Independent Boards and Innovation*

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Abstract

We develop a model and present supporting evidence for how independent boards influence the innovative search strategies of a firm. Shareholders hire a manager to run a firm for two periods. To supervise the manager, shareholders appoint a board of directors. In each period, the manager reports to the board of directors, proposing a strategy, which the board decides whether or not to approve. Riskier and "explorative" search strategies are less likely with independent - and assumedly less friendly - boards. Empirical identification relies on regulatory changes that caused shareholders to appoint a majority of independent directors. We find that firms with less independent and friendly boards are more likely to explore less crowded and newer and new-to-the firm technologies and to hire younger and new-to-the firm inventors. Firms with independent and less friendly boards tend to patent more and get more citations to their patents, though these effects are mediated by an increase in claims and insignificant in the tales of the citation distributions (completely failed and breakthrough inventions are not significantly influenced by the friendliness of the board).

Keywords: Corporate Governance, Innovation, Patents, Board Composition, Independent Directors

JEL Classification: G34, L14, L25, M21

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1 Introduction

The board of directors has an important role in the governance of corporations. Charged with overseeing and advising managers, it can effectively reduce agency costs that arise from the separation of ownership and control.

Several authors have argued that independent directors, with no ties to the company other than their directorship, are better suited to perform this role as they can credibly limit managerial discretion and are thus more likely to produce decisions that are consistent with shareholder-wealth maximization. (e.g. Fama and Jensen, 1983; Williamson, 1983).

Such limited managerial discretion, however, may have unintended effects on corporate innovation. A manager with limited discretion may be reluctant to engage in exploratory projects, since the value of those projects depends on the flexibility to adapt after observing outcomes. Friendly boards, whose interests are aligned with the manager, guarantee managerial discretion and may be more effective in motivating exploration and innovation.

We develop a simple two-period model to illustrate this phenomenon. Shareholders hire a manager and appoint a board to supervise the manager. In each period, the manager may propose to exploit a conventional business strategy or to explore an innovative business strategy. To implement the strategy, the manager needs approval from the board.

We show that an independent board, who does not necessarily agree with the manager, makes exploration less attractive to the manager since it prevents the manager from adapting strategies after observed outcomes. An independent board is thus effective when the goal is to motivate the manager to pursue conventional strategies.

Friendly boards, on the other hand, always approve managerial strategies. This managerial discretion encourages the manager to explore, since being able to freely adapt to observed outcomes allows the manager to take full advantage of exploration. A friendly board is effective when the goal is to motivate the manager to pursue more exploratory strategies.

Evidence for the model comes from observing search and hiring strategies for firms that were forced by regulatory changes to adopt more independent boards. Starting in 1999, stock exchanges and the Sarbanes-Oxley Act (SOX) required firms to have a majority of independent directors (for similar approaches, see Linck et al. 2009; Dunchin et al. 2010). Comparing firms that changed from less to more independent boards against firms that already had independent boards, we find increased output - but less exploration. Firms whose boards become more independent patent more and receive more citations to their patents, however, this effect is mediated by an increase in claims and is insignificant for uncited and highly cited patents. Firms whose boards become more independent also work in older technologies, more crowded, and more familiar technologies. Their inventive work force also becomes older and more insular. The model and results imply a more nuanced relationship between oversight and search; greater oversight appears to lead to greater effort and output, but less innovative exploration.

2 Related Literature

Most previous research argues that limiting managerial discretion is effective in reducing agency problems. There are a few exceptions. Aghion and Tirole (1997) and Burkart, Gromb, and Panunzi (1997) argue that allowing managerial discretion may enhance initiative. In their model, managers are willing to exert more effort to become informed if they know that they will have effective control. Adams and Ferreira (2007) argue that managerial discretion encourages the manager to share information with the board, improving the advisory role of the board. The above papers discuss different ways to allow managerial discretion, such as dispersed shareholder ownership or a friendly board of directors.

We provide an alternative role for managerial discretion based on the nature of the search and innovation process. In contrast to conventional projects, innovation is the result of experimentation with new ideas (Schumpeter, 1934; Arrow, 1969; Weitzman, 1979). The central tension that arises with experimentation is the one between "exploitation" and "exploration." Managerial discretion allows the manager to change course depending on outcomes, which is essential to fully capture the value of exploration.

In a setting where innovation arises from experimentation, Manso (2011) finds that optimal incentive schemes that motivate exploration exhibit substantial tolerance or even reward for early failure and reward for long-term success. Moreover, job security and timely feedback on performance are essential to motivate exploration. While Manso (2011) studies optimal compensation, termination, and feedback policies, the current paper studies the optimal allocation of control between the principal and the agent.

A large literature studies the role and influence of board characteristics (for an overview see Adams, Hermalin, and Weisbach, 2010; for the economic relevance of boards see Ahern and Dittmar, 2012). Much of the literature focuses on the role of independent board members (most recently e.g. Masulis and Mobbs, 2014; Brochet and Srinivasan, 2014). Several studies have analyzed how independent directors influence CEO compensation (e.g. Faleye, Hoitash, and Hoitash 2011; Coles, Daniel, and Naveen, 2008; Denis and Sarin, 1999; Core, Holthausen and Larcker, 1999), CEO appointments and dismissals (Knyazeva, Knyazeva, and Masulis, 2013; Guo and Masulis, 2011; Borokhovich, Parrino, and Trapani, 1996; Weisbach, 1988), adoption of antitakeover defenses (Brickley, Coles, and Terry, 1994) or takeover premiums (Cotter, Shivdasani, and Zenner, 1997; Byrd and Hickman, 1992). From these studies the picture emerges that independent board members increase board oversight. Whether such intensified board monitoring is beneficial or detrimental to shareholder wealth is much harder to answer though, and the correct answer seems to depend on the complexity of a firm's operations (Faleye, Hoitash, and Hoitash, 2011; Duchin, Matsusaka, and Oguzhan, 2010; Nguyen and Nielsen, 2010).

