is unconstrained by immediate, market and practical interests (Leyden & Menter, 2018) since it provides a general understanding of the (natural) phenomena underlying a given technological problem (e.g., Cassiman, Veugelers & Arts, 2018; Lim, 2004).[2]

Some previous studies sought to examine the innovative implications derived from the extent of adoption of applied and basic knowledge during technology development, such as by examining the (macro) processes of creative destruction, accumulation (Malerba & Orsenigo, 1995; Breschi et al., 2000), and knowledge flows across actors and countries (Leyden & Menter, 2018). We aim to extend this line of inquiry by narrowing the unit of analysis to the single technology (invention level). Notably, research has proven that intrinsic technology characteristics, such as the type of inventions' knowledge base, contribute to explaining when inventions turn into products (Nerkar and Shane, 2007; Chen et al., 2011; Ardito et al., 2020). Therefore, technology

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[1] This distinction occupied a key position since the report by Bush (1945), who laid the foundations of the American postwar science policy. Neither applied nor basic knowledge should necessarily be associated with incremental/radical knowledge. The distinction wants to reflect the fact that knowledge adopted during technology development may refer to something already existing and working to solve a given technological problem (i.e., applied knowledge), regardless of its radicalness, or to more general theories and understanding of phenomena that do not/cannot have a given purpose and application (i.e., basic knowledge), still regardless of their radicalness.

[2] For instance, in the semiconductor industry, basic knowledge refers to the comprehension of solid-state physics, quantum mechanics and basic chemistry, while applied knowledge targets the development/improvement of product, as well as manufacturing techniques and processes, starting from existing chemical products and processes. In the pharmaceutical industry, basic knowledge refers to the comprehension of the mechanisms and processes of disease, while applied research includes clinical trials, dosage testing and information regarding product labeling.

characteristics cannot be undervalued when compared to other relevant factors pertaining to the firm (e.g., strategy, business model, organization), network (e.g., alliance formation and type), and environmental level (e.g., market turbulence and competitiveness).

However, studies focusing on technology characteristics to explain innovation performance are scarce, and so are studies dealing with inventions' knowledge base. Only a few papers (Su & Lin, 2018; Wagner & Wakeman, 2016) have provided inspiring clues regarding the innovative potential of inventions embedding applied and/or basic knowledge by linking inventions to respective products on the market. On the other hand, some contrasting results can be recognized despite focusing on the same sector (i.e., pharmaceutical).[3] For instance, Su & Lin (2018) revealed that applied knowledge is associated with a higher likelihood and speed at which inventions become innovations; moreover, they found basic knowledge associated with a reduced time-to-market. Conversely, Wagner & Wakeman (2016) found a negative effect of applied knowledge on the likelihood of innovating and that time-to-market is not affected by applied and basic knowledge. Moreover, relevant gaps leading to additional avenues to extend the extant literature can be recognized. The first is the need to examine sectors other than the pharmaceutical sector.[4] The second relates to the analysis of the complementarity between applied and basic knowledge (i.e., their combination effect), as only their separate effects have been considered in previous studies. The third is about expanding previous studies' analysis to the profitability of innovations originating from a technology (if any), since such information is often missing. Finally, there is a need to provide a stronger theoretical framing of the influence of knowledge sources on commercialization outcomes. Previous studies are more exploratory and more interested in assessing the influence of various patent-based measures (including reference-based measures as a proxy for knowledge sources) on commercialization outcomes, without in-depth theoretical reasoning and implications.

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[3] However, the dependent variables were not always consistent among the studies as well as the data sources used.

[4] The pharmaceutical sector is the most studied domain since it is easier to link inventions to related products. Indeed, governmental organizations (e.g., the Food and Drug Administration through the Orange Book) provide this information.

The present paper addresses these gaps. Accordingly, following the recombinant search (Fleming, 2001; Fleming & Sorenson, 2004) and technological opportunities (Shane, 2001; Nerkar & Shane, 2007) perspectives, we propose hypotheses about the direct roles of having applied or basic knowledge as strongly characterizing inventions' knowledge base, as well as their complementarity,[5] in predicting three key performance measures. Two are related to innovation: (i) likelihood to innovate, i.e., to turn inventions into products/processes, and (ii) innovation speed in terms of time-to-market. The third is related to commercialization success or the profitability of innovation. Jointly considering these measures provides a novel and more comprehensive understanding of how various types of knowledge constituting inventions affect the invention-to-commercialization journey.

In particular, we do not restrict our analysis to the pharmaceutical sector and focus it on the SME context. Notably, SMEs engage in more innovative activities than large firms (Acs & Audretsch, 1988), although the former suffers the liability of smallness that places them at a higher risk of failure, especially if commercialization success is not achieved (Aldrich & Auster, 1986; Lefebvre, 2020). Moreover, SMEs are more likely to develop inventions for actual commercialization purposes rather than for defense or fencing.[6] That is, they have smaller technology portfolios mainly comprising core technologies and no dead-end and/or leftover solutions (de Rassenfosse, 2012). Hence, an analysis at the invention level is more reliable. Finally, while the individual contribution of each SME to the economy is negligible, SMEs are the most common type of firm in the economy. Thus, when taken together, their contribution to the gross domestic product and job creation, for instance, is undeniable (EC, 2020; Tewari et al., 2013).

[5] It has been suggested that future research should investigate the impact of both basic and applied knowledge and their interaction (Tödtling & Grillitsch, 2015) because the empirical literature has shown more complex knowledge processes such that applied and basic knowledge cannot simply be associated with analytic sectors (e.g., manufacturing sector) and synthetic sectors (e.g., biotech), and complementary effects may exist.

[6] Indeed, it has been argued that "incentives for and performance with preemptive patenting by the incumbents are expected to increase as market power increases [that is not usually the case of SMEs], because the ex-ante profits to preserve increase and the drop in profits due to entry if preemption does not occur is larger" (Ceccagnoli, 2009:90). We also acknowledge that some small firms have the incentive to be infringed and, hence, own patent trolls; however, most of these firms are nonproducing firms (Reitzig et al., 2007) and are beyond the scope of our investigation.

A unique dataset of Swedish patents owned by SMEs and individual inventors is used in the empirical analysis. Detailed information on the likelihood and timing of innovation, commercialization success and prior knowledge (measured by the patents' references to the nonpatent literature and previous patents) makes it possible to test the hypotheses. The results of our analysis reveal that inventions embedding applied knowledge are positively related to the likelihood of innovation and innovation speed to market. Inventions embedding basic knowledge positively have higher commercialization success, with negative returns occurring only at very high levels of basicness. Finally, the combination effect of sourcing both basic and applied knowledge during technology development is related to a slower speed to the market. These results are in line with the view that inventions based on applied knowledge follow more established technological trajectories. Hence, they should be relatively easy to convert into innovations (Adner & Snow, 2010; Nerkar, 2003), but due to strong competitive pressure, profits are modest. Conversely, inventions embedding basic knowledge are more difficult and/or riskier to transform into innovations (Gittelman & Kogut, 2003; van Beers, Berghäll & Poot, 2008). However, if such innovations are launched, the gains could be significant due to improved performance and distinctiveness (Ke, 2020; Sternitzke, 2010). Finally, recombining applied and basic knowledge concurrently may turn too complex to handle (Lopez-Vega, Tell & Vanhaverbeke, 2016; Rosenkopf & Nerkar, 2001), especially hampering innovation speed.

Overall, our contributions are threefold. First, we add to the literature concerning the conversion of inventions into innovations at the technology level by considering the knowledge base and three different performance measures, thereby adopting a more holistic approach. Second, we contribute to a better understanding of the commercialization success of inventions developed by SMEs. Third, we provide novel insights into whether and how basic and applied knowledge are complementary or substitutive.

2. Theory and hypotheses

The long and risky journey from a new technological idea to commercial profitability involves several steps. First, inventors/organizations spend resources on technology development, hence producing an invention. Second, the invention must lead to a product/process on the market (innovation). Third, innovation should be accepted by customers and yield profits (commercialization success) (Artz et al., 2010; Dutta & Hora, 2017; Khilji, Mroczkowski & Bernstein, 2006; Vinokurova & Kapoor, 2020). This is in line with the Schumpeterian view that invention and innovation do not overlap (Schumpeter, 1911, 1934). To date, extant research has provided a thorough understanding of technology development and what favors the impact of an invention on subsequent ones (Arthur, 2007; Arthur, 2009; Lanjouw & Schankerman, 2004; Messeni Petruzzelli et al., 2015; Trajtenberg, 1990). Relatedly, firms have become quite proficient at translating ideas into inventions – as demonstrated, for example, by the growing number of patents worldwide in almost all sectors (WIPO, 2019). In contrast, “companies often struggle with commercializing new technologies via the product development route” (Nasirov, Li, & Kor, 2021:522) and gaining profits. Notably, firms’ inventions reaching the market as new products/processes still constitute a small share of all the developed technologies – a phenomenon called the valley of death – and even fewer are ultimately profitable (Datta et al., 2015; Kirchberger & Pohl, 2016; Markham et al., 2010; McKinsey & Co., 2010). This matter challenges firms, which may not survive if their inventions do not overcome the valley of death. SMEs particularly face this problem since they are characterized by a lack of resource slack for recovery and limited options for spreading risk across various economic activities (Fackler et al., 2013; Daniel et al., 2015), as also evidenced by the increasing efforts dedicated to understanding how to improve the innovation performance of these companies in light of the liability of smallness (e.g., De Massis et al., 2018; Dutta & Hora, 2017). As such, factors favoring the conversion of inventions into innovations still require managerial and academic attention, especially in the SME context.

