Innovation Races and the Strategic Role of Cash Holdings: Evidence from Pharmaceutical Patents*

Enrique Schroth
University of Lausanne and
Swiss Finance Institute†

Dezsö Szalay
University of Warwick‡

Abstract

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JEL Classification: G39, L13, 031.

Keywords: Patent race, cash sensitivity, strategic effects, consistent estimation, incumbency.

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†Department of Finance, Bâtiment Extranef 251, CH-1015 Lausanne, Switzerland. Tel.: +41 21 692 3346. Fax: +41 21 692 3435. E-mail: enrique.schroth@unil.ch.

‡Department of Economics, Gibbet Hill Road, Coventry CV4 7AL, UK. Tel.: +44 24 7615 0048. Email: Dezso.Szalay@warwick.ac.uk.

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Abstract

Firms that race to innovate first may hold cash not only to invest timely but also to do it faster than the competitors, pushing them to hold more cash. We use data from US patents and their citations to identify and measure the dependency of innovation success on cash holdings in such races. We find that a firm's cash holdings increase its probability of winning a race while its rivals' cash decrease it. The cash sensitivity of winning increases through the mid 80s and the 90s. This increase is due to the increased concentration of incumbency strength among fewer incumbents. Hence, cash holdings have become strategically more important for the average, R&D-intensive, firm.

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A recent strand of the empirical corporate finance literature studies why American public firms are increasing their cash holdings.[1] As shown by Bates, Kahle and Stulz (2006), the average American public firm has more than doubled its cash to assets ratio over the last twenty years. A question that remains open is what has changed over time to make cash more valuable to the corporation.

Another strand of the literature highlights the role of corporate cash policy as insurance against the risk of giving up valuable investment opportunities. Within this literature, Bolton and Scharfstein (1990) and Froot, Scharfstein and Stein (1993) argue that the severity of a firm's risk of under-investment may strongly depend on what its rivals are doing. R&D intensive industries are a classic example of such interdependence because firms will race to innovate first to maximize the returns from their investment. In a racing environment, holding cash will be necessary not only to invest timely but also to do it faster than the competitors, pushing them to hold more cash. Therefore, cash will have an important *strategic* role and each firm's success in innovation will depend on its own cash and its rivals'.

This paper is about the measurement of the strategic value of cash holdings through the sensitivity of the firm's innovation success to its own cash and that of its competitors over time. It asks what has happened to this sensitivity through the 80s and the 90s, and whether or not this sensitivity has changed due to competitive pressure from its direct rivals. To answer these questions we construct a data set tailored to capture the strategic dimension of the R&D effort. We use data on the pre-clinical stage of the drug development process, where pharmaceutical firms race to secure, through a patent, exclusivity in the clinical trials and the marketing of the drug.

Our observational unit is a patent race. We construct all such races between 1975 and 1999 using all of the US patents in Category 3 (Drugs and Medical) in the NBER Patents and Citations Data File that can be merged with COMPUSTAT. Pharmaceutical patents are ideal because they belong to Cohen et al.'s (2000) 'discrete technology' category. Discrete innovations comprise single patents and firms use them for their original purpose: to block imitation.[2] Further, the patent grant summarizes the outcome of the pre-clinical drug discovery research, i.e., what firm was first. It is during this stage that the firms race to be the innovator, and thus when their research efforts are most interdependent.

Each observation associates the outcome of the race to the characteristics of all its competitors. With this empirical design we can estimate the parameters of a selection model of the winner in the Nash Equilibrium of the race. One source of heterogeneity across firms in the same race is their cash availability. Hence, we can directly ask whether the probability that a firm wins an innovation race depends on the firm's and on the firm's rivals' cash holdings.

One main challenge consists of identifying the competitors in each race. To identify the incumbents to each race, we exploit the link between each patent and its citations in the

NBER data base. The incumbents to the race are the firms that own the technology upon which the next innovation builds. Given that each patent must cite the technology it builds on, we are able to list all the incumbents for every race. Further, the citations count allows us to measure the value of the incumbency of each cited firm (Hall, Jaffe and Trajtenberg, 2005).

Identifying the entrants to each race is not as straightforward. Indeed, a large number of patent winners don't appear in the citations list. To find the entrants, we implement a method for scoring all firms that have won at least one patent in a given five year period as an entrant. This set is clearly very large. Our scoring method is derived from the same model that selects the winner, a multinomial logit model. We aggregate winning probabilities over a given time interval and transform the high-dimensional multinomial logit (which has as many dimensions as potential entrants) to a linear regression where the dimensionality becomes the number of cross-sectional units. From this estimation we can rank entrant firms in terms of the likelihood of winning a given patent in a given year. Building on this ranking we select a set of firms that contains the winner, conditional that an entrant wins, with a probability close to one.

Overall, we find that innovation success is very sensitive to cash holdings. Own cash increases the probability of winning and rivals' cash decreases it. This results is extremely robust and has been consistently measured over and above the factors that traditionally predict innovation success. Moreover, it has been identified using exogenous variation in cash holdings. Indeed, part of our empirical exercise deals with finding good instruments for cash holdings.

The cash balance is likely to be endogenous because it is chosen to increase the firm's competitiveness in the race. Since we specify the innovation success as a function of the cash holdings once they are given, we risk having unobservable firm characteristics in the residual that correlate with cash. Our choice of instruments for cash follows two different literatures. Following the cash management literature (Opler, Pinkowitz, Stulz and Williamson, 1999; Almeida, Campello and Weisbach, 2004), we instrument a firms' cash level with lags of cash, assets, outstanding debt and sales. Following the empirical industrial organization literature (Berry, 1994), we add measures of the rivals' competitive strength (average experience, lagged cash and incumbency of rivals). With these instruments, we compute Instrumental Variables estimators whenever we use linear estimators and implement Petrin and Train's (2003) two-stage method whenever we use non-linear estimators. Our set of instruments over-identify the parameters of our model.

We ask how the sensitivity of innovation to cash has changed over time and what has driven its evolution. The average overall sensitivity exhibits a U shape: high in the late 70s, low in the early 80s and increasing in the mid 80s through the 90s. We find that the increase in sensitivity has been more pronounced for entrant firms than for the average (where the average is taken over incumbents and entrants). Moreover, we show that the sensitivity for the average firm increases as the incumbency value per incumbent becomes more right-skewed. Further, our measured sensitivity is neither driven by a time trend nor changes in external costs of finance common to all players, e.g., benchmark interest rates or credit spreads.

The role of incumbency is crucial to interpret this evidence. Incumbents and entrants have different incentives to innovate: incumbents win to increase or preserve their market power and entrants win to start sharing the oligopoly rents. The empirical literature on the strategic effects in patent races suggests that incumbency is advantageous. Blundell, Griffith and Van Reenen (1999) have shown that incumbent firms' leadership persists along sequences of related innovations. Given that incumbency values do have a positive effect on the winning probability in our data, we conclude that fewer incumbent firms have accumulated more valuable innovations along the technology sequence and that this has made them more competitive. Therefore, the entrants and even the average incumbent have faced bigger disadvantages over time. In this sense, the average firm has been effectively more financially constrained by smaller winning probabilities, and has relied more on its own cash holdings to be successful.

Bates, Kahle and Stulz (2006) have recently shown that US firms hold twice as much cash than they did in 1980. Their results point to the increase in cash flow volatility and R&D expenditures as the main cause. In our patent race context, the winning probability is proportional to the per firm innovation hazard rates. In turn, lower hazard rates imply riskier cash flows and riskier R&D investments. We observe that the importance of the differences in cash holdings across pharmaceutical firms has increased. Therefore, our results suggest that the growing asymmetry between incumbent and entrant firms in the pharmaceutical industry, which seems to be itself a natural evolution of an industry with strong incumbency effects, may explain why the riskiness of the average firm has increased and why such firms appear to be more dependent on their own cash holdings.

Haushalter, Klasa and Maxwell (2007) show that firms hold more cash when their returns are more correlated with, and their capital intensities are closer, to the industry average. Hence they conclude that cash matters more in industries with more investment interdependence. Here we verify interdependence in the pre-clinical stage of drug development through the joint determination of all competitors' cash holdings and patenting probabilities. Our contribution to this literature is to show, with direct measures, that the changes in the strategic position of firms in an industry with interdependent investment significantly affect the value of cash holdings. Namely, the tougher the rivals, the more valuable the cash.

The change in the cash sensitivity of innovation due to strategic effects implies that the firm is not only financially constrained by its own exogenous characteristics but also by those of its rivals and of the race itself. Even cash-rich firms may compete with equally rich or richer ones, be forced to increase their spending to win and depend more, in equilibrium, on their internally generated resources. This is one important difference with the previous literature on investment and financing constraints (see Kaplan and Zingales, 2000, for a synthesis), where the typical exercise consists of comparing the average firm's cash sensitivity of R&D expenditures across samples of firms that are constrained and unconstrained according to only firm-specific characteristics (e.g., the KZ index, size, etc.).

Guedj and Scharfstein (2004) have also studied financing constraints and the role of cash in the pharmaceutical industry. They analyze variation in the investment continuation decisions in the stage that follows the patent grant, i.e., clinical trials. Financing constraints at this stage are driven less by competitive behavior within the industry and more by internal agency conflicts.

Following the critiques by Kaplan and Zingales (1997), Erickson and Whited (2000), and Alti (2003) recent empirical research has found ingenious ways to identify the severity of financing constraints for firm investment. For example, Almeida, Campello and Weisbach (2004) use the cash flow sensitivity of cash holdings to side-step measurement errors in Tobin's Q and Hennessy, Levy and Whited (2005) use an optimal investment rule that incorporates the interaction between marginal and average Q. Here we show that the comparison of the sensitivity of innovation to cash across different estimation periods is meaningful and informative of the tightness of financing constraints because the sensitivity is monotone in the strategic position of the firm.

In the following section we develop our hypothesis in the context of the relevant literature. Section II describes our data sources and summarizes our sample. Section III explains in detail the strategy used to estimate our model. We outline our main empirical challenges and explain how we overcome them. Section IV shows the results of estimating our model with patents won by entrant firms. We use these estimates to implement the pre-selection of entrants to each race. Section V shows the results of estimating the model with incumbents and entrants in all races. Section VI analyzes the determinants of the estimated cash sensitivity of innovation. We measure to what extent the cash sensitivity is explained by the strategic position of the average firm in a race (experience of competitors, incumbency concentration). Section VII concludes briefly.

I Hypothesis development

A Product innovation, patenting and corporate finance

There are recent contributions that study the relationship between innovation and financing frictions at the patenting level. Atanassov, Nanda and Seru (2005) study the relationship between innovation intensity and financing choice. They find that the more the firm is publicly financed, the more patents it receives in a given year. They use this result to argue that public finance is cheaper than relationship-based finance for firms pursuing more innovative projects. This evidence is strongly indicative of the existence of financing constraints for innovative investment. They use patent counts across all industries in a non-racing environment, where innovation success is independent of the characteristics of rival firms.

Guedj and Scharfstein (2004) study the optimality of continuation decisions at different phases of clinical trials for new drugs. Small firms face financing frictions due to agency costs, as the managers of small biotech firms with few patents will continue the development of patents that have failed previous trials. They focus on financing constraints after patents have been won, where the decisions to continue innovating are also independent of the rivals' actions.

B Why should cash matter?

We are silent as to what imperfection renders firms reliant on their cash holdings. Our goal is to measure accurately the cash sensitivity of innovation and to identify empirically its determinants. While there are several sources of imperfections in financing contracts, we note that all of them share at least one result: first-best investment is not feasible and second-best investment depends on available cash. This is summarized very clearly by Kaplan and Zingales (1997).[3]

Several authors have discussed the source of financing constraints for publicly traded firms. In Almeida, Campello and Weisbach (2004), firms have limited borrowing capacity due to liquidation costs. A higher cash availability allows firms to implement an investment closer to its first-best level. In Rochet and Villeneuve (2004), publicly traded firms face fixed costs of issuing securities when they need external finance. In Schroth and Szalay (2007), the equilibrium cost of finance increases with the amount borrowed when the R&D effort of firms in a patent race is unobservable and unverifiable.

One conclusion emerging of the literatures on financing constraints and on strategic R&D is that financing frictions will not only give rise to a positive dependency of the race's equilibrium winning probability on the firm's own cash holdings but also a negative dependency on the rivals' cash holdings. Omitting these interactions among firms would lead to a biased measurement of the sensitivity of innovation to cash holdings. Also, a common result in the literature is that factors that reduce the revenue side of the lender's individual rationality constraint increase the equilibrium cost of finance. In the context of a race, a smaller probability of winning will imply a lower expected payoff to the firm and therefore a lower expected repayment to the lender. As a result, the cost of finance will be higher for a given borrowed amount. The racing firm will therefore face tighter financing constraints when its competitors are tougher. As Blundell, Griffith and Van Reenen (1999) have shown, more incumbency gives firms an advantage over their competitors in the race. As a consequence, the dependency on cash should decrease with own incumbency and increase with the rivals'.

Bond, Harhoff and Van Reenen (2003) show that R&D flows do not adjust significantly during the research program once the program has been setup. Hence, the outcome of patent races depends on the initial R&D intensity and not in its time variation during the program. Therefore, the effects of cash holdings on the outcome of the race, if any, will be captured by a lagged vector of cash holdings. Further, if differences in cash holdings across players matter, then firms will also choose strategically how much cash to hold in first place to improve their competitiveness. In other words, we have to treat the lagged cash holdings as endogenous.

C Summary

We conclude that the right approach to study empirically the cash sensitivity of innovation is to focus on the given cash holdings of all competing firms as the determinants of the innovation success.

We summarize our discussion with the following working hypotheses:

Hypothesis 1 (cash matters strategically) The instrumented cash holdings have a positive effect on innovation success *over and above* experience and incumbency values. Moreover, the instrumented cash holdings of the rival firms in the race have a negative effect on innovation success.

We also conclude that we can test whether or not the cash sensitivity of innovation measures the tightness of financing constraints by determining if it is related to the race characteristics as predicted by the theory. Namely, we hypothesize that:

Hypothesis 2 (determinants of the cash sensitivity) The average effect of a firm's cash holdings on innovation is larger when the firm faces more experienced rivals and tougher incumbents.

II A first look at the data

A Pharmaceutical patents

The NBER Patents and Citations Data File records all utility patents granted in the United States between 1963 and 1999. It links the patents granted after 1975 to all the patents they cite and to the CUSIP code of their assignees.[4] This data set is an ideal starting point to identify the role of cash holdings in innovation races because each patent summarizes the outcome of the race, that is, who is the winner. Moreover, the outcome can be linked to the characteristics of the firms in the race. The link to the citations file allows us to identify the firms who own the technology over which a new innovation is built. As we shall see, this is a way to identify the incumbent firms for every race.

The CUSIP codes allow us to find the firms' financial information in COMPUSTAT. We match the firms in the NBER data to their COMPUSTAT's records one, two and three years before the patent application date. The US Food and Drug Administration estimates the length of the pre-clinical period to be between one and three years, with a mean of 18 months.[5]

Because we rely on patents as a measure of innovative success, we must focus on an industry where patents are crucial to reap the returns to R&D investment and where each single patent corresponds to one innovation race. This is the case for the drugs industry (see Levin et al., 1987, Cohen, Nelson and Walsh, 2000, and Hall, 2004).[6] We restrict our sample to patents in the technological category 3, i.e., Drugs and Medical, and the subcategories 31, 33 and 39: Drugs, Biotechnology, and Miscellaneous Drugs, respectively. Although we focus on pharmaceutical patents, we note that our method can be applied in a straight forward way to the study of any race in any industry provided that a satisfactory measure of success is available.