Several recent papers empirically study how corporate governance affects innovation, looking at determinants such as managerial compensation (Ederer and Manso, 2013; Baranchuk, Kieschnick, and Moussawi, 2014), firm's going public decision (Bernstein, 2012), private equity/venture capital involvement (Lerner, Sorensen, and Stromberg, 2011; Tian and Wang, 2014; Chemmanur, Loutskina, and Tian, 2014), anti-takeover provisions (Atanassov, 2013; Chemmanur and Tian, 2014), institutional ownership (Aghion, Van Reenen, and Zingales, 2013), financial market development (Hsu, Tian, and Xu, 2014), conglomerate structure (Seru, 2014), analyst coverage (He and Tian, 2013), and stock market liquidity (Fang, Tian, and Tice, 2013).

Almost all of this literature uses patent data to test their models. Raw patent counts are usually supplemented by the number of citations that a patent receives, as this measure correlates with financial and technical value (Harhoff 1999; Hall et al., 2005). Though less common, measures of originality and generality (Hall, Jaffe, and Trajtenberg 2001) have been used to measure breadth and impact of innovations, (see Lerner, Sorensen, and Stromberg, 2011 and Hsu, Tian, and Xu, 2014).

Most similar to the current study, Faleye, Hoitash, and Hoitash (2011) find that monitoring intensity, as proxied by independent director presence on boards and committees, correlates negatively with citation weighted patent counts. Kang et al. (2014) find a positive correlation of social connections and assumedly "friendly" boards on the same measure. Using a sample of German firms, Balsmeier, Buchwald, and Stiebale (2014) show that executives serving as directors on other firms' supervisory boards are positively correlated with the monitored firms' patenting activities, as long their home firm is innovative itself. Executives from non-innovative firms are negatively related to the monitored firms' patenting activity.

The current study refines these results with more nuanced measures and an investigation of the full distribution of citations. Using logit and quantile regression models, we show that independent boards have a positive correlation in the middle of the distribution but no significant influence in the tails. We use the rate of prior and self citation, along with Jaffe's (1986) measure of technological proximity, and the age of citation, to demonstrate decreased search. We also present novel measures, based on disambiguation of the inventor database (Li et al. 2014), to show that firms whose boards become more independent are less likely to hire younger and new to the firm inventors.

3 The Model

Shareholders hire a manager to run a firm for two periods. To supervise the manager, shareholders appoint a board of directors. In each period, the manager reports to the board of directors, proposing a strategy, which the board decides whether or not to approve.

Firm output in each period is either S ("success") or F ("failure"). The manager can always propose a conventional business strategy, which has a known probability p of success. At the beginning of the first period, the manager finds out whether a new business strategy is available, in which case he may propose it to the board in place of the conventional strategy. The new strategy has an unknown probability q of success, which may be either q_L or q_H, with $q_H > q_L$. Manager, board of directors, and shareholders may disagree about the distribution of q. They believe that q is equal to q_H with probability μ_M, μ_B, and μ_S respectively. The only way for them to learn about q is if the firm explores the new strategy.

All agents are risk-neutral and have a discount factor of one. They own shares in the firm, and thus maximize at each point in time the present value of the firm's future output.

We first consider the case of a friendly board, whose beliefs are aligned with the manager's beliefs ($\mu_B = \mu_M$). In this case, the problem turns into a standard bandit problem, since the manager and board have the same interest and beliefs, and thus act as if they were a single agent.

Proposition 1 *Under a friendly board, the firm explores the new strategy if and only if*

$$\mu_M \geq \frac{(1+q_L)(p-q_L)}{(1+q_L+q_H-p)(q_H-q_L)} \tag{1}$$

Proposition 1 shows that the firm engages in exploration if and only if the manager is sufficiently optimistic about the prospect of the new business strategy.

Now we consider the case of an independent board. In this case, the manager needs to consider the reaction of the board in deciding whether to propose a new business strategy.

Proposition 2 *Under an independent board, the firm explores the new strategy if and only if*

$$\mu_M \geq \frac{p - q_L}{q_H - q_L} \quad \textit{and} \quad \mu_B \geq \frac{(1 + q_L)(p - q_L)}{(1 + q_L + q_H - p)(q_H - q_L)} \tag{2}$$

or

$$\frac{(1 + q_L)(p - q_L)}{(1 + q_L + q_H - p)(q_H - q_L)} \leq \mu_M \leq \frac{p - q_L}{q_H - q_L}$$
$$\textit{and} \quad \frac{(1 + q_L)(p - q_L)}{(1 + q_L + q_H - p)(q_H - q_L)} \leq \mu_B \leq \frac{p - q_L}{q_H - q_L} \tag{3}$$

or

The manager will only propose a new business strategy if the board is optimistic enough to approve it. However, if the board is too optimistic about the new strategy, the manager may not propose it, since the board could compel the manager to stick with the strategy even after failure. In sum, the loss of control over future strategies of the firm imposed by an independent board makes a manager less likely to explore new business strategies.

Figure 1 shows the parameter regions in which the firm engages in exploration under different board structures. The shaded are represents the parameter region in which the firm engages in exploration under a friendly board. The dotted area represents the parameter region in which the firm engages in exploration under an independent board. As the figure illustrates, there is more exploration under a friendly board than under an independent board.

For most of the empirical analysis we will be studying how changes in board type induce exploration/exploitation. Propositions 1 and 2 show that more independent (friendly) boards motivate more exploitation (exploration).