To address this issue, we recall the notion that inventions differently contribute to innovation and commercialization success, if commercialized at all. In particular, heterogeneity in the conversion of inventions into (profitable) innovations can be explained at the invention level by looking at intrinsic technology attributes (Dosi, 1988; Granstrand, 1998; Wang et al., 2015). We draw on this broader view and focus on the characteristics of the knowledge embodied in inventions by following the recombinant search and technological opportunities perspectives. The recombinant search perspective recalls the notion that innovation is cumulative in nature (Breschi et al., 2000; van de Poel, 2003), so it is often a matter of reconfiguring what exists (Schumpeter, 1934). In detail, search agents (e.g., inventors) shape inventions' knowledge base and subsequent innovation performance on the basis of the knowledge components adopted in recombinant search processes (Fleming, 2001; Savino, Messeni Petruzzelli & Albino, 2017; Yayavaram & Ahuja, 2008). Knowledge components may be broadly categorized under applied and basic knowledge (Adner & Snow, 2010; Cassiman et al., 2018; Lim, 2004), as "[m]arkets differ in terms of the mixture of basic and applied knowledge that contributes to their knowledge base [and] in the degree of appropriability of technology" (Martin & Scott, 2000:440). In turn, we may have technologies originating from a search process that primarily relies on applied knowledge, basic knowledge, or a combination thereof.

The technological opportunities perspective further argues that innovation patterns are shaped by opportunities for value creation and value capture derived from the technology attributes of inventions (e.g., Shane, 2001; Nerkar and Shane, 2007). Therefore, the extent of applied and/or basic knowledge adopted during technology development, as characterizing inventions' knowledge base, may open (different) value creation and value appropriation opportunities that can explain whether and how firms' inventions proceed with the commercialization route (Chen, Chang & Hung, 2011; Wagner & Wakeman, 2016; Ardito et al., 2020). Following these lenses, we argue that attributes of inventions' knowledge base resulting from recombinant search processes may influence the likelihood, speed, and profitability of related innovations[7].

2.1. Inventions embedding applied knowledge

Pioneering technologies are usually considered the source of new successful products/processes, often by creating new markets (Ahuja & Morris Lampert, 2001; O'Connor & Rice, 2013). A different view, instead, highlights that new inventions extending an existing technology trajectory by combining existing technological solutions, i.e., applied knowledge, may still be a source of innovation (e.g., Ardito et al., 2016). Indeed, innovation can originate from ordinary rather than unusual creative processes based on previous learning and uses of applied knowledge (Adner & Snow, 2010; Lettl, Rost & von Wartburg, 2009).

Specifically, technologies originating from a search process highly relying on applied knowledge follow a more established technological trajectory, and there is more information concerning how they are built and can be adopted (Zander & Kogut, 1995). This facilitates the retention, transferability, and safer adoption of inventions embodying such knowledge by people and organizations involved in the innovation process (García-Muiña, Pelechano-Barahona & Navas-López, 2009; Teece, 1981), thus increasing the likelihood and speed at which innovation may occur.

Relatedly, a higher reliance on applied knowledge makes technology development path-dependent and avoids changes in organizational routines (Nelson, 2009). This, together with the more established nature of applied knowledge, also reduces the level of causal ambiguity (Reed &

[7] We acknowledge the existence of prior studies seeking to identify factors favoring better innovation and commercialization success. However, most of these studies do not consider innovation and commercialization success concurrently. Moreover, most studies consider antecedents and innovation performance at the firm level (Ardito et al., 2015; Artz et al., 2010; Chandy et al., 2006), i.e., what firms do/possess to launch technology-based products/processes. This approach overlooks a finer-grained analysis at the invention level, which may provide additional relevant information regarding the phenomenon under investigation (Wagner & Wakeman, 2016). Other studies focus on the technology level and even consider the characteristics of the knowledge base. Nevertheless, these scholars examine the commercialization of university patents and/or commercialization in terms of spinoff creation or licensing/selling events (Nerkar & Shane, 2007; Shane, 2001; Wang et al., 2015), which are different innovation paths from the phenomenon under investigation. Other scholars adopt imperfect proxies for innovation/commercialization success that are distant from actual downstream activities, such as the case of the number of patents and patent forward citations. Indeed, patents reflect inventions but not innovations, and patent citations do not capture market entry (Dziallas & Blind, 2019).

DeFillippi, 1990). Therefore, focusing on applied knowledge allows the maintenance of organizational continuity and the development of new products/processes with fewer problems (Nerkar, 2003). Stated differently, the (relevant) costs and time-consuming activities of creating and applying less established knowledge are substituted by the (less prominent) costs of identifying and applying knowledge that already exists and functions, with benefits in terms of likelihood to innovate and innovation speed. Thus, innovating firms are more likely willing and able to leverage inventions embedding applied knowledge. This may be especially true for SMEs since they cannot afford high R&D costs and long product development cycles due to financial constraints and the need to cope with high technological turbulence with scant resources (Moreno-Moya & Munuera-Aleman, 2016). That is, investing in inventions embodying applied knowledge would represent a way for SMEs to save resources and speed up the innovation process.

In addition, applied knowledge has already passed through some of the trial-and-error processes required for its successful application and acceptance by customers (Adner & Snow, 2010). Inventions based on such knowledge are hence considered more reliable and targeted to market needs, and more complementary assets and standards increasing their potential market value may have already been generated (Story et al., 2014). Thus, unlike pioneering technologies, a technology embodying applied knowledge tends to be more easily legitimated by a sector's user community and stakeholders (Katila, 2002; Turner, Mitchell & Bettis, 2012), further incentivizing firms to turn such inventions into innovations. The same can be said for SME inventions, since it is more important for SMEs than larger firms to avoid mistakes and meet customers' needs due to a higher risk of failure (Damanpour, 2010). Following this reasoning, we hypothesize the following:

Hypothesis 1a (H1a). SME inventions embedding applied knowledge are positively related to the likelihood of innovating and innovation speed.

On the other hand, the greater the applied knowledge embodied in a technology is, the lower the likelihood of developing distinctive technologies and, in turn, distinctive products/processes compared to current offerings. Indeed, the recombinant space to innovate is likely to be constrained in the presence of high levels of cumulativeness (Fleming, 2001; Nerkar, 2003). This also lowers the difference in value creation opportunities across companies (Ardito, Messeni Petruzzelli & Panniello, 2016), thereby increasing competitive pressure while decreasing potential profits from launched innovations. Additionally, since a technology based on applied knowledge may be more similar to other existing technologies, it will be more difficult to protect and/or avoid infringement risks, reducing opportunities to capture value and, hence, to obtain relevant profits (James et al., 2013). In other words, inventions embedding applied knowledge infrequently represent rare or strategic resources for their owners, leading to profitable innovations (Barney, 1991; Teece, Pisano & Shuen, 1997).

These issues are exacerbated for SMEs because they usually lack brand reputation, so their innovations, even if similar to others on the market, may be passed over in favor of those of larger and more reputable companies (UN, 2005). Moreover, even if SMEs protect their inventions, they do not usually have the resources for patent enforcement if others develop similar solutions based on the same available applied knowledge (Weatherall & Webster, 2014), especially if the infringing firm is larger. Therefore, we offer the following hypothesis:

Hypothesis 1b (H1b). SME inventions embedding applied knowledge are negatively related to commercial success.

2.2. Inventions embedding basic knowledge

Basic knowledge is usually not available as a ready-made input (Gittelman & Kogut, 2003; van Beers et al., 2008). Actually, an increased amount of basic knowledge requires increased effort to be effectively identified and integrated into innovation processes since departures from conventional technological trajectories become more relevant (Lim, 2004). For instance, Martin & Scott (2000) underline that the acquisition and internalization of advances in basic knowledge by search agents in the private sector often require intermediaries. Due to these difficulties, the likelihood of converting inventions embedding basic knowledge into innovations may decrease while increasing the innovation speed. In addition, reliance on basic knowledge during technology development is often conditional on the adoption of new organizational practices, whose implementation costs grow with the extent of basic knowledge adopted (Cassiman, Veugelers & Zuniga, 2008; Cockburn, Henderson & Stern, 1999). Thus, search agents risk slowing down or even hampering the conversion of inventions into innovations when exploiting inventions embedding basic knowledge.

These concerns are worsened by the fact that basic knowledge adheres to a logic that contradicts the economic logic (Gittelman & Kogut, 2003). Indeed, it aims to provide a general understanding of phenomena without targeting specific applications to solve technological problems and/or meet customers' needs (Belenzon & Schankerman, 2013; Roach & Cohen, 2012; Lim, 2004). Thus, the value associated with inventions mainly embodying basic knowledge is not univocal, and firms may struggle to identify valuable applications for those inventions (Arora, Belenzon & Patacconi, 2018; Cassiman, Di Guardo & Valentini, 2009). As such, the innovation process may slow down, or inventions based on basic knowledge may be discarded, ultimately reducing the likelihood of innovating. SMEs especially suffer in this regard, as they avoid risky innovation projects and face more difficulties, for instance, in identifying/acquiring skilled people who can manage basic knowledge for innovation purposes (Healy, Mavromaras & Sloane, 2015; Lefebvre, 2020). Thus, we hypothesize the following:

Hypothesis 2a (H2a). SME inventions embedding basic knowledge are negatively related to the likelihood of innovating and innovation speed.

Nevertheless, evidence reveals that many successful innovations are linked to the contribution of basic knowledge (Mansfield, 1991; Shibata, Kajikawa & Sakata, 2010). Thus, using basic knowledge makes it more difficult to convert inventions into innovations; however, economic return may be more relevant if the conversion process occurs. Indeed, basic knowledge is said to transform the search for technological innovations from trial-and-error learning to a more directed form of problem solving (Fleming & Sorenson, 2004; Nelson, 1982). Therefore, search processes involving basic knowledge allow search agents to deconstruct a product/process into its functional components and better anticipate how each component will work and interact with the other components (Arora, Belenzon & Suh, 2021). Consequently, they can identify the best innovation paths, especially when the search process is complex (Fleming and Sorenson, 2004), thus leading to more valuable innovations.