The race for the patent is the optimal stage to test for strategic interactions during the drug discovery process. The exclusivity rights on a new drug are only up for grabs during the pre-clinical stage. After that, only the patent holder may conduct the clinical trials without the threat of imitation. Further, new drugs are classified as 'discrete innovations' in the sense that they (i) comprise single patents and, (ii) the patents are used to block imitation, not to form patent pools (see Hall, 2004).

Panel A of Figure 1 shows that the total number of Category 3 US patents awarded per year has steadily increased since 1975. In 1999 there were almost 10,000 patents awarded. The total number of patents awarded between 1975 and 1999 is 91,565.

<INSERT FIGURE 1 ABOUT HERE>

1. Patent citations and market values

We use patent citations to measure the market value of each patent. Hall, Jaffe and Trajtenberg (2005) have argued that citations reflect economic value because if a citing firm is willing to invest in further developing an innovation, then this innovation must have been valuable in the first place. Indeed, they use the NBER Patents and Citations Data File to show that an additional citation per patent increases the firm's market value by 3% on average. Lanjouw and Schankerman (1999) identify a patent's private value through the decision to renew the patent. They also find that the count of received citations is among the best predictors of patent value, especially for pharmaceuticals.

Panel B of Figure 1 plots the average market value per patent each year, measured by the adjusted number of citations the patent receives. Following Hall, et al. (2002) we have corrected the bias in the raw count of citations per patent due to time differences in the propensity of applicants and reviewers to cite. The raw counts are therefore divided by the yearly factors they provide. While the total number of patents has increased, the value per patent doesn't show a clear trend. However, the market value per patent is the highest in the late 90s.

2. COMPUSTAT match

We cannot match all the patents to COMPUSTAT because not all winners are publicly traded firms. In fact, there is a large proportion of patents owned by universities. Table I summarizes and compares the main characteristics of the patents that can be matched with the those of the patent universe.

<INSERT TABLE I ABOUT HERE>

We find a COMPUSTAT match for the winners of about one third of the total number of patents. Panel A shows that there is little difference in terms of the mean and median number of firms cited by patent. Expectably, the patents that remain after the merge with COMPUSTAT are more valuable and the winners have more patenting experience. This difference is partially explained by the fact that the COMPUSTAT-merged sample has a much smaller proportion of patents with no citations.

In Panel B, we repeat this analysis within the 5 year intervals of our 25 year sample. The differences in patenting experience before and after the merge are pronounced. The differences between the average number of citations received and the average number of firms cited by patent are also significantly different from zero, but aren't large relative to their average values. However, it is clear that any inference based on the COMPUSTAT-merged sample is specific to the racing behavior for innovations of publicly traded firms with significant patenting experience.

B Who wins patents?

1. Incumbents and entrants

A key determinant of success in the racing environment of innovation is whether or not the competitor is an incumbent. In an innovation race, the incumbents are those firms with property rights over the technology upon which the next innovation builds. Blundell, Griffith and Van Reenen (1999) find that British manufacturing firms with more market dominance innovate more often. Hence, they argue, incumbents have an important advantage over entrants in the race for the next innovations along the sequence.[7] Therefore, to measure the effects of all competitors' cash constraints in a race correctly, we need to identify them *over and above* the effects of incumbency.

We also use the citations file to measure incumbency. If patent i cites patent j, then j represents part of the previously existing technology that j builds on. Moreover, the owner of j has an incumbency stake in the race for i. An incumbency measure based on citations is robust because it is actually the legal obligation of the applicant to cite all the prior art of the innovations he claims. In fact, the patent examiner, who must be a specialist in the field, examines these citations and decides which ones to be included finally in the award.

A firm is an entrant to a race if it owns no cited patents, or if the cited patents it owns are no longer valid, i.e., older than 20 years. Table II summarizes the main characteristics of incumbent and entrant patent winners in the data.

<INSERT TABLE II ABOUT HERE>

2. Differences in cash and size

Table II shows the average cash holdings and the total asset value of the winning firms, one year before the patent application. Winners appearing in the list of citations (incumbents) generally hold less cash on average and have a smaller average asset value than non-cited winners in the same five-year period. But the differences are relatively small for both variables in all periods.

The proportion of cash with respect to total assets is surprisingly steady for both types of winners over the whole sample period. This proportion ranges from 9.3% to 12.6% for incumbents and from 7.5% to 12.5% for entrants. Both types of winners hold the least amount of cash relative to assets between 1980 and 1984.

3. Incumbency

Clearly, incumbents differ in terms of their citations' value and age. The incentives of the incumbent to continue innovating depend on the value of the current technology and how long the incumbent expects to keep profiting from it. We measure incumbency with the citation counts for all cited patents of the same age owned by the same firm. Let $I0_{if}, I1_{if}, ..., I19_{if}$ denote the incumbency values of firm f for patent i for all the ages of citations. Hence, a firm is an entrant if and only if $Ia_{if} = 0$ for all $a = 0, 1, ..., 19$.

Table II summarizes the total incumbency index per firm per race, which is defined as

$$I_{if} = \sum_{a=0}^{19} Ia_{if} \times (20 - a) \,. \tag{1}$$

According to this definition, the younger and the more cited the patent, the larger its contribution to the total incumbency index of the firm. The average incumbency index of incumbent winners decreases sharply after 1979, but remains fairly constant until it increases again for the 1995-1999 period.

Table II shows also the proportion of races won by entrants and incumbents in each period. After the merge with COMPUSTAT, there are fewer patents won by incumbents. However, the merged data base still captures the same clear trend as the patent universe: the proportion of races won by incumbent firms increases over time.

4. Differences in experience

We use the number of patents accumulated by the firm in Category 3 one year before any given patent to measure the firm's patenting experience in the same field. Note that this is not the same measure as incumbency. The incumbency status of a firm to a race is based only on the count of *citations* in the same category that must also be *younger than 20 years*. Hence, firms with a lot of experience may be entrants to a given race.

The average number of patents accumulated by entrant winners is much larger than the incumbents'. An entrant winner between 1995 and 1999 has an average stock of 2,185 patents whereas an average incumbent has only about 300. This comparison illustrates clearly the difference between experience and incumbency in the patent race context. Both are key determinants of success for very different reasons. Superior patenting experience measures the firm's advantage to conduct R&D and file patents in the field (i.e., Category 3), whereas incumbency measures the firm's advantage to keep on innovating along a given technology sequence.

C Summary

The merger of the NBER Patents and Citations Data File with COMPUSTAT includes a third of all US Category 3 patents between 1975 and 1999. It is a sample of relatively more valuable patents won by larger firms with more experience patenting in the field with respect to the patent population. We learn that entrants to each race are not entrants to the pharmaceutical industry: they are large firms with superior patenting experience in this patent class.

We learn too that there are important differences between winning firms that are entrants or incumbents to any given patent. Entrant winners are slightly larger and hold about the same proportion of cash as incumbents do. They are also significantly more experienced than the incumbent winners. Although they have no advantages from incumbency, entrants win often. It seems that what they lack in incumbency, they make up in cash and experience. The fact that incumbent firms win increasingly more often over time suggests that their advantage has become stronger over time. Indeed, incumbency values also increase over time.

The conclusions from the previous discussion can only be considered preliminary because we have only compared the winners of races. We can only get an accurate inference through the comparison of success rates and the firm characteristics of *all* the firms in the race. This discussion has shown clearly that, in order to identify the effect of cash holdings on innovation we have to account for the other two main determinants of winning a race: experience and incumbency. To measure the effect of cash on the success probability over and above these two, we must also take into account the different value of patents raced for, and how this value modulates the relationship. We continue by explaining the econometric methodology to assess these effects and the empirical challenges that arise.

III The econometric strategy

A Nash equilibrium in innovation races

Our starting point is the probability that a firm f wins the race for a given patent i against all other firms $g \in \mathcal{F}_i$ who also compete for it. Let firm f's date of innovation, T_f, be random with a distribution

$$\Pr\left(T_f \leq \tau\right) = 1 - e^{-\lambda_f \tau},$$

where λ_f is the hazard rate of arriving and patenting the discovery. The winner is the first one to arrive at innovation. With independent Poisson processes $\forall f \in \mathcal{F}_i$, the probability that firm f wins race i is

$$\Pr(\text{firm } f \text{ wins race } i) = \Pr\left(T_f \leq T_g \ \forall g \in \mathcal{F}_i\right) = \frac{\lambda_f}{\sum_{g \in \mathcal{F}_i} \lambda_g}.$$

In the Nash equilibrium of the race, firm f's hazard rate can be written as a function of her given characteristics and the other player's hazard rates. The firm's choice of a hazard rate depends on her traditional sources of advantage, i.e., experience and incumbency. The firm's cash holdings will determine the borrowing costs to implement the desired hazard rate and will therefore condition the choice of λ in equilibrium (see Bond, Harhoff and Van Reenen, 2003).

Let the potentially relevant characteristics of each firm be its cash holdings, W_f, its patenting experience, E_f, the vector of the firm's incumbency values specific to that race, $\mathbf{I}_f$, and a vector of other control variables, $\mathbf{c}_f$. Therefore, the firms' best response hazard rates can be written as the system

$$\lambda_f = \lambda\left(W_f, E_f, \mathbf{I}_f, \mathbf{c}_f; \boldsymbol{\lambda}_{-f}\right) \ \forall f \in \mathcal{F}_i,$$

and a Nash Equilibrium is a vector of hazard rates $\boldsymbol{\lambda}^*$ that solves the system. Further, this implies that we can write each firm's equilibrium hazard rate and its winning probability as a function of all other firms' characteristics, i.e.,

$$\Pr\left(f \text{ wins race } i\right) = \frac{\lambda_f\left(\mathbf{W}, \mathbf{E}, \mathbf{I}, \mathbf{c}\right)}{\sum_{g \in \mathcal{F}_i} \lambda_g\left(\mathbf{W}, \mathbf{E}, \mathbf{I}, \mathbf{c}\right)} \quad \forall f \in \mathcal{F}_i. \tag{2}$$

Note that $\mathbf{W}, \mathbf{E}, \mathbf{I}$ and $\mathbf{c}$ are vector notation for the characteristics of all firms.

This representation is general enough to any form of competition within the racing framework. Firms could either choose directly their hazard rates of innovation or indirectly the level of R&D that maps concavely into the hazard rate. The crucial point here is that the Nash equilibrium winning probabilities can always be written as a function of all the competitor's given characteristics.

Note that we use a general setup based on Dasgupta and Stiglitz, (1980) and Reinganum, (1983) but the derivation of (2) doesn't depend on several of the commonly used assumptions in that literature. First, we don't need to assume that the winner of the race 'takes it all' but only that winning is the best outcome for any player. Second, we don't need to make assumptions about the intended use of the patent raced for. The intended use, e.g., to enforce it, license it, keep it for its option value, is irrelevant provided that we have a good cardinal measure of the firm's private value, which we do. The essential feature of this setup is that there is uncertainty in the outcome, and the robust result is that the winning probabilities can be written as a ratio of the a firm's hazard rate to the sum of all the competitors' due to the Poisson assumption. We now discuss an econometric specification that captures this result and tests directly for its comparative statics.

B A multinomial logit approach

We use a multinomial logit (MNL) specification to characterize the selection of a winner for every patent in our data set. This specification allows us to identify the comparative statics of equation (2). Under the MNL specification, firm f is selected as the winner of patent i from among the set of firms $\mathcal{F}_i$ if

$$\beta_W \ln W_f + \beta_E E_f + \boldsymbol{\beta}_I' \mathbf{I}_f + \boldsymbol{\gamma}' \mathbf{c}_f + \eta_f + \varepsilon_{if} \geq \max_{g \in \mathcal{F}_i} \beta_W W_g + \beta_E E_g + \boldsymbol{\beta}_I' \mathbf{I}_g + \boldsymbol{\gamma}' \mathbf{c}_g + \eta_g + \varepsilon_{ig},$$

where ε_{if} represents the randomness in the race outcome, which is unobserved by all the firms at the start of the race and is assumed to be distributed independently across firms with an extreme value distribution. This assumption implies that

$$\Pr(\text{firm } f \text{ wins race } i) = \frac{\exp(\beta_W \ln W_f + \beta_E E_f + \boldsymbol{\beta}_I' \mathbf{I}_f + \boldsymbol{\gamma}' \mathbf{c}_f + \eta_f)}{\sum_{g \in \mathcal{F}_i} \exp(\beta_W \ln W_g + \beta_E E_g + \boldsymbol{\beta}_I' \mathbf{I}_g + \boldsymbol{\gamma}' \mathbf{c}_g + \eta_g)}. \tag{3}$$

The parameters to estimate are β_W, β_E and the vectors $\boldsymbol{\beta}_I$ and $\boldsymbol{\gamma}$, while η_f represents the characteristics of f that are unobserved by the econometrician but known by all the firms.

The MNL specification is ideal for two reasons. First, the MNL is a very good approach to test the comparative statics of the *equilibrium* of the patent race precisely because it maps the given characteristics of the game directly into the winning probabilities. As in equation (2) , the MNL allows us to eliminate the equilibrium hazard rates and focus on the *observable* outcome, that is, who is the winner.

Second, the MNL is ideal for the racing setup because the winning probabilities are derived from the comparison of every competitors' vector of characteristics. A rejection of the null hypothesis that $\beta_W = 0$ implies that winning the race is determined jointly by all the competitor's cash holdings. In particular, our hypothesis that $\frac{\partial \Pr(f\ wins)}{\partial W_f} > 0$ and $\frac{\partial \Pr(f\ wins)}{\partial W_{g \neq f}} < 0$ is true if and only if $\beta_W > 0$.

A positive estimate of β_W would imply that firms are effectively cash constrained and the innovation investment is suboptimal with respect to the race equilibrium investment. Moreover, larger values of β_W imply a larger sensitivity of the probability of winning with respect to differences in cash holdings across firms in the race. We can then test whether or not the changes in sensitivity are explained by changes in the firm's strategic position. Higher sensitivities will be consistent with tighter financing constraints whenever they occur jointly with a worsening of the firm's strategic position. In such a case, the lower expected payoffs would make firms effectively more constrained and cash differences across players would matter more. [8]

C Estimation challenges

1. Specification

The base linear index for all our estimated specifications is

$$\beta_W \ln W_f + \beta_E E_f + \boldsymbol{\beta}_I' \mathbf{I}_f + \boldsymbol{\gamma}' \mathbf{c}_f, \tag{4}$$

where $\ln W_f$ is the logarithm of the value of cash holdings by firm f one year before the patent application, and E_f is the total number of patents accumulated by f also until one year before the patent application.[9] In $\mathbf{I}_f$ we include the total, time-adjusted, number of citations received by patents owned by f and cited by patent i for seven different vintages, i.e., $I0_{if}, I2_{if}, ..., I4_{if}$ and $\sum_{a=5}^{9} Ia_{if}$ and $\sum_{a=10}^{19} Ia_{if}$.[10]

To assess the effects of the value of the patent raced for in the equilibrium outcome, we split the sample into four sub-samples with the patents of each value quartile. We estimate the parameters of (4) in each quartile. The theoretical effect of the value of the patent on the equilibrium probabilities of winning is ambiguous. On one hand, a higher patent value implies a higher payoff to any firm in case it wins, which implies a looser ex-ante financing constraint. On the other hand, this change shifts all the player's best response hazard rates in the same direction (see Schroth and Szalay, 2007). The sample split allows us to address empirically the net effects of patent value on financing constraints by comparing the estimates of β_W across value quartiles. Note that the MNL specification cannot identify the effects of any variable that doesn't vary across firms in the race, so the parametric inclusion of the patent value into (4) is not a valid approach.