Another relevant question is which type of board should shareholders appoint. As Proposition 3 below shows, this will depend on whether the problem faced by shareholders is to motivate managers to be more or less innovative.

Proposition 3 *If the manager is optimistic relative to shareholders about innovation ($\mu_M > \mu_S$), then shareholders will appoint an independent board with $\mu_B = \mu_S$ to restrict exploration by the manager. Otherwise, if the manager is pessimistic relative to shareholders about innovation, then shareholders will appoint a friendly board ($\mu_B = \mu_M$) to motivate exploration by the manager.*

If the manager is more optimistic than shareholders about innovation, then shareholders need to restrict exploration by the manager, and thus will appoint an independent board. If the manager is more pessimistic than shareholders about innovation,

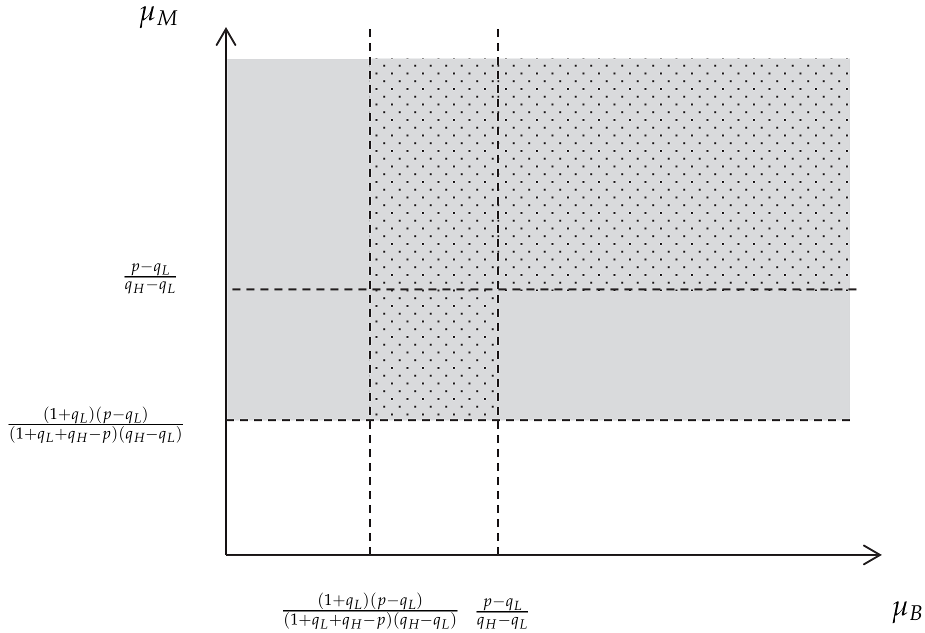


Figure 1: **Exploration region under different board structures.** The shaded area represents the parameter region in which the firm engages in exploration under a friendly board. The dotted area represents the parameter region in which the firm engages in exploration under an independent board.

then shareholders need to motivate the manager to explore more, and thus will appoint a friendly board.

Throughout this section we assumed that board members and managers maximize firm value and investigated how shareholders should choose board composition to provide incentives to the manager. Could shareholders do better if they offer a compensation packages to motivate the manager? It turns out that the optimal board composition derived in Proposition 3 achieves first-best. Therefore, an incentive contract could at best be equivalent to optimal board composition, but would be more costly and thus dominated.

To sum up, under an independent board, the manager loses control over the future strategies of the firm. This reduces the appeal of exploration, since exploration requires adaptability when implemented. A friendly board, on the other hand, allows discretion to managers and is thus effective in motivating exploration. Shareholders should appoint an independent board when they need to restrict exploration by the manager and a friendly board when they need to motivate exploration by the manager.

4 Identification strategy

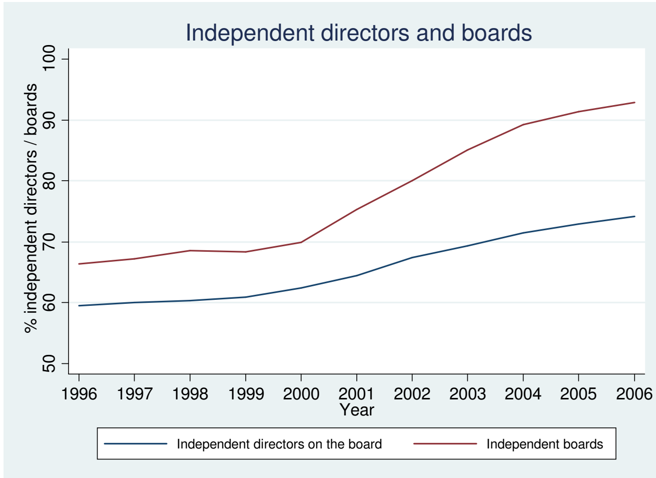
Identification for our study relies upon regulatory changes that forced public firms to increase the presence of independent directors on their boards in the early 2000s. The effects of those regulatory changes on variables other than innovation have been analyzed elsewhere (see e.g. Linck et al. 2009; and Dunchin et al., 2010, for a setup that is most similar to ours). In this section, we briefly describe the regulatory framework that is relevant to our analysis.

Initiated by recommendations of the Blue Ribbon Committee (BRC) in 1999, stock market rules of the NYSE and Nasdaq have been built upon the assumption that independent board members are better able to monitor managers. Subsequent to the BRC recommendations, the Securities and Exchange Commission (SEC) approved new corresponding rules in December 1999, requiring public firms to move to a fully independent audit committee with the next re-election or replacement of audit committee members. Further motivated by prominent corporate scandals, e.g. Enron, this rule was written into U.S. law in 2002 as a part of the Sarbanes-Oxley Act (SOX). It was followed by subsequent NYSE and Nasdaq regulations in 2003 that imposed even stricter requirements on board composition. In addition to having an audit committee composed of merely independent directors, both stock exchanges forced firms to have a majority of independent directors as regular board members, and the compensation and nomination committees had to consist of 100% independent board members (>50% if firms are listed on Nasdaq only).