Moreover, since basic knowledge provides search agents with novel cognitive schemas by departing from more established technical knowledge, its adoption reduces the risk of becoming cognitively constrained and trapped in local optima (Cassiman et al., 2018). This improves opportunities for value creation. Indeed, search agents may more easily engage in new innovation trajectories that eventually lead to technologies conducive to products/processes with higher performance and distinctiveness (Sternitzke, 2010; Ke, 2020), which will likely constitute a source of differentiation, competitive (first-mover) advantage, and, hence, increased profitability. In particular, SMEs appear to be better endowed to profit from basic knowledge since they allow for the unexpected and are better able to adapt to changes in the market than incumbent firms (Arora et al. 2015; Mowery, 2009). In turn, the opportunity to launch products/processes different from the current offerings reduces imitation and infringement risks, hence improving opportunities for value capture and increased profit. These are relevant aspects for SMEs, as reliance on basic knowledge offers a means to surpass competition and better secure profits (Gopalakrishnan & Bierly, 2006; Zona, Zattoni & Minichilli, 2013).

However, it must be acknowledged that as the level of basicness grows, the benefits of having inventions embedding basic knowledge may be outweighed by the fact that resulting innovations can be perceived as too alien by customers. That is, innovations highly dependent on less known and available solutions may be perceived as too distant from customers' conventional understanding (Arora, Belenzon & Patacconi, 2018; Cassiman, Di Guardo & Valentini, 2009), hence undermining their perceived value and, in turn, the profits originating from the underlying inventions. This problem may be particularly relevant in the SME context since compared to larger, R&D-oriented firms, SMEs may not be considered reliable when launching such novel innovations (Salavou & Avlonitis, 2008). Stated more formally:

Hypothesis 2b (H2b). SME inventions embedding basic knowledge have a curvilinear (inverted U-shaped) relation to commercialization success.

2.3. Inventions embedding applied and basic knowledge

Broadly speaking, applied and basic knowledge are both necessary to innovate. Several studies prove this notion, such as those about innovation across science, technology, and business fields (e.g., Xu et al., 2018; Surana, Singh & Sagar, 2020) and science-technology interactions in knowledge-based economies (e.g., Breschi & Catalini, 2010; Gómez, Salazar & Vargas, 2020; Tijssen, 2001). However, these studies look at innovation at higher levels of analysis (regions/nations, networks/ecosystems, firms).

Instead, looking at a single technology, integrating applied and basic knowledge implies that search agents engage in more complex recombinant search processes (e.g., Lopez-Vega, Tell & Vanhaverbeke, 2016; Rosenkopf & Nerkar, 2001). Indeed, applied and basic knowledge follow a different logic and are more salient to different stages of the innovation process, such that the advantages of relying on applied knowledge to innovate—being closer to downstream activities—are downsized by basic knowledge, being closer to upstream and nonmarket activities. As a result, the likelihood and speed at which inventions may be converted into innovation are hampered. This is exacerbated by the fact that a multidisciplinary competence base is usually lacking during technology development (e.g., having search agents able to manage both basic and applied knowledge over having search agents mainly able to work with applied knowledge), as in the SME context (Bianchi et al., 2010). Consequently, it will be more likely to terminate innovation processes before obtaining actual innovation outcomes or, at best, reach innovation outcomes slowly. Even if technology development is performed by a balanced pool of search agents, conflicts among them are likely to arise when they pursue a different logic, still hindering the more distant recombinant search processes merging applied and basic knowledge (Mohammed & Angell, 2004).

Relatedly, a greater extent of different knowledge (e.g., upstream vs. downstream) will likely increase the probability that inventions take more time to reach the market since it is more difficult to search and recombine basic knowledge over applied knowledge. That is, applied knowledge is more readily available than basic knowledge, so the latter may slow down the innovation process when search processes also include applied knowledge. Finally, particularly when firms lack resources, as in the case of SMEs, the ability to allocate adequate attention to bring distant ideas and perspectives to fruition is reduced (Koput, 1997; Li et al., 2012), thus limiting creative attitudes and recombination efforts, which are of vital importance when applied knowledge is intended to be combined with basic knowledge. Following these lines of inquiry, we propose the following:

Hypothesis 3a (H3a). SME inventions embedding applied and basic knowledge are negatively related to the likelihood of innovating and innovation speed in such a way that more basic knowledge makes the relevance of applied knowledge smaller.

However, if basic knowledge is managed to be combined with applied knowledge, the latter may be renewed. That is, basic knowledge may help to uncover new functionalities of applied knowledge and/or expand the recombinant space associated with it (Arora et al., 2021). In turn, the risk of developing a technology-based product similar to those based on the (same) applied knowledge is reduced. At the same time, the limits to appropriability that characterize reliance on applied knowledge may be reduced, with positive implications for profitability. This is particularly important when SME inventions and related products must be protected against stronger and nonresource-constrained competitors.

Furthermore, basic knowledge may not only expand the recombinant space associated with applied knowledge but also likely does so by providing a better understanding of how the knowledge component works (Fleming & Sorenson, 2004). As such, applied knowledge may be adopted more effectively, thus allowing the development of more valuable technology-based products that can be more easily accepted by customers than other product offerings. Additionally, if basic and applied knowledge are combined, the resulting technologies may present a better balance between the more common knowledge components, represented by applied knowledge, and the less market-related ones, represented by basic knowledge (Du et al., 2019). This may mitigate customers' reluctance to buy an innovation perceptibly distant from their values, as in the case of innovations based on inventions mainly embedding basic knowledge. This may be particularly true for SME inventions since they may be disregarded if too similar or too novel with respect to other offerings, especially those made by larger competitors (UN, 2005).

Hypothesis 3b (H3b). SME inventions embedding applied and basic knowledge are negatively related to the likelihood of innovating and innovation speed in such a way that more basic knowledge makes the relevance of applied knowledge greater.

3. Data, descriptive statistics and variables

3.1. Data

A detailed dataset of individual patents granted in Sweden in 1998 to Swedish firms and individual inventors is used. The dataset is based on a survey conducted in 2003−2004. The sample consists of

867 patents, and the survey response rate is 80 percent.[8] Since we are only interested in studying patents owned by SMEs and inventors, we will only include 825 of these patents in the analysis.

The dataset is unique because it contains information on *whether, when,* and *how* the patent has been commercialized as well as the profitability of the commercialization for the patentees. *This information concerning the commercialization process of the patents was collected by sending questionnaires via mail and direct telephone interviews with the inventors* (see Svensson 2007 for a more detailed description of the collection). The dataset has been complemented with information on patent renewal, patent family size, forward citations, and filing routes from the Espacenet (2019) website. Thus, the database includes information concerning several traditional patent value indicators. Furthermore, backward citations and references to the nonpatent literature for the patents were collected from the Orbit Intelligence FullPat database by Questel.[9] Patents are the unit of observation in this study.[10] Thus, no panel data analysis is possible.[11]

In the present study, innovation is a term indicating that a product or process innovation based on a patent has been introduced into the market—by the inventor, the inventing firm or an external firm that has licensed or acquired the patent. This definition is similar to that used in previous survey studies (Griliches, 1990; Morgan, Kruytbosch & Kannankutty, 2001; Svensson, 2007) and similar to the definition used in the CIS surveys, i.e., that the patent has been used commercially.

Since we use data on Swedish inventors and patents, we have to say something about what characterizes this country. Sweden is one of the leading countries in the world with respect to R&D and innovative activities according to the Innovative Scoreboard Index (EC, 2022). The relative strengths are with respect to R&D investment as a share of GDP, public–private copublications, lifelong learning, international scientific copublications, employed ICT specialists, and foreign

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[8] For a more thorough description of the dataset, data collection, and nonrespondents, see Svensson (2007).
[9] See https://www.questel.com/business-intelligence-software/orbit-intelligence/
[10] This means that we cannot bundle several patents underlying a specific product/innovation, as done by Wagner & Wakeman (2016) and Su & Li (2018). However, in section 3.3.3, we included an explanatory variable, *COMPLEXITY*, which takes account of whether several patents were needed to create an innovation.
[11] Only a few firms have more than one patent in the database.

doctorate students. However, relative weaknesses are government support for business R&D, non-R&D innovation expenditures and medium- and high-tech goods exports. Otherwise, Sweden has a large sector of small innovative firms, similar to many other OECD countries. As such, the Swedish context can be considered suitable to conduct our study, and related results could be generalizable, at least partially, to comparable European countries but also non-European countries.

3.2. Descriptive statistics

The 825 patents and the patent innovation rate across firm groups are described in Table 1.[12] As many as 408 patents (49 percent) were granted to individual inventors, and 117, 158, and 142 patents were granted to medium-sized firms (51–250 employees), small firms (11–50 employees), and microfirms (2–10 employees), respectively. The innovation rate for the whole sample is 62 percent. The higher innovation rate in the present study compared to that found in previous studies likely results from the focus solely on patents owned by small firms and individual inventors, as large (multinational) firms have many more defensive patents than small firms (Svensson 2002). As shown in Table 1, the innovation rate for firm groups is between 68 and 75 percent, whereas the rate for individuals is 51 percent.[13]

[Table 1]

In the upper part of Table 2, the number of backward citations and nonpatent literature references – proxies for applied and basic knowledge, as described in section 3.3 – across innovations are shown. Patents leading to innovation have more backward citations and nonpatent references than

[12] Regarding the filing routes, only eight of 867 patents were first filed abroad, and all of these were in the US. No patent was filed first with the EPO or WIPO and thereafter in Sweden. This pattern markedly contrasts with the filing routes of multinationals (see, for example, Guellec and van Pottelsberghe 2000). Various explanations may account for this result; for example, the patentees in the database used in this study are individuals and small firms, and the data cover patent filings in the 1990s, when it was still common to first file patents in the home country.

[13] A contingency table test suggests that this difference in the commercialization rate between firms and individuals is statistically significant at the one percent level (chi-square value of 30.55 with 3 df.).

patents without innovation. The differences are statistically significant. In the lower part of the table, we present the shares of patents that have at least one backward citation or nonpatent reference. Again, patents leading to innovation have significantly higher shares.

[Table 2]

Similar statistics are shown for patents with an innovation in Table 3. Profitable patents have significantly more backward citations than patents that have a 'break-even' or 'loss' outcome. There are also some differences with respect to the number of nonpatent literature references, but they are not significant.

