THE VALUE OF PATENTED INVENTIONS AT THE EXTENSIVE AND INTENSIVE MARGIN

Alfonso Gambardella
Bocconi University, Milan
alfonso.gambardella@unibocconi.it

Dietmar Harhoff
Ludwig-Maximilians-Universität (LMU) München
harhoff@lmu.de

Bart Verspagen
Maastricht University
b.verspagen@maastrichtuniversity.nl

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Abstract

By using survey data on a large sample of European patents, this paper estimates the determinants of the value of patent portfolios. We separate the impacts of the firm investments in resources and the inventor characteristics on the number vs. the average value of the patented inventions ("extensive" vs. "intensive" margin). We find that the extensive margin is sizable. Moreover, not only the investment in resources, but also inventor characteristics like past citations or education, affect the value of patent portfolio mainly through the former than the latter. Our findings suggest that, while in downstream innovation development firms may converge on fewer projects, the inherent features of upstream research imply that the economic value of the inventions rests to a good extent on the breadth of the inventions produced. We also find that the extensive margin is more important in complex than discrete industries, and that the lack of scientific knowledge or the originality of a research domain produce value by raising the number of patents in the portfolio rather than focussing on their average value.

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1. INTRODUCTION

Since the pioneering work of Teece (1986) and Rosenberg (1982), we know that the size and quality of downstream assets explain a good deal of the value created during the development, production and commercialization of innovations. However, a better understanding of the factors that affect the economic value of the earlier stages has become critical as well. For example, the rise of markets for technology, or the growing importance of ideas for future innovations and new products, suggest that firms increasingly want to assess the value of the "inventions." Within firms, the growing attention to the performance of research labs calls for a better understanding of the economic value of their outcomes, and the mechanisms that produce such values.

This paper addresses these issues by estimating the determinants of the economic value of a large sample of patents held by firms. In most industries patented inventions need to be developed, produced or commercialized, and thus, they are typical outcomes of the upstream part of the research process. Not all the inventions are patented. However, not only do patents cover a relevant share of invention output, they are also an important asset of the firm. Moreover, in markets for technology, patents are either the object of the transaction, or an important component of it. At the same time, companies use patents strategically to strengthen protection. Our analysis encompasses this point as well, and we study the determinants of the value of patents taking into account that they can also be used for this purpose. To fix our terminology, in this paper we speak of inventions to stress our focus on the upstream research outcomes, leaving the term innovation for more developed technologies, products or processes.

There is growing interest in the value of patents. An important distinction is between the value of the invention and that of the patent right. For example, the use of patent renewal fees, pioneered by Schankerman and Pakes (1986), only looks at the former, like the studies on the transfer of patent rights (Serrano, 2010). By contrast, citations (Trajtenberg, 1990), or other indicators (like the international coverage of a patent, or whether a patent is opposed or litigated – e.g., Harhoff et al., 2003; Lanjouw and Schankerman, 2004), are more likely to be correlated with the value of the invention. The estimated impacts of the patent or citation stock of the firms and their market value cover both the value of the inventions and the patent rights (e.g, Hall et al., 2005; Bessen, 2009; see also Arora et al., 2008, and Bessen, 2008).

This paper studies the value of the patented inventions as a whole. We dig into the mechanisms that produce valuable patents. Following Hausman et al. (1984), there is a vast literature on the relationships between R&D or other measure of investments on the number of patents at the firm-level. However, there is not much on the relationships between innovation or patent output and the resources, or other factors, invested in the specific project leading to an invention. At the same time, while the literature on indicators

provides insights on the distribution of patent value, it does not address the question of what determines it. Similarly, the main goal of the literature on the relationships between market value and patent counts, or citations, is to estimate the market evaluation of the marginal value of a firm's patents. In the empirical analysis of this paper, we study the impact of a rich set of factors. In particular, the inventors play an important role in the invention process (e.g., Gittelman and Kogut, 2003; Toivanen and Väänänen, 2012). Along with firm and technological factors, ours is one of the few studies that employs inventor's data to study the impact of inventor characteristics on the value of patents. Also, while a structural estimation of the patent premium is beyond the scope of this paper, we control for variables correlated with it.

We focus on the determinants of the economic value of a portfolio of related patents. This is important because the relevant technology is sometimes covered by more than one patent. To be sure, here we do not mean "equivalent" patents, or patent "families", as they are called. Equivalent patents regard the same invention patented in different patent offices around the world. Instead we mean inventions that are complementary from a technical point of view. This is increasingly common, as many firms nowadays apply for different patents covering the different components of an invention. The main question of this paper therefore arises from this perspective. The value of a portfolio of patents can increase either because the number of inventions increases or because of increases in the average value of the inventions in the portfolio. We study the extent to which the value of the portfolio is determined by the former or by the latter, and the factors that affect the "extensive" or the "intensive" margin.

To guide our empirical analysis, a model produces three equations to be estimated – one for the value of a portfolio of inventions as a function of the number of inventions that compose it, the total man-months invested in the portfolio, and other factors; a second equation for the number of inventions as a function of the total man-months and other factors; and a third equation for the man-months invested in the portfolio. The structural parameters of these equations (after instrumenting for the number of inventions and man-months) enable us to study five propositions.

The first proposition regards the limits to the economic value of a single invention. For as much as one can improve a single invention, we predict sharp diminishing returns to this effort. By contrast, value can be enhanced by "breadth," that is by raising the number of inventions that represent the components of a more complex invention. Our model enables us to test the extent to which the value of a portfolio of inventions rises through this extensive margin. Second, we estimate whether, apart from the addition of new inventions, the value of the portfolio increases because of the complementarity across them. Note that these are two different issues. New inventions increase the value of the portfolio because a continuing effort on a single invention exhibit diminishing returns. This does not imply complementarity, which is instead an additional effect produced by the rise in the number of inventions on the value of the portfolio.

Third, we test a natural implications of the previous two statements, to wit that diminishing returns to the single invention, and complementarity across inventions, are more pronounced in complex than discrete industries (chemicals and pharmaceuticals). Fourth, our model shows that any factor, like scientific knowledge, that enhances the probability of producing a successful invention reduces the number of inventions. However, it also enhances the investment of resources in the invention process, which raises value. Fifth, we show that the search for original inventions reduces the probability of success of the single inventions. However, firms try to offset this effect by raising the number of inventions in the portfolio. Thus, while science creates value via greater focus, the opposite is true for more novel inventions.

Our empirical results provide evidence of diminishing returns to the man-months invested in the individual invention on value, and complementarity across inventions. Moreover, both effects are more pronounced in complex vs discrete industries. We also find that the mechanisms by which scientific knowledge and the originality of the invention affect value work as predicted by our model. In general, we find that the effect of our covariates on the value of the patent portfolio comes largely through the number of inventions. We distinguish among three effects: the intensive margin, that is the effect of a covariate on the value of the portfolio given the number of inventions; the extensive margin, that is the effect of the covariate on the number of inventions that then raises proportionally the value of the portfolio; the complementarity effect, that is the additional effect of the covariate on the number of inventions, and then value, produced by the complementarity across the inventions. As a snapshot of our evidence, we estimate that the extensive margin accounts for nearly 50% of the elasticity of the value of a portfolio of inventions with respect to the man-month invested in it; the intensive margin accounts for about 35%; and the rest is the effect of man-months on the number of inventions generated by the complementarity. In sum, the total effect of man-months on value coming through the number of inventions accounts for almost three-fourth of the total impact of man-months on value. We obtain similar results for the past citations of the inventor or her education.

The next section develops our model. Section 3 presents the data. Section 4 presents our empirical results. Section 5 provides a concluding discussion.