Definitions of director independence vary slightly across each rule. SOX states in section 301 that a given director is independent if the person does not "accept any consulting, advisory, or other compensatory fee from the issuer" (except for serving the board), and is not an "affiliated person of the issuer or any subsidiary" (NYSE speaks of "no material relationship"; and Nasdaq requires no relationship that would interfere with "independent judgment"). The NYSE and Nasdaq regulations are strict. The independence assumption is already violated, for instance, if a director him- or herself or a direct family member was an employee of the firm during the previous three years, or a family member works for a third firm with which the given firm has a professional relationship, or a family member is connected to the firm's auditor.

These regulations made board changes necessary for a large group of firms. The number and fraction of independent board members was fairly stable until the year 2000. With the described board regulations becoming effective, more and more independent directors were appointed to corporate boards. Figure 2 illustrates the changes in board composition and committees for the sample of firms used in our study. It resembles a pattern that has been documented in other studies for differing sets of public

Figure 2



Notes: This graph illustrates the evolution of independent boards over the sampling period. A board is defined as independent if the majority of board members is classified as independent by the IRRC. Independent directors represents the average fraction of independent board members of all firms in the study. Details on sample construction and descriptive statistics are provided in section 5.

firms (e.g. Linck et al., 2008, and Dunchin et al., 2010). A detailed description of the sample composition is provided below (section 4). Board composition data are taken from the Investor Responsibility Research Center (IRRC). From 1996 to 2006 the IRRC tracked individual board members of all major public U.S. firms and indicated in their database whether an individual board member is independent, an employee of the firm or otherwise affiliated (former employee, employee of an organization that receives charitable gifts from the company, employee of a customer or supplier to the company, relative of an executive director, etc.).

Reflecting the previously introduced regulatory changes, Figure 2 shows an increase of independent director presence on corporate boards and committees from 2001 to 2006. Theoretical considerations about board control suggest that a crucial difference arise when a board switches from a minority to a majority of independent board members (Harris and Raviv, 2008).[1] It was further an explicit requirement of regulatory reforms. Thus, our analysis focuses on this variable. Our data shows that the proportion

[1]The fraction of independent board members provides more variation but has two major disadvantages. First, considering board voting behavior, it is likely that the influence of independent directors on board oversight does not linearly increase with the number or fraction of independent members but exhibits a jump when independent directors gain or lose the majority of votes. Second, the switch from a minority to a majority of independent directors was an explicit requirement of regulation, such that it is much more likely that observed changes in that regard happened involuntarily, which in turn improves the identification of causal effects.

of firms with a majority of independent board members stayed rather stable around 68% before 2000 and moved up to about 94% by 2006.

Our empirical identification of the relationship between board oversight and innovative firm activities stems from the difference between firms, who were already in compliance with the regulatory changes before 2001 (results are robust to taking later years or 2000 as a threshold value), and those firms who switch to a majority of independent directors (hereafter also referred to as an 'independent board') after regulatory changes became affective. Hence, all firms that were not required to change their board serve as a control group. In line with Dunchin et al. (2010), we define firms as treated when they switch to an independent board after 2000 and have an audit committee that contains 100% independent board members. The latter requirement helps to sort out potential voluntary switches, increasing the amount of truly exogenous increases of independent board members and making our main variable of interest less likely to be confounded by endogenous choice. The fraction of independent directors increased by 25% during 2001 to 2006 by noncompliant firms and by 9% with firms that fulfilled the regulatory requirements already before 2000.

5 Data

The dataset we built up for our study is determined by the joint availability of data on the composition of corporate boards and committees from the IRRC, basic firm level information on R&D investments and total assets from Compustat, and patent data from the NBER, the Fung Institute and the USPTO. The IRRC provides data on corporate board members for 3000 major public U.S. based firms from 1996 to 2006. Further data on the composition of corporate audit, compensation and nomination committees is provided for the same set of firms from 1998 onwards. Compustat has further information on almost all of the firms covered by IRRC. A major challenge for the empirical researcher interested in those firms' innovative activities is the identification and compilation of the corresponding patent portfolios. Researchers involved in the NBER patent data project have spent significant amounts of resources to identify patents that have been granted to U.S. based firms. The NBER patent database contains, however, only those patents that have been granted through 2006. Due to the time lag with which inventions are granted property rights (1-5 years) and the publication of corresponding data by the USPTO, this results in significantly truncated patent *application* data for all years after 2001. Researchers have found ways to use incomplete patent data for the years 2002 to 2006, exploiting the distribution of applications before 2002, but those approaches are not suitable to describe real phenomena, add much noise to econometric analyses, and lead to significant estimation errors in our case, because our sample of board data covers 50% of years for which the NBER data is severely truncated. The issue becomes even more prevalent if researchers want to take citations to patents into account that often occur several years after a patent has been granted. In terms of patent applications, the NBER data misses 18 percent of patent applications of U.S. based assignees identified in 2002, rising to 99 percent by 2006.[2]

Recently available disambiguations provide (updated monthly, see Fierro et al., 2014) detailed data for all patents granted by the USPTO. These data enable us to overcome the truncation of the NBER patent database and identify comprehensive patent portfolios of the firms in our sample up to the year 2007.[3] While most analyses consider only granted patents, we assign patent to the year it was applied for, in order to more accurately assess the impact of that year's variables. Since patent documents do not contain a unique identifier of assignees, one of the major obstacles that had to be solved was the match of firm names that appear in our sample with firm names that appear in ambiguous forms on the patent documents. Matching firm names between databases thus requires significant amounts of resources if done manually. The issue becomes obvious if one considers all patents that have been filed by U.S. based publicly listed firms (>500k). Hence, analyzing innovations of a relatively small amount of firms, using recent patent data, can become a labor-intensive challenge, and the disambiguation of assignee names as they appear on the patent documents alone will often not be sufficient. For individual researchers the costs and the time needed for data collection, cleaning and preparation, quickly exceed available capacities. Moreover, after disambiguating the assignee names as they appear on the patent documents, it is often necessary to aggregate patent data at the firm level and merge those aggregated numbers to other databases, like Compustat and IRRC. Given the high costs involved, most research that requires both large scale patent and firm level data still solely relies on the NBER patent database, restraining the analysis to periods ending latest in 2001.