[Table 3]

3.3. Variables

3.3.1. Dependent variables

In the main empirical analysis, we estimate how the characteristics of inventions' knowledge base affect 1) the probability that innovation occurs; 2) how long it takes until inventions turn into innovations, i.e., innovation speed; and 3) commercialization success, i.e., profitability.

Probability of innovation ($INNOV_i$). The probability that innovation occurs is a dummy variable that takes the value of 1 if the patent has been introduced on the market as a new product/process and 0 otherwise.

Innovation speed ($SPEED_i$). Innovation speed is a random variable showing how many years it takes until innovation occurs for patent i, measured from the time point of the patent application.[14]

Commercialization success (SUCCESS). Commercialization success represents patent commercialization performance in terms of accumulated profit estimated in 2004. In this year, inventors were asked to estimate the overall profitability of the patent. Profitability can only take on three different discrete values denoted by index k: Profit, k=2; Break-even, k=1; and Loss, k=0. Since this variable is measured as a categorical variable and not as a continuous variable and

[14] The application year is the easiest starting time point to measure and is directly available from the Swedish National Patent Office (PRV). Obviously, a patent can be commercialized before the grant date, but not before the application date.

owners were allowed to estimate whether commercialization would be profitable, we avoid serious problems with differences in accumulative profits for innovations that have various times in the market.

3.3.2. Explanatory variables

Applied knowledge (APPLIED). This variable is proxied by the number of backward citations to previous patents – excluding self-citations – from the patent and its family members (Ahuja & Morris Lampert, 2001; Ardito et al., 2016; Nerkar & Shane, 2007; Wong, 2013). Indeed, backward citations constitute the prior technological knowledge upon which a patent is based. Thus, they identify the link of an invention to solutions already applied to solve certain technological problems.

Basic knowledge (BASIC). This variable is proxied by the number of references to the nonpatent literature (Basse Mama, 2018; Fleming & Sorenson, 2004; Roach & Cohen, 2012; Sung et al., 2015). Notably, this type of reference still represents a share of the prior knowledge upon which an invention is based. However, it is knowledge that originates from basic research activities and/or that is not necessarily applied in products or even other inventions (e.g., knowledge diffused in journal articles, conference proceedings, books, and technical reports).

Overall, this recalls the view that applied knowledge is often codified in patents, while basic knowledge is codified in different types of documents, such as those previously mentioned (Rogers, 2010; Crowman, 2013).

*APPLIED*BASIC* is an interaction variable between the two independent variables.

Squared values of *APPLIED* and *BASIC* are also included for hypothesis testing and/or robustness checks. Patent applicants often add references to other patents and the nonpatent literature when submitting their applications. However, it is always the examiner at the patent office who ultimately decides which citations and references to include. Thus, both *APPLIED* and *BASIC* can be regarded as exogenous variables.

3.3.3. Control variables

We implement a set of controls identified in previous research (Svensson, 2007; Maurseth & Svensson 2020) covering patent, inventor, firm, and financial variables.[15] Inventor involvement in the commercialization process is important due to tacit knowledge (Maurseth & Svensson, 2020). We therefore control for the degree to which commercialization success depends on whether the inventor takes part in the commercialization process (*ACTIVE*). This variable is defined only for commercialized patents and can be included only in the profitability model.

Several characteristics of the inventors and the inventing firm that might be related to the probability of commercialization and successful commercialization are included as control variables. However, since a high proportion of the patents are owned by individual inventors (running solo firms), we are not able to include traditional explanatory variables such as firm age and variables from the company's financial statements. The size of the inventing firm is measured by three additive dummies: *MEDIUM*, *SMALL* and *MICRO*. The reference group is then that the patent is owned by inventors with solo firms.

We have three variables representing the financial situation of the invention. *GOVFIN* measures the percentage of R&D costs covered by government agencies. Similarly, the variable *PRIVFIN* shows the percentage of the R&D costs covered by external private venture capital (PVC). *OTHFIN* represents the percentage of R&D costs covered by universities and research foundations.

On the invention level, we have several variables. Sometimes, several patents are required to create a product. We consider this issue in the estimations. The dummy variable *COMPLEXITY* assumes a value of 1 if more than one patent is required to create a product and 0 otherwise. *INVNBR* measures the number of inventors of the patent. *DURE* measures the number of years between patent application and patent grant. *UNIV* is a dummy variable that takes the value of 1 if

[15] Since many patent-owning inventors in the database do not run any company, traditional explanatory variables such as age of the company and variables from the financial statement of the company cannot be included in the estimations.

the invention behind the patent was created at a university and 0 otherwise. *SEX* and *ETH* measure the shares of female and non-European inventors. Definitions and descriptive statistics of the explanatory variables are shown in the Appendix, Table A1.

Since patenting and innovations are known to vary considerably between industries and technology classes (Levin et al. 1987), we also include additive dummies for 25 different industry classes designated by Breschi et al. (2004).[16] These are based on the IPC technology class system. A patent may belong to several different IPC classes. However, it is not possible to determine the main IPC class since the classes are listed in alphabetic order for each patent in Espacenet (2019). Therefore, a patent in our database may belong to as many as four different industry classes. Consequently, the 25 technology class dummies are not mutually exclusive. The distribution of technology classes on patents is shown in Appendix Table A2. The data are divided into six different kinds of regions according to NUTEK (1998): large-city regions, university regions, regions with important primary city centers, regions with secondary city centers, small regions with private employment, and small regions with government employment. Five additive dummies are included in the estimations for these six groups.

3.3.4. Possible endogeneity problems

Concerning endogeneity, it can occur (1) when the outcome variable is a predictor of an explanatory variable and not simply a response to it, called "simultaneity bias", and (2) when important explanatory variables are omitted from the model, called "omitted variable bias".

In our case, commercialization always occurs after patent development, i.e., patent characteristics cannot be influenced by the likelihood and/or speed of commercialization, as well as by its success. Thus, simultaneity bias is unlikely. However, backward citations can be assigned by either the applicant or a patent examiner. In our database, nonpatent references can be divided into references made by applicants, *BASIC-A*, and examinators, *BASIC-E*. It is more likely that

[16] There are 30 industry classes in Breschi et al. (2004). However, we had to reduce the number of industry classes to 25 due to the limited number of observations in some classes (see Appendix Table A2).

simultaneity problems would occur if nonpatent references by the applicant are included. Therefore, we will re-estimate all models including *BASIC-E* instead of *BASIC* to check for possible simultaneity problems.

Omitted variable bias may be an issue if key explanatory variables are excluded in the estimations. A natural objection against our model would be that traditional firm variables measuring age, profitability, growth, human capital, and R&D investment are not included. Since a high proportion of the patents in the database are owned by individual inventors who are sole proprietors, we are not able to include traditional explanatory variables normally available from incorporated companies' financial statements. However, we do have some of them, and the most important is size of the inventing firm/inventor: *MEDIUM*, *SMALL*, and *MICRO*, where the reference group is inventors with solo firms. Notwithstanding, by including as many variables as available on inventor and invention level, we argue that omitted variable bias is minimized. This is consistent with the majority of invention-level studies (e.g., Nerkar & Shane, 2007; Messeni Petruzzelli et al., 2015; Su & Lin, 2018), which do not necessarily include firm-level variables because they focus on the invention level. Last but not least, the dummies for technology classes and regions described above will represent unobserved factors that may further reduce omitted variable bias.

4. Statistical models

Since the innovation analysis focuses on an "event" to occur, probit and survival (duration) analyses are used in the statistical estimations. The event here is that the patent turns into an innovation, and it is also measured when innovation occurs. First, a survival distribution function and a hazard function are estimated and plotted in the empirical analysis. The survival function, $S(t)$ in equation (1), shows how a large share of the patents survive beyond a time point, t. The hazard function, $h(t)$ in equation (2), shows the conditional probability of a patent leading to innovation in a specific time period Δt, given that it has "survived" (no innovation) until time point t. The hazard can also be expressed as a function of the probability density function, *f(t)*, and the survival function (Allison, 2010):

$$S(t) = Pr(T > t) = 1 - F(t) \quad , \tag{1}$$

$$h(t) = \frac{f(t)}{S(t)} = \lim_{\Delta t \to 0} \frac{Pr(t \le T < t + \Delta t | T \ge t)}{\Delta t} \quad . \tag{2}$$

4.1. Probit model

In the analysis of probability, a probit model (Hoetker, 2007) estimates how different factors influence the decision to commercialize the patent:

$$INNOV_i^* = \boldsymbol{X_i \theta} + u_i \quad , \tag{3}$$

$$INNOV_i = 1 \text{ if } INNOV_i^* > 0 \text{ and } 0 \text{ otherwise,}$$

where $INNOV_i$* is a latent index, $\mathbf{X_i}$ is a vector of explanatory variables that influence the probability that the patent is commercialized and $\boldsymbol{\theta}$ is a vector of parameters to be estimated. $\mathbf{u_i}$ is a vector of normally distributed residuals with a mean of zero and a variance equal to 1.

4.2. Survival model

In the survival analysis, the dependent variable, T_i, is a random variable representing the number of years until commercialization started for patent *i*, measured from the time point of the patent application.[17] Most patents in the database were applied between 1994 and 1997, and the end point of observation in the database was 2004. Patents not yet commercialized in 2004 are “right-censored” (341 observations). Furthermore, an expired patent cannot be commercialized. If the patent is not yet commercialized and expires before 2004, the patent is right censored in this expiration year.[18] A total of 185 patents are right censored before 2004 due to expiration and 156 at the end point of observation.