2. THEORY

2.1 A Model of the Patent Portfolio Decision

Set-up. We assume the following sequence of decisions when firms start an invention project. They first design the structure of an invention, and the underlying innovation that should arise from it. In particular, they conceive the inventions that compose the innovation, and invest resources in raising the probability

that the inventions will work – that is, that they are technically sound and they will pass the patentability threshold of the patent office. We label this probability *P*, which is therefore the probability that a single invention will be patented. For simplicity, we assume that this probability is the same for all the inventions in the portfolio. The firm then decides that the innovation is composed of *N* inventions, and at this stage, these *N* inventions are patented. We assume that the innovation will not work unless all the component inventions work and pass the patentability threshold. This simplifies matters because we can write the probability that the whole innovation will work, and produce economic returns, as P^N. After the inventions are patented, the firm observes whether the inventions work or not. If they do, the firm invests time H_i, $i = 1, 2, \ldots N$, on each invention in the portfolio to develop it. We assume that the value of the portfolio is $V = K\left(\sum_{i=1}^{N} H_i^{\mu}\right)^{\frac{\alpha}{\mu}}$, where μ measures the returns from investing in the single invention, $\frac{\alpha}{\mu} > 1$ measures the complementarity across them, and *K* accounts for any other factor, not under the control of the firm, that affects *V* (demand, productivity).

We also assume that the cost of developing the innovation is $W\sum_{i=1}^{N} H_i$, where *W* is the unit cost of *H*, and that $P = exp(-Z/Q)$, with $Z, Q > 0$. This expression has a simple interpretation. The probability of success of each invention depends on a random variable distributed according to an exponential distribution. Success occurs whenever this random variable is greater than a threshold *Z*, which implies that the probability of success is the expression above for *P*, with *Q* being the expected value of the random variable. We posit that, apart from H_i and *N*, firms choose *Q*, with costs $C(Q)$ (C_Q, $C_{QQ} > 0$, where subscripts denote derivatives). Thus, firms can choose the distribution of *P*; at the same time, *P* is a function of other factors *Z* not under the control of the firm. We also assume a sequential unfolding of information. In particular, when the firm chooses *Q*, it does not observe *Z*. After choosing *Q*, and before choosing *N*, the firm observes a signal for *Z*. This captures the idea that the background research that leads to setting a distribution for *P*, produces broader information about this distribution. Figure 1 summarizes the sequence of events and the choices of the firm.

The firm optimization problem is

$$\underset{\{H_i\};N;Q}{Max}\, E_{\Omega}\left[K\left(\sum_{i=1}^{N} H_i^{\mu}\right)^{\frac{\alpha}{\mu}} - W\sum_{i=1}^{N} H_i\right] e^{-\frac{ZN}{Q}} - C(Q)$$

FIGURE 1 ABOUT HERE

where Ω denotes the information set available at each step of the optimization process.

Optimal H_i, N, Q. We optimize backward. The first order condition (*foc*) with respect to the generic H_i is

$$\alpha K\left(\sum_{i=1}^{N} H_i^{\mu}\right)^{\frac{\alpha}{\mu}-1} H_i^{\mu-1} = W \tag{1}$$

It is easy to see that if we take the ratio of any two of these *focs* $H_i = H$, $\forall\ i = 1, 2, \ldots N$,. We can then write

$$\alpha K N^{\frac{\alpha}{\mu}-1} H^{\alpha-1} = W \tag{2}$$

and

$$H = \left(\frac{\alpha K}{W}\right)^{\frac{1}{1-\alpha}} N^{\theta-1} \tag{3}$$

where $\theta \equiv \dfrac{\alpha(1-\mu)}{\mu(1-\alpha)}$.

From (2), $W\sum_{i=1}^{N} H_i = WNH = \alpha K N^{\frac{\alpha}{\mu}} H^{\alpha}$. Similarly, $V = KN^{\frac{\alpha}{\mu}} H^{\alpha}$. Replace H in both expressions with (3); the optimization problem becomes

$$\underset{N;Q}{Max}\, E_{\Omega}(1-\alpha)K\left(\frac{\alpha K}{W}\right)^{\frac{\alpha}{1-\alpha}} N^{\theta} e^{-\frac{ZN}{Q}} - C(Q)$$

whose *foc* with respect to N is

$$E_{\Omega}\left(\theta N^{\theta-1} e^{-\frac{ZN}{Q}} - N^{\theta} e^{-\frac{ZN}{Q}} \frac{Z}{Q}\right) = 0$$

or $N = \theta Q \bar{Y}_S$, where $\bar{Y}_S \equiv E\left(Z^{-1} \middle| S\right)$ and S is the signal that is observed at this stage. Replace the expression for N in the profit function and define $C(Q) = Q^{\beta} \cdot X$, where X is a set of exogenous variables affecting costs, and $\beta > \theta$. We obtain

$$\underset{Q}{Max}\, E_{\Omega}(1-\alpha)K\left(\frac{\alpha K}{W}\right)^{\frac{\alpha}{1-\alpha}} \left(\theta Q \bar{Y}_S\right)^{\theta} e^{-\theta} - Q^{\beta} X$$

whose *foc* is

$$E_{\Omega}\,(1-\alpha)K\left(\frac{\alpha K}{W}\right)^{\frac{\alpha}{1-\alpha}}\theta Q^{\theta-1}\left(\theta\overline{Y}_S\right)^{\theta}e^{-\theta}=\beta Q^{\beta-1}X \qquad (4)$$

where the expectation is now across the realizations of the signal S, which is not observed at this stage. Define $Q^{\beta}{\cdot}X = WM$, that is the total cost for improving the probability of success of the patented inventions is equal to the total man-months M invested in the invention process times the unit wage W. From (4), after rearranging terms, $E_{\Omega}\Psi\left(\frac{\alpha K}{W}\right)^{\frac{\alpha}{1-\alpha}}\left(Q\overline{Y}_S\right)^{\theta}=M$, where $\Psi\equiv\frac{1-\mu}{\mu\beta}\theta^{\theta}e^{-\theta}$. This yields $Q=\overline{Y}^{-1}\left[\frac{M}{\Psi}\left(\frac{\alpha K}{W}\right)^{-\frac{1}{1-\alpha}}\right]^{\frac{1}{\theta}}$, where $\overline{Y}$ is the expected value of $\overline{Y}_S$ across the realizations of S, i.e., $\overline{Y}=E_{\Omega}\overline{Y}_S$. Moreover, we assume that $\overline{Y}=\left(E_{\Omega}\overline{Y}_S^{\theta}\right)^{\frac{1}{\theta}}$, a condition consistent with quite a few distributions (e.g., Weibull).

Estimated equations, *M*, *N*, *V*. Replace the optimal expression of Q in $C(Q)$, and solve for M using $C(Q) = WM$. After rearranging terms, using lower case letters to denote logs, we obtain

$$m=const+\frac{\beta}{\beta-\theta}\overline{y}-\frac{\theta}{\beta-\theta}x-\frac{1}{1-\alpha}\left(1+\frac{\alpha\theta}{\beta-\theta}\right)w+\frac{\beta}{(\beta-\theta)(1-\alpha)}k+error \qquad (5)$$

which the M-equation that we estimate.

To obtain the N-equation, replace the expression for the optimal Q in the expression for the optimal N. This yields

$$n=const+\left(\overline{y}_S-\overline{y}\right)+\frac{1}{\theta}m+\frac{1}{(1-\alpha)\theta}w-\frac{1}{(1-\alpha)\theta}k+error \qquad (6)$$

Notice that, unlike (5), in (6), N depends on the signal S, and in particular it depends on the update on the distribution of P provided by the signal compared to the lack of it. In the next section, we provide a specific interpretation of the information provided by this signal that we then test with our data.