Since we have a 25-year sample, we also expect the parameters in (4) to change over time. For the same reasons as with patent value, we study time as a modulator of the relationship between cash holdings and innovation success, and the best way to study this relationship is to use five five-year samples and to compare the model estimates across time. In short, we estimate every given specification for every value quartile and five-year period combination.

2. Endogenous cash holdings

The cash sensitivity is measured here through β_W, which is identified through the variation in success frequencies and differences in cash holdings across firms. Knowing that the level of cash they hold relative to their competitors before the race are a crucial determinant of the success probability, firms will choose how much cash to hold before the race starts as a function of the other players' and their own characteristics. Since it is likely that there are several unobservable characteristics of the firm that drive this choice, it is likely that $\ln W_f$ and η_f are correlated.

To estimate β_W consistently, we use a set of instruments for $\ln W_f$ that are at the same decision stage as the unobservables in η_f. Hence, we minimize the risk of any residual correlation between η_f and the projection of $\ln W_f$ on its instruments. The instruments we use are:

1. the logarithm of cash, two and three years before the patent application;
2. the logarithms of total assets, two and three years before the patent application;
3. the logarithms of sales, two and three years before the patent application;

4. the logarithms of total debt outstanding, two and three years before the patent application;

5. the averages of each of the previous variables for *all the other* rival firms in the same race;

6. the average patenting experience for *all other rival* firms in the same race;

7. the average incumbency value per firm per vintage for *all other* rival firms in the same race.

Our choice of instruments is based in the previous literature of the demand for cash holdings (Opler et al., 1999; Almeida, et al. 2004) plus determinants related to the competition a firm expects to face in the race. The lags of cash and total assets are used to capture differences in the levels of cash and the lags of sales and debt are used to capture differences in the changes in cash holdings. The rivals' averages of these variables, experience and incumbency are used to measure the expected toughness of competitors. Indeed, if cash is chosen to minimize the need of external finance and its costs, then this choice will depend in the expected winning probability, which in turn is a function of the rivals' average characteristics.

We use the same set of instruments for each estimation. Our choice of instruments will be subject to a test of over-identifying restrictions.

3. Defining the set of firms in each race

It is crucial to determine the set of firms racing for each patent, i.e., $\mathcal{F}_i$. As we discussed earlier, the incumbents are found in the citations of each patent and their incumbency values are given by the citations received by their cited patents. However, we don't have a list of entrants, except for the winner for entrant-won races.

In principle, any firm in the same industrial classification (e.g., 2 digit SIC code) as the firms who win patents in Category 3 is a potential entrant. However, it is clear that too many firms have severe disadvantages with respect to the likely winners and effectively don't participate in the race. Hence, our goal is to define for every patent a subset of the top ranked non-cited firms in the industry in terms of their likelihood of winning a given race at a given time. We continue by explaining how we rank and choose the entrant selection size for each race.

IV Evidence from patents won by non-cited firms

The goal of this section is to select systematically those firms that are most likely to be racing for any given patent among the set of all firms that are not cited but have won at least one patent in Category 3 in a given five-year period. Hence, we need to implement first a ranking criterion and then to decide on the size of the selection. As we shall see below, the scoring step follows from the assumed data generating process, i.e., from (3) . Therefore, we can already use the estimates computed in this step to make inference about our hypotheses.

A Entrant scoring

Clearly, the set to select the top ranked firms from is large. Estimating a MNL selection model for the whole set is infeasible. To solve this problem, we follow Berry's (1994) approach: to transform the non-linear representation of the average equilibrium winning probabilities in (3) into a linear relationship of the observed winning percentages, which is estimable using linear methods.[11]

The method is as follows. Since (3) computes the probability of selection of a given firm to a race, it can also be used in the aggregate to measure the share of patents won by a given firm over a period of time. Let $\mathcal{F}_i^I$ and $\mathcal{F}_i^E$ be the sets of incumbents and entrants, respectively and $\mathcal{F}_i \equiv \mathcal{F}_i^I \cup \mathcal{F}_i^E$. Let s_{jt} be the share of patents that firm f wins as an entrant in year t, i.e., the probability that j wins an 'average' patent in t. Let s_{0t} be the probability that the typical patent in t is won by any of the incumbents. From (3) we take logarithms on s_{jt} for any firm $f \in \mathcal{F}_i^E$ and s_{0t} to obtain

$$\begin{aligned}\ln s_{ft} - \ln s_{0t} \;=\;& \beta_W \ln W_{ft-1} + \beta_E E_{ft-1} + \boldsymbol{\beta}_I' \mathbf{I}_{ft-1} + \boldsymbol{\gamma}' \mathbf{c}_{jt} + \eta_{ft} \\ & - \ln \sum_{g \in \mathcal{F}_i} \exp(\beta_W \ln W_{gt-1} + \beta_E E_{gt-1} + \boldsymbol{\beta}_I' \mathbf{I}_{ft-1} + \boldsymbol{\gamma}' \mathbf{c}_{gt} + \eta_{gt}) \\ & - \ln \sum_{g \in \mathcal{F}_i^I} \exp(\beta_W \ln W_{gt-1} + \beta_E E_{gt-1} + \boldsymbol{\beta}_I' \mathbf{I}_{gt-1} + \boldsymbol{\gamma}' \mathbf{c}_{gt} + \eta_{gt}) \\ & + \ln \sum_{g \in \mathcal{F}_i} \exp(\beta_W \ln W_{gt-1} + \beta_E E_{gt-1} + \boldsymbol{\beta}_I' \mathbf{I}_{ft-1} + \boldsymbol{\gamma}' \mathbf{c}_{gt} + \eta_{gt})\end{aligned}$$

Note that $\boldsymbol{\beta}_I' \mathbf{I}_f = 0$ for all $f \in \mathcal{F}_i^E$. Note too that the sum of the incumbents indices, i.e., $\sum_{g \in \mathcal{F}_i^I} \exp(.)$ is constant across f and varies only across time. Hence, this term can be simply written as a constant plus yearly dummies, simplifying the model to

$$\ln s_{ft} - \ln s_{0t} = \beta_0 + \boldsymbol{\beta}_1' \mathbf{d} + \beta_W \ln W_{ft-1} + \beta_E E_{ft-1} + \boldsymbol{\gamma}' \mathbf{c}_{ft} + \eta_{ft}, \tag{5}$$

where $\mathbf{d}$ is a vector of the four yearly dummy variables in each five-year estimation sample. This transformation is very intuitive. It says that the differences across entrant firms' share of patents won in a year relative to the share of patents won by incumbents is explained by the differences across the entrant firms' characteristics in the same period. Hence, if we treat the unobservable η_{ft} as the structural error, we can estimate the parameters, $\beta_0, \boldsymbol{\beta}_1, \beta_W, \beta_E$ and $\boldsymbol{\gamma}$ from the regression of $\ln s_{ft} - \ln s_{0t}$ on $\ln W_{ft-1}, E_{ft-1}$ and $\mathbf{c}_{ft}$ for *all* potential entrant firms in t.

This procedure has several advantages. One big advantage is that this method transforms the dimensionality of the selection problem into the number of cross-sectional units in the panel. Hence, we can use a very large number of potential entrants every period. In fact, we use all firms who win at least a patent in a fixed five-year period. Another advantage is that we can use a straightforward instrumental variables estimator because the model is estimable by linear methods.

The biggest advantage is that the dependent variable is by itself the score we need in order to rank firms in terms of the likelihood of participating in each race. Indeed, the predicted $\ln s_{ft} - \ln s_{0t}$ ranks all firms active in t according to the probability that they might win against a given set of incumbents.

B Results

1. Cash holdings and patenting experience

We estimate (5) by stacking the five yearly winning shares cross-sections of all entrants in each five-year estimation period and patent quartiles.[12] We use an instrumental variables estimator in all cases, and the set of instruments described above. All estimations also include dummy variables for each year, and $\mathbf{c}_f$ includes 2-digit SIC code fixed effects. The results are shown in Table III.

<INSERT TABLE III ABOUT HERE>

Panel A of Table III shows positive estimates of β_W for the patents in the upper half of the value distribution. In both cases, we can reject with more than 99% confidence that $\beta_W = 0$. This result supports our hypothesis that the winning probability for an average patent in the period-value cluster depends positively on the firm's own cash holdings and negatively on the competitors'. The lack of sensitivity in the lower half of the value distribution may be due to the fact that there are many patents of little value, for which little cash is required in the first place. Patenting experience matters little in explaining patenting success in this period, most likely because patent experience differences across firms in this period are small. Our specification test statistic is distributed χ^2 under the null hypothesis that the instruments used over-identify the model's parameters. The value obtained in all cases is well in the acceptance region.

In Panel B we see that the estimates of β_W are positive and significantly different from zero in all but the first quartile of the patent value sampling distribution. Note that the estimate decreases as we go from the second to the fourth quartile. The most likely explanation for this result is that, as patent value increases, financing constraints are looser because the payoff in the good states is higher.

Experience now has an estimated positive effect on the probability of winning in the top three quartiles, as differences in experience across firms get more pronounced. As before, we cannot reject the null hypothesis that the instruments used over-identify the model's parameters.

Throughout Panels C, D and E we see positive estimates of β_W. In almost all cases they are significantly different from zero with 99% confidence. It is clear from these results that the differences in cash holdings across entrant firms are an important predictor of the differences in success probabilities *over and above* experience. Given that our instruments for cash over-identify the model's parameters, we attribute this effect to the fact that financing constraints bind significantly. Further, the fact that the estimated coefficients are smaller in races for more valuable patents is consistent with financing constraints for entrants being looser in races with a higher expected payoff.

2. Cash sensitivity across time

Several comparisons of our estimates across time but within quartiles are in order too. The intercept coefficient decreases across time clusters. The negative of the intercept is interpreted as the average index of the incumbents competitiveness to the races for a given period. We saw earlier that the incumbents' winning frequency had an upward trend, which is captured here by the downward trend in the estimated intercepts. Finally, the estimates of β_W also increase over time, although not as clearly.

To have a more clear picture of the evolution of this sensitivity over time, we interpret our estimates of β_W in terms of the changes in the expected number of patents won per year given changes in cash holdings and experience. These results are reported in Table IV.

C Interpretation of results

Table IV shows that our estimates of β_W are not only statistically significant, but also economically significant. There we report the expected change in the number of patents by a given firm in a given year with respect to a change in a one sample standard deviation increase in the firm's cash holdings, *ceteris paribus*. The values of all other variables are set to their sample mean. We report below each estimate the average number of patents per firm per year in the sample to highlight their relative importance. We also report the changes in patents per firm per year with respect to one sample standard deviation in increase in the patenting experience of the firm.

<INSERT TABLE IV ABOUT HERE>

We see in Table IV that cash holdings differences across entrant firms predict significant differences in patents won per year. Overall, the estimated expected increase in the average number of patents per firm per year given an increase in one sample standard deviation of cash holdings is between 0.24 and 2.4. In the period of highest sensitivity, the average increase in patents per year with respect to a one sample standard deviation in cash holdings is of around 50% of the patents won. After the mid 70s, this increase is above 20% for all quartiles.

These changes are illustrated also in Figure 2. Panel A shows the changes in the number of patents and Panel B shows the changes corrected for overall patenting activity. In both cases, the sensitivity has increased. The increase in sensitivity is most pronounced from 1990 to 1999.

<INSERT FIGURE 2 ABOUT HERE>

We note that the increase in sensitivity has occurred jointly with the fact that incumbents have become more competitive over time. The more competitive the incumbents, the smaller the success probability of an entrant, the lower the expected payoff from the race and the higher the financing costs given a cash balance. Hence, it appears that financing constraints for entrants as a whole have become tighter over time. We analyze this effect formally in Section VI, using these results and those for the full sample.

The effect of a one sample standard deviation increase in cash holdings is generally more powerful than a one sample standard deviation increase in patenting experience, in the case of entrants. The effects here range from 0.17 to 0.81 patents per year. The importance of cash holdings relative to experience for entrants seems to have increased slowly in the mid 70s and 80s and fast in the 90s.

D Entrants' selection

We use the estimates reported in Table III to predict the score of each firm. The score is the probability that an entrant firm wins a representative period t patent and it is computed from $\hat{\beta}_0 + \hat{\boldsymbol{\beta}}_1'\mathbf{d} + \hat{\beta}_W \ln W_{ft-1} + \hat{\beta}_E E_{ft-1} + \hat{\boldsymbol{\gamma}}'\mathbf{c}_{ft}$ for all firms that win at least one patent as an entrant. This implies a group of between 11 to 45 firms per year and patent value quartile. We rank firms according to their score within the year and value quartile. Since there are 25 years in our sample and four value quartiles, we generate 100 rankings.

Panel A of Table V reports the average cumulative scores, i.e., winning probabilities, for the top ranked firms. The predicted probability that the winning entrants is within the top ten firms, given that the winner of the patent is an entrant, is on average 0.76. The winner is almost surely within the top fifteen. Hence, there is little gain to include as entrants to a race firms ranked below 20 or 15.

<INSERT TABLE V ABOUT HERE>

In what follows, the set of entrants to any patent will be the top ten entrants in the same year and value quartile. Using fifteen entrants would certainly increase the chances that our set captures all the sources of interaction between competitors but it would come at a very high computational cost. The dimensionality of the MNL estimation with incumbents and entrants is already large. We have estimated the models that follow with fifteen entrants in the last five year period value quartiles and have observed extremely similar results. They are available to the reader upon request. We note too that for entrant won races, we use the actual winner and the top nine in addition to the winner. The actual winner has a top ten score almost always.

In the next Section we estimate the model's parameters using all patents, and the characteristics of both incumbents and entrants as they simultaneously determine the winner. This will provide further insight into the role of cash holdings in relation to specific characteristics of each patent raced for, e.g., the incumbency value.

V Evidence from all patents

A Selection description

1. Number of incumbents

Panel B of Table V shows that almost 95% of patents cite fewer than 10 firms. However, the incumbency values of some of these are insignificant because the citations are too old or receive no citations themselves. The right column shows the cumulative relative contribution of each firms' incumbency value to the total incumbency value of patent i. From (1), the total incumbency value is simply the sum of all firm's incumbency values, i.e., $I_i = \sum_{f \in \mathcal{F}_i} I_{if}$. The cumulative incumbency value of the first four incumbents relative to the patent's total incumbency value is on average 95% and has a median of 100%.

Our set of competing firms in a race, $\mathcal{F}_i$, contains the four incumbents with the highest incumbency value and the ten entrants with the highest estimated winning scores in the estimation cluster. Tables VI and VII summarize the main characteristics of this selection.

<INSERT TABLE VI ABOUT HERE>

2. Cash holdings and total assets

The comparison between entrants and incumbents in our selection for each race is very similar to the comparison between winning entrants and winning incumbents that we discussed previously. Entrants have slightly more assets than the average incumbents. Both types of competitor's roughly hold 10% of their assets in cash, except between 1985 and 1989, when they hold around 12%. Entrants to each race are also much more experienced, and their experience advantage increases over time.

3. Evolution of incumbency values

Table VII summarizes the incumbency values of the selected incumbents (as we discussed above, the incumbency values of the remaining cited firms are negligible). Panel A shows these summaries for the whole patent universe and Panel B does it for the patents remaining after the COMPUSTAT merge and usable for our next estimation stage.

