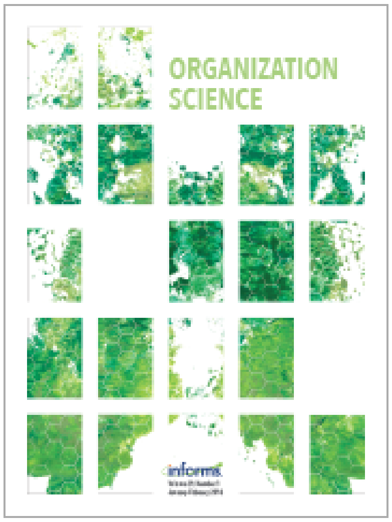

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Learning to Be Edison: Inventors, Organizations, and Breakthrough Inventions

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This study examines whether inventors' past stock of inventions affects the rate at which they produce technological breakthroughs, as well as the role of organizational contingencies in moderating this effect. The breakthrough rate depends on the rate at which an inventor generates inventions and the probability that each of these inventions is a breakthrough. We argue that inventors with larger patent records generate a higher rate of inventions, but the single inventions that they generate each have a lower probability of being a breakthrough. Longitudinal data of 5,144 European inventors and fixed-effects estimation confirm these predictions and reveal that the net effect of the inventors' stock of past inventions on the breakthrough rate is positive—that is, more established inventors display a higher rate of breakthroughs than brand-new inventors. We also confirm the role of organizational contexts in shaping inventors' productivity. In particular, firms' control over research and development targets lessens the advantage of established inventors with regard to the rate of breakthrough generation.

Keywords: breakthrough inventions; R&D organization; individual inventors; inventive experience
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Introduction

Innovation is at the core of firms' competitive advantage in knowledge-based industries. However, achieving and sustaining a competitive edge through innovation is not easy. First, not all inventions are alike; many inventions are not worthy of much attention, and only a few outliers are breakthroughs—that is, inventions that the technological community recognizes as highly valuable (Ahuja and Lampert 2001).[1] Second, modern competitive contexts demand that firms consistently produce breakthroughs over time to maintain or increase their competitive advantage (e.g., D'Aveni 1994, Shilling and Hill 1998). Thus, firms are increasingly required to boost their *rate of breakthrough generation*, which entails two components: the *rate of invention* and the *probability of any invention being a breakthrough*.

Extant research contributions related to breakthrough inventions focus on the breakthrough rate as a whole, without disentangling its two components (see Ahuja and Lampert 2001), or else they consider only the probability of any invention being a breakthrough (see Singh and Fleming 2010). In doing so, they neglect an inherent trade-off in the process leading to breakthroughs (March 1991). Increasing the invention rate typically relies on the exploitation and refinement of well-known paths (e.g., Sørensen and Stuart 2000), whereas raising the probability that any invention is a breakthrough often demands the exploration of "outside-the-box" approaches (e.g., Azoulay et al. 2011). This study tries to shed light on this tension, as it arises from the firm decision to rely on established inventors (or employees with a strong record of past inventions) versus brand-new inventors (with few or no inventions). The former are typically provided with a vast repertoire of well-known heuristics to exploit (Chase and Simon 1973), whereas the latter are naturally more receptive to exploring fresh ways of thinking (Jeppesen and Lakhani 2010). We posit that established inventors tend to follow familiar paths (Audia and Goncalo 2007, Levinthal and March 1993, Rhee and Haunshild 2006), which leads to a higher invention rate than that produced by brand-new inventors but also lowers the probability that any given invention that they produce is extremely valuable. Because of these contrasting forces, whether inventors with a greater stock of past inventions are in a better or worse position to generate a consistent flow of breakthroughs is theoretically ambiguous. However, the organization of research and development (R&D) might mitigate this trade-off between the higher inventive rate of established inventors and the greater impact of brand-new inventors' inventions. In particular, a firm's crucial decision in designing R&D processes is whether to retain control over R&D goals and centrally set specific targets or to allow inventors to fix their own goals independently (Aghion et al. 2008, Stern 2004, Panico 2009). We hypothesize that when R&D targets are centrally defined, inventors with a greater record of past inventions display a lower rate of breakthrough generation compared with situations in which they choose their targets autonomously. The reason is that the disadvantages of a centrally targeted R&D, in terms of lower autonomy (e.g., Cardinal 2001) and performance appraisal pressure (e.g., Staw et al. 1981), are particularly salient for established inventors. In contrast, the benefits, in terms of guidance and supervision throughout the inventive process (e.g., Stokes 1999), should be particularly pronounced for brand-new inventors.

We test our theory with data about 5,144 European inventors, drawn from the PatVal-EU survey, which includes the universe of granted European Patent Office (EPO) patents during 1993–1997. The PatVal-EU survey also contains information about inventors' age, mobility, type of employer, and characteristics of R&D projects. For the purposes of this study, we reconstruct the patent history of each inventor in the survey from 1978, or the year the EPO began receiving patent applications, to 1999. Our test includes three steps. First, we employ a survival regression model to examine the relationship between the individual stock of past inventions and inventive rate. Second, through a linear probability model, we analyze how prior creative output affects the likelihood that an invention is a breakthrough. Third, using a survival regression model, we estimate how the stock of inventions affects inventors' rate of breakthrough generation. The empirical analysis uses individual fixed effects to control for unobserved individual factors (e.g., innate ability) that remain constant over time and may influence both creative performance and the stock of past ideas. The results show that the net effect of the stock of past inventions on the breakthrough rate is positive: more established inventors display a higher rate of breakthroughs than brand-new inventors. However, when organizations retain control over R&D targets, the positive relationship between inventors' past invention records and rate of breakthrough generation decreases.

This study contributes to R&D organization and innovation literature in several ways. First, we add to the recent stream of organization research that focuses on invention as an outcome with multilevel antecedents that combine to affect invention outcomes (e.g., Gupta et al. 2007). Corporate inventors do not operate in a vacuum; they are embedded in an organizational context that shapes their behavior and performance. In this regard, this study shows that firms' control over R&D targets moderates the impact of individual abilities on invention outcomes.

Second, we complement extant research on how individual skills influence firm inventive capability (e.g., Lacetera et al. 2004). The design of an R&D strategy implies a decision about not only how much to invest but also how and whom to invest in, because the way firms allocate resources among corporate inventors determines the outcome of their R&D processes (Cabral 2000). In particular, our findings reveal that allocating more resources to the most prolific inventors may be associated with a significant change in both the productivity and the direction of a firm's R&D efforts.

Third, we address an issue that has been widely debated in creativity and innovation literature—namely, the choice between experienced and inexperienced individual researchers. Most prior studies address the extent to which ideas are novel or how much they diverge from past solutions (e.g., Argote and Miron-Spektor 2011, Audia and Goncalo 2007, Gino et al. 2010). We complement this research by focusing on breakthroughs (i.e., highly valuable inventions, regardless of their novelty) and consider both the breakthrough rate and its components.

Fourth, we offer insights for the research on breakthrough inventions (e.g., Ahuja and Lampert 2001, Girotra et al. 2010, Singh and Fleming 2010). Specifically, we show the importance of disentangling the drivers of the rate of breakthrough inventions into its two components, the rate of inventions on the one hand and the probability of any invention being a breakthrough on the other. Doing so improves our understanding of the overall process for generating breakthrough inventions. In particular, we show that the same factors that hamper the likelihood of any single invention being a breakthrough can enhance the breakthrough rate.

The rest of this article proceeds as follows: In the next section, we derive our theoretical predictions. After we describe our data and empirical strategy, we provide the results. We conclude with a discussion of the implications of our findings.

Theory and Hypotheses

Corporate Inventor Experience and the Rate of Breakthrough Generation

In modern environments, competitive advantage is increasingly transitory. Intense rivalry, the continual rise of appealing substitute products, and fragmented and fickle customer tastes all contribute to a state of constant disequilibrium (D'Aveni 1994), such that most firms' profits derive from inventions produced in the very recent past (Shilling and Hill 1998). In this scenario, successful firms are those able to increase the *pace* of inventions, to move from one competitive position to another amid the turbulence. However, the positive skew of the invention value distribution is marked, such that many inventions are not worthy, and only a few are extremely valuable (Harhoff et al. 1999). Consistent with prior literature (e.g., Ahuja and Lampert 2001), we define breakthroughs as extremely valuable inventions whose importance is reflected in the recognition they receive from the technological community. Breakthroughs enable firms to challenge the existing technological order (Tushman and Anderson 1986) or engage in corporate renewal, business growth, and new business development (Ahuja and Lampert 2001).