We extended the reach of the NBER patent database by combining it with USPTO and Fung Institute data, including patent citations and other detailed information within each patent document. We started with standardized assignee names provided by the USPTO for all patents granted through December 31, 2012. These standardized assignee names are largely free of misspellings but still contain many name abbreviations for individual firms. The crucial advantage of the standardized USPTO assignee names is that they are time invariant and have been used by the NBER patent project team to disambiguate firm names. For almost all firms that received at least one patent between

[2]The numbers are derived by comparing all patent applications in the NBER database with all patents in the Fund Institutes database as published in April 2014.

[3]We gather patent data through 2007, because we will estimate regressions of firms' patenting activities in year t on board data and controls in *t*-1, reflecting that patenting activities need some time to be influenced by boards and simultaneous determination of variables may otherwise confound the estimation.

1975 and 2006 the NBER provides a unique time invariant assignee. We took all variations of standardized assignee names that belong to a given single firm as a training set, and gave all granted patents that appear with the same standardized assignee name after 2006 the same unique NBER identifier.[4] These information enabled us to track firms' patenting activity over significantly longer time periods, overcoming truncation issues of patent applications and generally increasing the accuracy of available patent portfolios.

Finally, we merged unique time invariant Compustat identifiers to the patent assignee identifiers as they are provided by the NBER. It is worthwhile to note that in our analysis we take only those firms into account for which the NBER has identified Compustat matches, and we assigned zero patents only to those firms where the NBER team searched for but could not find matches with any patent. In this regard we deviate from other studies that assign zero patents also to those firms that have not been tested to appear as a patent assignee or not. We avoid this measurement error at the expense of a smaller but more accurate dataset.

In order to circumvent potential selection effects to confound our estimation of the relationship between board oversight and innovation, we further removed all firms that entered the sample in the year 2000 or later, such that the remaining firms can be observed over a timespan where the previously described regulatory changes took place. As we estimate firm fixed effects models we further removed all firms that appear only once in the data. Finally, we arrive at a sample of 6676 observations on 932 firms observed during the period from 1996 to 2006 for which we could gather all information of interest. All firms in the sample combined have applied for 337,465 patents during the sample period. Table 1 presents summery statistics on the dataset.

Descriptive analysis The patenting activities of the firms in our sample show the typical skewness with a mean of ~51 patents and a median of 2 patents. Related measures like the amount of R&D investment, citation-weighted patent counts and claim-weighted patent counts show similar distributions with and high concentration among the most active firms. We calculated the number of patents that cite a given patent based on all USPTO granted patents by April 2014. The number of citations falls naturally from 1996 to more recent years. In our estimations we employ time fixed effects to account for these differences across time that presumably concern all firms equally on average. 774 firms (80%) have applied for at least one patent during the sampling period.[5]

[4]Based on the first assignee that appears on the patent document. It allowed us to identify ~250k additional patents granted to U.S. based assignees after 2006.

[5]The results presented below are robust to excluding those firms from the analysis.

Table 1 - Descriptive statistics

Variable	N	mean	p50	sd	min	max
log(R&D)	6676	3.122	3.349	2.246	0	9.408
log(Total assets)	6676	7.353	7.194	1.525	2.877	13.53
Board size	6676	9.214	9	2.532	3	26
Independent board	6676	0.0671	0	0.250	0	1
Patents	6676	50.55	2	234.5	0	5261
Cite-weighted patents	6676	538.1	4	3194	0	108496
Claim-weighted patents	6676	943.9	25	4540	0	88533
Highly cited patents (1%)	6676	0.496	0	2.325	0	44
Highly cited patents (10%)	6676	4.753	0	24.39	0	660
One time cited patents	6676	33.42	1	163.6	0	3887
Av. cite per patent	6676	11.56	0	60.40	0	1215
Patents without cites	6676	17.13	0	95.75	0	4033
Backward citations	6676	1086	23	4682	0	101943
Self-citations	6676	165.3	0	951.8	0	22415
Av. age of back-cites	4163	8.729	8.685	3.196	0	24
Patents in new classes	6676	1.249	0	3.764	0	227
Patents in old classes	6676	49.30	2	233.7	0	5259
Technological proximity	5835	0.465	0.535	0.395	0	1
Av. tenure of inventors	5835	1.944	1.173	2.376	0	20
Av. age of inventors	5835	3.570	3.250	3.784	0	29

Notes: This table reports summary statistics of all variables used in the study. Board size is the number of board members. Independent board is an indicator variable that indicates whether the majority of board members are independent. Highly cited patents (1%/10%) are patents that fall into the 1%/10% most cited patents within a given 3-digit class and application year. Self-citations are the number of cites to patents held by the same firm. Av. age of self-cites is the average time in years between the year of application of each cited patent and the year of application of a given patent, aggregated at the firm level. Patents in new/old classes is the number of patents that are filed in classes where the given firm has filed no/at least one other patent beforehand. Technological proximity is the technological proximity between the patents filed in year t to the existing patent portfolio held by the same firm up to year t-1, and is calculated according to Jaffe (1989). Av. tenure of inventors is the average time in years since each inventor that appears on a patent filed in year t first appeared on another patent applied for by the same firm. Av. age of inventors is the average time in years since each inventor that appears on a patent filed in year t first appeared on the first other patent since 1975, irrespective of the specific assignee. The latter two variables are set to zero if a firm's inventor does not previously appear in the database. Further information on variable definitions and data sources are provided in the text.