To derive the value equation, recall that $V=KN^{\mu}H^{\overline{\alpha}}$. In our empirical analysis we only have data on the man-months invested in portfolio before the generation of the patented invention. We therefore need to replace the development costs H with the pre-patent costs M. To do so, note that $WNH=\alpha KN^{\mu}H^{\overline{\alpha}}$. Replace H with (3), and N and Q with their optimized expressions. From (4) one obtains

$\frac{1-\mu}{\mu\beta}e^{-\theta}WNH\left(\frac{\bar{Y}}{\bar{Y}_S}\right)^{\theta} = WM$, and therefore $H = \propto \frac{M}{N}\left(\frac{\bar{Y}_S}{\bar{Y}}\right)^{\theta}$. Replace this expression in the expression for *V*. Use lower case letters for logs. We obtain

$$v = const + k + \alpha \cdot m + \frac{\alpha(1-\mu)}{\mu}n + \alpha\theta(\bar{y}_s - \bar{y}) + error \qquad (7)$$

which is the value equation that we estimate. In (7), the value of the signal also matters. The proxy of value that we measure in this paper is the expected value of the portfolio at the moment in which the patent is granted. Thus, our expression for *V* needs to be multiplied by P^N. However, as showed, given the optimal *N*, $P^N = e^{-\theta}$, and thus this term is captured by the constant term of (7).

2.2 Propositions

Our model provides a guide to test some empirical propositions. We define the *extensive margin* to be the percentage increase in the economic value of a portfolio of inventions produced by a unit percentage increase in the number of inventions *N*, given the resources *M* invested in the invention process. The *intensive margin* is the equivalent definition with *N* in lieu of *M*.

We first study the extent of the diminishing returns to the single invention, as opposed to the creation of value via the expansion of the number of inventions. Inventions are increasingly complex, and they are typically composed of many inventions. This squares with the fact that we look at patents. A single inventive step, which gives rise to one patent, tends to be focussed and specific to a particular invention. Moreover, the inventive step that makes an invention patentable is typically a technical matter, as implied by the very nature of the patentability requirement that looks at the technical rather than economic features of the invention. This is corroborated, for example, by Astebro and Dahlin (2005) who show that technical feasibility is important for the decision to patent an invention, but not for the decision to commercialize it. As a result, for as much work one can put in improving a specific inventive step, the returns to this additional efforts are likely to phade away rapidly. By contrast, a greater economic value can be created by adding and combining different technical features or inventions after some initial effort on the first invention. In terms of our model, this suggests that the elasticity μ is small. From (7), this implies that the elasticity of *V* with respect to *N* is higher than the elasticity of *V* with respect to *M*.

Proposition 1. *Diminishing returns with respect to the resources invested in the individual inventions (small μ) imply that the extensive margin is higher than the intensive margin; that is,* $\mu < ½ \rightarrow \frac{\alpha(1-\mu)}{\mu} > \alpha$.

The extensive margin can be enhanced by the complementarity across the N inventions. Proposition 1 does not imply complementarity. The individual inventive steps may simply add to the value of the invention because it is more beneficial from an economic point of view to invest additional resources in a different invention rather than insisting on the same one. This is the essence of diminshing returns. Yet, the inventions can also be complementary with one another in the sense that increasing effort on one of them raises the value of the others. In terms of our model, this means that $\alpha > \mu$, and therefore that the impact of N on V is even larger, as implied by the fact that a larger difference between α and μ raises $\frac{\alpha(1-\mu)}{\mu}$.

Proposition 2. *Stronger diminishing returns (smaller μ) and complementarity (higher $\frac{\alpha}{\mu}$) raise the extensive margin.*

The argument developed so far rests on the idea that, by themselves, the technical features of the individual inventions only provide a limited contribution to economic value. Not only is value enhanced by reallocating resources to additional inventions, but complementarity may also enhance this effect. However, these effects are more likely to be pronounced in complex rather than discrete industries. The prototypical example is the chemical and pharmaceutical industries in which the patented inventions are most often individual compounds. In these industries the relationships between technical and economic value is more direct, and usually technical improvements lead to greater economic values. For instance, a new compound, which is the outcome of a technical effort and challenge, implies that the firm has developed a new invention that can be used for some specific economic purpose. By contrast, in all the other industres, typically based on the mechanical and electronics paradigm, technical inventions do not directly produce economic value. It is in these cases that the inventive steps need further developments to generate value, and they normally need additional features that stem from complementary inventions. For example, in many of these industries the final new product, process or innovation is a system, whether a small or a large system, composed of different elements that normally correspond to different inventive steps. In this respect, there are both stronger diminishing returns to investing in the individual invention, and complementarity across inventions. As a result, we expect that in the discrete industries the difference between the impacts of the extensive and intensive margins be smaller than in the more complex industries. In addition, we expect the extensive margin to be small because of the lack of significant complementarity across the discrete inventions.

Proposition 3. *The extensive margin $\frac{\alpha(1-\mu)}{\mu}$, and its gap with the intensive margin α are lower in*

discrete industries (chemicals and pharmaceuticals).

In our model we have shown that the invention process is affected by factors that generate information signals. Two factors in particular affect these signals: the scientific-intensity and the originality of the research. Scientific knowledge implies that the inventors have a good deal of information about the process at the outset of the process itself. This is inherent in the very nature of science. Science provides information and ability to predict (e.g., Arora and Gambardella, 1994). As a result, this means that any signal about the invention process that takes place at a later stage is likely to be less informative than if the process did not rely on science as much. Another way to see this is that the lack of science means that as the inventors work on a problem, they raise a lot of new information that was not available before. Thus, the signals that occur during this stage can make a difference compared to the earlier stages. Similarly, a more original research topic implies that there is less experience about it to predict outcomes at the outset of the research. Again, a lot of information arises during the actual work, and thus the signals that arise after the process starts are more informative. Note that we treat science and originality as two different dimensions. More science makes the signal less informative, and similarly for originality.

In our model, we capture these effects by looking at the difference between the expected value of *Y* before or after the signal, i.e., the ratio $\frac{\overline{Y}_S}{\overline{Y}}$. As well known (e.g., Milgrom and Roberts, 1981), under fairly weak conditions, a signal raises the posterior expectation compared to a more neutral signal. Thus, when the signal is more informative, the ratio $\frac{\overline{Y}_S}{\overline{Y}}$ increases. Scientific knowledge then means that this ratio is not large. The inventors know the distribution of *P* at the outset of their research, and this information does not change much at later stages. As a result, our key prediction, from (6), is that the availability of scientific knowledge reduces. In fact, we have to be precise about this point. Our model says that *N* pre-determined *ex-ante* by the choice of *Q*, i.e., of the distribution of *P*. As the inventors enter into the process, the signals that they get during this activity are not informative, and thus, when they pick *N*, it is pretty much the level of *N* pre-determined when choosing *Q*. In turn, as our model shows, the choice of *Q* corresponds to the choice of *M*, viz. the amount of resources to be invested in the invention process. Thus, once we control for *M*, the impact of science in (6) is negative, in the sense that inventors not guided by scientific knowledge will raise *N* to a greater extent. Interestingly, we expect though that scientific knowledge is more effective in guiding the invention process, and thus ultimately it has to have a positive effect on it. But this pertains to its impact on $\overline{Y}$, i.e. the *ex-ante* value for the distribution of P, not the ratio $\frac{\overline{Y}_S}{\overline{Y}}$. For example, as Fleming and Sorenson (2004) point out, science provides a greater ability to recombine knowledge. Thus, inventors can explore more alternative paths, and more generally this makes

the invention process more productive. To the extent that this raises $\overline{Y}$, we do not observe this effect in (6), i.e., on N, but in (5), i.e., on M. That is, following our previous logic, scientific knowledge provides the firms with higher productivity in the invention process. Thus, they invest more resources in it, M, which produces a higher N. However, those who lack science compensate in part this frustration on N later on, when they get signals from the invention activity. Thanks to these signals, they raise N, for given M.

Similarly, for more original projects, the positive effect on N, given M, takes place tcanks to the greater

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whether riginality raises

in Europe are presented in Giuri *et al.* (2007).[1] In this paper we focus on the private value of the patents held by firms. Thus, all the samples that we use in our analyses rule out all the PatVal-EU patents held by universities, individuals or non-profit institutions. We consolidated all the firms according to their ultimate parents by using *Who Owns Whom* (several years).