<INSERT TABLE VII ABOUT HERE>

The incumbency value per incumbent firm has a U shape except for the extreme vintages (less than one and more than ten years old). For the five vintages in between there is a steady increase in incumbency value from 1985 until 1999. The incumbency value of the extreme vintages decrease monotonically. Very old citations are unlikely to have a major effect on racing behavior. Hence, we expect that the increase in the incumbency values of younger vintages gives incumbents an important advantage over entrants. The distribution of the incumbency value per incumbent firm is also more right-skewed in the 90s with respect to the 80s for the intermediate vintages. As a result, we also expect the incumbency advantages to be concentrated in some but not all incumbents to a race. In the next section we discuss the estimation of the model and the measurement of these effects.

B Method

Our goal now is to estimate the parameters of (3) by maximum likelihood using the set of selected ten entrants and four incumbents to each race. The estimation is not straightforward because some firm characteristics may be omitted. If these firm characteristics, represented by η_f, are correlated with some explanatory variable, then the errors in the selection of the winner of the race are not independent of the linear index and the MNL formula in (3) is no longer valid.[13]

We argued previously that $\ln W_f$ must be correlated with η_f. To solve this problem, we follow the control function approach proposed by Petrin and Train (2003). This approach consists of estimating η_f consistently with a first stage regression of $\ln W_f$ on its instruments. Since the projection of $\ln W_f$ on its instruments is uncorrelated with η_f, the residual of this regression is the correlated component. Hence, the model can be estimated in two stages, where the second stage computes the maximum likelihood estimates of (3), including the first stage residuals, $\hat{\eta}_f$, in the linear index. Following also Petrin and Train (2003), we use a bootstrap estimator for the parameter estimates' standard errors.

Table VIII shows the estimates of our base specification for all patents awarded between 1995 and 1999. The estimates of the cash sensitivities for whole sample period (1975 to 1999) are shown in Table IX. For parsimony, we omit here the parameter estimates for all other four time periods. The inference is qualitatively similar to period 1975-1999. The results are available upon request.

<INSERT TABLE VIII ABOUT HERE>

C Base case results

1. Cash holdings

Table VIII shows positive and statistically significant (with 99% confidence) estimates of β_W for the patents in all quartiles. Hence, the probability that a firm wins an average patent in each period-value cluster depends positively on the firm's own cash holdings and negatively on the competitors' cash holdings. The estimate of β_W is also positive and significant with at least 95% confidence all but the third quartile between 1980 and 1994, and for all but the first quartile between 1975 and 1979. Otherwise its zero.

We showed previously that cash holdings differences across entrants were a very powerful determinant of the differences in winning probabilities across entrants for entrant won patents. Here we compare entrants and incumbents and use all patents and the differences in cash matter too. In the next subsection we will interpret these estimates to study the time pattern of this sensitivity.

2. Experience and incumbency

Patenting experience has a positive and significant effect in all cases, in line with our expectations. The experience effect was small and sometimes insignificant in the estimations that compared only entrant firms. Now we are selecting the winner from among entrants and incumbents, where experience differences are more pronounced. The larger estimates pick up this effect.

The effect of the value of less than one year old patents is almost always zero. These patents may be too young to pick up any effect, or too young for the incumbent to cannibalize their value with newer patents building on them. Patents aged between one and five years have a strong effect on the probability of success: the more valuable the incumbent firm's own patents, the more likely it is to keep on winning and the more valuable the other incumbent's patents, the less likely it is to do so. This effect is seen very clearly in all estimation subsamples. Older patents have still a positive effect, but much smaller and sometimes nil. This confirms our point that the effect of cash holdings can only be measured accurately once we account for the other two important determinants of innovation success: incumbency and experience.

There are two interpretations for the positive coefficient of the incumbency value. The first is that the incumbent has more incentives to keep competition soft than the entrant to make competition tougher in the innovation sequence. The second is that previous innovations may create better technological opportunities to the previous winners (incumbents) than to the previous losers (entrants). We believe that our estimates are more likely to capture the first effect. Indeed, the incumbency value coefficient will capture technological opportunity only to the extent that it favours one type of player more than the other because the left hand side of (2) is the probability of winning conditional on the fact that there is a winner. Hence, the component of technological opportunity common to all players cancels out. Further, a patent award is by definition a public disclosure of a new technology, so the advantageous effects of technological opportunity through incumbency should show up in only very young citations. The evidence shows they show up in citations older than one and as old as five years.

3. Other results

The firm's size, measured by total assets has a negative effect on the winning probability. Size is used mainly as a control variable, but the negative sign is hard to interpret. Even though size is likely to affect the financing conditions of the firm, e.g., through collateral, it appears to have no clear effect on the winning probability over cash, experience and incumbency. Hence, it is possible that size rather affects the sensitivity of the winning probability to cash by loosening financing constraints. In our next specification we study the role of size as a proxy for easier access to external finance, following an approach similar to the sample splits in Almeida, et al., (2004) or Whited (2006).

Note too that the first stage error component is significant almost everywhere. This implies that our first stage control function approach has effectively captured important correlated unobservable components.

D Interpretation

Table IX shows a significant sensitivity of the winning probability to cash holdings. We set the values of all other variables to their sample mean and evaluate the effect of a one sample standard deviation increase in cash on the probability of winning a given patent. The increase in the winning probability ranges up to 0.11 (quartile 4, 1975-1979). The effects are the strongest in the 90s, ranging between 0.04 and 0.08, and the proportion of patents won per year per firm in those same years ranges between 0.07 and 0.1.

<INSERT TABLE IX ABOUT HERE>

There is no clear trend in the sensitivity to cash holdings, as there was when we compared entrant patents only. It is clear though that the 90s have seen an apparent average tightening of financing constraints, as the sensitivity increases with respect to the 80s and catches up to the levels of the late 70s. Also, the effects of cash are often stronger than the effects of experience, although not as often as in the case of entrants only.

E Controlling for access to external finance

1. Specification

We follow here the literature on external financing constraints and allow for the dependency of innovation success on cash to change according to measures of the firm's access to external finance. As in that literature, we expect larger firms to be less constrained than smaller ones: all other things constant, larger firms have more non-liquid assets that can be used as collateral to improve financing conditions for a given investment and require less cash of their own. Similarly to the size sample-split approach, we expect the success probability should be less sensitive to cash for lager firms. Hence, we specify the linear index in (3) as

$$\beta_W \ln W_f + \beta_{WS} \ln W_f \times \ln S_f + \beta_E E_f + \boldsymbol{\beta}_I' \mathbf{I}_f, \tag{6}$$

where S_f is total asset value. We predict that $\beta_W > 0$, $\beta_{WS} < 0$ and the total effect of a change in cash holdings is positive. The results are shown in Table X.

<INSERT TABLE X ABOUT HERE>

Note too that this effect is different from the effect where large firms can hold more cash because they have more assets. That effect is already captured through the instruments in the first stage.

2. Results and Interpretation

This specification fits the data slightly better than the previous one. Pseudo-R^2 coefficients have increased slightly. The effect of size has now a clear interpretation, as the negative estimate of β_{WS} in most cases confirms that cash holdings matter less for larger firms.

In Table XI analyzes the total effects of one sample standard deviation changes in cash holdings and experience. The effects are of almost the same size as those in Table IX, and also economically significant when compared to the average number of patents per year per firm.

<INSERT TABLE XI ABOUT HERE>

Figure 3 shows the time pattern of the changes in winning probabilities with respect to changes in cash holdings. There is a clear U shaped pattern for all patents in the top three value quartiles. This pattern coincides with the pattern of incumbency values for all vintages between 1 and 5 years old. It suggests strongly that the increase in the sensitivity of innovation success to cash holdings, especially in the 90s, is picking up this effect.

<INSERT FIGURE 3 ABOUT HERE>

VI Explaining the changes in the cash sensitivity of innovation

Our results so far have shown that differences in cash holdings across firms in the same race for a drug patent are powerful predictors of the differences in winning probabilities across these firms, over and above experience and incumbency values. In particular, firms with more cash are more likely to win. We have identified this effect through the comparison of success rates across races and across firms within races. Therefore, success also depends on how much more cash the firm has relative to its rivals.

A Facts about the cash sensitivity of innovation

The sensitivity of the average firm's probability of winning patent races in the drugs industry with respect to cash holdings has increased in the 90s with respect to the early 80s. We observe this pattern when the sensitivity is measured using either the set of all potential entrants over entrant won patents only or the set of incumbents and pre-selected entrants over all patents. In the former case, the sensitivity increases throughout the whole sample period.

What explains these changes in the cash sensitivity over time? What has changed exogenously over this period to account for such patterns? To answer these question we make three observations based on our results: (i) incumbents have won an increasing share of patents over time; (ii) incumbency values have a positive effect on the winning probability; and (iii) the time pattern of the average sensitivity mirrors the time pattern of the average incumbency value per incumbent per race; i.e., decreasing until 1985, and increasing thereafter.

From observations (i) and (ii), we learn that the average cash sensitivity for all potential entrants, over races won by entrants, moves together with the incumbents' winning intensity. Hence, as entrants face effectively tougher incumbents, the selection of those who have any chance of winning depends more on their cash holdings.

B Determinants of the sensitivity

Observation (iii) is better illustrated in Table XII, which analyzes the determinants of the estimated sensitivities of the probability of winning a given patent with respect to cash holdings. We regress the 20 sensitivity values of each time period and patent value quartile combination, as reported in Table XI, on the possible determinants.

<INSERT TABLE XII ABOUT HERE>

Our main regressor is the average incumbency value per incumbent firm in the average race in the estimation cluster. We show the estimates of its effects on the cash sensitivity in columns (1) through (7). To keep the specification parsimonious, we use the incumbency value of citations from two vintages: younger and older than five years of age. As we saw before, the vintages younger than five years old have the most significant effects on the winning probabilities. All the specifications include either a time trend or time dummies.

Columns (1) and (2) report the OLS estimates of the effects of the incumbency value with and without an intercept. The model without an intercept provides the best fit, whereas the model with intercept is rejected. In column (2), the coefficient on the average incumbency value per firm is positive (0.0219), and significant with 90% confidence. Columns (3) and

(4) report a more efficient, quartile-specific, random effects estimator. Both cases show that the average cash sensitivity for both incumbents and the selected entrants is positively associated with the average incumbency value per incumbent. The coefficient is significant with 95% or 99% confidence. An increase of one sample standard deviation of the average incumbency value (0.48) is associated with an average increase of the cash sensitivity of $0.48 \times 0.022 = 0.011$. This increase is significant relative to the average sample sensitivity (0.03), and almost doubles the contemporaneous effect of the time trend.

Table XII shows clearly that the average cash sensitivity for both incumbents and the selected entrants moves together with the average incumbency value per incumbent. Increases in the average incumbency value per incumbent increase the competitiveness of incumbents with respect to entrants, and thus with respect to the average firm in the race. Moreover, the skewness of the incumbency value per incumbent follows a similar pattern too: it decreases until the mid 80s, then increases. Therefore, fewer incumbents have become more competitive with respect to the remaining incumbents and the entrants in any given race. The average sensitivity is then essentially capturing the incumbency *concentration* over the set of firms in the race, and it is higher when the average firm faces a tougher incumbent. We conclude from this evidence that some incumbent firms have accumulated more valuable innovations along the technology sequence and this has made them more competitive. As a result, firms without ownership of the building technologies have faced bigger disadvantages over time. Facing smaller probabilities of winning, the average firm has become effectively more financially constrained and has relied more on their own cash holdings to be successful.

Columns (5) and (6) show that the co-movement is robust to adding further controls for time-changing costs of finance. We include the five-year average annual Bank Prime loan rate and the five-year average of the Moody's AAA corporate, one year to maturity, credit spread (the results for BAA ratings are very similar and thus omitted). Both have no significant effect on the cash sensitivity. Our sensitivity measure adjusts to changes in the asymmetry between competing firms, i.e., the incumbency values, and not to changes in factors that affect all firms symmetrically, e.g., the benchmark cost of finance. Therefore, we have clearly identified a large increase in the importance of internal resources to finance innovation in pharmaceuticals since the mid 80s due to changes in the strategic environment and not in the external financing environment.

Naturally, the average firm, and especially entrants, have used their patenting experience to counter the more concentrated incumbency disadvantage, but the effect of experience has remained steady. It has only partially substituted the advantages of using own cash. In deed, columns (8) and (9) of Table XII show that the cash sensitivity of winning is not associated with either the entrants' nor the incumbents' experience.

Our results point to a natural evolution of an industry where incumbency gives an advantage. In such a case, the asymmetry between entrants and incumbents will typically grow. Bates, Kahle and Stulz (2006) show that the typical U.S. public firm holds twice as much more cash in 2004 than it used to do in 1980. They attribute this change mainly to the increase in cash flow volatility and R&D expenditures. The cash holdings of the firms racing for drugs have not increased as dramatically, but the importance of the differences in cash holdings certainly has. Moreover, decreases in the winning probability in the context of patent races map one to one into per firm innovation hazard rates, which in turn imply riskier cash flows and riskier R&D investments. Hence, increases in the competitive advantage of incumbents imply increases in the volatility of entrants' cash flows and R&D investment. Therefore, we believe that our results are in line with those of Bates et al. (2006). Further, this paper provides an explanation to what is behind the increase in riskiness for pharmaceutical firms that are entrants to given technology lines.

VII Concluding remarks

This paper has shown that the cash holdings of a firm and of its competitors' in an innovation race matter. These effect are robust, and have been consistently measured over and above the factors that traditionally predict innovation success. We have attributed the average increased dependency of innovation success on cash holdings to the increased concentration of the competitive advantage of technology leaders over laggards in the pharmaceutical industry.

Our inference is limited only to the pharmaceutical industry because we have used only data on drugs patents. It is not clear whether or not patent data mirror well the strategic behavior towards innovation in other industries. However, our empirical methodology is applicable to any industry where firms derive larger benefits from innovating first. Future applications of it would require accurate data on innovation counts.

The increased dependency of cash seems to be an economy-wide phenomenon. Future research could apply our methods to industries where innovators have first-mover advantages to see if the reason there is also the growing asymmetry between incumbents and entrants. Future research could also ask what has had a more powerful effect on the importance of cash for innovation: changes in the industry's strategic environment or changes in the external financing conditions.

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Footnotes

1. See Bates, Kahle and Stulz (2006) and Foley, Hartzell, Titman and Twite (2007).
2. Firms that develop 'complex technologies' (software, electrical equipment) accumulate bundles of patents to induce rivals to negotiate property rights over complementary technologies (Hall, 2004).
3. This consensus synthesizes from the debate between Fazzari, Hubbard and Petersen (1988, 2000) and Kaplan and Zingales (1997, 2000). The basic intuition of why cash holdings matter goes back to Keynes (1936, p. 196).
4. See Hall, Jaffee and Trajtenberg (2002) for a description of its contents, and Jaffee and Trajtenberg (2002) for an extensive summary of the data, and a discussion of its main uses and value.
5. US FDA's Center for Drug Evaluation and Research Handbook, available at:

   http://www.fda.gov/cder/handbook/.
6. It is widely acknowledged that firms in many other industries use other mechanisms to protect the competitive advantages of R&D (e.g., superior marketing, customer service, client switching costs). In such industries, patent records do not represent well the innovations and the races for them.
7. The advantage of incumbents over entrants in innovation races is explained by the 'efficiency effect': entrants have little incentives to innovate whenever they expect tough competition from the incumbents' coexisting old technology. The oligopolist firms have greater incentives to remain a 'soft' oligopoly that the entrants to compete in a 'tough' one.
8. Kaplan and Zingales (1997) show that optimal investment may well be convex or concave in the firm's cash holdings and therefore the investment sensitivity to cash flow is not informative of the tightness of financing constraints. Note that here we measure the sensitivity of the *outcome* of the race, i.e., who wins, and not of the *input* to the race, i.e., investment.
9. All of the results that follow are identical when using two instead of one-year lags for cash holdings and firm size. The results are available upon request.
10. We have also estimated all the specifications that follow with the twenty yearly vintages. The effects of patents older than five years are very small compared to the effects of the younger ones. Hence, we group all citations older than five years in the two vintages proposed above, i.e., the 5 to 10 and the 10 to 20 year-old citations. For parsimony, we report only the specification that groups the twenty vintages in seven. This grouping has virtually no effect on the estimates of all other parameters.