Figure 3

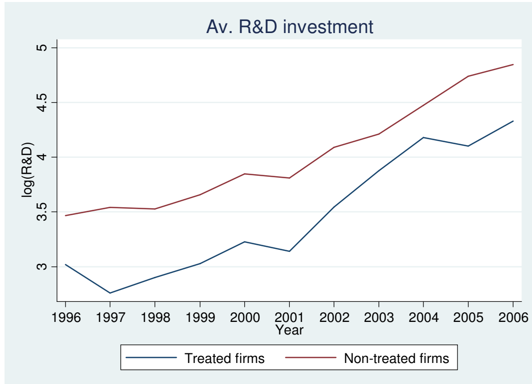
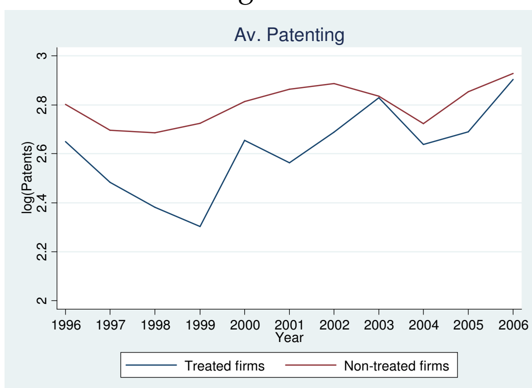


Figure 4



In order to reduce the skewness in R&D investments and patenting activities across firms we take the logarithm of those variables (+1) for most analyses. Figures 3 to 6 illustrate how the average amount of R&D investments, applied patents, cite-weighted patents and claim-weighted patents evolve over time. To reduce the influence of the varying proportion of non-patenting firms per year in the sample the graph is based on firms that that filed at least one patent per year. We separate those firms that switch form a minority to a majority of independent directors on the board after 2000, referred to as 'treated firms', and all other 'non-treated firms'. R&D investments rose almost constantly over the sampling period for all firms (Figure 3). The average number patents and its cite- and claim-weighted counter parts show a gap between treated and non-treated firms up the year ~2001 that subsequently narrowed (Figures 4 to 6). The descriptive analysis thus points to potential positive effects of changes in board independence on patenting activity.

Figure 5

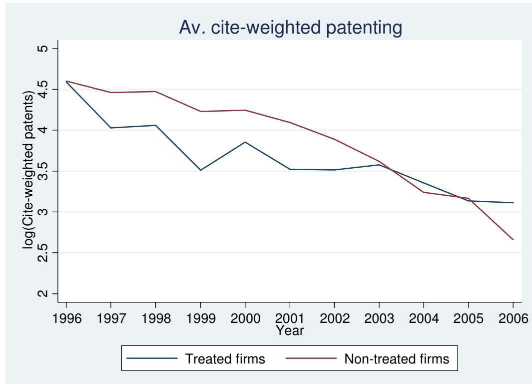
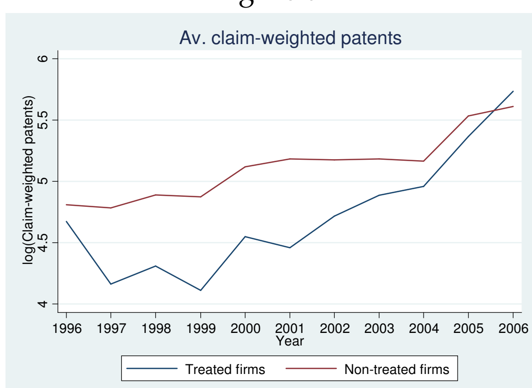


Figure 6



Notes: Figures 3 to 6 illustrate how the average amount of R&D investments, granted patents, cite-weighted patents and claim-weighted patents, respectively, evolve over time. Firms that switch form a minority to a majority of independent directors on the board in 2001 or later are 'treated firms', and all other firms considered as 'non-treated firms'. Details on sample construction and descriptive statistics are provided in section 3.

In order to analyze the relationship between board oversight and patenting more systematically we estimate the following model:

$$log(patents_{it}+1) = \beta_0 + \beta_1 * independent\ board_i * post_t + \beta_2 * board\ size_{it} \\ + \beta_3 * log(R\&D)_{it} + \beta_4 * log(total\ assets)_{it} + \delta_t + \alpha_i + \epsilon_{it}$$

where $patents_{it+1}$ is the number of patent grants of firm *i* in year *t+1* between 1996 and 2006. In alternative regressions we will exchange the number of patent grants with several different variables that allow us to assess the firms' innovative search and success in more detail. Our main explanatory variable of interest is a dummy that indicates whether a given firm has switched from a minority to a majority of independent board members in the year 2001 or later when regulatory changes became effective. Under the assumption that changes in patenting by firms that switched to majority of independent board members have been comparable to changes in patenting by other firms in the absence of a switch to an independent board β_1 captures the effect of increased board oversight through independent directors on patenting by the affected firms.[6]

Three separate variables control for differences across firms and over time in patenting that are determined by board size, firm size and the investments in research and development (R&D).[7] *Board size* measures the number of board members as we want to insulate the effect of board independence from potentially confounding contemporary changes in the number of directors. Further, we found that the firms in our sample differ significantly in terms R&D spending and size, two variables that are naturally positively related to firms patenting activities. Firm fixed effects α_i control for any unobserved variation that is time invariant. Year fixed effects further control for variation in the macroeconomic environment and patenting over time that affected all firms.