3.2 Dependent Variables, *V* and *N*

Following Harhoff et al. (2003), the PatVal-EU survey asks the inventors: "*Suppose that on the day on which this patent was granted, the applicant had all the information about the value of the patent that is available today. In case a potential competitor of the applicant was interested in buying the patent, what would be the minimum price (in Euro) the applicant should demand?"* The survey offers a menu of 10 interval responses: less than €30K; 30-100K; 100-300K; 300K-1M; 1-3M; 3-10M; 10-30M; 30-100M; 100-300M; more than 300M. We are confident about this measure. We show in Gambardella et al. (2008) that its distribution is skewed to the left, and in general it conforms to other distributions of the value of patents or inventions in the literature (Harhoff et al., 1999; Scherer and Harhoff, 2000; Astebro, 2003); it is also strongly correlated with some standard indirect indicators of patent value, and for a subsample of 354 patents it is not different from the distribution of responses given by company managers (Gambardella et al., 2008).

PatVal-EU also asks the inventor whether the patent is part of a group (portfolio), and if so whether the number of patents in the portfolio falls into one of the following intervals: 2; 3-5; 6-10; 11-20; >20. The exact definition that we use is whether the focal patent is part of "a group of patents which crucially depend on each other in terms of their value, or in a technical way." The survey also asks to respond to the same question above for the whole set of patents in the portfolio. In this case, the menu is composed of 12 interval responses: the first nine intervals are the same; the final three intervals are now 300M-1B, 1-3B, and more than 3B.

The proxy for *V* that we use in our regressions is the geometric mean of the boundaries of the intervals for the value of the whole patent portfolio. The distribution of this variable is also skewed to the left, and similar to the one of the individual patent values, with, of course, a longer tail. The proxy for *N* is equal to 1 for all the patents that the respondent declared not to be part of a group. For the patents declared to be part of a group, *N* is equal to the geometric mean of the boundaries of the other intervals (N = 20-40 for the last class.) About two-thirds of the PatVal-EU patents are singletons, i.e. $N = 1$. To build more confidence in our value measure, Appendix 1 shows that the average value of the portfolio – i.e., the ratio

[1] Giuri et al. (2007) only report about patents in six countries. Data about Denmark and Hungary were collected later.

of our proxies V and N – is highly correlated with several indirect indicators of patent value associated to the focal PatVal-EU patents.

A potential concern with survey-based measures like our proxies for V and N is that they may be affected by shocks associated with some characteristics of the respondents that do not have much to do with the relevant characteristics of the variables for our purposes. For example, in our case, inventors who are particularly excited about their inventions may boost the evaluation of their patents or the extent of the related patents. We are not particularly concerned about these problems for two reasons. The first one is that, as we shall see, we instrument for N in the value equation (5), which removes the potential bias due to a common shock affecting both N and V. Second, the problem of a respondent shock would be relevant if we looked at the predicted values or number of patents. Since our analysis focusses on the impacts (elasticities) of the covariates on the dependent variables, this is a less important concern.

Finally, we could have employed alternative measures of the number of technically related patents derived directly from patent data. We did not follow this route because technically connected patents coming out of a given research project are not easy to identify. We could have looked at the patents of the same inventor, in a given technological area, and around the same time. However, it is not clear that technically related patents are produced by the same inventor, or in similar technological classes, or around the same time. More generally, this required some assumptions about the search algorithm, and it is not obvious that these assumptions produce fewer errors than asking the inventor.

3.3 Covariates

Table 1 defines all the variables that we employ in our analysis. Along with the endogeneity of N in (5), we control for the endogeneity of the total man-months invested in the project leading to the portfolio of patents (M). Note that controlling for the endogeneity of M tackles the same problem mentioned earlier about potential common respondent shocks across surveyed variables. The next section discusses the instruments for these endogenous variables.

TABLE 1 ABOUT HERE

We control for four sets of factors in our regressions: i) characteristics of the technological projects; ii) characteristics of the firms; iii) characteristics of the inventor; iv) patent premium. Since PatVal-EU surveyed a specific patent, the controls below refer to that patent. While this is not a problem for the two-thirds singleton patents in our regressions, for the remaining patents, the surveyed patent is a random patent of the portfolio. Since the patents in the portfolio are related, we expect their characteristics to be correlated with those of the focal patent.

We control for the characteristics of the innovation project by using 30 technology class dummies, dummies for the priority year of the patent (1993-7), and dummies for the countries in which the patent was invented.[2] In addition, GOVFUND is a dummy taking the value 1 if the funding of the research leading to this patent came from Government research programs or related government funds. Subsidies to R&D are common in Europe, both from the European Union and the national or even regional governments. This variable accounts for the costs of the project, correlated for instance with the wage W or parameters of the cost function $C(\cdot)$ in our model. The variables SCIENCE and ORIGINALITY account for the importance of science as a source of knowledge for the patented invention, and for whether the patent is a relatively original one. In this respect, we follow Ahuja and Lampert (2001), and define originality according to the number of references listed in the patent. The variables SCIENCE and ORIGINALITY are the two key proxies that we employ to test Propositions 4a and 4b.

We control for the characteristics of the firms by using dummies for their size, consolidated at the level of its ultimate parent: SMALL_PARENT and MEDIUM_PARENT account for ultimate parents with up to 100 and between 100-250 employees, while larger firms are the default class. In addition, we control for their level of R&D. The variable RD is their R&D expenditures in 1995, and RD_MISSING is a dummy for the observations in which the firm R&D is not available. We also control for the relative specialization of the firm in the technology class of the patent (RTA). Since PatVal-EU mirrors the distribution of patents in the population, the use of the PatVal-EU patents to compute RTA is unlikely to introduce any particular bias.

We control for several characteristics of the inventor. Apart from the dummies for AGE and EDUCATION, YEARINORG accounts for the impact of the experience of the inventor inside the organization. The variable MOTIVATION proxies for the motivation of the inventor (Cohen and Sauermann, 2010). The dummy MALE controls for gender.

We also conducted an extensive data collection to retrieve all the EPO patents of our inventors before the PatVal-EU patent, and the citations to these patents. We construct INVENTOR_CITES, i.e., the average number of citations within 5 years to patents of the inventor with priority year 3 or more years before the focal patent. A three-year lag reduces the links between the patents that we use as a basis for the citations to the inventor, and the patents related to the focal patent. For example, patents with priority date closer to the focal patent may be part of similar research investments, while we need a measure of the inventor ability or expertise as independent as possible from the focal patent. At the same time, we could not use

[2] We retrieved the technology classes from the ISI-INIPI-OST concordance classification between patent IPC classes and the 30 technology classes elaborated by the German Fraunhofer Institute of Systems and Innovation Research (ISI), the French Patent Office (INIPI) and the Observatoire des Sciences and des Techniques (OST). See Giuri *et al*. (2007) for details.

longer gaps from the priority date (more than 3 years) because our sample includes inventors in the early stages of their career. Note that we use the average citations received by the past patents of the inventor (rather than the number of past patents or the total number of past citations), which limits potential scale effects associated with age or past availability of resources. As a robustness check, we ran all our regressions using the maximum number of citations received by any patent of the inventor with priority three or more years before the focal patent, and the results do not change. We employ two other controls for the inventor, INVENTOR_BREADTH and NOT_INVENTOR. They account for the specialization of the inventor's past successes and whether the inventor is an occasional inventor.

We employ four controls for the value associated with the patent protection of the invention – the so-called "patent premium." Our first control is PROTECTION, which is the sum of two survey questions aimed at assessing the extent to which the invention was patented for reasons related to its protection. The second control is IPC4_NOFIRMS. A higher share of patents held by universities, public research institutions or individuals produces a greater diffusion of knowledge in the technological class, which reduces the value of the patent. In part this is a general effect due to stronger competition faced by each technology holder in the area because academic and non-profit institutions, as well as individuals, have greater incentives to diffuse the technology. The same effect can be thought of, at least in part, as reducing the patent premium because the greater diffusion of knowledge is likely to impinge on the specific knowledge or technology associated with the patent of each firm.