11. Berry (1994) discusses this method for the estimation of the average determinants of the indirect utility function when agents make discrete consumption choices. The method is general enough to apply to many other contexts, e.g., ours.

12. An alternative is to compute patent winning shares over five years and estimate the model with only one cross-section of participating firms. The yearly aggregation has the advantage that it captures better the dynamics of entry and exit, as it defines shares only with firms observed participating in one year. Further, this aggregation allows for rankings that change yearly and uses also time variation in experience and cash.

13. The MNL probability that f wins the race is $\Pr(\text{firm } f \text{ wins race } i) = \int_{A_{\boldsymbol{\varepsilon}_i}} dG(\boldsymbol{\varepsilon}_i')$, where $A_{\boldsymbol{\varepsilon}_i}$ is the set of $\boldsymbol{\varepsilon}_i$ that lead to the selection of f over all other firms $g \in \mathcal{F}_i$, i.e.,

$$A_{\boldsymbol{\varepsilon}_i} = \{\boldsymbol{\varepsilon}_i | \begin{matrix} \beta_W \ln W_f + \beta_E E_f + \boldsymbol{\beta}_I' \mathbf{I}_f + \boldsymbol{\gamma}' \mathbf{c}_f + \eta_f + \varepsilon_{if} \geq \\ \max_{g \in \mathcal{F}_i} \beta_W W_g + \beta_E E_g + \boldsymbol{\beta}_I' \mathbf{I}_g + \boldsymbol{\gamma}' \mathbf{c}_g + \eta_g + \varepsilon_{ig} \end{matrix} \}.$$

If the joint distribution $G(\varepsilon_{i1}, \varepsilon_{i2}, ..., \varepsilon_{iF_i})$ is of the extreme value type and all η_f are observable, then the MNL probability that firm f is selected is

$$\frac{\exp(\beta_W \ln W_f + \beta_E E_f + \boldsymbol{\beta}_I' \mathbf{I}_f + \boldsymbol{\gamma}' \mathbf{c}_f + \eta_f)}{\sum_{g \in \mathcal{F}_i} \exp(\beta_W \ln W_g + \beta_E E_g + \boldsymbol{\beta}_I' \mathbf{I}_g + \boldsymbol{\gamma}' \mathbf{c}_g + \eta_g)}.$$

If η_f is unobservable, then the errors $\varepsilon_{if} + \eta_f$ are correlated with $\ln W_f$ and the integration to obtain the MNL formula is not possible.

Table I: Summary of the patents in the NBER Database before and after the match to COMPUSTAT

This table summarizes the main characteristics of all US patents in the NBER Database between 1975 and 1999, in the technological category 3 (Drugs and Medical), subcategories 31, 33 and 39. It shows he results of matching the patent awards to their citations and to their assignees' financial data in COMPUSTAT. All citation counts are corrected for yearly differences in the propensity to cite using the adjustment factors provided by Hall, et al., (2002).

Panel A: Summary of the matches over the whole sample period (1975-1999)

	Number of patents	Number of cited firms		Number of citations received		Patents accumulated by the winner	
		Mean (Standard deviation)	Median	Mean (Standard deviation)	Median	Mean (Standard deviation)	Median
All patents in NBER (A)	91,656	4.010 (4.669)	3	0.753 (2.534)	0.216	149.129 (270.003)	33
Patents with matched assignees (B)	31,039	3.968 (4.161)	3	0.825 (2.390)	0.296	275.524 (351.935)	131
P-value ($H_0 : \mu_A - \mu_B = 0$)		0.172		0.000		0.001	

Table I, continued

Panel B: Summary of the matches at each five-year period

	Number of patents	Number of cited firms Mean (Standard deviation)	Median	Number of citations received Mean (Standard deviation)	Median	Patents accumulated by the winner Mean (Standard deviation)	Median
1. From 1975 to 1979							
All patents in NBER (A)	8,312	2.123 (1.381)	2	0.728 (1.157)	0.351	33.701 (49.997)	12
Patents with matched assignees (B)	4,069	2.167 (1.445)	2	0.780 (1.316)	0.350	42.652 (46.726)	25
P-value ($H_0 : \mu_A - \mu_B = 0$)		0.050		0.000		0.000	
2. From 1980 to 1984							
All patents in NBER (A)	10,341	2.737 (2.025)	2	0.748 (1.239)	0.394	92.682 (125.809)	37
Patents with matched assignees (B)	4,414	2.794 (2.037)	2	0.787 (1.385)	0.394	140.398 (134.391)	102
P-value ($H_0 : \mu_A - \mu_B = 0$)		0.062		0.059		0.000	
3. From 1980 to 1984							
All patents in NBER (A)	14,448	3.244 (2.700)	2	0.718 (1.163)	0.385	135.782 (206.488)	37
Patents with matched assignees (B)	5,462	3.484 (2.876)	3	0.781 (1.360)	0.396	224.557 (230.016)	160
P-value ($H_0 : \mu_A - \mu_B = 0$)		0.000		0.007		0.000	
4. From 1980 to 1984							
All patents in NBER (A)	21,186	3.911 (3.731)	3	0.714 (1.146)	0.366	172.088 (282.673)	38
Patents with matched assignees (B)	7,325	4.218 (3.992)	3	0.817 (1.314)	0.383	312.031 (348.238)	188
P-value ($H_0 : \mu_A - \mu_B = 0$)		0.000		0.000		0.000	
5. From 1980 to 1984							
All patents in NBER (A)	37,369	5.133 (6.201)	3	0.795 (1.565)	0.218	182.568 (326.741)	36
Patents with matched assignees (B)	9,769	5.331 (5.628)	4	0.891 (1.432)	0.236	434.697 (453.162)	260
P-value ($H_0 : \mu_A - \mu_B = 0$)		0.000		0.000		0.000	

Table II: Summary statistics of the patent winners in the NBER Database

This table summarizes the main characteristics of the winners of all US patents in the NBER Database between 1975 and 1999, in the technological category 3 (Drugs and Medical), subcategories 31, 33 and 39. The total incumbency index of firm f in patent i is defined as:

$$I_{if} = \sum_{\substack{\forall j \text{ cited by } i \\ \text{owned by } f}} \#(citations_j) \times (20 - age_j),$$

where j is a patent cited by i that is at most 20 years old and that has been cited $\#(citations_j)$ times. All firms that own at least one of the patents cited by i that contributes positively to its incumbency value are classfied as the incumbents to that patent. Patent winners that are not incumbents are classified as an entrant to the race for the patent. All citation counts are corrected for yearly differences in the propensity to cite using the adjustment factors provided by Hall et al. (2002).

		Cash holdings one year before patent ($ Millions)	Total assets one year before patent ($ Millions)	Patents accumulated by the winner	Number of citations received (corrected)	Incumbency Index	Proportion of patents won: After match with COMPUSTAT	Proportion of patents won: Before match with COMPUSTAT
1. From 1975 to 1979								
Incumbent Winners	Mean	241.364	2,187.744	49.189	0.725	238.469	0.289	0.550
	Standard Deviation	(182.309)	(2,174.927)	(59.845)	(1.376)	(698.279)	(0.453)	(0.498)
	Observations	856	856	2,567	2,567	2,567	856	2,567
Entrant Winners	Mean	280.969	2,267.456	161.642	0.755	*NA*	0.711	0.450
	Standard Deviation	(214.164)	(2,024.886)	(143.102)	(1.123)		(0.453)	(0.498)
	Observations	2,103	2,103	6,037	6,037		2,103	6,037
2. From 1980 to 1984								
Incumbent Winners	Mean	377.349	4,064.571	132.842	0.722	117.338	0.386	0.657
	Standard Deviation	(270.983)	(4,753.242)	(137.684)	(1.288)	(337.773)	(0.487)	(0.475)
	Observations	1,198	1,198	3,661	3,661	3,661	1,198	3,661
Entrant Winners	Mean	369.046	4,903.361	703.802	0.776	*NA*	0.614	0.343
	Standard Deviation	(290.366)	(5,307.917)	(444.496)	(1.293)		(0.487)	(0.475)
	Observations	1,909	1,909	7,581	7,581		1,909	7,581
3. From 1985 to 1989								
Incumbent Winners	Mean	695.150	5,510.010	210.914	0.669	98.533	0.384	0.665
	Standard Deviation	(743.006)	(5,476.525)	(240.588)	(1.015)	(311.977)	(0.486)	(0.472)
	Observations	1,520	1,520	4,848	4,848	4,848	1,520	4,848
Entrant Winners	Mean	708.548	5,630.285	1,930.572	0.843	*NA*	0.616	0.335
	Standard Deviation	(773.050)	(6,233.403)	(937.203)	(1.606)		(0.486)	(0.472)
	Observations	2,443	2,443	10,889	10,889		2,443	10,889
4. From 1990 to 1994								
Incumbent Winners	Mean	911.323	9,709.647	271.897	0.707	95.047	0.399	0.700
	Standard Deviation	(1,129.975)	(9,125.851)	(340.712)	(1.262)	(320.758)	(0.490)	(0.458)
	Observations	2,017	2,017	7,072	7,072	7,072	2,017	7,072
Entrant Winners	Mean	1,174.322	9,848.718	2,053.102	0.808	*NA*	0.601	0.300
	Standard Deviation	(1,282.219)	(9,008.386)	(1,028.775)	(1.186)		(0.490)	(0.458)
	Observations	3,035	3,035	14,865	14,865		3,035	14,865
5. From 1995 to 1999								
Incumbent Winners	Mean	1,411.071	14,271.320	295.380	0.850	120.659	0.454	0.775
	Standard Deviation	(1,496.463)	(11,447.310)	(407.733)	(3.694)	(368.084)	(0.498)	(0.418)
	Observations	3,018	3,018	12,519	12,519	12,519	3,018	12,519
Entrant Winners	Mean	1,596.365	13,756.320	2,184.703	0.827	*NA*	0.546	0.225
	Standard Deviation	(1,310.266)	(9,192.063)	(938.460)	(4.082)		(0.498)	(0.418)
	Observations	3,624	3,624	4,725	4,725		3,624	4,725

Table III: Estimates of the model's parameters for patents won by non-cited firms

This table shows the estimates of the parameters of the model that selects a winner to each patent from the set of all non-cited firms that won at least one patent in the same five-year period. The estimates were computed using an instrumental variables estimator, following Berry's (1994) method. The estimable model is:

$$\ln s_{ft} - \ln s_{0t} = \beta_W \ln W_{ft-1} + \beta_E E_{ft-1} + \boldsymbol{\gamma}' \mathbf{c}_{ft} + \eta_{ft},$$

where s_{ft} is the share of patents won by firm f in year t, and s_{0t} is the share of patents with self-cited winners, i.e., won by an incumbent. The regressors are listed below. The instruments for cash holdings are the logarithm of sales, cash, assets and outstanding debt, all in years $t-2$ and $t-3$, and the averages of sales, assets, outstanding debt and accumulated patents by all other firms in the same period. The estimates' standard errors are computed using a covariance matrix estimator robust to correlation within the same 2-digit SIC code. They are shown in brackets under the parameter estimate. The estimation uses all US patents won by listed firms in COMPUSTAT, between 1975 and 1999, in the technological category 3 (Drugs and Medical), subcategories 31, 33 and 39. Patents are classified into quartiles according to the number of citations they receive. The number of citations is asjusted to reflect time differences in the propensity to cite, using the factors provided by Hall, et al., (2002). All specifications include dummy variables for all but one of the 2-digit SIC codes observed in the sample and for all but one of the sample years.

Panel A: Estimation Period from 1975 to 1979

	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	0.053	0.044	0.207	0.129
before the patent was awarded ($\ln W_{ft-1}$)	(0.118)	(0.092)	(0.057)***	(0.038)***
Total patents accumulated by the firm	−0.0004	0.0015	0.0000	0.0007
up to one year before the award (E_{ft-1})	(0.001)	(0.001)*	(0.001)	(0.001)
Constant	−4.465	−5.093	−5.756	−5.226
	(0.711)***	(0.458)***	(0.326)***	(0.242)***
Number of observations	72	131	158	147
R^2	0.06	0.23	0.30	0.21
F statistic	2,869.714	26,203.956	46,417.519	17.265
P value of F Statistic	0.000	0.000	0.000	0.000
Test of Over Identifying Restrictions	6.120	9.746	12.171	19.787
P value of χ^2 statistic	0.865	0.940	0.935	0.535

Panel B: Estimation Period from 1980 to 1984

	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	0.101	0.267	0.159	0.144
before the patent was awarded ($\ln W_{ft-1}$)	(0.088)	(0.074)***	(0.064)**	(0.058)**
Total patents accumulated by the firm	0.0003	0.0007	0.0012	0.0007
up to one year before the award (E_{ft-1})	(0.000)	(0.000)**	(0.000)***	(0.000)*
Constant	−3.775	−5.776	−6.248	−6.014
	(0.460)***	(0.347)***	(0.377)***	(0.327)***
Number of observations	65	110	136	130
R^2	0.15	0.31	0.34	0.23
F statistic	319.918	28.156	33.911	105.087
P value of F Statistic	0.000	0.000	0.000	0.000
Test of Over Identifying Restrictions	7.841	9.110	19.128	6.595
P value of χ^2 statistic	0.727	0.909	0.262	0.980

Table III, continued.

Panel C: Estimation Period from 1985 to 1989

	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	0.233	0.145	0.135	0.101
before the patent was awarded ($\ln W_{ft-1}$)	(0.127)*	(0.053)***	(0.056)**	(0.046)**
Total patents accumulated by the firm	0.0001	0.0006	0.0008	0.0005
up to one year before the award (E_{ft-1})	(0.000)	(0.000)***	(0.000)***	(0.0002)**
Constant	−5.958	−6.389	−6.527	−5.928
	(0.876)***	(0.306)***	(0.318)***	(0.371)***
Number of observations	65	138	178	199
R^2	0.05	0.46	0.47	0.31
F statistic	10.882	19,485.801	1,341.881	8.365
P value of F Statistic	0.000	0.000	0.000	0.000
Test of Over Identifying Restrictions	3.183	26.334	33.785	16.578
P value of χ^2 statistic	0.988	0.092	0.009	0.829

Panel D: Estimation Period from 1990 to 1994

	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	0.207	0.279	0.218	0.176
before the patent was awarded ($\ln W_{ft-1}$)	(0.076)***	(0.052)***	(0.036)***	(0.038)***
Total patents accumulated by the firm	0.0001	0.0001	0.0005	0.0004
up to one year before the award (E_{ft-1})	(0.000)	(0.000)	(0.000)***	(0.000)***
Constant	−6.38	−7.247	−7.164	−6.586
	(0.427)***	(0.332)***	(0.193)***	(0.186)***
Number of observations	98	131	220	211
R^2	0.24	0.39	0.49	0.44
F statistic	723.838	2,346.024	37.223	88.97
P value of F Statistic	0.000	0.000	0.000	0.000
Test of Over Identifying Restrictions	9.265	1.586	9.310	7.605
P value of χ^2 statistic	0.902	1.000	0.952	0.990

Panel E: Estimation Period from 1995 to 1999

	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	0.298	0.228	0.209	0.262
before the patent was awarded ($\ln W_{ft-1}$)	(0.050)***	(0.044)***	(0.044)***	(0.047)***
Total patents accumulated by the firm	0.0004	0.0002	0.0003	0.0003
up to one year before the award (E_{ft-1})	(0.0001)***	(0.0001)**	(0.0001)***	(0.0001)***
Constant	−8.61	−7.788	−7.177	−8.449
	(0.394)***	(0.269)***	(0.238)***	(0.353)***
Number of observations	180	135	77	146
R^2	0.52	0.53	0.50	0.51
F statistic	26.986	91.423	37.758	5,898.445
P value of F Statistic	0.000	0.000	0.000	0.000
Test of Over Identifying Restrictions	29.743	13.748	6.205	12.666
P value of χ^2 statistic	0.028	0.617	0.961	0.758

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] The F-statistic is computed under the null hypothesis that all the model's parameters are zero.
[c] The χ^2 statistic is computed under the null hypothesis that the instruments provide enough exogenous variation to overidentify the model's parameters.