Because of both hypercompetition and the positive skew of the invention value distribution, firms have an incentive to exploit their resources to generate a consistent stream of breakthrough inventions—that is, to increase their *rate of breakthrough generation*. To this end, while leveraging their internal human resources in the quest for breakthroughs, firms must decide whether to rely more on inventors with a strong record of past inventions (i.e., established inventors) or on inventors with no or few past inventions (i.e., brand-new inventors). This decision has been widely debated in creativity literature, which has focused on the impact of past creative outcomes on the extent to which inventors' ideas diverge from their current knowledge trajectory (e.g., Audia and Goncalo 2007, Gino et al. 2010). Yet the effect of inventors' past invention records on the rate of breakthrough generation, which is jointly determined by the *rate of invention* and *the probability of any invention being a breakthrough*,[2] has not been studied previously.

We argue that the stock of past inventions induces inventors to exploit familiar approaches rather than explore new paths. This choice has crucial implications for the returns on their inventive activity (March 1991). On the one hand, exploiting well-known approaches ensures a reasonable payoff in a short amount of time; that is, it increases the rate at which inventions are generated (Sørensen and Stuart 2000). On the other hand, exploring novel paths likely raises the probability that any invention generated is a technological breakthrough. Inventors thinking "outside the box" draw from an invention value distribution that is not only more uncertain (which implies higher variance) but also more valuable (Jeppesen and Lakhani 2010, Manso 2011). Both a higher variance and a greater expected value increase the likelihood of any invention being a breakthrough (Girotra et al. 2010).

Established inventors are more likely to exploit familiar approaches for several reasons. First, with their past stock of inventions, such inventors' idea generation heuristics are well consolidated (Chase and Simon 1973) and effective for increasing the speed at which new inventions get produced (Audia and Goncalo 2007). In addition, for established inventors, following a "myopic" path could be particularly convenient if the adoption of new paths implies some sunk costs (Levinthal and March 1993). In this case, the net benefits of any novel approach could be inferior to the gross benefits of old approaches whose sunk costs have already been paid. These two arguments suggest that, compared with brand-new inventors, established inventors are both more effective and more efficient when exploiting familiar approaches. Accordingly, they may want to allocate their time and effort to exploitative projects close to their extant competences. Furthermore, a "reputation effect" may reinforce the established inventors' incentive to choose exploitative paths. Because of their vast track record of inventions, these inventors' better reputational position might result in even stronger motivations to search for safe solutions; failure entails a greater reputational loss for such researchers (e.g., Rhee and Haunshild 2006). For example, consider an inventor confronted with the choice between developing a new antidepressant based on a serotonin inhibitor or developing one based on a substance P receptor blocker approach (Cabral 2000). The first approach would provide a low probability of failure but a limited payoff in the case of success because of the incremental nature of the invention. The second path would imply the promise of a substantial payoff in the case of success as well as a significant probability of failure because it would represent a radical invention. Because of their higher reputational capital, established inventors would face a stronger social penalty in the case of failure, which may lead them to safer, albeit less valuable, choices.

All in all, we predict that established inventors, by relying on well-known approaches, display a higher rate of invention and a lower likelihood of any invention being a breakthrough compared with brand-new inventors.

HYPOTHESIS 1. *The larger the inventor's stock of past inventions, the higher the rate of new invention generation.*

HYPOTHESIS 2. *The larger the inventor's stock of past inventions, the lower the probability that a future invention is a breakthrough.*

Considering the trade-off that results from corporate inventors' prior output, organizations that aim to increase the rate of breakthrough generation face a critical tension when allocating their (scarce) resources among inventors. On the one hand, allocating resources to the most prolific inventors increases the inventive rate, because these inventors likely exploit well-known approaches and display a higher invention rate. On the other hand, such an allocation diminishes the likelihood of any new invention being extremely valuable, because breakthroughs result from outside-the-box thinking.

Understanding whether the higher inventive rate of established inventors eventually overcomes the higher impact of inventions by brand-new inventors has rich implications for the organization of R&D. Unfortunately, it is difficult to predict ex ante which effect will dominate, as exemplified by the old diatribe regarding the relative importance of "quantity versus quality" in the creative process. The evolutionary theory of creativity offers one perspective, arguing that producing high-impact contributions is a probabilistic function of quantity (Dennis 1966, Simonton 1997). Consistent with this view, it is far easier to affect the sheer quantity of inventions than their value, which remains largely unpredictable (Mariani and Romanelli 2007). According to this line of reasoning, the impact of any factor on the breakthrough rate is largely mediated by its impact on the quantity of inventions generated rather than on the value of any particular invention. It follows that the positive effect of the stock of past inventions on the inventive rate is stronger than the negative effect on the probability of any invention being a breakthrough. As a result, established inventors have a higher rate of breakthrough generation.

Some scholars disagree with this emphasis on the "quantity effect" to produce breakthroughs. For example, Fleming (2007, p. 70) suggests that in the quest for breakthroughs, enhancing the average value of inventions is at least as important as increasing the sheer number of inventions: "Organizations rarely invent breakthroughs if their average shot is worth little." Accordingly, he highlights the importance of individual (and organizational) factors in determining the invention value in general and the likelihood of any invention being a breakthrough in particular.

We conclude that whether established inventors are in a better position than brand-new inventors to increase the production of breakthroughs on a consistent basis is a theoretically ambiguous question, and we thus formulate two concurrent hypotheses.

Hypothesis 3A. *The larger the inventor's stock of past inventions, the higher the rate of breakthrough generation.*

Hypothesis 3B. *The larger the inventor's stock of past inventions, the lower the rate of breakthrough generation.*

The organization of R&D might mitigate or solve the trade-off resulting from inventors' prior inventive output. Although new ideas are inherent to individuals, the organizational design of the R&D structure and processes influence the intensity, direction, and productivity of inventors' efforts (Ahuja et al. 2008). Firms might decide to start projects with a clear target centrally defined, or they might fund people without limiting ex ante the scope and latitude of their research trajectories (e.g., Azoulay et al. 2011). In the next section, we examine this distinction to draw testable implications about the moderating role of the nature of R&D on the relationship between successful inventive experience and the generation of breakthrough inventions.

The Moderating Role of R&D Organization: Managerial Control Over R&D Target

A major challenge for firms designing the internal organization of R&D is how much control to exert over R&D (e.g., Aghion et al. 2008, Stern 2004). Control refers to "any process by which managers direct attention, motivate, and encourage organizational members to act in desired ways to meet the firm's objectives" (Cardinal 2001, p. 22). Such a broad definition encompasses many dimensions of R&D control. For example, it could involve the extent to which employees are allowed to disclose the findings of research or even the extent to which they can access cutting-edge equipment without asking for permission (Stern 2004). However, the most prominent dimension of control is probably whether firms or corporate inventors decide on the topics and direction of research projects (Panico 2009). In this respect, firms might decide to establish a clear invention problem and ask inventors to find a solution (what we call "centrally targeted R&D"); alternatively, they might decide to let inventors pursue the research paths they prefer.

Genzyme, a successful biotechnology company acquired recently by Sanofi, represents a clear example of centrally targeted R&D. Genzyme's goal is to capture value from the treatments of rare diseases caused by enzyme deficiency conditions, which usually afflict a very small percentage of the world's population. However, because of the severity of the disorders and the absence of effective treatments, finding a therapy would be extremely profitable. Therefore, Genzyme's R&D efforts are primarily devoted to finding drugs that cure these specific diseases.

Instead, in companies such as Google and 3M, researchers enjoy great autonomy regarding the choice of R&D target. Google's well-known philosophy of "20% time" allows engineers to spend 20% of their working hours pursuing projects that are not necessarily in their job scope, without formal control. Similarly, employees at 3M can spend up to 15% of their time pursuing individual projects of their own choice, without needing to justify or disclose the project to a manager.