The rationale for the third control, IPC4_COMP, is that if the firm is the only patent applicant in the field, the patent premium is small because it is unlikely that other organizations have the assets or the absorptive capacity to copy or to use the unpatented technology. By contrast, if there are quite a few of these firms, the patent shelters from the use of the technology by others. The large sample of PatVal-EU applicants, along with the stratification of the PatVal-EU sample, which reflects the distribution of the population of patents, ensures that this variable is a good proxy of the Herfindhal that we would obtain if we employed the full population. Moreover, following our consolidation of the PatVal-EU applicants, the Herfindhal is computed by considering applicants to be different only if they belong to unaffiliated organizations. Finally, the use of IPC4_NOFIRMS ensures that we control for the extent to which IPC4_COMP is affected by the presence of applicants different from firms.[3] Our fourth control is RACE. If a race is going on, patenting gives a lead with respect to neck-to-neck competitors.

[3] An alternative to IPC4_COMP would be a measure of the product market competition of the firm, but it is much harder to find information on product market competitors associated to the specific technological class of the patent.

3.4 Instruments

We use four instruments: BLOCKING, NEW_INVENTION, INTRATECY, and SERENDIPITY. We tried several alternative instruments. However, not only are the four instruments that we employ well justified, as we shall discuss below, but they also prove to be statistically relevant and robust, as we shall see in the next section. We employ the first three instruments as covariates in the N-equation (6), and we exclude them from the value-equation (5). Thus, they identify N in the value equation. We exclude SERENDIPITY from both the N- and V-equations. Then, SERENDIPITY identifies the impact of the other endogenous variable, M, in both equations.[4]

The variable BLOCKING is a dummy that measures whether one reason for patenting the invention is to block rivals from patenting similar inventions. This is a key measure of what is typically called "strategic" patenting. Strategic patenting is normally associated with the creation of several intertwined patents that help to protect the invention, and more generally that block rivals in many domains or directions in which the focal invention could be developed (Ziedonis, 2004). Thus, we expect this variable to be positively correlated with N. Similarly, NEW_INVENTION is a dummy that takes the value 1 if the PatVal-EU respondent declared that the invention was patented as it is because any additional improvements might have resulted in a different patent. Thus, we take this variable as proxying for some underlying characteristics of the technology that favors the differentiation of inventions, and therefore a higher N. Finally, INTRATECY measures the business cycle in the country. This affects the investments in innovation, and thus both N and M.

The variable SERENDIPITY measures whether the invention is the outcome of a the "stroke of genius" rather than a well planned research project. As such, these projects correspond to a lower M. Moreover, as implied by the definition in Table 2, the serendipitous inventions are not furthered in a formal project. This makes it a natural instrument for M. These projects do not give rise to new investments in man-months because of information about the patent value, or about N, that becomes available after the initial decision about M.

In principle, all these instruments could have a direct impact on V or N. However, as we shall see in the next section, the Hansen J-statistics suggests that their exclusion is not statistically significant.

[4] In principle, from our model in Section 2 we could develop a structural equation for M as a function of N. The reason why, empirically, we only append a reduced form equation for M is that we did not have any good instrument to identify N in the M-equation.

4. EMPIRICAL RESULTS

4.1 GMM Estimation and Results

Table 2 presents our joint GMM estimation of (5), (6), and (7). Table 3 shows that our instruments are strong and relevant. In particular, as noted, the Hansen J-statistics indicates that are our identification depends on exclusion restrictions that are not statistically significant. The *M*-equation, which is the first stage regression of *M*, confirms the strength of our instruments. In this equation, SERENDIPITY, INTRATECY and RACE are significant and have the expected signs. Similarly, in the *N*-equation, the three instruments excluded from the *V*-equation are significant. In particular, BLOCKING and NEW_INVENTION have a positive sign. The former reflects our prior that in order to strengthen the protection of an innovation firms build patent "fences" around it, as suggested by Ziedonis (2004); the latter reflects some intrinsic differentiability of the technology across inventions. The variable INTRATECY has a positive and significant sign in the *N*-equation. In the full-fledged first stage regression of *N* (not shown here), which employs SERENDIPITY in lieu of *M*, INTRATECY has the expected negative sign. Thus, the higher interest rates during the business cycles reduces the investment in resources for invention *M*, but once we control for it, firms respond by increasing the number of trials *N*. While, as we shall see below, this is not our test of Proposition 4a and 4b, it may be that this is a response to the higher uncertainty implied by the higher interest rates. Finally, in the first stage regressions of *N* and *M*, the F-statistics that tests for the significance of the four excluded instruments of our GMM regressions are well above 10, the threshold most commonly invoked in these cases.

TABLES 2 AND 3 ABOUT HERE

The estimated elasticity of *V* with respect to *N*, $\frac{\alpha(1-\mu)}{\mu}$, is higher than that of *V* with respect to *M*, α, which corroborates Proposition 1. We estimate $\frac{\alpha(1-\mu)}{\mu}$ = 1.503, which is high and well measured. The estimated α is 0.347, and it is also well measured. This yields an estimated μ equal to 0.188 (p-value < 0.01), which entails fairly sharp diminishing returns. In addition, $\frac{\alpha}{\mu} = 1.850$, which implies a fairly pronounced complementarity among the technologies in the portfolio, as predicted by Proposition 2. The estimated elasticity of *N* with respect to *M*, which is the inverse of θ in our model, is equal to 0.495. Since $\theta \equiv \frac{\alpha(1-\mu)}{\mu(1-\alpha)} = 2.302$, than its inverse is equal to 0.434, which is close to 0.495. Moreover, when we tested the difference between these two coefficients we found that it is insignificantly different from zero, which suggests that our estimates are consistent with the structure of our model.

To test Proposition 3, we run (5), (6), and (7) separately for the chemical and pharmaceutical industries (discrete industries), and all the other industries (complex industries). We distinguished between the two using our 30 technology class dummies. In particular, the 30 technology classes are aggregated in five macroareas: chemical and pharmaceuticals (which covers organic fine chemistry, macromolecular chemistry & polymers, pharmaceuticals & cosmetics, biotechnology, agriculture & food chemistry,

deviation and the mean of the variable from Table 2. We compared it with the same expression for RD, SCIENCE, ORIGINALITY, INVENTOR_CITES, and INVENTOR_BREADTH, on the ground that these variables account for the change in N associated with the width of the portfolio produced by genuine research goals. We find that in the former case the impact is 0.131 (p-value < 0.01), while in the latter case it is 0.122 (p-value < 0.10), which suggests that protection and genuine breadth of inventions are of comparable importance in determining N.

4.2 Relative importance of the extensive vs intensive margin

Our structural estimations enable us to deepen our understanding of the relative importance of the extensive vs intensive margin. By using lower case letters to denote logs, $v \equiv n + (v - n)$, where $(v - n)$ is the average value of the patents in the portfolio. This divides the total value of the portfolio in the effect of n and that of $(v - n)$, which depends on both n and the factors that affect both n and v. By using subscripts to denote elasticities, we can first decompose the elasticity of V with respect to M as $n_m + [v_m + (v_n - 1)\cdot n_m]$, where the first term is the effect on the value of the portfolio generated by the increase in N produced by M, while the second term (inside the square brackets) is the impact of M on the average value of the patents in the portfolio. In turn, this is composed of the direct impact of M on the average value of V, i.e., v_m, and the indirect impact due to the fact that the increase in N produced by M affects the average value through the complementarity relationships across the patents in the portfolio – that is, for each new patent added to the portfolio, the average value increases because of complementarity. From the structure of our model it is easy to see that, ultimately, the total elasticity of V with respect to M is equal to 1. However, this decomposition enables us to assess the components of it.