Table IV: Economic significance of the estimates of the model's parameters estimated using patents won by non-cited firms

This table shows the change in the expected number of patents won per year per firm with respect to cash holdings and previous patenting experience. The changes and their standard errors (shown underneath them in brackets) are estimated using the delta method on the model estimates shown in Table III. The estimation uses all US patents won by firms listed in COMPUSTAT, between between 1975 and 1999, in the technological categoty 3 (Drugs and Medical), sub-categories 31, 33 and 39. Patents are classified into quartiles according to the number of citations they receive. The number of citations is adjusted to reflect yearly differences in the propensity to cite, using the factors provided by Hall, et al. (2002).

	Changes with respect to one sample standard deviation increase in the firm's:							
	Cash holdings, one year before the patent was awarded				Patents accumulated, one year before the patent was awarded			
	Quartiles of the number of citations by patent				Quartiles of the number of citations by patent			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1. Estimation Period: 1975-1979								
Change in the expected number of patents per firm per year	0.0706 (0.2342)	0.0187 (0.2324)	0.6949 (0.2245)***	0.3922 (0.1358)***	0.0765 (0.169)	0.4106 (0.1972)**	0.0733 (0.1331)	0.1544 (0.1334)
Patents per firm per year	2.1017	2.5813	2.6458	2.2007	2.1017	2.5813	2.6458	2.2007
2. Estimation Period: 1980-1984								
Change in th expected number of patents per firm per year	0.1305 (0.1407)	1.1378 (0.3849)***	0.4647 (0.2193)**	0.4689 (0.2211)**	0.1741 (0.1008)*	0.2545 (0.1903)	0.7083 (0.2048)***	0.2754 (0.1574)*
Patents per firm per year	1.7130	2.4505	2.5752	2.1004	1.7130	2.4505	2.5752	2.1004
3. Estimation Period: 1985-1989								
Change in the expected number of patents per firm per year	0.5440 (0.3159)*	0.6228 (0.2575)**	0.5227 (0.2462)**	0.3808 (0.1953)*	0.0793 (0.1894)	0.6581 (0.1488)***	0.7843 (0.1795)***	0.3955 (0.1905)**
Patents per firm per year	1.9820	2.6213	2.6699	2.1722	1.9820	2.6213	2.6699	2.1722
4. Estimation Period: 1990-1994								
Change in the expected number of patents per firm per year	0.2410 (0.1672)	1.3742 (0.3218)***	1.2416 (0.2556)***	0.8676 (0.2129)***	0.2299 (0.1596)	0.1385 (0.1136)	0.5046 (0.1218)***	0.4215 (0.1115)***
Patents per firm per year	2.2611	2.6167	2.9050	2.5984	2.2611	2.6167	2.9050	2.5984
5. Estimation Period: 1995-1999								
Change in the expected number of patents per firm per year	2.4275 (0.4772)***	1.3188 (0.3708)***	1.1925 (0.318)***	1.6341 (0.38)***	0.8164 (0.224)***	0.3928 (0.2021)*	0.5224 (0.1514)***	0.5821 (0.2152)***
Patents per firm per year	4.2556	3.1744	2.9776	3.1855	4.2556	3.1744	2.9776	3.1855

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.

Table V: Selection of firms that race for each patent

This table describes the selection of cited and non-cited firms for every patent race. Potential entrants are ranked according to the predicted probabilities of winning a patent in every given year, using the model and the estimates is Table III. The incumbency value of patent i, citing all firm f's patents, is defined as:

$$I_i = \sum_{\forall\ cited\ f} \sum_{\substack{\forall j\ cited\ by\ i \\ owned\ by\ f}} \#(citations_j) \times (20 - age_j),$$

where j is a patent cited by i that is at most 20 years old and that has been cited $\#(citations_j)$ times. All firms that own at least one of the patents cited by i that contributes positively to its incumbency value are classfied as the incumbents to that patent. Patent winners that are notincumbents are classfied as an entrant to the race for the patent. All citation counts arecorrected for yearly differences in the propensity to cite using the adjustment factors provided by Hall et al. (2002).

Panel A: Selection of firms that are not cited by the patent ('Entrants')

Cumulative probability of winning, given that the winner is not a cited firm

Ranking	Mean	Median
1	0.096	0.108
5	0.392	0.400
10	0.757	0.774
15	0.955	0.971
20	1.000	1.000
Number of selections	100	

Panel B: Selection of firms that are cited by the patent ('Incumbents')

Number of firms cited per patent		Cumulative relative incumbency values per cited firm		
Number	Cumulative frequency	Ranking	Median	Mean
1	26.25	1	0.707	0.699
2	47.02	2	0.980	0.861
3	61.91	3	1.000	0.923
4	72.05	4	1.000	0.951
5	79.49	5	1.000	0.966
10	94.52	10	1.000	0.986
Number of patents	91,656	Number of patents		91,656

Table VI: Summary statistics of the characteristics of the firms selected to each race

This table summarizes the main characteristics of the firms selected as the most likely participants in every given patent race. The selection includes the top four cited firms (incumbents) according to their contribution to the incumbency value of every patent and the top ten non-cited firms (entrants) according to the predicted probability of winning every given patent among the set of all non-cited firms with at least one patent in the same year. The probabilities are predicted using the model and the estimates reported in Table III. Each selection includes the actual winner, and it is done for all US patents in the NBER Database, between 1975 and 1999, category 3 (Drugs and Medical), subcategories 31, 33 and 39.

		Cash holdings, one year before patent award ($ Millions)	Total assets, one year before patent award ($ Millions)	Patents accumulated by the winner
1. From 1975 to 1979				
Selected Incumbents	Mean	218.303	2,019.305	35.618
	Standard Deviation	(85.474)	(1,029.481)	(44.165)
	Observations	5,878	5,878	5,878
Selected Entrants	Mean	276.385	2,776.869	129.301
	Standard Deviation	(140.380)	(2,317.138)	(113.864)
	Observations	29,590	29,590	29,590
2. From 1980 to 1984				
Selected Incumbents	Mean	350.492	3,059.526	96.876
	Standard Deviation	(130.734)	(2,102.791)	(123.386)
	Observations	7,351	7,351	7,351
Selected Entrants	Mean	419.558	4,672.930	477.353
	Standard Deviation	(232.966)	(5,357.519)	(283.267)
	Observations	31,070	31,070	31,070
3. From 1985 to 1989				
Selected Incumbents	Mean	549.988	4,405.751	153.849
	Standard Deviation	(356.459)	(2,572.547)	(213.735)
	Observations	10,406	10,406	10,406
Selected Entrants	Mean	900.992	7,444.320	959.211
	Standard Deviation	(1,704.136)	(8,988.671)	(682.861)
	Observations	39,630	39,630	39,630
4. From 1990 to 1994				
Selected Incumbents	Mean	975.789	9,688.180	219.141
	Standard Deviation	(527.601)	(6,298.604)	(318.013)
	Observations	13,977	13,977	13,977
Selected Entrants	Mean	1,252.073	12,399.550	1,201.756
	Standard Deviation	(1,304.270)	(11,031.950)	(764.014)
	Observations	50,520	50,520	50,520
5. From 1995 to 1999				
Selected Incumbents	Mean	1,323.478	14,451.770	289.835
	Standard Deviation	(703.680)	(5,122.284)	(423.305)
	Observations	19,501	19,501	19,501
Selected Entrants	Mean	1,832.491	18,354.430	1,363.011
	Standard Deviation	(1,232.780)	(10,099.930)	(926.430)
	Observations	66,354	66,354	66,398

Table VII: Average incumbency values of incumbent firms selected to each race

This table shows the average incumbency values for each selected incumbent firm, conditional on the age of the citations. The selection includes the top four cited firms (incumbents) according to their contribution to the incumbency value of every patent The table reports the summary statistics for all US patents with observed citations in the NBER Database, between 1975 and 1999, in category 3 (Drugs and Medical), subcategories 31, 33 and 39, and for all patents that can be matched to COMPUSTAT using the CUSIP numbers of the firms selected to each race.

Panel A: Value of citations per selected incumbent, using all patents with observed citations

	Age of citations, in years						
	$Age < 1$	$1 \leq Age < 2$	$2 \leq Age < 3$	$3 \leq Age < 4$	$4 \leq Age < 5$	$5 \leq Age < 10$	$10 \leq Age < 20$
1. From 1975 to 1979							
Mean	1.976	0.851	1.662	2.039	2.447	6.084	1.87
Standard Deviation	(9.074)	(5.916)	(11.192)	(12.077)	(14.227)	(19.047)	(8.816)
Skewness	9.754	27.704	20.806	17.249	18.598	11.461	9.372
Number of Incumbents	9,579	9,579	9,579	9,579	9,579	9,579	9,579
2. From 1980 to 1984							
Mean	1.46	0.267	0.361	0.410	0.373	4.821	4.725
Standard Deviation	(9.239)	(1.290)	(1.547)	(1.970)	(1.760)	(19.276)	(17.494)
Skewness	13.857	10.018	9.467	9.069	10.145	12.248	9.751
Number of Incumbents	13,440	13,440	13,440	13,440	13,440	13,440	13,440
3. From 1985 to 1989							
Mean	1.248	0.235	0.302	0.334	0.336	1.59	6.092
Standard Deviation	(9.185)	(1.737)	(1.518)	(1.425)	(1.592)	(5.405)	(29.612)
Skewness	16.539	34.431	27.664	8.381	9.364	8.247	13.218
Number of Incumbents	18,779	18,779	18,779	18,779	18,779	18,779	18,779
4. From 1990 to 1994							
Mean	0.985	0.285	0.393	0.426	0.410	1.404	4.136
Standard Deviation	(9.231)	(1.942)	(2.289)	(2.209)	(2.442)	(4.441)	(29.619)
Skewness	27.052	23.170	23.791	21.473	25.302	10.487	15.589
Number of Incumbents	27,899	27,899	27,899	27,899	27,899	27,899	27,899
5. From 1995 to 1999							
Mean	1.406	0.542	0.595	0.548	0.525	2.228	2.002
Standard Deviation	(15.158)	(3.526)	(3.745)	(3.167)	(2.772)	(6.891)	(8.094)
Skewness	22.098	18.599	25.669	20.837	17.708	12.963	8.142
Number of Incumbents	47,688	47,688	47,688	47,688	47,688	47,688	47,688

Table VII, continued

Panel B: Value of citations per selected incumbent, using all patents matched to COMPUSTAT

	Age of citations, in years						
	$Age < 1$	$1 \leq Age < 2$	$2 \leq Age < 3$	$3 \leq Age < 4$	$4 \leq Age < 5$	$5 \leq Age < 10$	$10 \leq Age < 20$
1. From 1975 to 1979							
Mean	2.327	0.791	1.499	1.771	2.113	6.277	2.178
Standard Deviation	(9.976)	(4.761)	(8.800)	(9.263)	(9.239)	(15.834)	(9.763)
Skewness	9.098	13.060	18.402	16.439	8.965	4.529	9.263
Number of Incumbents	5,878	5,878	5,878	5,878	5,878	5,878	5,878
2. From 1980 to 1984							
Mean	1.823	0.260	0.368	0.458	0.406	5.292	5.642
Standard Deviation	(10.431)	(1.285)	(1.635)	(2.283)	(1.939)	(19.267)	(19.535)
Skewness	10.272	10.152	10.126	8.564	9.814	9.580	9.508
Number of Incumbents	7,351	7,351	7,351	7,351	7,351	7,351	7,351
3. From 1985 to 1989							
Mean	1.374	0.250	0.308	0.357	0.390	1.712	5.847
Standard Deviation	(9.291)	(2.167)	(1.717)	(1.549)	(1.813)	(5.205)	(19.722)
Skewness	15.356	31.237	31.896	8.557	8.887	6.331	10.194
Number of Incumbents	10,406	10,406	10,406	10,406	10,406	10,406	10,406
4. From 1990 to 1994							
Mean	0.977	0.250	0.374	0.444	0.443	1.520	3.341
Standard Deviation	(7.361)	(1.409)	(1.883)	(2.259)	(2.910)	(4.725)	(18.816)
Skewness	15.460	15.592	22.010	22.210	23.574	10.753	21.933
Number of Incumbents	13,977	13,977	13,977	13,977	13,977	13,977	13,977
5. From 1995 to 1999							
Mean	0.994	0.507	0.563	0.500	0.460	2.280	2.220
Standard Deviation	(7.515)	(3.195)	(2.821)	(2.142)	(1.946)	(6.673)	(8.699)
Skewness	13.692	16.761	23.748	21.552	16.498	13.292	7.329
Number of Incumbents	19,501	19,501	19,501	19,501	19,501	19,501	19,501

Table VIII: Estimates of the model's parameters for all usable patents

This table shows the estimates of the parameters of the model that selects a winner of each patent from the set of pre-selected entrants and incumbents. The estimates were computed using maximum likelihood and Petrin and Train's (2003) method to instrument endogenous regressors in the multinomial logit setup. The estimable model is:

$$\Pr(\text{firm } f \text{ wins race } i) = \frac{\exp(\beta_W \ln W_f + \beta_S S_f + \beta_E E_f + \boldsymbol{\gamma}' \mathbf{c}_{if} + \eta_f)}{\sum_g \exp(\beta_W \ln W_g + \beta_S S_g + \beta_E E_g + \boldsymbol{\gamma}' \mathbf{c}_{ig} + \eta_g)}.$$

where the regressors are listed below, and η_f represents the unobserved firm characteristics that are correlated with cash. The instruments for cash holdings are the logarithms of cash, sales, total assets and outstanding debt, all lagged two and three years, and the averages of cash, sales, debt and accumulated patents of all other rival firms in the same race. The standard errors of the parameter estimates are computed using a bootstrap estimator. They are shown in brackets underneath the parameter estimate. The estimation uses all US patents won by COMPUSTAT firms from 1975 to 1999, in the techonological category 3 (Drugs and Medical), subcategories 31, 33 and 39. Patents are classified into quartiles according to the number of citations received. The number of citations is asjusted for time differences in the propensity to cite, using the factors provided by Hall, et al., (2002).