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[18] This assertion requires some modification. An expired patent cannot be commercialized. However, the invention behind the patent can still be commercialized. This occurs only once in the database. This observation is considered as a

Measurement of the starting point of commercialization in years is a rough measure. Therefore, $SPEED_i$ is "interval-censored" for commercialized patents (526 observations). If the patent is commercialized within the first year, $SPEED_i$ takes an interval-censored value between 0.1 and 1, if within the second year, between 1.1 and 2, etc. Since interval-censored observations are included, the accelerated failure time (AFT) model is the appropriate statistical model[19] (Allison, 2010):

$$log(SPEED_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots\ldots + \beta_k x_{ik} + \sigma\eta_i, \quad (4)$$

where ε is a random disturbance term, the β's and σ are parameters to be estimated, and x are explanatory variables (the same as in the probit model). η:s can have various distributions corresponding to different AFT models, e.g., the log-normal, log-logistic, exponential, Weibull and gamma models. All these models are run in the empirical part. Using likelihood-ratio tests, it is possible to decide which of the models best fits the data. After recalculation of the parameters, it can be estimated how an increase in the explanatory variables influences the survival time.

4.3. Profitability model

The dependent variable *SUCCESS* is an ordinal one. Since it is possible to order the three alternatives, an ordered probit model is applied and can be described as follows (Greene, 1997):

$$y_i^* = \boldsymbol{X_i\alpha} + \varepsilon_i \quad , \quad (5)$$

where $\mathbf{X_i}$ is a vector of patent characteristics and technology dummies. The vector of coefficients, $\boldsymbol{\alpha}$, shows the influence of the independent variables on the profit level. The residual ε_i represents the

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noncommercialized patent and is right-censored. The fact that noncommercialized patents are right censored in the expiration year does not alter the results of the estimations.

[19] We also estimated how explanatory variables influence the commercialization choice using the Cox (1972) proportional hazards model. The results for the main variables of the Cox estimations are similar to those of the AFT models. A disadvantage of the Cox model is that the dependent variable cannot be interval censored. We make two adjustments to minimize this problem. First, if the patent is commercialized within the first year, *SPEED* takes the midpoint value of that period, i.e., 0.5; if within the second year, the value is 1.5, etc. Second, we use an approximation of the Cox model, called the "exact method", to account for the fact that two events do actually not occur at the same moment, even if there are tied event times in the sample (Allison, 2010). On the other hand, an advantage of the Cox model compared to the AFT model is that one does not need to choose between different residual distributions. Another advantage is that the quantitative effects can be interpreted in terms of how an increase in the explanatory variables affects the hazard. However, all in all, the AFT model is considered as the main model due to the interval censoring.

combined effects of unobserved random variables and random disturbances. The residuals are assumed to have a normal distribution, and the mean and variance are normalized to 0 and 1, respectively. The latent variable, y_i^*, is unobserved. The model is based on the cumulative normal distribution function, $F(\boldsymbol{X\alpha})$**,** and is estimated via maximum likelihood procedures. The difference from the two-response probit model here is that a parameter (threshold value), ω, is estimated by **α**. The probabilities $P_i(y=k)$ for the three outcomes are as follows:

$$P_i(0) = F(-\boldsymbol{X\alpha}) \quad ,$$

$$P_i(1) = F(\omega - \boldsymbol{X\alpha}) - F(-\boldsymbol{X\alpha}) \quad , \qquad (6)$$

$$P_i(2) = 1 - F(\varpi - \boldsymbol{X\alpha}) \quad ,$$

$$where \sum_{k=0}^{2} P_i(k) = 1 \quad .$$

The threshold value ω must be larger than 0 for all probabilities to be positive.

An objection to the sample and the chosen statistical model would be that the patents, which are commercialized, are not a random sample of patents but have specific characteristics that led to them being commercialized in the first place. This could result in misleading parameter estimates. An appropriate statistical model is therefore an ordered probit model with sample selectivity (Greene 2002). In the first step, a probit model estimates how different factors influence the decision to commercialize the patent:

$$d_i^* = \boldsymbol{X_i\theta} + u_i \quad , \qquad (7)$$

$$d_i = 1 \ if \ d_i^* > 0 \ and \ 0 \ otherwise,$$

where d_i* is a latent index and d_i is the selection variable indicating whether the patent is commercialized. $\mathbf{X_i}$ is a vector of explanatory variables that influence the probability that the patent is commercialized, and **θ** is a vector of parameters to be estimated. $\mathbf{u_i}$ is a vector of normally distributed residuals with a mean of zero and a variance equal to 1.

From the probit estimates, the selection variable d_i is then used to estimate a full information maximum likelihood model of the ordered probit model (Greene 2002).[20] In addition, the first-step probit model is re-estimated. The residuals [ε, u] are assumed to have a bivariate standard normal distribution and correlation ρ. There is selectivity if ρ is not equal to zero.

5. Results of the estimations

In Figure 1, the hazard and inverted survival functions across backward citations (*APPLIED*) are estimated by the life-table method (actuarial method).[21] The patent application year is set to 0. The inverted survival functions increase steeply at the beginning, but they level off after 4–5 years. The hazard function (conditional probability) is highest during the first three years after the application. The survival functions suggest that the gap increases over time and that the hazard is higher primarily for patents with backward citations. Both a log-rank test and a Wilcoxon test (see Allison, 2010) show the difference between the survival functions to be highly significant.[22] Similar functions for patents with and without nonpatent references (*BASIC*) are shown in Figure 2. Patents with nonpatent references have both a higher innovation rate and a higher hazard function than patents without such references, with a significant difference between the groups.[23]

[Figure 1]

The estimates in Figures 1 and 2 show the bivariate correlation between 1) likelihood and speed of innovation and 2) references to previous patents and the nonpatent literature. Now, we turn to the multivariate analysis. In all three models (probit, survival, and ordered probit), we include the same explanatory variables, with some exceptions. The financing variables are not included in the

[20] Note that this is not a two-step Heckman model. No lambda is computed and used in the second step.
[21] The survival functions are inverted in the figures for pedagogical reasons. Survival means that the patent is not commercialized. Therefore, the normal survival function would start at 1 and then decrease.
[22] The chi-squared statistics are 11.94 and 7.19, respectively, significant at the 1% level for 1 df.
[23] The chi-squared statistics for the log-rank and Wilcoxon tests are 7.10 and 3.51, respectively, significant at the 1% and 10% levels for 1 df.

profitability model, and *ACTIVE* is defined only for commercialized patents and can be included only in the profitability model (section 5.3).

[Figure 2]

5.1. Estimations of the probit model

The probit estimations are shown in Table 4. As an overall goodness-of-fit test, the percentage of correctly predicted observations is approximately 65 percent in all models. *APPLIED* always has a positive and significant relation to the probability of innovation. *BASIC* and the interaction term (*APPLIED*BASIC*) are never significant. The squared values are also not significant. Regarding marginal effects (Model 3a), if a patent has one more backward citation (*APPLIED* increases by 1), then the probability of an innovation increases by 1.29 percentage units.

[Table 4]

5.2. Estimations of the survival model

The results of the AFT model are described in Table 5. Estimating the model with different residual distributions shows that the lognormal distribution had the best overall performance with respect to the likelihood value.[24] The results for *APPLIED* echo the positive relation found in the probability model. More backward citations imply a faster innovation speed. The result for *BASIC* is ambiguous. The sign and significance of the parameter vary depending on whether squared variables (Model 3b) or interaction terms (Model 3c) are included, and in many of the models, *BASIC* has no relation at all to the time-to-market. Finally, the estimated parameter of the interaction term *APPLIED*BASIC* is positive and significant in Model 3c. Thus, patents combining applied and basic knowledge have a longer time-to-market for innovation. The quantitative interpretation of the estimated parameters is as follows: if the number of backward citations (*APPLIED*) increases by 1, the time to launch a product decreases by 2.69 percent (Model 3a) or

[24] The most general distribution, gamma, did not converge.

4.51 percent (Model 3c).[25] Concerning the interaction effect, if *APPLIED*BASIC* increases by 1, then the time to launch a product increases by 1.43 percent (Model 3c).

[Table 5]

5.3. Estimations of the profitability model

The results of the ordered probit estimations with sample selectivity are shown in Table 6. Parameter ρ is significant at the 1 percent level in all estimations. This indicates that selectivity is present and that the two-step procedure should be used. Furthermore, the likelihood ratio tests show that the explanatory power of the models improves significantly when selectivity is used. The selection equation estimations are almost identical to the results of Model 3a in Table 4.

In contrast to the results in sections 5.1 and 5.2, *APPLIED* never has any positive relation to the profitability of commercialization. On the other hand, *BASIC* always has a strong, positive and significant relationship with profitability. However, the squared value of *BASIC* has a negative and significant impact, indicating that innovations resulting from inventions embedding basic knowledge lose their profitability potential. Finally, the interaction term *APPLIED*BASIC* is never significant.

Turning to the size interpretation of the important estimated parameters, if *BASIC* increases by 1, the probability of successful commercialization increases by 2.3 percentage points, while the probability of a break-even or loss result decreases by 0.8 and 1.5 percentage points, respectively (Model 3c).

[Table 6]

Summarizing the results of all the statistical models, *APPLIED* is positively related to the likelihood of innovating and innovation speed (i.e., accelerates the innovation process), thus confirming H1a. However, H1b is not supported since *APPLIED* has no significant relation to *SUCCESS*, probably indicating that modest profits can still be attained. *BASIC* has inconsistent effects on the likelihood of innovating and on innovation speed. Thus, we contend that H2a is not supported. Conversely,

[25] The quantitative interpretation of the effect of the explanatory variables (also dummies) on survival time is carried out as follows. If the explanatory variable increases by 1 unit, the survival time changes by $100(e^{\beta}-1)\%$.

H2b is confirmed since the linear term of *BASIC* is positively related to *SUCCESS* (i.e., faster innovation speed), while its squared term is negatively related to *SUCCESS* (i.e., slower innovation speed), thus suggesting an inverted U-shaped relationship. The interaction term is negatively related to innovation speed but has no clear effect on the likelihood of innovating, partially supporting H3a. H3b is not supported since no significant relation of the interaction terms is found with respect to the profitability measure.

5.4. Robustness

We extended the analysis of backward citations to test for the originality of the patent with respect to both the technology class and geographical origin of the cited patents, as suggested by Trajtenberg et al. (1997). *Technology* and *geography* represent the technological and geographical roots of the patent. The larger the value of these Herfindahl indexes is, the broader the technological and geographical roots of the underlying research.[26] Furthermore, we also measured the maturity of backward citations based on the maximum, average, and minimum time between the application dates of cited and citing patents. However, these extended estimations did not show any clear pattern for *technology*, *geography or maturity* in any of the models (probability, survival, or profitability). In fact, the estimated parameters of these variables were largely insignificant. This may further reinforce the reliability of our main outcomes.