We can perform the same decomposition for any other covariate X. In this case, we have to take into account that X also affects M. In general, the elasticity of V with respect to X can be decomposed as $(n_x + n_m \cdot m_x) + [(v_x + v_m \cdot m_x) + (v_n - 1)\cdot(n_x + n_m \cdot m_x)]$. As before, the first term into the brackets is the effect on the value of the portfolio generated by the increase in N produced by X. This also takes into account the effect coming through M. The second term (inside the square brackets) is the impact on the average value of the patents in the portfolio composed of the direct impact of X on the average value and the impact depending on the complementarity or substitution across the patents in the portfolio.

Table 5 shows the estimated decomposition of the elasticity of V with respect to M, and some other key covariates of our model. The table also reports the total impact of M or X, and the total impact coming through N, i.e., $v_n \cdot n_m$ or $v_n \cdot (n_x + n_m \cdot m_x)$. We can then assess the relative importance of both the impact of each variable on the number vs average value of patents in the portfolio, and that of the intensive vs extensive margin.

TABLE 5 ABOUT HERE

Table 5 first shows that the elasticity of N and the elasticity of the average value of the portfolio are roughly similar, 0.505 and 0.586. Thus, investment in resources in the invention process raises the value of the portfolio by increasing both the number of patents and their average value. However, as also discussed in the previous section, the impact through N is sizable, producing an elasticity of 0.744. This stems from the direct effect of M on N, and the effect of N on the average value produced by the complementarity across patents.

The sizable effect of N arises for other covariates as well. We focus on the inventor's human capital, and look at the effects of education and the quality of her past citations as a proxy for her experience with past successes. Table 5 shows that a PhD produces a portfolio whose value is, other things being equal, 41.2% higher than the baseline case of an inventor with a high school degree or lower. The extensive margin covers more than half of it (28.8%). Interestingly, the extensive margin is only slightly higher for an inventor with a BA or Master compared to a high school degree. This suggests that the prototypical model of research education, a PhD, produces stronger effects on the ability to create value through a higher number of inventions than via the intensive margin. The same pattern arises from the inventor's past citations. The extensive margin is equal to 0.319, more than half of the intensive margin, and the total elasticity is equal to 0.510.

Finally, SCIENCE has a negative effect on N and a positive one on M. The negative direct effect on N, which depends on a greater ability to focus on the right options, produces a negative effect on the value of the portfolio. However, this is compensated by the positive effect of SCIENCE on M, which in turn raises N. Table 5 shows that this indirect effect makes the overall effect of SCIENCE on the value of the portfolio positive. However, note that the total elasticity, 0.133, is not significant. This suggests an interesting bifurcation between two models. The first model relies on scientific knowledge, produces fewer inventions that are more likely to be the right hits, and it is associated with a higher M. The second model does not rely on scientific knowledge. However, it compensates the lack of scientific knowledge with a greater number of trial inventions. This only produces a slightly smaller value than the more structured scientifically-based invention process. In short, the extensive margin can compensate for the lack of good scientific knowledge.

4.3 Robustness checks

Our first robustness check employs three indirect indicators of patent value as alternative dependent variables: the number of forward citations up to 5 years since the patent's grant, the number of countries in which the patent is applied for, and the number of equivalent patents, i.e., the number of patent offices

in which the invention has been patented. All three variables refer to the focal PatVal-EU patent. Thus, they correspond to the value of the individual patent, which is the marginal value of the portfolio. As a result, the impact of *N* now corresponds to the elasticity of the value of the portfolio minus 1. We find that the forward citations are correlated with *N*, but not with M, while the number of States or of the equivalent patents are correlated with *M* but not with *N*. This is not unexpected. Forward citations have a skewed distribution, like our value measure, and like *N*, while the distribution of *M* is less skewed. This suggests that *N* is more likely to capture the longer tail of the forward citations. At the same time, when EPO patents are applied for in many countries, or they have many equivalent patents, they are more likely to be associated with larger investments in resources *M*. This is because in order to spread the larger firxed cost *M*, firms seek larger markets, and thus they look for protection in more countries, and from different patent offices. Most importantly, this suggests that citations, number of countries and number of equivalents only capture partial dimensions of the value of patents. Only our measure of value is correlated with both *N* and *M*, and thus mirrors a more comprehensive set of dimensions of the value of patents. Appendix 2 reports the impacts of *N* and *M* on our three indicators of patent value.

Our second robustness check has to do with the potential concern that in our analysis we only employ observations for which none of the dependent and independent variables are missing. The PatVal-EU survey covers 8515 patents by firms. Moreover, as noted in Section 3.1, the PatVal-EU patents were selected carefully to avoid biases in the sample. Since in our analyses we only employ 4639 observations, it is natural to ask whether the missing value influence our results.

We then run a probit regression whose dependent variable takes the value 1 if the observation is in our sample of 4639 patents, and zero if it is anyone of the other 8515 patents assigned to firms and surveyed by PatVal-EU. The regressors are all the indirect indicators of value employed in Appendix 1, along with the dummies for countries, technological sectors, and priority years. The goal of this robustness check is to assess whether the sample that we use is correlated with our indirect indicators of value. Appendix 3 shows that none of these indicators is statistically significant. Moreover, a Wald-test cannot reject the nul hypothesis that the all the indicators employed in the probit regression are equal to zero. In sum, our sample does not imply a selection of more or less valuable patents.

5. DISCUSSION AND CONCLUSIONS

This paper provides four contributions. First, we show that the resources invested in the invention process – that is, before the downstream investments to develop, produce and commercialize the innovation – raise the value of a portfolio of inventions to a good extent through the number of patents produced and not only via the expected value of the individual patents. This suggests, for example, that it is not always

a good strategy to insist on one specific invention by concentrating resources on it. Spreading resources across technically related inventions can generate a more valuable impact.

Our second contribution is that, while the invention process is often described as uncertain and subject to many vagaries, investments in resources – man-months in our particular case – matter. The pioneering

contributions that will resolve the problems that we are unable to address in this paper.

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Table 1: Definition of variables and descriptive statistics (4639 obs.)

Variable, Definition	*Mean*	*Sd*	*Min*	*Median*	*Max*
Endogenous Variables					
V: Value of the patent portfolio. Geometric mean of the boundaries of the PatVal-EU classes: ≤€30K; 30-100K; 100-300K; 300K-1M; 1-3M; 3-10M; 10-30M; 30-100M; 100-300M; 300M-1B; 1-3B; ≥3B (3-10B to compute mean of the last class) (in 000 euros)	65403.3	$4.79 \cdot 10^5$	5.477	547.723	$5.48 \cdot 10^6$
N: Number of patents that "crucially depend on each other in terms of their value, or in a technical way." N = 1 if patents do not belong to a portfolio, otherwise = geometric mean of the boundaries of the PatVal-EU classes: 2; 3-5; 6-10; 11-20; ≥ 20. (20-40 to compute the mean of the last class)	3.286	5.309	1	1	28.284
M: Total man-months invested in the portfolio of patents. Geometric mean of the boundaries of the PatVal-EU classes: ≤1; 1-3; 4-6; 7-12; 13-24; 24-48; 48-72; 72-96; 96-120; ≥120 (120-144 to compute mean of the last class)	25.044	37.303	1	8.485	131.453
Characteristics of the project					