Estimation Period from 1995 to 1999	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	0.616	0.688	0.917	0.646
before the patent was awarded ($\ln W_f$)	(0.041)***	(0.062)***	(0.069)***	(0.050)***
Logarithm of total assets, 1year	−1.128	−0.933	−0.470	−0.508
before patent was awarded ($\ln S_f$)	(0.064)***	(0.092)***	(0.096)***	(0.099)***
Total patents accumulated by the firm	0.001	0.001	0.000	0.000
up to one year before the award (E_f)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Citations received by the firm's cited patents, by age (in years):				
$Age < 1$	0.003	−0.002	−0.003	−0.019
	(0.006)	(0.006)	(0.029)	(0.015)
$1 \leq Age < 2$	0.244	0.169	0.676	0.230
	(0.022)***	(0.023)***	(0.121)***	(0.020)***
$2 \leq Age < 3$	0.235	0.187	0.483	0.169
	(0.021)***	(0.025)***	(0.075)***	(0.019)***
$3 \leq Age < 4$	0.121	0.109	0.267	0.087
	(0.021)***	(0.023)***	(0.063)***	(0.019)***
$4 \leq Age < 5$	0.193	0.156	0.114	0.082
	(0.025)***	(0.034)***	(0.087)	(0.021)***
$5 \leq Age < 10$	0.094	0.115	0.006	0.021
	(0.009)***	(0.014)***	(0.015)	(0.005)***
$10 \leq Age < 20$	0.044	0.017	0.074	0.056
	(0.003)***	(0.006)***	(0.012)***	(0.004)***
First stage error	−0.090	−0.458	−1.745	−1.133
component ($\hat{\eta}_g$)	(0.087)	(0.164)***	(0.142)***	(0.105)***
Number of observations	29,789	13,483	8,754	21,823
χ^2 statistic	2,799.746	1,429.349	1,026.918	1,889.034
P value of χ^2 statistic	0.000	0.000	0.000	0.000
Pseudo R^2	0.224	0.236	0.297	0.221

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] The χ^2 statistic is computed under the null hypothesis that all the model's parameters are zero.

Table IX: Economic significance of the estimates of the model's parameters esimated with all usable patents

This table shows the change in the expected probability of winning a given patent with respect to cash holdings and previous patenting experience. The changes and their standard errors (shown underneath them in brackets) are estimated using the delta method on the model estimates shown in Table VIII. The estimation uses all US patents won by firms listed in COMPUSTAT, between between 1975 and 1999, in the technological categoty 3 (Drugs and Medical), sub-categories 31, 33 and 39. Patents are classified into quartiles according to the number of citations they receive. The number of citations is adjusted to reflect yearly differences in the propensity to cite, using the factors provided by Hall, et al. (2002).

	Changes with respect to one sample standard deviation increase in the firm's:							
	Cash holdings, one year before the patent was awarded				Patents accumulated, one year before the patent was awarded			
	Quartiles of the number of citations by patent				Quartiles of the number of citations by patent			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1. Estimation Period: 1975-1979								
Change in the expected probability of winning a patent	0.0171 (0.0119)	0.0094 (0.0041)**	0.0279 (0.0051)***	0.1124 (0.0074)***	0.0785 (0.0162)***	0.0291 (0.0063)***	0.0107 (0.0035)***	0.0315 (0.0048)***
Patents per firm per year	0.0969	0.0882	0.0836	0.0813	0.0969	0.0882	0.0836	0.0813
2. Estimation Period: 1980-1984								
Change in th expected probability of winning a patent	0.0422 (0.0104)***	0.0071 (0.004)*	−0.0033 (0.0031)	0.0101 (0.0039)***	0.0447 (0.0081)***	0.0166 (0.0036)***	0.0629 (0.0041)***	0.0633 (0.0045)***
Patents per firm per year	0.0952	0.0869	0.0814	0.0784	0.0952	0.0869	0.0814	0.0784
3. Estimation Period: 1985-1989								
Change in the expected probability of winning a patent	0.0727 (0.0168)***	0.0014 (0.0034)	−0.0060 (0.0036)*	0.0287 (0.0045)***	0.0441 (0.0067)***	0.0689 (0.0041)***	0.0821 (0.0037)***	0.0682 (0.0035)***
Patents per firm per year	0.0914	0.0838	0.0793	0.0770	0.0914	0.0838	0.0793	0.0770
4. Estimation Period: 1990-1994								
Change in the expected probability of winning a patent	0.0823 (0.0078)***	0.0623 (0.0054)***	0.0024 (0.0022)	−0.0072 (0.0023)***	0.0226 (0.0042)***	0.0495 (0.004)***	0.0684 (0.0029)***	0.0592 (0.003)***
Patents per firm per year	0.0923	0.0864	0.0784	0.0767	0.0923	0.0864	0.0784	0.0767
5. Estimation Period: 1995-1999								
Change in the expected probability of winning a patent	0.0446 (0.0035)***	0.0533 (0.0057)***	0.0848 (0.0085)***	0.0426 (0.0039)***	0.0587 (0.0027)***	0.0904 (0.0052)***	0.0270 (0.0039)***	0.0310 (0.0025)***
Patents per firm per year	0.0901	0.1056	0.0772	0.0762	0.0901	0.1056	0.0772	0.0762

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.

Table X: Estimates of the model's parameters for all usable patents

This table shows the estimates of the parameters of the model that selects a winner of each patent from the set of pre-selected entrants and incumbents. The estimates were computed using maximum likelihood and Petrin and Train's (2003) method to instrument endogenous regressors in the multinomial logit setup. The estimable model is:

$$\Pr(\text{firm } f \text{ wins race } i) = \frac{\exp(\beta_W \ln W_f + \beta_S S_f + \beta_E E_f + \boldsymbol{\gamma}'\mathbf{c}_{if} + \eta_f)}{\sum_g \exp(\beta_W \ln W_g + \beta_S S_g + \beta_E E_g + \boldsymbol{\gamma}'\mathbf{c}_{ig} + \eta_g)}.$$

where the regressors are listed below, and η_f represents the unobserved firm characteristics that are correlated with cash. The instruments for cash holdings are the logarithms of cash, sales, total assets and outstanding debt, all lagged two and three years, and the averages of cash, sales, debt and accumulated patents of all other rival firms in the same race. The standard errors of the parameter estimates are computed using a bootstrap estimator. They are shown in brackets underneath the parameter estimate. The estimation uses all US patents won by COMPUSTAT firms from 1975 to 1999, in the techonological category 3 (Drugs and Medical), subcategories 31, 33 and 39. Patents are classified into quartiles according to the number of citations received. The number of citations is asjusted for time differences in the propensity to cite, using the factors provided by Hall, et al., (2002).

Panel A: Estimation Period from 1975 to 1979

	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	0.475	−0.035	0.638	3.361
before the patent was awarded ($\ln W_f$)	(0.200)**	(0.099)	(0.100)***	(0.215)***
Logarithm of cash holdings times	−0.033	0.035	−0.013	−0.199
total assets ($\ln W_f \times \ln S_f$)	(0.021)	(0.011)***	(0.010)	(0.022)***
Total patents accumulated by the firm	0.007	0.003	0.001	0.003
up to one year before the award (E_f)	(0.001)***	(0.001)***	(0.000)***	(0.000)***
Citations received by the firm's cited patents, by age (in years):				
$Age < 1$	−0.042	−0.096	−0.051	−0.009
	(0.106)	(0.062)	(0.039)	(0.021)
$1 \leq Age < 2$	0.733	0.118	0.026	0.048
	(0.154)***	(0.022)***	(0.011)**	(0.011)***
$2 \leq Age < 3$	0.104	0.086	0.026	0.005
	(0.041)**	(0.021)***	(0.012)**	(0.005)
$3 \leq Age < 4$	0.035	0.088	0.035	0.008
	(0.025)	(0.015)***	(0.009)***	(0.005)*
$4 \leq Age < 5$	0.042	0.054	0.022	0.035
	(0.018)**	(0.012)***	(0.007)***	(0.006)***
$5 \leq Age < 10$	0.038	0.033	0.015	0.023
	(0.016)**	(0.008)***	(0.005)***	(0.003)***
$10 \leq Age < 20$	−10.316	−12.555	−12.400	−11.636
	(467.420)	(529.325)	(496.626)	(684.447)
First stage error	−1.018	−1.613	−1.388	1.486
component ($\hat{\eta}_g$)	(0.233)***	(0.129)***	(0.133)***	(0.349)***
Number of observations	2,807	9,515	11,661	10,219
χ^2 statistic	184.285	434.396	370.479	732.633
P value of χ^2 statistic	0.000	0.000	0.000	0.000
Pseudo R^2	0.150	0.108	0.077	0.176

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] The χ^2 statistic is computed under the null hypothesis that all the model's parameters are zero.

Table X, continued.

Panel B: Estimation Period from 1980 to 1984

	Quartiles for Numbers of Citations by Patent (1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	0.441	−0.343	−0.818	0.208
before the patent was awarded ($\ln W_f$)	(0.224)**	(0.143)**	(0.143)***	(0.131)
Logarithm of cash holdings times	0.044	0.062	0.096	0.011
total assets ($\ln W_f \times \ln S_f$)	(0.014)***	(0.011)***	(0.014)***	(0.013)
Total patents accumulated by the firm	0.001	0.001	0.002	0.002
up to one year before the award (E_f)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Citations received by the firm's cited patents, by age (in years):				
$Age < 1$	−0.250	−0.178	−0.196	−0.062
	(0.202)	(0.086)**	(0.125)	(0.034)*
$1 \leq Age < 2$	1.375	0.729	0.602	0.398
	(0.532)***	(0.129)***	(0.067)***	(0.038)***
$2 \leq Age < 3$	1.637	0.627	0.442	0.238
	(0.268)***	(0.108)***	(0.058)***	(0.029)***
$3 \leq Age < 4$	0.261	0.382	0.297	0.151
	(0.105)**	(0.090)***	(0.045)***	(0.023)***
$4 \leq Age < 5$	0.921	0.317	0.313	0.204
	(0.173)***	(0.071)***	(0.046)***	(0.031)***
$5 \leq Age < 10$	0.014	0.034	0.025	0.001
	(0.012)	(0.006)***	(0.004)***	(0.003)
$10 \leq Age < 20$	0.024	0.028	0.020	0.017
	(0.014)*	(0.007)***	(0.004)***	(0.003)***
First stage error	−1.246	−1.271	−2.015	−1.527
component ($\hat{\eta}_g$)	(0.236)***	(0.256)***	(0.213)***	(0.192)***
Number of observations	3,392	9,136	13,123	11,014
χ^2 statistic	184.898	296.688	881.076	834.065
P value of χ^2 statistic	0.000	0.000	0.000	0.000
Pseudo R^2	0.126	0.078	0.165	0.190

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] The χ^2 statistic is computed under the null hypothesis that all the model's parameters are zero.

Table X, continued.

Panel C: Estimation Period from 1985 to 1989

	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	0.529	0.476	−0.086	0.651
before the patent was awarded ($\ln W_f$)	(0.167)***	(0.118)***	(0.103)	(0.074)***
Logarithm of cash holdings times	0.014	−0.059	−0.005	−0.040
total assets ($\ln W_f \times \ln S_f$)	(0.015)	(0.010)***	(0.010)	(0.008)***
Total patents accumulated by the firm	0.001	0.001	0.001	0.001
up to one year before the award (E_f)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Citations received by the firm's cited patents, by age (in years):				
$Age < 1$	−0.151	−0.183	−0.083	−0.018
	(0.257)	(0.042)***	(0.033)**	(0.016)
$1 \leq Age < 2$	2.853	1.209	0.579	0.265
	(0.509)***	(0.144)***	(0.073)***	(0.043)***
$2 \leq Age < 3$	1.212	1.087	0.654	0.215
	(0.284)***	(0.108)***	(0.055)***	(0.026)***
$3 \leq Age < 4$	0.601	0.548	0.161	0.119
	(0.167)***	(0.094)***	(0.034)***	(0.026)***
$4 \leq Age < 5$	0.863	0.473	0.16	0.095
	(0.165)***	(0.089)***	(0.041)***	(0.021)***
$5 \leq Age < 10$	0.145	0.228	0.175	0.089
	(0.037)***	(0.022)***	(0.015)***	(0.010)***
$10 \leq Age < 20$	0.007	0.028	0.005	0.007
	(0.006)	(0.005)***	(0.003)	(0.003)***
First stage error	−0.544	0.305	−0.776	−0.690
component ($\hat{\eta}_g$)	(0.134)***	(0.178)*	(0.112)***	(0.088)***
Number of observations	4,003	12,183	16,526	15,617
χ^2 statistic	345.685	1,075.617	1,519.107	1,561.553
P value of χ^2 statistic	0.000	0.000	0.000	0.000
Pseudo R^2	0.203	0.215	0.229	0.254

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] The χ^2 statistic is computed under the null hypothesis that all the model's parameters are zero.

Table X, continued.

Panel D: Estimation Period from 1990 to 1994

	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year	1.251	1.212	−0.138	−0.491
before the patent was awarded ($\ln W_f$)	(0.132)***	(0.123)***	(0.070)**	(0.082)***
Logarithm of cash holdings times	−0.009	−0.005	0.023	0.042
total assets ($\ln W_f \times \ln S_f$)	(0.010)	(0.010)	(0.005)***	(0.007)***
Total patents accumulated by the firm	0.000	0.001	0.001	0.001
up to one year before the award (E_f)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Citations received by the firm's cited patents, by age (in years):				
$Age < 1$	−0.122	−0.139	−0.03	−0.016
	(0.113)	(0.111)	(0.025)	(0.011)
$1 \leq Age < 2$	1.001	1.261	0.429	0.305
	(0.170)***	(0.129)***	(0.048)***	(0.032)***
$2 \leq Age < 3$	1.041	0.509	0.456	0.123
	(0.137)***	(0.085)***	(0.042)***	(0.022)***
$3 \leq Age < 4$	0.142	0.227	0.136	0.175
	(0.044)***	(0.045)***	(0.036)***	(0.020)***
$4 \leq Age < 5$	0.482	0.253	0.075	0.048
	(0.091)***	(0.054)***	(0.027)***	(0.016)***
$5 \leq Age < 10$	0.147	0.156	0.143	0.03
	(0.032)***	(0.024)***	(0.014)***	(0.009)***
$10 \leq Age < 20$	0.031	0.035	0.009	0.002
	(0.007)***	(0.007)***	(0.003)***	(0.003)
First stage error	−1.308	−1.627	−1.268	−1.87
component ($\hat{\eta}_g$)	(0.167)***	(0.144)***	(0.090)***	(0.098)***
Number of observations	7,539	11,302	22,904	19,982
χ^2 statistic	427.708	794.330	1,682.844	2,045.315
P value of χ^2 statistic	0.000	0.000	0.000	0.000
Pseudo R^2	0.134	0.169	0.184	0.261

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] The chi^2 statistic is computed under the null hypothesis that all the model's parameters are zero.

Table X, continued.