Allocating corporate inventors to a centrally targeted R&D project might affect both the sheer quantity of inventions produced and the likelihood of any invention being breakthrough. In this respect, two sets of arguments produce opposite expectations.

The first suggests that centrally targeted R&D could be detrimental to both the quantity of inventions and the probability of any of them being a breakthrough. The rate of inventions may decrease because firm control over the R&D targets limits the autonomy of inventors to allocate efforts and resources: any choice about the strategy to achieve the target, or about switching to a new target, requires managerial approval. Hence, inventions become more difficult to produce, because they require negotiations and discussions with managers (Azoulay et al. 2011). Centrally targeted R&D also implies the dissipation of many potentially valuable ideas that never become inventions because, according to the managers, they do not conform to the target (and so are not relevant for the organization) or are less profitable than other alternatives proposed (Stern 2004, Aghion et al. 2008). Also, the probability of any invention being a breakthrough may decrease because strict control by higher-level managers could exert psychological constraints to produce high-impact inventions. Employees in these stressful situations may overexploit their knowledge—that is, choose incremental solutions based on their extant competences—even when doing so does not bring about any benefit (Cowen 1952, Staw et al. 1981).

A second set of arguments suggests instead that centrally targeted R&D might enhance both the invention rate and the probability of any invention being a breakthrough. With regard to the invention rate, a target outcome imposed by a third party can act as a reference for inventors. It therefore increases perceptions of competence and encourages inventors to complete the task (Dahl and Moreau 2007). Moreover, because too much choice can paralyze decision making (Iyengar and Lepper 2000), imposing constraints, such as a clear goal or specific instructions, can avoid the "blank-page" effect in creative work (Stokes 1999). Regarding the likelihood of any invention being a breakthrough, managerial control over the R&D objective, by directing the scope of search, may limit the combination of overly diverse knowledge elements, which often results in awkward outputs (Taylor and Greve 2006).

We argue that the first set of arguments prevails in the case of established inventors, whereas the second set likely prevails among brand-new inventors. In other words, the benefits associated with centrally targeted projects are particularly salient for brand-new inventors, leading them to produce more inventions that are more likely to be valuable. The disadvantages instead should be especially pronounced for established inventors, who become less productive in terms of both the inventive rate and the probability of any invention being a breakthrough.

Brand-new inventors lack the competence to manage the inventive process efficiently and thus benefit from a target outcome as a form of encouragement (Dahl and Moreau 2007). Furthermore, they have not already developed their own research trajectory, and with no constraints on targets, they could easily become overwhelmed by the choice among a large number of goals (Iyengar and Lepper 2000, Stokes 1999). Because of their tendency toward exploratory attitudes, brand-new inventors also frequently confront dead ends. More discipline and limitations on the paths they may pursue thus might be beneficial and help them avoid awkward or worthless combinations (Taylor and Greve 2006).

In contrast, established inventors, with their proficiency and expertise, do not benefit much from managerial supervision and guidance. Instead, the need to discuss and negotiate with managers about any new target that they would like to propose, or even the best way to achieve the established target (Azoulay et al. 2011), makes their stocks of past inventions a less productive asset. Established inventors cannot leverage their consolidated heuristics to generate ideas as much as they would without any firm control. Analogously, managerial selections of ideas that eventually will become inventions may imply a greater penalty for established inventors than for brand-new inventors. In the most likely case, among the many ideas for achieving a certain centrally fixed target, managers select only the solution that seems the most profitable to them (Aghion et al. 2008). The loss, in terms of the number of ideas discarded, is clearly greater for established inventors, in that they are able to propose more solutions. Furthermore, established inventors confronted with strict managerial control are prone to overexploit their past approaches (Staw et al. 1981). Unlike brand-new inventors, they possess well-established ways of thinking, which lead them, in stressful situations, to "play it safer" than is optimal; this translates into a lower probability that any invention is a breakthrough. Therefore, we hypothesize the following.

HYPOTHESIS 4. *Being allocated to a centrally targeted R&D project negatively moderates the relationship between the individual stock of past inventions and the rate of new invention generation.*

HYPOTHESIS 5. *Being allocated to a centrally targeted R&D project negatively moderates the relationship between the individual stock of past inventions and the probability that a future invention is a breakthrough.*

In terms of the rate of breakthrough generation, the previous two hypotheses suggest that centrally targeted R&D produces a penalty for inventors with greater records of past inventions, in that both their inventive rate and the likelihood of any invention being a breakthrough decrease. As a result, firms' control over the R&D target reduces the trade-off determined by inventors' stock of past inventions, such that established inventors assigned to a centrally targeted R&D project display a lower breakthrough rate than when they are free to pursue independent research paths. We thus predict the following.

HYPOTHESIS 6. *Being allocated to a centrally targeted R&D project negatively moderates the relationship between the individual stock of past inventions and the rate of breakthrough generation; that is, if the relationship between the stock of past inventions and the rate of breakthrough generation is positive* (*Hypothesis* 3A), *it becomes less positive. If it is negative* (*Hypothesis* 3B), *it becomes more negative.*

Methods

Sample and Data

To examine our hypotheses, we use a unique, extensive data set that combines information from the PatVal-EU survey with patent information from the EPO Worldwide Patent Statistical (PatStat) database. The PatVal-EU survey, conducted in 2003–2004, includes inventors of 9,550 patents granted by the EPO. The population of patents from which we selected the target sample consists of all EPO-granted patents with priority date between 1993 and 1997. Unlike previous patent surveys, this approach represents the entire universe of patents in European Union (EU) countries and all technological fields. The survey collects information about the individual inventors, their employer organizations, inventive processes, and the resulting patents. For the surveyed inventors, we downloaded all EPO patents on which they were listed before 1999 and collected the names of all coinventors. The appendix describes the sampling process, as well as the procedures for identifying PatVal-EU inventors and their coinventors.

For the purpose of this study, we consider inventors employed in private companies (rather than in research organizations) and drop inventors for whom we lack information about the year of birth, education, year in which they achieved their degree, type of employer, or mobility. The final sample covers 5,144 inventors for whom we had full information records and complete patenting histories. The observation window starts in 1978, the year the EPO began receiving patent applications, and runs through 1999. We ended the data collection in 1999 to ensure sufficient time to measure the patented inventions' value, according to the number of forward citations received. For each patent, we collected information about the technological (International Patent Classification, or IPC) class, the name of coinventors, and the date of the application (day, month, and year). If two or more patents were filed on the same date, we dropped the one with fewer forward citations. In the end, we obtained 35,005 patents that listed the inventors in our sample. We then traced the inventors' careers from their beginning; the entry date of an inventor in our sample is 1978 if she achieved the highest educational degree before this year, or the year she received the highest educational degree otherwise. At the inventor level, our data cover 40,149 observation spells, each of which starts after a new invention (or the beginning of the inventor's career) and ends with another invention or censoring.

Measures

Dependent Variables. To test our theory, we estimate three equations with different dependent variables. The first, *INVENTION*, is the rate at which an inventor produces a generic patented invention. The second dependent variable, *BREAKTHROUGH_INVENTION*, is a dichotomous variable that takes a value of 1 if the invention is a breakthrough and 0 otherwise. We consider the rate at which an inventor produces breakthroughs as a third dependent variable. Breakthroughs refer to patented inventions in the top 5% of the distribution in terms of citations received from subsequent patents (Ahuja and Lampert 2001, Phene et al. 2005, Singh and Fleming 2010). Thus, we employ a dichotomous variable that takes a value of 1 if the patent is in the top 5% of the distribution of EPO patents invented in the same year (application date) and in the same ISI-INPI-OST technological category, and 0 otherwise.[3] The number of citations a patent receives correlates with other measures of its technological and economic value, including consumer surplus (Trajtenberg 1990), patent renewal rates (Harhoff et al. 1999), contribution to firm market value (Hall et al. 2005), and inventor assessments of its economic value (Gambardella et al. 2008). Of the 35,005 patents in our sample, 2055 are breakthroughs, according to our measure.

Explanatory Variables. *STOCK_OF_PAST_INVENTIONS* is the number of patents the inventor applied for in the past.[4] Because this output-based measure of experience may also proxy for inventor ability, we include inventor fixed effects to capture the effect of the inventor experience, net of other innate characteristics.