COUNTRIES: Dummies for the country in which the first inventor listed in the patent is located (DE, DK, ES, FR, HU, IT, NL, UK)			--		
TECHNOLOGICAL_CLASSES: Dummies for the 30 ISI-INIPI-OST technology classes in which the patents are classified (+)			--		
YEAR: Dummies for the priority year of the patent (1993-7)			--		
GOVFUND: Dummy = 1 if the funding of the research leading to this patent came from Government research programs or related government funds	0.060	0.237	0	0	1
SCIENCE: Dummy = 1 if the PatVal-EU inventor ranked 4 or 5 (on a 0-5 scale) the importance of any of the following sources of knowledge for the patented invention: university, other non-profit labs, technical conferences, scientific literature	0.495	0.500	0	0	1
ORIGINALITY: Dummy = 1 if the patent has a number of references ≤ than the median of the PatVal-EU patents (4)	0.595	0.491	0	1	1
Characteristics of the firm					
SMALL_PARENT: Dummy = 1 if ultimate parent of the applicant is a small firm (≤ 100 employees)	0.081	0.273	0	0	1
MEDIUM_PARENT: Dummy = 1 if ultimate parent of the applicant is a medium firm (100-250 employees)	0.061	0.24	0	0	1
LARGE_PARENT: Dummy = 1 if ultimate parent of the applicant is a large firm (≥ 250 employees)	0.858	0.349	0	0	1
RD: R&D expenditures of the firm in 1995 (000 euros)	739.197	1378.037	0.912	1	8387.898
RD_MISSING: Dummy = 1 if RD is missing	0.555	0.497	0	1	1
RTA: Revealed technological advantage of the ultimate parent of the applicant in the technological field (30 technological classes) of the patent = share of firm patents in the field over field patents on total patents. Obtained using PatVal-EU data.	11.366	13.633	0.024	7.711	185.143
Characteristics of the inventor					
AGE_30: Dummy = 1 if inventor's age < 30	0.050	0.217	0	0	1
AGE_30-40: Dummy = 1 if inventor's age is 30-40	0.354	0.478	0	0	1
AGE_40-50: Dummy = 1 if inventor's age is 40-50	0.311	0.463	0	0	1
AGE_50-60: Dummy = 1 if inventor's age is 50-60	0.244	0.430	0	0	1
AGE_60: Dummy = 1 if inventor's age > 60	0.041	0.199	0	0	1
PRECOLLEGE: Dummy = 1 if the inventor has a high-school or lower degree	0.156	0.363	0	0	1
BA/MASTER: Dummy = 1 if the inventor has a BA or Master	0.558	0.497	0	1	1

PHD: Dummy = 1 if the inventor has a PhD	0.286	0.452	0	0	1
MALE: Dummy = 1 if the inventor is a male	0.982	0.134	0	1	1
MOTIVATION: Sum of the scores (b/w 1-5) to four PatVal-EU questions regarding the extent to which the inventor is motivated by: i) money; ii) career; iii) prestige/reputation; iv) satisfaction with solving the problem	13.41	3.341	4	14	20
YRINORG: Number of years (in 2006) that the inventor has been employed with the applicant organization	25.036	10.241	1	22	83
INVENTOR_CITES: Average number of citations within 5 years to patents of the inventor with priority year 3 or more years before the focal patent	0.551	1.072	0	0	14.583
INVENTOR_BREADTH: 1 – Herfindhal of the IPC3 classes of the inventor's past patents up to 1 yr before the focal patent	0.186	0.295	0	0	0.942
NOT_INVENTOR: Dummy = 1 if the normal job of the patent inventor is not to be an inventor	0.184	0.388	0	0	1
Controls for Patent Premium					
PROTECTION: Sum of the scores (b/w 1-5) to two PatVal-EU questions regarding the applicant's motivation for patenting the invention: i) obtain exclusive rights to commercialize the invention; ii) prevent others from imitation	7.906	2.098	0	8	10
RACE: Dummy = 1 if inventor declared that the invention had to be patented quickly because other firms or researchers were working on the same idea	0.290	0.454	0	0	1
IPC4_NOFIRMS: Share of individual or non-profit applicants in the IPC4 class of the patent	0.097	0.081	0	0.077	0.6
IPC4_COMP: 1 – Herfindhal of the share of different applicants in the IPC4 class of the patent	0.934	0.072	0	0.956	0.995
Excluded Instruments					
BLOCKING: Dummy = 1 if inventor ranked focal patent 4 or 5 on a 1-5 scale to the question whether the patent was aimed at blocking rivals	0.485	0.500	0	0	1
NEW_INVENTION: Dummy = 1 if inventor declared that further improvements could result in another invention to be patented separately	0.100	0.300	0	0	1
INTRATECY: 3-yr moving average of the interest rate of the country before the priority date of the patent	5.649	2.218	1	5.781	11.729
SERENDIPITY: Dummy = 1 if, as stated in the formulation of the PatVal-EU question, "the idea for the invention came from pure inspiration or creativity or from your normal job (which is not inventing), and was not further developed in a (research or development) project (and it was patented without further research or development costs)"	0.123	0.329	0	0	1

(+) The 30 technology classes are: Electrical devices, electrical engineering, electrical energy; Audio-visual technology; Telecommunications; Information technology; Semiconductors; Optics; Analysis, measurement, control technology; Medical technology; Organic fine chemistry; Macromolecular chemistry, polymers; Pharmaceuticals, cosmetics; Biotechnology; Materials, metallurgy; Agriculture, food chemistry; Chemical and petrol industry, basic materials chemistry; Chemical engineering; Surface technology, coating; Materials processing, textiles, paper; Thermal processes and apparatus; Environmental technology; Machine tools; Engines, pumps, turbines; Mechanical Elements; Handling, printing; Agricultural and food processing, machinery and apparatus; Transport; Nuclear engineering; Space technology, weapons; Consumer goods and equipment; Civil engineering, building, mining.

Table 2: Joint estimation of the *V*-, *N*-, and *M*-equations, GMM

	Dependent Variables		
Covariates	*V*	*N*	*M*
CONSTANT	0.834*** 0.359	-5.005*** 0.000	10.285*** 0.000
Endogenous Variables			
N	1.503*** 0.000		
M	0.347*** 0.000	0.495*** 0.000	
Characteristics of the project (^)			
GOVFUND	0.077 0.624	-0.075 0.151	0.282*** 0.000
SCIENCE	0.056 0.463	-0.074*** 0.006	0.173*** 0.000
ORIGINALITY	-0.058 0.410	0.036* 0.062	-0.022 0.537
Characteristics of the firm			
SMALL_PARENT	-0.016 0.898	-0.017 0.630	0.124* 0.069
MEDIUM_PARENT	-0.133 0.364	-0.051 0.169	0.008 0.904
RD	-0.003 0.925	0.024** 0.012	0.019 0.298
RD_MISSING	-0.101 0.661	0.144** 0.020	0.116 0.324
RTA	0.038 0.288	0.011 0.290	-0.049*** 0.007
Characteristics of the inventor			
AGE_30-40	0.250 0.120	-0.013 0.787	0.165** 0.035
BA/MASTER	0.052 0.609	-0.059* 0.087	0.218*** 0.000
PHD	0.025 0.870	0.051 0.254	0.284*** 0.000
MALE	0.227 0.430	0.068 0.228	0.058 0.621
MOTIVATION	0.264* 0.051	0.042 0.252	0.112* 0.064
YRINORG	0.139 0.230	-0.047 0.118	-0.020 0.736
INVENTOR_CITES	0.122 0.287	0.114*** 0.000	0.198*** 0.000
INVENTOR_BREADTH	-0.343 0.141	0.126* 0.052	0.370*** 0.001
NOT_INVENTOR	0.258*** 0.004	-0.003 0.906	-0.183*** 0.000
Control for patent premium			
PROTECTION	0.869*** 0.000	0.044 0.241	0.163** 0.016
RACE	0.177* 0.098	0.073** 0.021	0.226*** 0.000
IPC4_NOFIRMS	-0.636 0.329	-0.243 0.193	0.524 0.114
IPC4_COMP	1.886** 0.036	0.050 0.850	-0.947* 0.067
Excluded Instruments			
BLOCKING		0.087*** 0.000	-0.015 0.694
NEW_INVENTION		0.161*** 0.003	0.407*** 0.000

AGE_40-50	0.242	0.002	0.179**	INTRATECY	2.115***	-4.765***
	0.155	0.972	0.034		0.000	0.000
AGE_50-60	0.372	0.040	0.197**	SERENDIPITY		-0.287***
	0.044	0.464	0.032			0.000
AGE_60	0.349	0.056	0.197	# obs. 4639		
	0.177	0.453	0.117			

All variables, but dummies, in logs; log(1+variable) if variable can take value 0; robust *p*-values below estimates; $^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.10$; equations include country dummies, 30 dummies for technological sectors, dummies for patent priority years, and weights to adjust the oversampling of important patents in PatVal-EU. Weights = inverse of the relative shares of important patents cited at least once or opposed in the sample and in the population of EPO patents with the same priority dates as the PatVal-EU sample ("important" PatVal-EU patents = cited at least once or opposed). (^) Includes countries dummies, technology sector dummies, and dummies for priority years.