[6] As can be seen in Figure 2, not all firms switched from a friendly to an independent board at the same time, because directors were allowed to fulfill their contracts that were signed before the law change. In principal, this gives firms room for strategic choice that could confound our identification. Therefore, we checked whether the time between the law change and compliance is correlated with pre-SOX innovative activity of the firms in our sample. In order to test this, we first defined a variable that measures the years until the board actually changed from friendly to independent although SOX and other regulations were already active (2003). We found 17 firms with a one year lag, 14 with a two year lag and 8 with a three year lag. Then, we regressed time lag until compliance on firms' average amount of R&D, patents, cites and claims before 2001 (results are robust to taking 2000 or 2002 instead). As we did not find any significant correlation between compliance lags and pre-treatment innovative activity, we are confident that our estimation is not biased by systematic choice of more or less innovative firms to switch later or earlier.

[7] All results presented below are robust to including different or additional control variables that have been employed by other studies, e.g. Galasso and Simcoe (2011).

6 R&D, patents, cite-weighted patents, claim-weighted patents

We will first explore the impact of friendly boards on patent count and citations and then establish how friendly boards correlate with exploration. We first estimate regressions of the logarithm of firms' R&D investments, the number of patent grants applied for in that year, the number of cite-weighted grants and grants weighted by the number of claims of each patent. With the first model we want to assess potential changes in R&D investments after board oversight increases, which might be responsible for subsequent changes in patenting activities.[8] The latter two models address the concern that any effect on the number of patents might be only weakly related to the value of the inventions that those patents represent. Cite-weighted patent counts have been frequently used in the literature to assess the value of firms' innovations, because previous studies have shown that citations by other patents are positively correlated with firms' value and patent renewals (Harhoff 1999; and Hall et al., 2005). We also estimate a regression of claim-weighted patent counts. Inclusion of claims as control variable in the citation model indicates strong mediation by claims - it appears that independent boards correlate positively with the number of claims. Table 2 presents the corresponding results in columns *a* to *e*.

Figures 7 to 10 illustrate the dynamic effect of a switch to an independent board on patenting graphically. For the graphs we defined dummy variables for the specific times before and after firms changed to an independent board. t_0 defines the year of the switch, t_{n-1} defines the number of years before the switch, and t_{n+1} the corresponding years after the switch. Then, we ran regressions including these variables instead of the single dummy variable in the baseline model beforehand. As we still include year fixed effects the coefficients represent the relative change in patenting per year that is attributable to the board change.

The results shown in Table 2 point out that an increase in board oversight through a change to an independent board is unrelated to the level of firms' R&D investments. It is worthwhile to mention, however, that standard OLS regressions without firm fixed effects indicate a decline in R&D investment that is statistically significant at the 1% level (*not presented*).

Tighter control by the board might have incentivized managers to spend more effort to show innovative success.

[8] Alternative regressions with R&D investments scaled by total assets reveal similar results.

Table 2 - Patenting

	(a) R&D	(b) Patents	(c) Citations	(d) Citations	(e) Claims
log(no. claims)				0.740**	
				(0.011)	
log(R&D)		0.017	-0.005	-0.011	0.008
		(0.031)	(0.053)	(0.039)	(0.055)
log(Total assets)	0.593**	0.238**	0.225**	-0.031	0.345**
	(0.042)	(0.057)	(0.086)	(0.050)	(0.094)
Board size	0.010	0.022	0.004	-0.002	0.008
	(0.007)	(0.013)	(0.020)	(0.011)	(0.021)
Independent board	-0.050	0.292**	0.661**	0.295**	0.495**
	(0.052)	(0.079)	(0.114)	(0.075)	(0.134)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	6676	6676	6676	6676	6676
R^2	0.179	0.190	0.101	0.901	0.103

Notes: All explanatory variables are lagged by one period. Board size is the number of board members. Independent board is a dummy that indicates firms that switched from a minority of independent board members to a majority of independent board members in 2001 or later. R&D in column *a* is the logarithm of the amount of R&D spent (in million US$). Patents is the logarithm of the number of patent grants applied for in a given year (b). Cite-weighted patents is the logarithm of all citations that the granted patents applied for in *t* received later from other patents (c,d). Claim-weighted patents is the logarithm of the number of claims that each patent application contained (e). Heteroskedasticity-robust standard errors that account for autocorrelation at the firm level are reported in parentheses.Coefficients: ** Significant at 1%, * Significant at 5% level