To test the moderation effect produced by being allocated in a *CENTRALLY_TARGETED_R&D* project, we draw on information provided by the survey. Specifically, if the idea originated outside the firm's control, such as one that came from an individual inventor's inspiration, we regard the inventor as employed in a noncentrally (or independently) targeted R&D activity. In contrast, if the invention was the main achievement or a by-product of a firm-sanctioned research project, we regard the inventor as involved in a centrally targeted R&D project. Because this information is available only for the surveyed patents, and because a small fraction of the inventors in our sample have more than one PatVal-EU patent, we use the inventor average of this variable, as provided by the surveyed patents, to define the targeted nature of all the other (unsurveyed) projects of the same inventor in the same organization, and we exclude mobile inventors from the sample when we introduce the interaction term. In the Robustness Checks section, we provide evidence for the reliability of our measure. This measure is largely time invariant, which could create a problem if we sought to estimate the effect of a centrally targeted R&D project per se in a regression with fixed effects for each inventor. However, because we are interested in the interaction between the R&D decentralization and the stock of past inventions, we can use the inventors' fixed effects to exploit differences both within inventors (i.e., change in the stock of past inventions over time) and across inventors allocated to different types of R&D projects. In other words, we can compare the effect of being allocated to targeted versus untargeted R&D projects for inventors who have undergone the same change in their experience.

Controls. *TECH_DIVERSITY* measures the dispersion of the stock of past inventions across diverse technological fields, corresponding to the following indicator:

$$TECH\_DIVERSITY_i = 1 - \sum_k \left(\frac{n_k}{n}\right)^2,$$

where n is the total number of patents, and n_k is the number of patents in each of the 129 IPC3 technological classes k.[5]

We then include controls for *INVENTOR_AGE*, which might influence both the quantity and the quality of inventions (e.g., Hall et al. 2007, Jones 2010, Levin and Stephan 1991).[6] We also control for inventors' *MOBILITY*, or the number of times an inventor changes employers in a specific period. To control for other sources of ideas and knowledge from which the inventor might benefit, we include a measure of *SOCIAL_DIVERSITY*, or the ratio of different coinventors listed on the focal inventor's patents to the total number of collaborations. For example, if an inventor patented with 10 coinventors and 5 are different people, this measure equals 0.5. The number of different coinventors thus accounts for exposure to this form of diverse experience.

At the organizational level, we control for the type of employer, which may change over time in the case of mobile inventors: large (i.e., more than 250 employees), medium (between 100 and 250 employees), or small firms (fewer than 100 employees). The corresponding dummies are *LARGE_FIRM_DUMMY*, *MEDIUM_FIRM_DUMMY*, and *SMALL_FIRM_DUMMY*, respectively.

Finally, because time-varying factors may influence the invention process, all our estimates include dummy variables for the calendar year and technological classes. Table 1 lists these variables, along with their definitions.

Empirical Strategy

Our empirical study involves two levels of analysis: inventor (Hypotheses 1, 3, 4, and 6) and invention (Hypotheses 2 and 5). To test Hypotheses 1 and 4, which pertain to the inventive rate, we use an event history analysis rather than count models. Count models constrain the events to occur in an arbitrarily chosen period (i.e., calendar year), and they also assume that the unconditional rate of event occurrence is constant (e.g., King 1989), which represents an unrealistic assumption for creative processes because productivity likely changes over the course of an inventor's career.[7] Furthermore, count models assume that events in any period are independent of one another, which is not accurate for our context, because prior productivity clearly can affect current invention rates. Because we have data about the day of the EPO patent application, as our baseline specification we use a continuous Cox regression model (see Sørensen and Stuart 2000). The Cox model does not make parametric assumptions about the form of duration dependence in the hazard rate, which is important because incorrect parametric assumptions may lead to biased estimates of the effects of the covariates on the hazard rate (Blossfeld and Rohwer 1995). In a Cox model, the hazard rate is the product of an unspecified baseline rate $h(t)$ and a term that specifies the influences of covariates in X:

$$HazardRate_t = h(e)\exp(\beta x). \qquad (1)$$

To test Hypotheses 1 and 4, the dependent variable in Equation (1) is the rate at which inventor i generates new inventions—that is, the inventor's hazard inventive rate at time t. We use the *STOCK_OF_PAST_INVENTIONS* (before time t) as our explanatory variable to test Hypothesis 1. We then use the interaction between the *STOCK_OF_PAST_INVENTIONS* and *CENTRALLY_TARGETED_R&D* to test Hypothesis 4. We therefore estimate the following equation:

$$\begin{aligned} INV\_RATE_{it} = f(&STOCK\_OF\_PAST\_INVENTIONS_{it},\\ &STOCK\_OF\_PAST\_INVENTIONS_{it}\\ &\times CENTRALLY\_TARGETED\_R\&D_{it}, controls). \end{aligned} \qquad (2)$$

To control for omitted variables at the individual level, we also employ a survival fixed-effects estimation, stratified across individual inventors, and remove dummy variable coefficients from the partial likelihood function (Allison 1996). The estimation produces an approach similar to the conditional maximum likelihood for logistic regressions. Allison (2002) shows that this estimation produces approximately unbiased estimates for a wide variety of conditions, which makes it preferable to a simpler dummy variable model. To correct for intragroup correlations across errors, we compute robust standard errors for all specifications.

To test Hypotheses 2 and 5 (regarding the probability that any invention is a breakthrough), we estimate a second equation that employs a dichotomous dependent variable, equal to 1 if invention j, generated by inventor i at time t, is a breakthrough (0 otherwise):

$$\begin{aligned} BKT\_PROB_{it} = f(&STOCK\_OF\_PAST\_INVENTIONS_{it},\\ &STOCK\_OF\_PAST\_INVENTIONS_{it}\\ &\times CENTRALLY\_TARGETED\_R\&D_{it}, controls). \end{aligned} \qquad (3)$$

We use a linear regression model rather than a logistic (or probit) model for three reasons. First, a linear probability model provides a direct estimate of the interaction between the stock of past invention and the targeted nature of R&D. Second, including fixed effects

Table 1 Definitions of the Variables Used in This Study

Variable	Definition
BREAKTHROUGH_INVENTION	Dummy that takes a value of 1 if the patent is in the top 5% of the value distribution of patents invented in the same year (in terms of application date) and technological ISI-INPI-OST class. The robustness check uses the top 2% definition. *Source*: EPO database.
STOCK_OF_PAST_INVENTIONS	Number of patented inventions accumulated until time t. *Source*: EPO database.
CENTRALLY_TARGETED_R&D	The variable takes a value of 1 if the invention was the main achievement or a by-product of a research project whose target was defined ex ante by the firm. It takes a value of 0 in all other cases. For non-PatVal-EU patents, we use the inventor's average of the above dichotomous variable. *Source*: PatVal-EU.
TECH_DIVERSITY	1 − the Herfindahl index of patent concentration, within the 129 IPC3 classes, at time t. It takes a value of 0 when the number of accumulated patents is zero. *Source*: EPO database.
INVENTOR_AGE	Age of the inventor at time t. *Source*: PatVal-EU.
MOBILITY	Number of times the inventor has changed employers. *Source*: PatVal-EU.
SMALL_FIRM_DUMMY	Dummy that takes a value of 1 if the inventor works for a firm with less than 100 employees. *Source*: PatVal-EU.
MEDIUM_FIRM_DUMMY	Dummy that takes a value of 1 if the inventor works for a firm with more than 100 and fewer than 250 employees. *Source*: PatVal-EU.
LARGE_FIRM_DUMMY	Dummy that takes a value of 1 if the inventor works for a firm with more than 250 employees. *Source*: PatVal-EU.
SOCIAL_DIVERSITY	Number of different coinventors divided by the total number of collaborations. It takes a value of 0 when the number of patents is zero. *Source*: EPO database.
YEAR_DUMMY	Dummies for 1978–1999. *Source*: EPO database.
TECHNOLOGICAL_CLASS_DUMMY	Dummies for ISI-INPI-OST classes. *Source*: EPO database.

in a linear probability model does not imply the exclusion of any observation. Third, the potential bias of the linear probability model is greatly reduced or even null (Horrace and Oaxaca 2006), because the predicted probabilities lie between 0 and 1.