Table 3: Tests for strong and relevant instrument, *V*- and *N*-equations in Table 3

Underidentification tests

Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified)

e2.83856(Ha)8m46521(l)-1.35449(e)8.204865(a)-52.02975(i)-1521(l)-1.35 2.33-2acb7a1hueentsfien

V-equation

Table 4: Joint estimation of the V-, N-, and M-equations, GMM (discrete vs complex indusries)

	Dependent Variables (discrete industries)			*Dependent Variables (complex industries)*		
Covariates	*V*	*N*	*M*	*V*	*N*	*M*
N	0.503			2.001***		
	0.387			0.000		
M	0.304	0.749***		0.335***	0.435***	
	0.028	0.003		0.000	0.000	
SCIENCE	0.132	0.019	0.025	0.048	-0.074**	0.190***
	0.539	0.730	0.790	0.581	0.014	0.000
ORIGINALITY	-0.012	-0.024	-0.161*	-0.098	0.053**	0.003
	0.952	0.734	0.067	0.238	0.011	0.943
# obs.		935			3704	

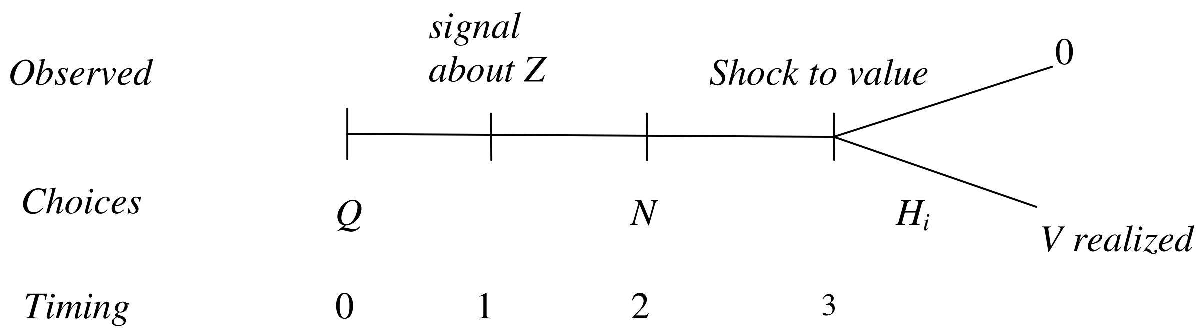
Regressions include all the covariates of the full sample regression in Table 2. All variables, but dummies, in logs; log(1+variable) if variable can take value 0; robust p-values below estimates; ***p < 0.001, **p < 0.05, *p < 0.10; equations include country dummies, dummies for the specific technological sectors of the macrosector in the sample, dummies for patent priority years, and weights to adjust the oversampling of important patents in PatVal-EU (See Table 2.) Discrete industries = chemicals and pharmaceuticals. Complex industries = electrical engineering, instruments, mechanical engineering, process engineering

Table 5: Elasticities of number vs average value of patents, intensive vs extensive margins

Elasticity wrt	*Elasticity of N (1)*	*Elasticity of Average Value (2)*	*Total Elasticity*	*Extensive Margin*
	Components and total elasticity			
	n_m	$v_m + (v_n - 1)\cdot n_m$	*(1) + (2)*	$v_n \cdot n_m$
M	0.495*** 0.000	0.596*** 0.000	1.091*** 0.000	0.744*** 0.000
	$n_x + n_m \cdot m_x$	$v_x + v_m \cdot m_x + (v_n - 1)\cdot(n_x + n_m \cdot m_x)$	*(1) + (2)*	$v_n \cdot (n_x + n_m \cdot m_x)$
INVENTOR_CITES	0.212*** 0.000	0.298*** 0.001	0.510*** 0.000	0.319*** 0.000
PhD vs. High-School	0.192*** 0.000	0.220 0.112	0.412*** 0.005	0.288*** 0.001
BA/Master vs. High-School	0.049 0.131	0.152 0.139	0.201* 0.070	0.073 0.146
SCIENCE	0.012 0.673	0.122 0.101	0.133 0.102	0.018 0.674

Lower case letters denote logs, and subscripts denote the basis of the elasticity. p-values below estimates; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 1: Sequence of the Invention-Innovation Decisions



APPENDIX 1: Correlation b/w average value of the patent portfolio and indirect indicators, OLS

Variable	Estimates	Variable	Estimates	Variable	Estimates
CITES	0.315***	OP	0.240**	CONSTANT	5.266***
	0.000		0.011		0.000
CLAIMS	0.143***	ACCEX	0.145		
	0.006		0.202	*Statistics*	
STATES	0.165**	PCT	0.229***	# obs.	6160
	0.011		0.003	Adjusted R^2	0.103
EQUIVALENTS	0.263***	OBS3PARTY	0.830**		
	0.000		0.033		

Dependent variable: *V*/*N*. All variables, but dummies, in logs; log(1+variable) if variable can take value 0; robust *p*-values below estimates; $^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.10$; equation includes country dummies, 30 dummies for technological sectors, dummies for patent priority years, and weights to adjust the oversampling of important patents in PatVal-EU. (Weights, SEE TABLE 2.) All observations clustered around the ultimate parent of the applicant. CITES = # forward citations up to 5 years after the priority date; CLAIMS = # of claims at grant; STATES = # of EPO countries in which the patent has been applied for; EQUIVALENTS = # of equivalent patents; OP, ACCEX, PCT, OBS3PARTY = dummies = 1 if the patent was opposed, the applicant requested an accelerated examination procedure, the patent is a PCT, the patent was subject to observations by 3rd parties before the grant (according to art.115 of the EPC). All these indicators refer to the focal PatVal-EU patent. Regression employs all the available observations (6160).

APPENDIX 2: GMM estimation using indirect indicators of *V*

Variables	*Dependent Variable of the V-equation*		
	CITES	STATES	EQUIVALENTS
N	0.225**	-0.038	-0.085
	0.024	0.619	0.379
M	0.019	0.046***	0.035**
	0.197	0.000	0.030
# obs.	4639	4639	4639

Same log-log GMM system as in Table 2 with CITES (= # forward citations up to 5 years since the patent's grant), STATES (# of countries in which the patent is applied for), and EQUIVALENTS (# of patent offices in which the invention has been patented), as dependent variables; $^{***}p< 0.001$, $^{**}p < 0.05$, $^{*}p < 0.10$.

APPENDIX 3: Probit estimation, dependent variable = 1 for the 4639 observations in the sample

Variable	Estimates	Variable	Estimates	Variable	Estimates
CITES	-0.016	OP	0.028	CONSTANT	0.498***
	0.536		0.624		0.000
CLAIMS	-0.043	ACCEX	0.008		
	0.149		0.925	# obs.	8515
STATES	-0.045	PCT	-0.015		

	0.173		0.697	H0: 8 coeff. = 0	
EQUIVALENTS	0.018	OBS3PARTY	-0.011	Wald test statistics	5.11
	0.438		0.961	*p*-value, χ^2 (8, d.f.)	0.746

All variables, but dummies, in logs; log(1+variable) if variable can take value 0; robust *p*-values below estimates; $^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.10$; equation includes country dummies, 30 dummies for technological sectors, dummies for patent priority years, and weights to adjust the oversampling of important patents in PatVal-EU. (Weights, see Table 2. Definition of covariates, see Appendix 1.) All observations clustered around the ultimate parent of the applicant.