Finally, we measure nonpatent references as citations made by patent examiners, *BASIC-E* (instead of *BASIC*), and re-estimate all models (see section 3.3.4). By excluding references made by applicants, we hoped to avoid possible endogeneity problems. The results in Appendix Table A3 are similar to those in Tables 4–6. The recombination effect (*APPLIED*BASIC*) has a somewhat lower significance level in the survival model (Model 3c), and *BASIC* is only significant at the 10-percent level in Model 3a when examining the profitability for commercialization. Otherwise, we do not find any systematic differences with the baseline estimations.

[26] These are constructed as Herfindahl indexes, as suggested by Trajtenberg et al (1997).

6. Discussion and conclusions

This paper studies whether and how the characteristics of the knowledge embodied in SME inventions are related to their innovation and commercialization success. Hypotheses concerning these relationships are proposed following the recombinant search and technological opportunities perspectives. Econometric estimations assessing these arguments are based on a sample of individual Swedish patents owned by SMEs and inventors, information on the invention characteristics and commercialization journey of which is available from primary and secondary sources.

The results reveal that SME inventions embedding applied knowledge, ceteris paribus, are more likely to lead to a product and do so more quickly. This is in line with arguments contending that applied knowledge is easier and safer to apply to commercial ends; in addition, it is more established, hence facilitating market acceptance (Adner & Snow, 2010; Ardito et al., 2016; Nerkar, 2003). These are all advantages for SMEs seeking to minimize risks and R&D costs. On the other hand, innovation originating from such inventions appears to be neither detrimental to profitability nor exceptionally profitable. This can be explained by the weak distinctiveness of these innovations with respect to competing offerings and/or by the fact that the inability to effectively capture the created value (Ardito et al., 2016; James et al., 2013) prevents the creation of superior competitive advantage; nevertheless, modest profit may be attained. Conversely, inventions building on basic knowledge, ceteris paribus, are related neither to a high probability of innovation nor to a fast launch of a product. Explanations can be found in the lack of capacity of SMEs in terms of knowledge distant from the market logic and the need to engage in more resource-intensive and riskier innovation projects (Damanpour, 2010; Lefebvre, 2020). However, when such inventions become innovations, they are profitable; only innovations resulting from inventions mainly embedding basic knowledge lose their profit potential. Indeed, distinctive and better performing innovations may originate from SME inventions embodying basic knowledge, and these can be more easily protected (Fleming & Sorenson, 2004; Ke, 2020). Notwithstanding, an excessive reliance on basic knowledge could lead to innovations not being easily accepted by customers, especially if commercialized by SMEs (Arora et al., 2018; Salavou & Avlonitis, 2008). Finally, inventions based on the recombination of applied and basic knowledge complicate the innovation process (Du et al., 2019) such that product launch is slowed, although conclusions on the probability of a product launch or on profitability cannot be drawn.

6.1 Implications for theory

From a theoretical perspective, first, we add to the literature dealing with the conversion of inventions into products, with a focus on a single technology. Notably, factors at this level of analysis have been recognized to have relevant explanatory power in predicting innovation performance (Maurseth & Svensson, 2020; Wagner & Wakeman, 2016). Among these, technology attributes have been highlighted (Ardito et al., 2020; Nerkar & Shane, 2007). We add to this line of inquiry by delving into the characteristics of inventions' knowledge base in terms of reliance on applied and basic knowledge. In fact, scant attention has been given to this issue in general, and the few studies considering it provide contradictory results (Su & Lin, 2018; Wagner & Wakeman, 2016). Particularly, our results are in line with Su & Lin (2018) for what concerns the role of applied knowledge; that is, applied knowledge increases both innovation likelihood and innovation speed. Conversely, we find the effects of basic and applied knowledge on innovation likelihood and speed as negligible, in accordance with Wagner & Wakeman (2016). On one side, we acknowledge our findings are not fully coherent with any of the previous studies. On the other side, they are at least coherent with one or the other study when focusing on a given type of knowledge sourcing, avoiding creating further confusion among the specific effects of applied and basic knowledge and, hence, allowing us to offer more reliable conclusions.

Relatedly, all in all, we further corroborate the recombinant search and technological opportunities perspectives concerning the view that knowledge components shaping inventions' knowledge base are conducive to explaining innovation performance by affecting value creation and appropriation opportunities. We specifically do so by matching inventions with related products and profitability level, information that is usually extremely difficult to collect, especially in the SME context. To the best of our knowledge, no prior research has linked factors at the invention level – including characteristics of the knowledge base – to a direct profitability measure, thus improving the reliability of our contribution.

Second, studies on this topic focused on the SME context are absent. Specifically, by showing whether and how SME inventions embedding applied and/or basic knowledge are related to innovation and commercialization success, we contribute to identifying how SMEs should design R&D processes to innovate. That is, we complement the literature seeking to provide a better understanding of how to improve the innovation performance of SMEs (Kumar et al., 2012; Moreno-Moya & Munuera-Aleman, 2016; Parida, Westerberg & Frishammar, 2012; Salavou & Avlonitis, 2008) by exploring a novel level of analysis (i.e., the invention level instead of the more frequently considered firm and network levels) and considering multiple performance measures simultaneously.

Finally, researchers have studied the tendency to rely on applied/basic knowledge to develop an invention and whether this tendency has improved certain quality indicators, such as the impact of the invention in terms of knowledge flow, for developing subsequent inventions (Callaert, Grouwels & Van Looy, 2012; Callaert et al., 2006; Messeni Petruzzelli et al., 2015; Tijssen, 2002). However, studies on actual innovation and commercialization success are scarce. Moreover, an accurate analysis of the complementarity between basic and applied knowledge (i.e., their combination effect) when capturing whether an invention leads to an actual product/process is also missing. This is a matter for research that seeks to understand the degree to which pursuing R&D activities that follow different trajectories is conducive to better innovation performance, e.g., research about science-technology linkages (Acosta & Coronado, 2003; Breschi & Catalini, 2010).

6.2 Implications for practice

Our results have several important implications for SME managers and policymakers. We advise managers who want to innovate quickly to exploit inventions embodying applied knowledge. However, this comes with the risk of not reaping relevant profits, meaning that such approaches may help SMEs survive in the short term but may not help them attain a sustainable competitive advantage. Conversely, managers seeking greater profit should invest in inventions embedding basic knowledge even if they may never reach the market or reach the market slowly. Thus, SMEs leveraging inventions embedding basic knowledge face relevant risks if they need to enter the market quickly or do not have slack resources to compensate for failure. One could call for an ambidextrous approach that involves applied and basic knowledge. However, we discourage managers from investing in inventions embodying both types of knowledge. Indeed, the innovation processes will be slower, without any assurance of higher profits. Instead, we suggest that SME managers develop a technology portfolio including inventions based on either applied or basic knowledge to address different innovation objectives. Overall, being aware of which technology characteristics favor higher commercialization success places SME managers in a better position to design recombinant search processes in R&D activities, thus making the front end of product development less fuzzy (Markham, 2013).

From a policy perspective, relying on basic knowledge helps SMEs develop inventions that are more profitable throughout the innovation process. Thus, policymakers should reduce the risks associated with managing basic knowledge, which are particularly harmful for SMEs. In particular, since SMEs appear to effectively manage applied knowledge to innovate, it is important that policy actions be directed toward helping SMEs reconcile applied and basic research. This can be done, for instance, by providing incentives to SMEs to engage in projects with lower technology readiness levels, where publishing scientific articles is mandatory. The rationale would extend SMEs' absorptive capacity with regard to basic knowledge. Other actions may further encourage cooperation between universities and firms, e.g., granting public R&D financing or proposing incentives to participate in university spin-offs and facilitate technology transfer from the academic to the entrepreneurial sectors.

6.3 Limitations and future research directions

As with most studies, this paper has several limitations that may open further lines of inquiry. First, the sample is composed of Swedish patents granted in 1998. Thus, future research should corroborate our findings using a wider and more recent sample of patents. In turn, researchers could invest effort in building datasets linking inventions to new products instead of using imperfect proxies for innovation, such as patent forward citations. Moreover, as mentioned in section 3.1, Sweden is one of the innovation leaders in the world, and the results would be applicable for inventors/SMEs in similar countries. Future research may conduct similar studies in different contexts, e.g., emerging markets and less innovative economies.

Second, some nonsignificant results have emerged. This does not mean that a certain variable has no relevance at all, since there may be moderating variables that can strengthen/decrease the effect of the considered variable on a certain performance outcome. Future studies may identify and investigate relevant moderating factors, perhaps at different levels of analysis.

Third, since many patent-owning inventors in the database do not run any company, traditional explanatory variables such as the age of the company and variables from the financial statement of the company cannot be included in the estimations. While this issue is not necessarily constraining in providing reliable results at the invention level, as in our case, future studies may still want to adopt multilevel studies of technology commercialization (e.g., Ardito et al., 2020).

Fourth, we acknowledge that patents represent only a subsample of all developed inventions. Further research could consider this issue. Finally, we acknowledge that studies are delving into specific types of nonpatent references. An extension of this would be disentangling the effects of each type of nonpatent reference (e.g., Marx & Fuegi, 2020).

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TABLES

Table 1. Patents leading to innovation across firm sizes, number of patents and percent.

Kind of firm where the invention was created	Innovation		Total	Percent commercialized
	Yes	No		
Medium-sized firms (51−250 employees)	88	29	117	75 %
Small firms (11−50 employees)	108	50	158	68 %
Micro-firms (2−10 employees)	105	37	142	74 %
Individual inventors (1−4 inventors)	207	201	408	51 %
Total	508	317	825	62 %

Table 2. Backward citations and non-patent literature references across innovation, average number, and percent.