Hypotheses 3 and 6 refer to the rate of breakthroughs. We employ Cox regression models with the inventor as the unit of the analysis. Unlike Model 3, the "failure" event is a breakthrough rather than a generic invention. We adjust the standard errors for intragroup correlation and also perform a fixed-effects Cox regression. The estimated model is as follows:

$$\begin{aligned} BKT\_RATE_{it} = f(&STOCK\_OF\_PAST\_INVENTIONS_{it},\\ &STOCK\_OF\_PAST\_INVENTIONS_{it}\\ &\times CENTRALLY\_TARGETED\_R\&D_{it},\ controls). \end{aligned} \quad (4)$$

Results

Table 2 provides the descriptive statistics for the main variables, and Table 3 summarizes the pairwise

Table 2 Descriptive Statistics

Variable	No. of obs.	Mean	SD	Min	Max
		Inventor level			
BREAKTHROUGH_INVENTION (at spell t)	40,149	0.051	0.220	0	1
INVENTION (at spell t)	40,149	0.872	0.334	0	1
STOCK_OF_PAST_INVENTIONS	40,149	12.494	24.721	0	306
CENTRALLY_TARGETED_R&D	40,149	0.653	0.455	0	1
TECHNOLOGICAL_DIVERSITY	40,149	0.225	0.265	0	0.895
INVENTOR_AGE	40,149	46.008	9.180	18	82
MOBILITY	40,149	0.309	0.515	0	2
SOCIAL_DIVERSITY	40,149	0.436	0.337	0	1
MEDIUM_FIRM_DUMMY	40,149	0.067	0.250	0	1
SMALL_FIRM_DUMMY	40,149	0.086	0.280	0	1
		Invention level			
BREAKTHROUGH_INVENTION	35,005	0.059	0.235	0	1
STOCK_OF_PAST_INVENTIONS	35,005	13.330	25.974	0	305
CENTRALLY_TARGETED_R&D	35,005	0.665	0.449	0	1
TECHNOLOGICAL_DIVERSITY	35,005	0.232	0.266	0	0.895
INVENTOR_AGE	35,005	45.467	8.997	18	80
MOBILITY	35,005	0.276	0.481	0	2
SOCIAL_DIVERSITY	35,005	0.442	0.331	0	1
MEDIUM_FIRM_DUMMY	35,005	0.061	0.240	0	1
SMALL_FIRM_DUMMY	35,005	0.073	0.261	0	1

Table 3 Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10
					Inventor level					
1 *BREAKTHROUGH_INVENTION* (at spell *t*)	1.000									
2 *INVENTION* (at spell *t*)	0.089***	1.000								
3 Log *STOCK_OF_PAST_INVENTIONS*	0.009	0.065***	1.000							
4 *CENTRALLY_TARGETED_R&D*	0.024***	0.076***	0.170***	1.000						
5 *TECH_DIVERSITY*	0.006	0.073***	0.488***	0.002	1.000					
6 Log *INVENTOR_AGE*	−0.036***	−0.148***	0.281***	−0.145***	0.249***	1.000				
7 Log *MOBILITY*	−0.026***	−0.152***	−0.183***	−0.058***	−0.072***	0.020***	1.000			
8 *SOCIAL_DIVERSITY*	0.001	0.042***	0.168***	0.037***	0.250***	0.055***	−0.058***	1.000		
9 *MEDIUM_FIRM_DUMMY*	−0.027***	−0.059***	−0.130***	−0.082***	−0.077***	0.031***	0.123***	−0.061***	1.000	
10 *SMALL_FIRM_DUMMY*	−0.017***	−0.114***	−0.160***	−0.116***	−0.072***	0.083***	0.194***	−0.129***	−0.082***	1.000
					Invention level					
1 *BREAKTHROUGH_INVENTION*	1.000									
2 Log *STOCK_OF_PAST_INVENTIONS*	0.003	1.000								
3 *CENTRALLY_TARGETED_R&D*	0.019***	0.170***	1.000							
4 *TECH_DIVERSITY*	0.000	0.476***	−0.020***	1.000						
5 Log *INVENTOR_AGE*	−0.025***	0.310***	−0.135***	0.280***	1.000					
6 Log *MOBILITY*	−0.014*	−0.179***	−0.052***	−0.052***	0.012*	1.000				
7 *SOCIAL_DIVERSITY*	−0.004	0.145***	0.022***	0.240***	0.068***	−0.044***	1.000			
8 *MEDIUM_FIRM_DUMMY*	−0.024***	−0.131***	−0.082***	−0.071***	0.025***	0.122***	−0.062***	1.000		
9 *SMALL_FIRM_DUMMY*	−0.008	−0.152***	−0.107***	−0.056***	0.071***	0.170***	−0.111***	−0.072***	1.000	

*$p < 0.10$; ***$p < 0.01$.

correlations among the variables. The large number of observations in our sample reduces concerns about multicollinearity.

Table 4 provides the estimated results of the three equations. All regressions employ inventor fixed effects. Specification 1 includes only the stock of past inventions, in addition to the control variables, and tests Hypotheses 1–3. Specification 2 includes information about centrally targeted R&D and its interaction with the stock of past inventions to test Hypotheses 4–6. In this second specification, we restrict the analysis to the sample of nonmobile inventors—that is, inventors who do not change employers during their career. This restriction actually extends our measure of targeted R&D (which pertains to the surveyed projects) to other projects pursued by the inventor within the same organization. This conservative decision reduces the number of observations compared with specification 1. Clearly, the variables for inventors' mobility and types of organizations cannot be estimated. In a robustness check, we use the sample of observations that includes mobile inventors but limit the patents to those applied for during the time considered by the survey (e.g., after 1993), with no relevant changes in the results.

Our key explanatory variable, *STOCK_OF_PAST_INVENTIONS*, shows a positive effect on the rate of invention (*INV_RATE*), and the correlation is statistically significant at the 1% level, which provides support for Hypothesis 1. In particular, a 1% increase in the stock of past inventions produces a 1.62% increase in the inventive rate (specification 1.1). In support of Hypothesis 2, the *STOCK_OF_PAST_INVENTIONS* is negatively correlated with the probability that an invention is a breakthrough (*PROB_BKT*). A 1% increase in the stock of recent patents decreases the likelihood of a single invention being a breakthrough by 0.02 percentage points (specification 1.2). To determine the rate of generation of breakthroughs, specification 1.3 in Table 4 shows which of the two effects prevails. The *STOCK_OF_PAST_INVENTIONS* exerts a positive and statistically significant effect on the rate of breakthroughs (*BKT_RATE*); a 1% increase in the stock of past inventions increases the breakthrough rate by approximately 1.37%. This finding supports Hypothesis 3A, because the positive effect of the stock of past inventions on the invention rate is stronger than the negative effect on the probability of any invention being a breakthrough.

Our theory also posits that the nature of the research projects in which the inventors are involved moderates the effect of successful inventive experience. In specification 2, we include the *CENTRALLY_TARGETED_R&D* variable and its interaction with

Table 4 Inventive Rate, Probability of Breakthrough, and Breakthrough Rate (Fixed-Effects Estimations)

	Specification					
	1 (Stock of past inventions)			2 (Stock of past inventions and targeted R&D)		
Variable	1.1 (*INV_RATE*)	1.2 (*PROB_BKT*)	1.3 (*BKT_RATE*)	2.1 (*INV_RATE*)	2.2 (*PROB_BKT*)	2.3 (*BKT_RATE*)
Log *STOCK_OF_PAST_INVENTIONS*	1.622***	−0.020***	1.372***	1.604***	−0.011	1.555***
	(0.049)	(0.005)	(0.100)	(0.058)	(0.007)	(0.139)
(Log *STOCK_OF_PAST_INVENTIONS*) × *CENTRALLY_TARGETED_R&D*				−0.096**	−0.009*	−0.245**
				(0.042)	(0.006)	(0.105)
CENTRALLY_TARGETED_R&D				0.402***	−0.018	−0.060
				(0.151)	(0.030)	(0.650)
TECH_DIVERSITY	−0.492***	0.002	−0.634***	−0.453***	−0.007	−0.749***
	(0.080)	(0.011)	(0.217)	(0.090)	(0.014)	(0.250)
Log *INVENTOR_AGE*	−7.709***	0.171	−3.579	−7.876***	0.137	−5.172*
	(1.002)	(0.113)	(2.295)	(1.188)	(0.136)	(2.674)
SOCIAL_DIVERSITY	1.076***	0.001	1.261***	1.074***	0.001	1.360***
	(0.038)	(0.005)	(0.122)	(0.043)	(0.007)	(0.144)
Log *MOBILITY*	−0.207**	−0.005	−0.057			
	(0.083)	(0.015)	(0.253)			
MEDIUM_FIRM_DUMMY	−0.127	−0.003	0.010			
	(0.114)	(0.022)	(0.355)			
SMALL_FIRM_DUMMY	−0.113	0.027	0.088			
	(0.103)	(0.021)	(0.285)			
Year dummies included?	YES	YES	YES	YES	YES	YES
Observations	40,149	35,005	40,149	28,786	25,878	28,786
Log likelihood	−61,501.040		−3,813.118	−49,154.560		−3,110.067
χ^2	3,594.366		468.542	2,591.185		364.724
R^2		0.004			0.004	