Panel E: Estimation Period from 1995 to 1999

	Quartiles for Numbers of Citations by Patent			
	(1)	(2)	(3)	(4)
Logarithm of cash holdings, 1 year before the patent was awarded ($\ln W_f$)	0.939	0.806	1.380	0.308
	(0.096)***	(0.118)***	(0.142)***	(0.126)**
Logarithm of cash holdings times total assets ($\ln W_f \times \ln S_f$)	−0.066	−0.035	−0.053	0.029
	(0.009)***	(0.011)***	(0.013)***	(0.012)**
Total patents accumulated by the firm up to one year before the award (E_f)	0.001	0.001	0.000	0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Citations received by the firm's cited patents, by age (in years):				
$Age < 1$	0.003	−0.002	−0.003	−0.02
	(0.006)	(0.006)	(0.029)	(0.015)
$1 \leq Age < 2$	0.24	0.173	0.674	0.241
	(0.022)***	(0.023)***	(0.120)***	(0.019)***
$2 \leq Age < 3$	0.224	0.182	0.48	0.171
	(0.020)***	(0.024)***	(0.074)***	(0.018)***
$3 \leq Age < 4$	0.12	0.102	0.265	0.085
	(0.020)***	(0.024)***	(0.063)***	(0.019)***
$4 \leq Age < 5$	0.194	0.15	0.11	0.081
	(0.024)***	(0.033)***	(0.086)	(0.021)***
$5 \leq Age < 10$	0.098	0.113	0.006	0.021
	(0.009)***	(0.013)***	(0.015)	(0.005)***
$10 \leq Age < 20$	0.044	0.017	0.072	0.055
	(0.003)***	(0.006)***	(0.012)***	(0.004)***
First stage error component ($\hat{\eta}_g$)	−0.811	−1.494	−1.872	−1.742
	(0.089)***	(0.147)***	(0.135)***	(0.097)***
Number of observations	29,789	13,483	8,754	21,823
χ^2 statistic	2493.025	1330.706	1018.776	1868.082
P value of χ^2 statistic	0.000	0.000	0.000	0.000
Pseudo R^2	0.199	0.220	0.295	0.218

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] The χ^2 statistic is computed under the null hypothesis that all the model's parameters are zero.

Table XI: Economic significance of the estimates of the model's parameters estimated with all usable patents

This table shows the change in the expected probability of winning a given patent with respect to cash holdings and previous patenting experience. The changes and their standard errors (shown underneath them in brackets) are computed using the delta method on the model estimates shown in Table X. The estimation uses all US patents won by firms listed in COMPUSTAT, between between 1975 and 1999, in the technological categoty 3 (Drugs and Medical), sub-categories 31, 33 and 39. Patents are classified into quartiles according to the number of citations they receive. The number of citations is adjusted to reflect yearly differences in the propensity to cite, using the factors provided by Hall, et al. (2002).

	Changes with respect to one sample standard deviation increase in the firm's:							
	Cash holdings, one year before the patent was awarded				Patents accumulated, one year before the patent was awarded			
	Quartiles of the number of citations by patent				Quartiles of the number of citations by patent			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1. Estimation Period: 1975-1979								
Change in the expected probability of winning a patent	0.0153 (0.0119)	0.0129 (0.0043)***	0.0285 (0.0054)***	0.1054 (0.0071)***	0.0841 (0.0166)***	0.0310 (0.0063)***	0.0125 (0.0036)***	0.0334 (0.005)***
Patents per firm per year	0.0969	0.0882	0.0836	0.0813	0.0969	0.0882	0.0836	0.0813
2. Estimation Period: 1980-1984								
Change in th expected probability of winning a patent	0.0411 (0.0104)***	0.0058 (0.004)	−0.0019 (0.0031)	0.0111 (0.004)***	0.0437 (0.008)***	0.0169 (0.0036)***	0.0649 (0.0041)***	0.0625 (0.0045)***
Patents per firm per year	0.0952	0.0869	0.0814	0.0784	0.0952	0.0869	0.0814	0.0784
3. Estimation Period: 1985-1989								
Change in the expected probability of winning a patent	0.0742 (0.0167)***	−0.0010 (0.0034)	−0.0074 (0.0035)**	0.0213 (0.0047)***	0.0438 (0.0066)***	0.0711 (0.0042)***	0.0833 (0.0038)***	0.0718 (0.0036)***
Patents per firm per year	0.0914	0.0838	0.0793	0.0770	0.0914	0.0838	0.0793	0.0770
4. Estimation Period: 1990-1994								
Change in the expected probability of winning a patent	0.0801 (0.0077)***	0.0617 (0.0054)***	0.0028 (0.0022)	−0.0054 (0.0023)**	0.0232 (0.0043)***	0.0498 (0.004)***	0.0694 (0.0029)***	0.0609 (0.0031)***
Patents per firm per year	0.0923	0.0864	0.0784	0.0767	0.0923	0.0864	0.0784	0.0767
5. Estimation Period: 1995-1999								
Change in the expected probability of winning a patent	0.0201 (0.0025)***	0.0342 (0.0047)***	0.0798 (0.0082)***	0.0380 (0.0036)***	0.0597 (0.0027)***	0.1006 (0.0054)***	0.0243 (0.0038)***	0.0326 (0.0026)***
Patents per firm per year	0.0901	0.1056	0.0772	0.0762	0.0901	0.1056	0.0772	0.0762

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.

Table XII: Analysis of the changes in the cash sensitivity of winning a patent

This table shows the analysis of the determinants of the sensitivity of the probability of winning a given patent with respect to cash holdings. The analysis is conducted through a linear regression of the sensitivity measure, shown in Table XI, on the factors shown below. Each observation used in the analysis is formed by pairing the sensitivity estimate of each estimation cluster with the average value of the potential determinant in the same cluster. The 20 observations correspond to all the time period-patent value quartile combinations. The parameters associated to each regressor are estimated by ordinary least squares (OLS) or with a quartile-specific, random effects estimator (RE).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimator	OLS	OLS	RE	RE	RE	RE	RE	OLS	RE
Average citations received by the cited patents, by age (in years):									
$Age < 5$	0.0291	0.0219	0.0219	0.02656	0.0257	0.0237			
	(0.0205)	(0.0112)*	(0.0106)**	(0.0098)***	(0.0132)**	(0.0126)*			
$Age \geq 5$							0.0034		
							(0.0023)		
Time period (1 to 5)	0.0086	0.0059	0.0059		0.0073	0.0073	0.0065	0.0542	0.0542
	(0.0067)	(0.0026)**	(0.0025)**		(0.0037)**	(0.0054)	(0.0027)**	(0.0339)	(0.0313)*
Time dummies				Yes					
Five-year average bank prime yearly loan rate					−0.0007				
					(0.0015)				
Five-year average AAA yearly Moody's credit spread						−0.0024			
						(0.0085)			
Average incumbents' experience in estimation cluster								−0.0004	−0.0004
								(0.0006)	(0.0006)
Average entrants' experience in estimation cluster								−0.0001	−0.0001
								(0.0001)	(0.0001)
Constant	−0.0132								
	(0.0308)								
Number of observations	20	20	20	20	20	20	20	20	20
Adjusted R^2	0.014	0.482						0.410	
F statistic	1.13	10.31						5.63	
P value	0.345	0.001						0.007	
χ^2 statistic			22.901	23.411	23.46	19.324	23.07		19.863
P value of χ^2 statistic			0.000	0.000	0.000	0.000	0.000		0.000
Hausman test			0.170	0.00	0.48	0.11	0.13		0.11
P value			0.92	1.00	0.98	0.99	0.99		0.95

[a] Estimates followed by ***, ** and * are statistically different from zero with 0.01, 0.05 and 0.1 significance levels, respectively.
[b] The χ^2 and F statistics are computed under the null hypothesis that all the model's parameters are zero.
[c] The Hausman Test statisitic is computed under the null hypothesis that the Random Effects estimator is consistent.

Figure 1: This figure plots the total number of patents awarded per year (Panel A) and the time series of the average number of adjusted citations per patent (Panel B). It uses all US patents in the NBER Patents and Citations Data File between 1975 and 1999, in the technological category 3 (Drugs and Medical), subcategories 31, 33 and 39. All citation counts are corrected for yearly differences in the propensity to cite using the adjustment factors provided by Hall, et al., (2002).

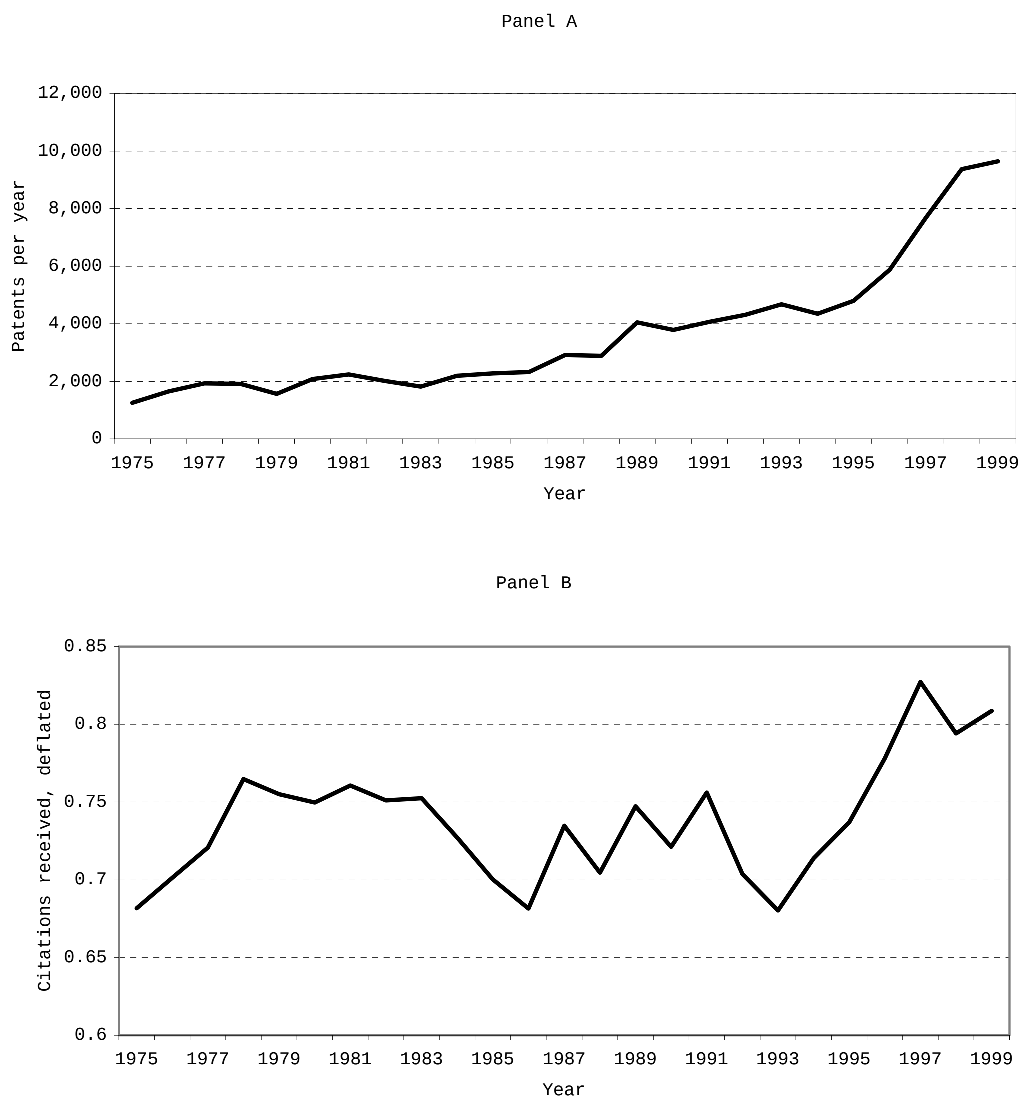

Figure 2: This figure plots the average change in the number of patents per entrant firm per year with respect to an increase of a one sample standard deviation of the firm's cash holdings. We use the estimates of the model in (5), which are reported in Table III. This model estimates the selection of a winning entrant among all firms who have won at least one patent in the same five year period as an entrant. The model is estimated for each patent value quartile and each five-year periods. Panel A shows the expected change in the number of patents and Panel B shows the expected change in the number of patents relative to the average number of patents per firm per year. The thick solid plot uses the estimates for the patents in the first quartile of the value distribution;the thin solid plot uses the second quartile; the dashed plot uses the third and the dotted plot the fourth.

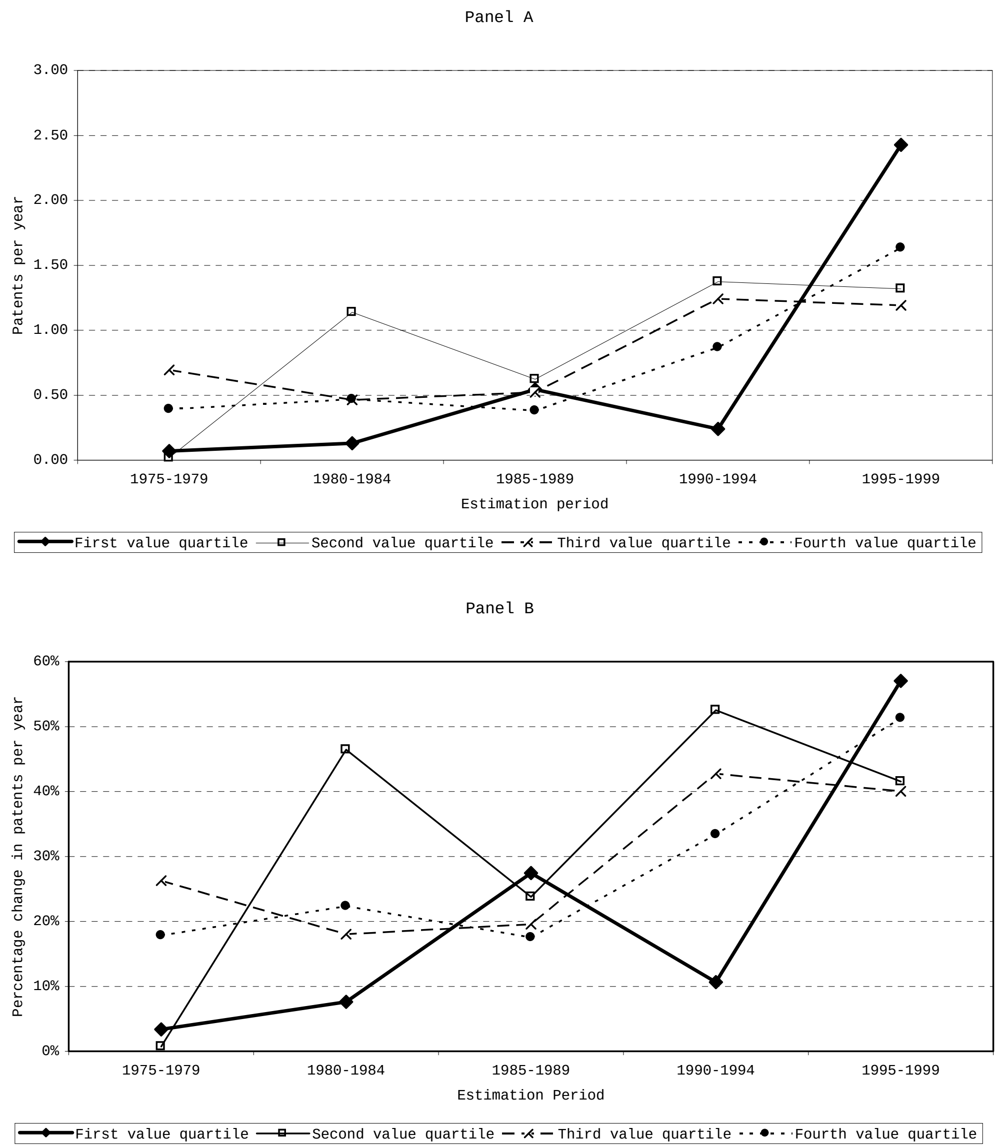

Figure 3: This figure plots the average change in the probability of winning a given patent with respect to an increase of a one sample standard deviation of the firm's cash holdings. We use the estimates of the model in 3, which are reported in Table X. This model estimates the selection of a winning firm among a set of pre-selected incumbents and entrants. The model is estimated for each value quartile and each five-year period. The thick solid plot uses the estimates for the patents in the first quartile of the value distribution;the thin solid plot uses the second quartile; the dashed plot uses the third and the dotted plot the fourth.