Measure of backward citations and non-patent references	Innovation		All	Difference between means (t-test)
	Yes	No		
Average number of backward citations per patent	4.78	2.81	4.02	5.43 ***
Average number of non-patent references per patent	0.71	0.52	0.63	1.74 *
				Chi-square test (1 df)
Percent of patents with at least 1 backward citation	59.4	45.7	54.2	14.77 ***
Percent of patents with at least 1 non-patent reference	40.7	30.0	36.6	9.77 ***
Total number of patents	508	317	825	

Table 3. Backward citations and non-patent literature references across profitability, average number.

Measure of backward citations and non-patent references	Commercialization outcome			
	Profit	Break-even	Loss	All
Average number of backward citations per patent	5.49	3.86	4.15	4.81
Average number of non-patent references per patent	0.79	0.45	0.75	0.71

Note: For backward citations, the mean for ‘profit’ is significantly different from ‘break-even’ at the 10-percent level, and from ‘loss’ at the 5-percent level. For NPLs, no means are significant different from each other.

Table 4. Empirical estimations of the Probit model.

Dependent variable				*INNOV*				
Statistical model				Probit model				
Explanatory variables	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 3c	Model 3d
APPLIED	0.035***	0.036**			0.034***	0.043**	0.044***	0.044**
	(9.8 E-3)	(0.017)			(0.010)	(0.019)	(0.013)	(0.020)
(APPLIED)^2		–1.0 E-4				–1.0 E-4		2.0 E-4
		(7.0 E-4)				(7.0 E-4)		(9.0 E-4)
BASIC			0.057	0.059	0.016	–0.080	0.057	–0.018
			(0.041)	(0.066)	(0.038)	(0.079)	(0.052)	(0.11)
(BASIC)^2				2.0 E-4		6.8 E-3		5.2 E-3
				(4.4 E-3)		(5.5 E-3)		(6.1 E-3)
*APPLIED*BASIC*							–8.8 E-3	–7.2 E-3
							(6.8 E-3)	(8.4 E-3)
FIRM1	0.50***	0.50***	0.51***	0.51***	0.50***	0.49***	0.48***	0.48***
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
FIRM2	0.30**	0.30**	0.32**	0.32**	0.30**	0.30**	0.29**	0.29**
	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)
FIRM3	0.54***	0.54***	0.57***	0.57***	0.53***	0.54***	0.52***	0.53***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
STATFIN	–0.01***	–0.01***	–9.1 E-3***	–0.01***	–0.01***	–0.01***	–0.01***	–0.01***
	(2.8 E-3)	(2.8 E-3)	(2.8 E-3)	(2.8 E-3)	(2.8 E-3)	(2.8 E-3)	(2.8 E-3)	(2.8 E-3)
PRIVFIN	2.0 E-4	2.0 E-4	6.9 E-4	7.0 E-4	2.0 E-4	–1.0 E-4	–1.0 E-4	–1.0 E-4
	(3.6 E-3)	(3.7 E-3)	(3.6 E-3)	(3.6 E-3)	(3.6 E-3)	(3.7 E-3)	(3.6 E-3)	(3.6 E-3)
OTHFIN	–2.1 E-3	–2.1 E-3	–2.3 E-3	–2.3 E-3	–2.2 E-3	–2.4 E-3	–1.7 E-3	–2.1 E-3
	(5.1 E-3)	(5.1 E-3)	(5.1 E-3)	(5.1 E-3)	(5.1 E-3)	(5.1 E-3)	(5.1 E-3)	(5.1 E-3)
COMPLEXITY	0.37***	0.37***	0.41***	0.41***	0.37***	0.35***	0.36***	0.35***
	(0.13)	(0.13)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)
INVNBR	–0.015	–0.015	–0.015	–0.015	–0.017	–0.016	–0.018	–0.014
	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.080)	(0.079)	(0.080)
DURE	0.011	0.011	–1.8 E-3	–1.9 E-3	0.010	0.010	0.012	0.011
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
UNIV	–0.34	–0.34	–0.40	–0.40	–0.35	–0.33	–0.36	–0.34
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)	(0.32)	(0.31)	(0.32)
SEX	0.30	0.30	0.20	0.20	0.30	0.28	0.29	0.27
	(0.33)	(0.34)	(0.33)	(0.34)	(0.34)	(0.34)	(0.34)	(0.34)
ETH	–0.39	–0.39	–0.32	–0.32	–0.40	–0.37	–0.40	–0.40
	(0.33)	(0.33)	(0.31)	(0.31)	(0.33)	(0.33)	(0.33)	(0.33)
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech. Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	–496.3	–496.3	–502.4	–502.4	–496.2	–495.2	–495.4	–494.8
Test vs. restricted model	106.4***	106.4***	94.2***	94.2***	106.6***	108.0***	108.2***	109.4***
% of correctly predicted obs.	65.3	65.3	64.5	64.6	65.5	65.1	65.1	65.0

Note: The total number of observations equals 825, 508 of which equal 1 for *COM*. Standard errors are in parentheses and ***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively. Intercepts as well as individual region and technology dummies are available from the authors upon request.

Table 5. Empirical estimations of the AFT model.

Dependent variable	log (*SPEED*)							
Statistical model	Accelerated failure time (AFT) model							
Explanatory variables	Log-normal model							
	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 3c	Model 3d
APPLIED	–0.028***	–0.014			–0.027***	–0.034*	–0.046***	–0.035*
	(9.9 E-3)	(0.018)			(0.010)	(0.019)	(0.014)	(0.019)
(APPLIED)^2		–5.0 E-4				–3.0 E-4		–5.0 E-4
		(6.0 E-4)			–0.020	(6.0 E-4)		(6.0 E-4)
BASIC			–0.045	0.082	(0.041)	0.22**	–0.080	0.13
			(0.040)	(0.077)		(0.089)	(0.050)	(0.12)
(BASIC)^2				–7.7 E-4*		–0.014***		–0.011**
				(4.1 E-4)		(4.5 E-3)		(5.3 E-3)
*APPLIED*BASIC*							0.015**	9.1 E-3
							(7.2 E-3)	(8.9 E-3)
FIRM1	–0.81***	–0.82***	–0.82***	–0.81***	–0.81***	–0.80***	–0.77***	–0.78***
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
FIRM2	–0.56***	–0.57***	–0.57***	–0.56***	–0.56***	–0.55***	–0.54***	–0.54***
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
FIRM3	–0.68***	–0.70***	–0.71***	–0.73***	–0.68***	–0.71***	–0.66***	–0.71***
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
STATFIN	0.011***	0.010***	0.011***	0.012***	0.011***	0.011***	0.011***	0.011***
	(3.7 E-3)	(3.7 E-3)	(3.7 E-3)	(3.7 E-3)	(3.7 E-3)	(3.6 E-3)	(3.7 E-3)	(3.6 E-3)
PRIVFIN	–8.0 E-4	–1.2 E-3	–1.5 E-3	–2.0 E-3	–1.0 E-4	–1.6 E-3	–1.1 E-3	–1.7 E-3
	(4.3 E-3)	(4.3 E-3)	(4.3 E-3)	(4.3 E-3)	(4.3 E-3)	(4.3 E-3)	(4.3 E-3)	(4.3 E-3)
OTHFIN	1.1 E-3	1.2 E-3	2.0 E-3	2.5 E-3	1.3 E-3	1.9 E-3	1.0 E-3	1.0 E-3
	(6.3 E-3)	(6.3 E-3)	(6.3 E-3)	(6.3 E-3)	(6.3 E-3)	(6.3 E-3)	(6.3 E-3)	(6.3 E-3)
COMPLEXITY	–0.37***	–0.37***	–0.42***	–0.41***	–0.37**	–0.33**	–0.35**	–0.33**
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
INVNBR	0.021	0.017	0.022	0.012	0.021	0.020	0.020	3.5 E-3
	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.094)	(0.094)	(0.094)
DURE	0.036	0.038	0.043	0.046	0.036	0.041	0.032	0.039
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
UNIV	0.44	0.43	0.49	0.50	0.45	0.44	0.50	0.47
	(0.39)	(0.39)	(0.39)	(0.39)	(0.39)	(0.39)	(0.39)	(0.39)
SEX	–0.38	–0.35	–0.29	–0.23	–0.37	–0.30	–0.35	–0.29
	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)
ETH	0.45	0.56	0.30	0.24	0.45	0.47	0.43	0.52
	(0.40)	(0.42)	(0.40)	(0.40)	(0.41)	(0.42)	(0.40)	(0.42)
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech. Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Scale parameter σ	1.48***	1.48***	1.49***	1.48***	1.48***	1.46***	1.47***	1.46***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Log-likelihood	–1167.3	–1166.9	–1170.7	–1168.9	–1167.2	–1161.9	–1165.1	–1161.4
Test vs. restricted model	116.6***	117.4***	109.8***	113.4***	116.8***	127.4***	121.0***	128.4***

Note: The total number of observations equals 825, 508 of which are interval-censored observations and 317 right-censored. Standard errors are in parentheses and ***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively. Intercepts as well as individual region and technology dummies are available from the authors upon request.

Table 6. Empirical estimations of the profitability model.