Notes. Standard errors are clustered by inventor. Specifications 1.1 and 2.1 refer to the inventive rate (*INV_RATE*) and feature Cox regression analyses at the inventor level. Specifications 1.2 and 2.2 refer to the probability of an invention being a breakthrough (*PROB_BKT*) and use a linear probability model at the invention level. Specifications 1.3 and 2.3 show the rate of breakthrough generation (*BKT_RATE*) using Cox regressions at the inventor level.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

STOCK_OF_PAST_INVENTIONS. The estimated results for *STOCK_OF_PAST_INVENTIONS* confirm the positive effect of successful inventive experience on both the inventive rate (*INV_RATE*) and the breakthrough rate (*BKT_RATE*) (see specifications 2.1 and 2.3, respectively, in Table 4), as well as the negative correlation with the probability of producing a breakthrough (specification 2.2 in Table 4), although this effect is statistically not significant.

However, the effect of the *STOCK_OF_PAST_INVENTIONS* is negatively moderated by inventors being employed in *CENTRALLY_TARGETED_R&D* projects. The sign of the interacted term is negative and statistically significant at the 1% level on the rate of invention generation (*INV_RATE*): the overall effect of prior inventive output on the rate at which inventors produce inventions remains positive, but its magnitude decreases when they are employed in R&D projects whose goals are centrally established ex ante. This finding provides support for Hypothesis 4.

Hypothesis 5 is also confirmed. When established inventors are employed in targeted R&D projects, the probability that any invention is a breakthrough decreases (specification 2.2). As a result, consistent with Hypothesis 6, when established inventors are allocated to a centrally targeted R&D, the breakthrough rate, although positive overall, decreases (specification 2.3).

The signs of the other covariates mostly conform to our expectations and are consistent across specifications. Inventors employed in *CENTRALLY_TARGETED_R&D* projects display a higher inventive rate, and there are no statistically significant effects on the probability that an invention is a breakthrough or on the rate of generation of breakthroughs. Mobile inventors show a lower inventive rate, but there is no statistically significant effect on either the probability of producing a breakthrough or the rate at which breakthroughs are produced. The *TECH_DIVERSITY* variable correlates negatively with the inventive rate and the rate of breakthrough generation, whereas the effect on the probability of an invention being a breakthrough is not statistically significant.

Therefore, more specialized inventors are more productive; specialization prevails over the benefits that the breadth of experience across different fields may give them in recombining different types and sources of ideas. The variable *SOCIAL_DIVERSITY* has a positive and statistically significant effect on both the inventive and breakthrough rates, but it has no impact on the probability that an invention is extremely valuable. The *INVENTOR_AGE* of the inventors exerts a significantly negative effect on inventions' productivity and a positive, although not statistically significant, effect on the probability of any invention being a breakthrough. The overall effect remains negative on the rate of breakthrough generation (specifications 1.3 and 2.3 in Table 4).

Robustness Checks

A limitation of our empirical test is that the measure of centrally targeted R&D is available for the surveyed patents only. We therefore assume that the R&D projects in the PatVal-EU survey are representative of all R&D projects undertaken by the same inventor in the same organization, and we use the average of the variable for unsurveyed projects by each inventor. In support of this approach, we note that the PatVal-EU survey randomly picked patents from the entire patent population, which implies that the population characteristics of the R&D projects should be well represented by the random sample. Furthermore, the reliability of our measure increases as the number of inventions realized by each inventor decreases; at the extreme, if an inventor had produced only the inventions surveyed in PatVal-EU survey, our measure would be totally reliable. In truth, most inventors in the sample produce only one or two inventions throughout their careers.

However, to exclude the possibility that our findings are driven by a misuse of the variable measuring R&D centralization, we perform two robustness checks. First, to relax the assumption that the type of R&D project reported in the survey is representative of all other projects developed earlier by the same inventor in the same organization, we use the sample of patents applied for during the time period considered by the survey only (i.e., those applied for after 1993) and replicate the regressions in Table 4. In this case, we also include mobile inventors and control for mobility. For this sample, the entry date of the survival analysis is the date of the last invention before 1993 for inventors that had already patented before this date; for those without patents before 1993, the entry date is the year in which they arguably started working. Our estimated results (available from the authors upon request) are fully consistent with those in Table 4, suggesting that the assumption about the use of the targeted R&D indicator does not produce biases in the estimated results.

Second, we provide evidence that the potential measurement error associated with our assumption is marginal, because managerial control over the R&D target is largely path dependent and consistent across a firm's projects. For a smaller sample of inventors for which we have multiple surveyed inventions, we estimate two linear probability models. The dependent variable is whether their latest patent is the result of a *CENTRALLY_TARGETED_R&D* project. The covariates common to both specifications are the inventor's age, the number of past inventions, mobility, technological and social diversity, the type of employer organization, and the technological and year dummies. One specification also uses a variable that indicates whether the previous patent was the outcome of a *CENTRALLY_TARGETED_R&D* project. Table 5 presents the estimated results of both regressions.

The linear probability model in specification 1.1 in Table 5 explains only 13% of the variance in the dependent variable. When we add information about the nature of the inventor's previous project, whether centrally targeted or not, we can explain 27% of this variance (specification 1.2). The added variable is also the most important (in terms of magnitude) and statistically significant predictor of whether inventors are employed in similar subsequent projects.

An additional concern pertains to alternative explanations consistent with our findings, such as the positive correlation between the inventors' stock of past inventions and the inventive rate. It might be that successful inventors receive more resources, which increases their productivity. To rule out this potential explanation, we use information drawn from the PatVal-EU survey about the monetary resources (*MONETARY_COST*) allocated to the specific R&D project in which the inventor has been employed, and that led to the surveyed patent. We then regress this variable on the past stock of inventions and control for individual fixed effects. Specification 1.3 in Table 5 shows that the relationship between inventors' past inventive output and the resources they receive is statistically not significant, which works against the interpretation that more productive inventors receive greater endowments that in turn increase their productivity.

We also check whether our results are robust to the inclusion of age and mobility as dummy variables. We define the age of the inventors by using three dummy variables: one for inventors younger than 40 years old, another for inventors between 40 and 50 years old, and the last one for inventors older than 50 years old. *MOBILITY* equals 1 if the inventor has changed employers before the date of the focal patent, and 0 otherwise. The estimates (see Table 6) confirm our results.

Furthermore, we check whether established inventors, with their more exploitative search mode, tend to draw from a distribution with both lower expected value and

Table 5 Ordinary Least Squares Regressions: Persistence of Centrally Targeted Research for Inventors and Monetary Resources

	Specification		
	1.1	1.2	1.3
Variable	(*CENTRALLY_ TARGETED_R&D*)[a]	(*CENTRALLY_ TARGETED_R&D*)[a]	(Log *MONETARY_ COST*)
CENTRALLY_TARGETED_R&D (in previous project)		0.404*** (0.031)	
Log *STOCK_OF_PAST_ INVENTIONS*	0.027 (0.017)	−0.001 (0.014)	0.246 (0.231)
TECH_DIVERSITY	0.007 (0.058)	0.045 (0.048)	−0.118 (0.523)
Log *INVENTOR_AGE*	−0.234*** (0.078)	−0.132* (0.070)	−2.589 (12.827)
SOCIAL_DIVERSITY	−0.014 (0.051)	0.005 (0.042)	0.614 (0.873)
Log *MOBILITY*	0.035 (0.044)	0.043 (0.037)	−0.655*** (0.249)
MEDIUM_FIRM_DUMMY	−0.061 (0.063)	−0.059 (0.053)	0.097 (1.123)
SMALL_FIRM_DUMMY	−0.104 (0.064)	−0.079* (0.048)	−9.014*** (1.689)
Year dummies included?	YES	YES	YES
Technology dummies included?	YES	YES	YES
Inventor dummies included?	NO	NO	YES
Observations	1,129	1,129	4,269
R^2	0.128	0.273	0.116

Note. Standard errors are clustered by inventor.
[a]Specifications denote dependent variables in the current project.
$^{*}p < 0.10$; $^{***}p < 0.01$.

lower variance, especially if they get allocated to a centrally targeted R&D project. Thus we perform two regressions. With a first Poisson regression, we aim to capture the impact of experience on the expected value of the inventions; the dependent variable is the number of forward citations received by each patent in the sample, after controlling for year and technology dummies. Then, in an ordinary least squares regression, we seek to determine the impact of experience on the variance of the patent value. The dependent variable in this case is the (log) square of residuals of the first regression. The estimated results (available from the authors upon request) indicate that the stock of past inventions, both per se and in interaction with firm control over the R&D goal, correlates negatively with the expected value of the inventions and their variance.

Finally, we check whether our results are robust to different thresholds for defining breakthrough inventions. In addition to the top 5% of the distribution of patents applied in the same year and technological class, we employ a top 2% cutoff for inventions in the same value distribution. We find no significant changes in the estimated results.

Discussion and Conclusions

This study analyzes whether the individual stock of past inventions affects the rate of breakthrough generation and how firms' control over R&D targets moderates this relationship. On average, inventors with a stronger record of inventions display a higher inventive rate and thus are more likely to achieve a breakthrough in a given time interval. However, the positive impact of prior output decreases when organizations allocate inventors to R&D projects with a centrally defined target, rather than allowing them to pursue independent research avenues. Our study in turn contributes to extant literature in several ways.

First, it contributes to organization research by focusing on invention as the outcome of multilevel antecedents that interact. Despite some recent contributions treating invention as a multilevel phenomenon, there is still little empirical work that describes how factors from different organizational levels interact to determine the quantity and type of resulting inventions (e.g., Gupta et al. 2007). Our study shows that the organizational context in which corporate inventors are embedded shapes their behavior and performance. Specifically, setting central targets for R&D negatively moderates the

Table 6 Inventive Rate, Probability of Breakthrough, and Breakthrough Rate with Dummies for Age and Mobility (Fixed-Effects Estimations)

	Specification					
	1 (Stock of past inventions)			2 (Stock of past inventions and targeted R&D)		
Variable	1.1 (*INV_RATE*)	1.2 (*PROB_BKT*)	1.3 (*BKT_RATE*)	2.1 (*INV_RATE*)	2.2 (*PROB_BKT*)	2.3 (*BKT_RATE*)
Log *STOCK_OF_PAST_INVENTIONS*	1.561*** (0.049)	−0.019*** (0.005)	1.337*** (0.099)	1.571*** (0.055)	−0.010 (0.007)	1.519*** (0.139)
Log *STOCK_OF_PAST_INVENTIONS* × *CENTRALLY_TARGETED_R&D*				−0.139*** (0.041)	−0.009* (0.005)	−0.266** (0.103)
CENTRALLY_TARGETED_R&D				0.508*** (0.149)	−0.019 (0.030)	−0.002 (0.644)
TECH_DIVERSITY	−0.536*** (0.078)	0.002 (0.011)	−0.647*** (0.216)	−0.515*** (0.087)	−0.006 (0.013)	−0.760*** (0.247)
INVENTOR_AGE_40–50 (dummy)	−0.049 (0.044)	0.002 (0.007)	0.037 (0.122)	−0.037 (0.051)	0.004 (0.009)	0.069 (0.138)
INVENTOR_AGE_over50 (dummy)	0.114* (0.064)	−0.008 (0.011)	0.025 (0.200)	0.180** (0.074)	−0.002 (0.012)	0.187 (0.221)
SOCIAL_DIVERSITY	1.046*** (0.037)	0.001 (0.005)	1.243*** (0.122)	1.039*** (0.042)	0.002 (0.006)	1.337*** (0.144)
MOBILITY (dummy)	−0.196*** (0.069)	0.003 (0.012)	−0.014 (0.233)			
MEDIUM_FIRM_DUMMY	−0.124 (0.110)	−0.004 (0.022)	0.059 (0.362)			
SMALL_FIRM_DUMMY	−0.116 (0.096)	0.023 (0.020)	0.089 (0.259)			
Year dummies included?	YES	YES	YES	YES	YES	YES
Observations	40,149	35,005	40,149	28,786	35,005	28,786
Log likelihood	−61,605.934		−3,814.566	−49,225.994		−3,111.938
χ^2	3,814.977		461.780	2,754.566		351.877
R^2		0.004			0.004	

Notes. Standard errors are clustered by inventor. Specifications 1.1 and 2.1 refer to the innovative rate (*INV_RATE*) and feature Cox regression analyses at the inventor level. Specifications 1.2 and 2.2 refer to the probability of an invention being a breakthrough (*PROB_BKT*) and use a linear probability model at the invention level. Specifications 1.3 and 2.3 show the rate of breakthrough generation (*BKT_RATE*) using Cox regressions at the inventor level.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

impact of the inventors' records of past inventions on both the inventive rate and the probability of any invention being a breakthrough and, as a result, on the rate of generation of breakthroughs.

Second, this study provides insights into how individual skills may shape firm R&D outcomes (e.g., Lacetera et al. 2004). Firm inventive performance is determined by the amount of resources dedicated to R&D. However, designing an R&D strategy means choosing not only how much to invest but also how and whom to invest in Cabral (2000). In this respect, a key decision is the allocation of resources to inventors endowed with different abilities. We show that the way resources are allocated may condition the intensity and the direction of R&D activity.

Third, this study relates to literature pertaining to the effect of experience on creative output. Previous contributions have focused on the generation of novel ideas, defined by the extent to which they diverge from past solutions (e.g., Audia and Goncalo 2007, Gino et al. 2010). In relation to these contributions, our study shifts the focus of analysis to address breakthrough inventions as the outcome of interest, defined by their impact and recognition in the technological community rather than their novelty. Furthermore, we investigate inventors' rates of breakthrough generation, rather than the probability of any single invention being a breakthrough (which, together with the inventive rate, still is one of the components of the breakthrough rate). With our different focus, our results complement previous findings. For example, prior research concludes that inventions by more prolific inventors are less likely to be novel (e.g., Audia and Goncalo 2007). However, when inventors reapply their direct task experience in teams, controlling for any reputation effect, experience leads to more novel inventions (Gino et al. 2010). We show that more established inventors also display a higher breakthrough rate because of their higher inventive rate. It would be interesting to explore whether our finding also holds for the rate of production of novel ideas to determine whether and in what situations allocating resources to prolific inventors might counteract firm technological obsolescence.

Fourth and finally, this study contributes to research aimed at understanding the determinants of breakthroughs (e.g., Ahuja and Lampert 2001, Girotra et al. 2010, Singh and Fleming 2010). We argue the rate of breakthroughs depends on factors that affect both the probability that an invention is a breakthrough and the inventive rate. Moreover, we show that the same factors that hamper the likelihood of any single invention being a breakthrough can enhance the breakthrough rate. In this respect, our study contributes to the debate about the relationship between the total number of individual ideas and the value of that person's best ideas (e.g., Dennis 1966, Simonton 1999). In particular, we find evidence that the rate of breakthrough generation is largely influenced by factors that influence the number of ideas, rather than their value.

This study also has some limitations. One issue is that the use of archival data prevents the determination of causality. Some of the controls that we use (e.g., type of employer, inventor age), as well as some of our robustness checks, partially address this concern. Yet we cannot guarantee that the stock of patents produced in the past increases the ability to generate new ideas, rather than just the ability to produce "patentable" inventions. Nevertheless, unreported analyses (available from the authors upon request) show that the patentability of inventions produced by established inventors is not significantly greater than the patentability of those produced by brand-new inventors.[8] In addition, because we lack data about the resources spent to achieve a breakthrough, we cannot make definitive statements about efficiency. To overcome these limitations, additional research should adopt an experimental approach that treats experience in creative tasks exogenously, as Gino et al. (2010) do at the team level.