Dependent variable	*SUCCESS*							
Statistical model	Ordered probit model with sample selection							
Explanatory variables	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 3c	Model 3d
APPLIED	3.7 E-3	0.014			4.0 E-3	–2.2 E-3	3.4 E-3	–2.2 E-3
	(8.7 E-3)	(0.015)			(9.2 E-3)	(0.019)	(0.015)	(0.019)
(APPLIED)^2		–4.1 E-4				–1.1 E-4		1.9 E-4
		(5.0 E-4)				(5.4 E-4)		(7.7 E-4)
BASIC			0.068***	0.21**	0.067**	0.23**	0.065**	0.31**
			(0.027)	(0.087)	(0.028)	(0.10)	(0.030)	(0.12)
(BASIC)^2				–7.6 E-3**		–8.1 E-3*		–0.011**
				(3.8 E-3)		(4.5 E-3)		(5.0 E-3)
*APPLIED*BASIC*							4.4 E-4	–8.2 E-3
							(6.6 E-3)	(9.5 E-3)
FIRM1	0.56***	0.54***	0.66***	072***	0.69***	0.70***	0.69***	0.69***
	(0.18)	(0.18)	(0.20)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
FIRM2	0.50***	0.50***	0.57***	0.64***	0.60***	0.63***	0.60***	0.63***
	(0.15)	(0.15)	(0.17)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
FIRM3	0.13	0.12	0.18	0.21	0.20	0.19	0.20	0.19
	(0.14)	(0.14)	(0.15)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
ACTIVE	0.30**	0.31**	0.32**	0.33**	0.33**	0.32**	0.33**	0.33**
	(0.14)	(0.14)	(0.15)	(0.17)	(0.16)	(0.16)	(0.16)	(0.16)
COMPLEXITY	–0.072	–0.072	–0.065	–0.051	–0.064	–0.048	–0.064	–0.046
	(0.13)	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)
INVNBR	0.069	0.067	0.077	0.080	0.083	0.076	0.083	0.076
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
DURE	4.4 E-3	6.3 E-3	5.8 E-3	0.011	6.5 E-3	0.012	0.064	0.014
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
UNIV	0.022	0.024	–0.14	–0.099	0.14	–0.096	–0.14	–0.074
	(0.36)	(0.37)	(0.42)	(0.44)	(0.43)	(0.44)	(0.43)	(0.44)
SEX	–0.074	–0.056	–0.10	–0.036	–0.081	–0.050	–0.081	–0.059
	(0.31)	(0.31)	(0.32)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
ETH	0.61	0.70	0.50	0.38	0.44	0.44	0.44	0.39
	(0.34)	(0.33)	(0.37)	(0.39)	(0.38)	(0.37)	(0.38)	(0.38)
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech. Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ρ	–1.00***	–1.00***	–0.91***	–0.85***	–0.88***	–0.87***	–0.88***	–0.88***
Log-likelihood	–934.6	–934.5	–933.2	–930.9	–933.1	–930.8	–933.1	–930.3
Test vs. restricted model	9.3***	8.5***	9.6***	6.6***	5.2**	5.8**	5.2**	5.9**

Note: n=818 in the selection equation and 501 in the ordered probit model. The selection model estimates are almost identical to Model 3a in Table 4. Standard errors are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Intercepts as well as individual region and technology dummies are available from the authors upon request.

Appendix

Table A1. Descriptive statistics of explanatory variables.

Explanatory variables	Definition	All observations (825 observations) Mean	All observations (825 observations) Std. dev.	*COM* = 1 (501 observations) Mean	*COM* = 1 (501 observations) Std. dev.
APPLIED	The number of backward citations to other patents by the patent and its family members	4.07	5.93	4.83	6.57
$(APPLIED)^2$	Squared value of *APPLIED*	51.7	181.4	66.4	224.6
BASIC	The number of references to non-patent literature	0.63	1.66	0.72	1.93
$(BASIC)^2$	Squared value of *BASIC*	3.16	29.66	4.24	37.7
APPLIED BASIC*	Interaction term between *APPLIED* and *BASIC*	5.12	13.58	6.04	14.96
ACTIVE	Dummy that equals 1 if inventors were active during the first commercialization phase and 0 otherwise	-----	-----	0.87	0.34
FIRM1	Dummy that equals 1 if the invention was created in a medium-sized firm (101−1000 employees) and 0 otherwise	0.13	0.34	0.15	0.35
FIRM2	Dummy that equals 1 if the invention was created in a small firm (11−100 employees) and 0 otherwise	0.23	0.42	0.26	0.44
FIRM3	Dummy that equals 1 if the invention was created in a micro-company (2−10 employees) and 0 otherwise	0.16	0.37	0.20	0.40
STATFIN	Percentage of R&D-costs financed by government authorities.	7.06	18.58	-----	-----
PRIVFIN	Percentage of R&D-costs financed by private venture capital firms or business angels.	3.14	14.44	-----	-----
OTHFIN	Percentage of R&D-costs financed by universities and research foundations.	2.73	14.39	-----	-----
INVNBR	Number of inventors	1.34	0.66	1.33	0.65
DURE	Number of years between application and granting of the patent	2.71	1.65	2.73	1.68
UNIV	Dummy that equals 1 if the invention was created at university, and 0 otherwise.	0.048	0.21	0.039	0.19
SEX	Share of female inventors	0.023	0.14	0.023	0.14
ETH	Share of non-European inventors	0.030	0.16	0.024	0.15

Table A2. Distribution of technology class dummies.

Id	Technologies	No. of patents	Id	Technologies	No. of patents
1	Electrical engineering	30	16	Chemical engineering	53
2	Audiovisual technologies	18	17	Surface technologies	10
3	Telecommunication	17	18	Material processing	51
4	Information technologies	11	19	Thermal processes	23
5	Semiconductors	4	20	Environmental technologies	27
6	Optics	9	21	Machine tools	54
7	Control technologies	67	22	Engines	24
8	Medical technologies	53	23	Mechanical elements	53
9	Organic chemistry	4 *	24	Handling	124
10	Polymers	2 *	25	Food processing	39
11	Pharmaceutics	11	26	Transport	82
12	Biotechnology	6 *	27	Nuclear engineering	3 *
13	Materials	6	28	Space technologies	19
14	Food chemistry	7	29	Consumer goods	97
15	Basic materials chemistry	18	30	Civil engineering	175

Note: The 825 patents have 1,097 technology classes. A patent can have more than one technology class, i.e., the technology dummies are not mutually exclusive. An asteria * means that there are too few observations to include a dummy for the technology class, since estimations do not converge.

Table A3. Re-estimation with nonpatent references by examinators.

Dependent variable	*INNOV*		log(*SPEED*)		*SUCCESS*	
Statistical model	Probit model		AFT model		Ordered probit model with sample selection	
Explanatory variables	Model 3a	Model 3c	Model 3a	Model 3c	Model 3a	Model 3c
APPLIED	0.036***	0.045***	–0.028***	–0.045***	4.5 E-3	9.0 E-3
	(0.010)	(0.014)	(0.010)	(0.014)	(9.3 E-3)	(0.015)
BASIC	–0.0131	0.025	4.9 E-3	–0.058	0.067*	0.081**
	(0.049)	(0.062)	0.057	(0.068)	(0.040)	(0.041)
*APPLIED*BASIC*		–8.7 E-3		0.015*		–3.9 E-3
		(8.0 E-3)		(8.8 E-3)		(7.0 E-3)
Log-likelihood	–496.3	–495.7	–1167.3	–1165.9	–935.5	–937.9
Test vs. restricted model	106.4***	107.6***	116.6***	119.4***	5.2**	5.1**
% of correctly predicted obs.	65.3	65.8	---	---	---	---
ρ	---	---	---	---	–0.86***	–0.86***

Note: The total number of observations equals 825, 508 of which equal 1 for *COM*. Standard errors are in parentheses and ***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively. Control variables, intercepts as well as individual region and technology dummies are available from the authors upon request.

FIGURES

Figure 1. Survival distribution and Hazard functions across APPLIED, 825 observations.

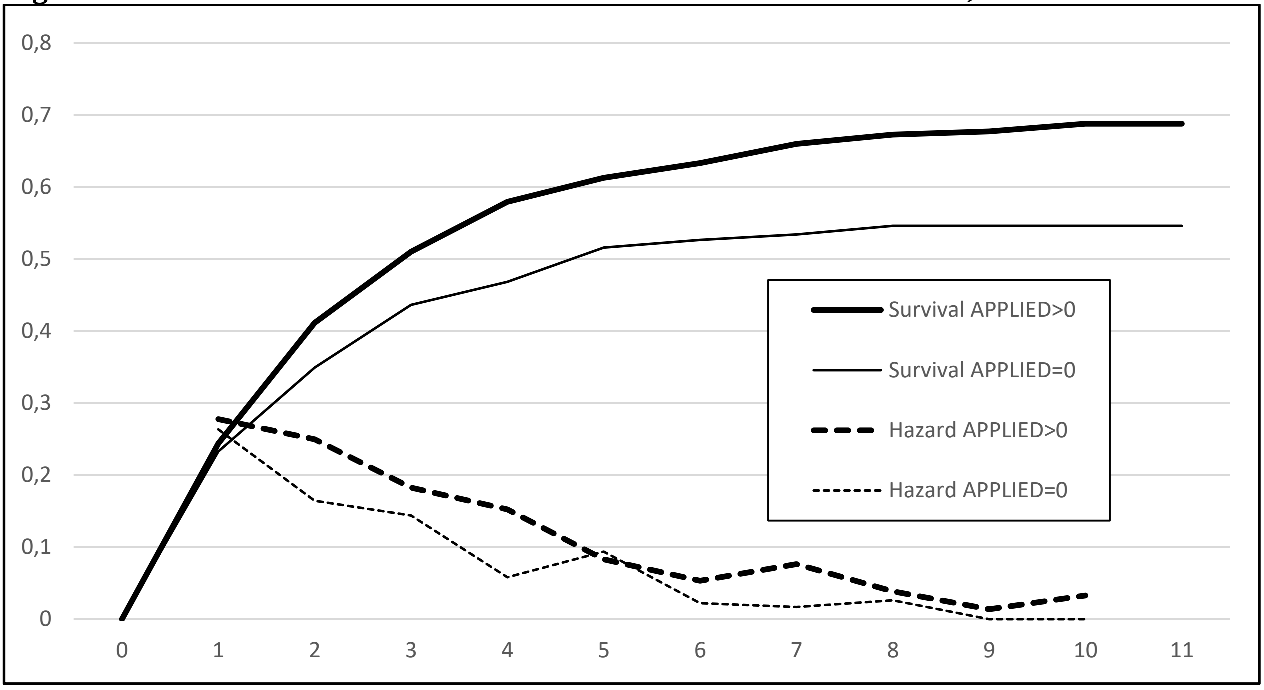

Figure 2. Survival distribution and Hazard functions across BASIC, 825 observations.