Furthermore, our definition (and measure) of breakthroughs may sound deterministic. However, we build on a consolidated stream of literature that defines breakthroughs as inventions lying on the right-hand tail of the invention value distribution and that measures breakthroughs as a fixed percentage of extremely valuable inventions (e.g., Ahuja and Lampert 2001, Phene et al. 2005, Singh and Fleming 2010). This definition captures the idea that, because of the skewed distribution of inventions, only a few are ever really valuable for companies.

Finally, by construction, our sample does not include any R&D project that has not produced (at least) one patented invention. Therefore, our findings should be interpreted conditional on the project having produced at least one patented invention. This issue appears unlikely to cause any major problems in our study, though, as the set of controls that we introduce and the estimation method are intended to lessen, if not solve, this potential issue.

Despite these limitations, our study offers notable managerial implications. The first implication pertains to the optimal allocation of resources between established and brand-new inventors. Our theory and empirical findings both suggest that firms should rely on brand-new inventors when trying to pick *one* breakthrough out of a sample of ideas or inventions. For example, companies increasingly launch competitions, open to external participants, for inventive ideas, with the best idea eventually being financed and developed (e.g., Jeppesen and Lakhani 2010). Our findings indicate that a company's best strategy may be to select ideas produced by brand-new inventors. In contrast, in more traditional internal R&D processes, firms do not just consider one breakthrough; rather, they try to enhance the number of breakthroughs that inventors produce in any given time interval. In this case, the most effective strategy for increasing the rate of breakthroughs is to rely on established inventors. On average, the greater inventive rate of established inventors overcomes the higher value of inventions generated by brand-new inventors. However, when companies assign inventors to centrally targeted R&D projects, the productivity of established inventors diminishes, along with their abilities to rapidly generate a breakthrough. Our argument applies to the process leading to breakthrough inventions, which do not necessarily correspond to novel (or divergent) inventions; that is, established inventors might increase the rate of breakthrough generation by building on consolidated trajectories, rather than by exploring novel paths. Companies could try to resolve the trade-off between the higher inventive rate of established inventors and the higher impact of inventions produced by brand-new inventors by designing R&D teams composed of both types of inventors. However, further analysis is required to determine the extent to which mixed R&D teams actually represent an optimal solution.

Our research also revamps insights into how to manage and organize the invention process, particularly for breakthrough inventions. The results highlight the importance of factors that influence the rate of breakthrough generation by affecting the rate of invention, not just the value of single inventions. Overall, it seems that any factor influences the rate of breakthrough *mainly* through the inventive rate rather than through the probability of any invention being a breakthrough. For example, social diversity has a positive impact on the inventive rate, probably because it provides inventors with access to a broader set of knowledge and skills; this translates into a higher breakthrough rate as well. In this respect, a further implication of our study is that firms should seriously consider invention strategies based on parallel research projects, rather than betting all their resources on one or just a few predetermined options (Nelson 1961). The extent to which organizations should exploit such order statistic effects to achieve breakthroughs is beyond the scope of this research. We leave it as an intriguing question for further studies.

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Appendix

PatVal-EU Sampling Procedure

For a complete description of the PatVal-EU sampling procedure, see Giuri et al. (2007); this appendix provides a brief summary. The population of patents from which we selected our target sample consists of all EPO-granted patents with priority between 1993 and 1997. We first assigned these patents to countries according to the location of the first inventor listed. At the time of the survey, patents from France, Germany, Italy, the Netherlands, Spain, and the United Kingdom represented 42.2% of total EPO patents by country of first inventor, and 88.0% of the EPO patents indicated a country of the first inventor from among the EU-15. The share of questionnaires submitted to inventors in each country reflects the country share of patents in the overall population.[9] To address the highly skewed distribution of patent values, we oversampled "important" patents, or patents that had been opposed or received at least one citation, which produced approximately 15% additional observations for these patents at the aggregate EU-6 level (43.2%), compared with the initial population (28.5%).

Our goal was to obtain 10,000 usable questionnaires from the inventors, with target numbers of 3,500 from Germany, 1,750 from France, 1,750 from the United Kingdom, 1,250 from Italy, 1,250 from the Netherlands, and 500 from Spain. The response rate in the pilot surveys determined the number of questionnaires to send to the inventors in each country to obtain returns close to these targets. In the end, we selected a stratified sample of 27,531 EPO patents comprising all opposed or cited patents from 1993 to 1997, as well as a random sample of uncited and unopposed patents from the same period. The response rate was 32.75%.

Identifying Inventors and Coinventors

We performed the procedure[10] to provide a unique identifier for PatVal-EU inventors and their coinventors and to match inventors with their patents on the EPOLINE patent database of the European Patent Office that covers more than 1,260,000 patent files with application dates ranging from June 1978 to July 2002. We performed the identification using several criteria (i.e., inventor's last name, inventor's first name and part of it, street and/or city address, IPC code, name of the patent applicant) that we combined into 38 different subsets, each consisting of three or four criteria. The procedure matched information from the PatVal-EU patents with data displayed in the EPOLINE patents. The query was carried out using MYSQL version 4. The MYSQL control center was applied as the SQL interface. All Java classes were constructed with Eclipse. The search resulted in 38 data sets containing potential matches, each with an expected match quality, assigned according to the specific subset of criteria employed. We merged the 38 data sets into one master database and checked the records manually to remove duplicate patent applications and wrong matches.

Endnotes

[1]Breakthrough inventions do not necessarily correspond to highly novel inventions that diverge from existing solutions. Very novel ideas might not be technologically or economically valuable; some incremental solutions can turn out to be extremely valuable.

[2]Because the breakthrough rate #Br (i.e., the expected number of breakthroughs in any time unit) is equal to the inventive rate #Inn (i.e., the number of inventions in any time unit) multiplied by the likelihood of any invention being a breakthrough Prob_{Br}, the impact of any variable X on the (log of) rate of breakthrough is equal to $\partial \log \#\text{Br}/\partial X = \partial \log \#\text{Inn}/\partial X + \partial \log \text{Prob}_{\text{Br}}/\partial X$.

[3]We obtain the 30 ISI-INPI-OST technologies, defined by the Fraunhofer Institute for Systems and Innovation Research (ISI), Institut National de la Propriété Industrielle (INPI), and Observatoire des Sciences and des Techniques (OST), by aggregating the IPC codes. See Giuri et al. (2007) for a detailed description of the use of this classification with PatVal-EU data.

[4]We do not have information about inventive failures or unpatented inventions. However, by controlling for inventor age and professional age (i.e., the number of years elapsed since the inventor earned the highest education degree and the number of years of invention potential) in robustness checks, we can compare inventors who, given their age and professional experience, produced different numbers of patents over the course of their careers and therefore represent different failure rates. These results are available from the authors upon request.

[5]See http://www.wipo.int/classifications/ipc/en/ (accessed November 25, 2013).

[6]Levin and Stephan (1991) and Hall et al. (2007) examine the relationship between age and scientific productivity to solve the complicated issue of disentangling age effects from cohort effects. Because our aim is to estimate the net effect of inventive experience, after we control for other age-related experience, we follow the identification method adopted by Levin and Stephan (1991) so that the cohort effects are captured by individual fixed effects. Similarly, we do not control for the stage of the inventors' career (e.g., the number of years spent in the job), because this effect would be already captured by the year and inventors' fixed effects.

[7]A Poisson model with age and year dummies would control for temporal changes in productivity across the overall time

span of the analysis, but it cannot control for the possibility that an inventor's productivity changes within each period.

[8]In this robustness check, we measure the patentability of an invention as (a) the time lag between the application and the grant date and (b) the number of different countries in which the invention is protected by a patent. The results indicate that inventors' experience does not correlate with any of these measures.

[9]We also undersampled the share of German and French patents and oversampled patents from other countries to obtain sufficiently large samples for all countries.

[10]This search was conducted in collaboration with Karin Hoisl (University of Munich).

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