Figure 7

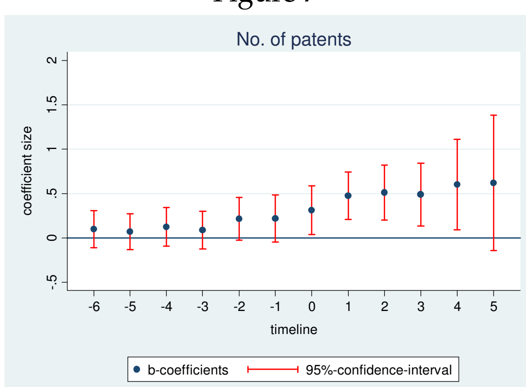


Figure 8

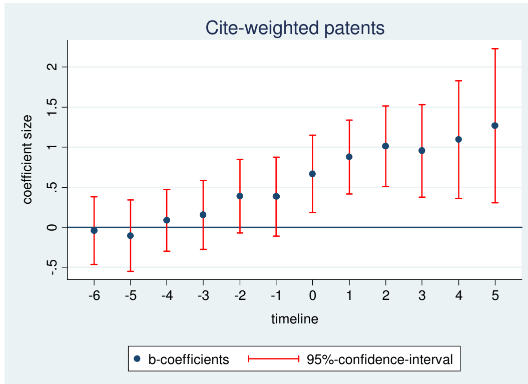


Figure 9

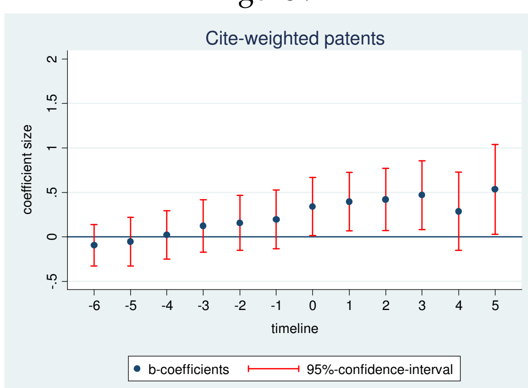
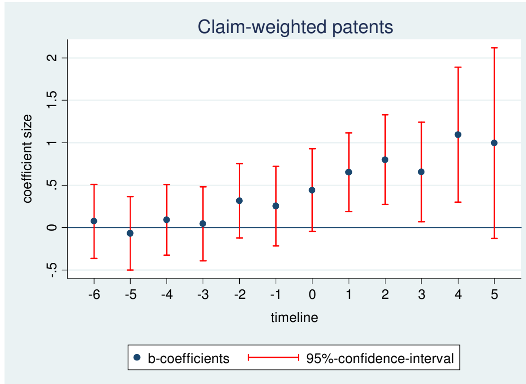


Figure 10



Notes: Figures 7 to 10 illustrate the effect of a change in board independence on patenting over time. For the graphs we defined dummy variables for the time firms changed from a minority of independent board members to an independent board. t_0 indicates the year of the switch and t_{n-1} indicates the years before the switch, and t_{n+1} the corresponding years after the switch. Coefficients are taken from a regression as introduced in section 3, but with the t_n dummies instead of the one dummy variable indicating a majority of independent board members. Figure 9 is derived from regressions including the number of claims as an additional control variable.

7 Citations

In this section, we exploit more detailed information contained in the citations that a patent receives (forward citations). As we know that the patent citation as well as patent value distribution is highly skewed and the citation-value relationship is most likely not linear, we split the distribution into subcategories that intend to separate particular successful, average patents and unsuccessful patents. Specifically, we consider 5 categories: (1) patents that received cites within the highest percentile (top 1%) among all patents in the same 3-digit patent class and application year, (2) patents that received cites within the highest centile (10%) among all patents in the same 3-digit patent class and application year, (3) patents that received at least one citation (median is 0), (4) the average number of citations per patent, and (5) patents that received no citation. Table 3a presents the corresponding results. Table 3b presents all models as presented in Table 3a, but with additional control for the number of claims.

In line with our previous patent regressions we see a positive effect of board oversight on patenting. This is consistent with Kang et al. 2014 who show a marginally significant and positive correlation between board independence and citation-weighted patenting, from a similar but earlier sample of firms. Interestingly, however, the estimated effect is by far the largest for patents that received exactly one citation, while the estimated effect on particular successful patents (top 1% or top 10%) is only about one

Table 3a - Differences in patenting

	(a) Top 1%	(b) Top 10%	(c) Cited	(d) Av. citations	(e) No cites
log(R&D)	0.010	0.021	0.027	0.040*	0.050
	(0.007)	(0.013)	(0.025)	(0.016)	(0.036)
log(Total assets)	0.042**	0.109**	0.211**	0.153**	0.206**
	(0.015)	(0.031)	(0.049)	(0.035)	(0.061)
Board size	0.007*	0.006	0.013	0.011	0.030*
	(0.004)	(0.006)	(0.012)	(0.007)	(0.013)
Independent board	0.054*	0.077	0.357**	0.149**	0.121
	(0.025)	(0.039)	(0.067)	(0.042)	(0.088)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	6676	6676	6676	6676	6676
R^2	0.174	0.229	0.190	0.232	0.317

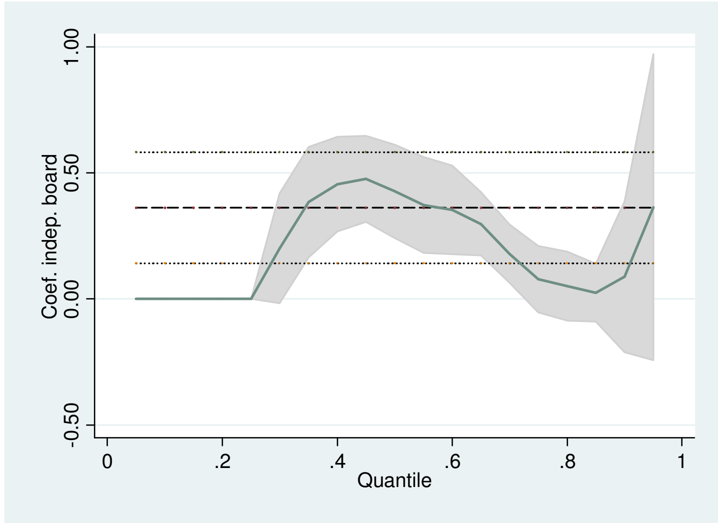
Notes: All explanatory variables are lagged by one period. Board size is the number of board members. Independent board is a dummy that indicates firms that switched from a minority of independent board members to a majority of independent board members in 2001 or later. Highly cited patents (1%/10%) is the logarithm of the number of patents that fall into the highest percentile/centile of citations received within a given 3-digit patent class and application year. Cited patents is the logarithm of the number of patents that received at least one citation. Av. cites per patent is the logarithm of the average number of cites per patent. Patents without cites is the logarithm of the number of patents that received no citation. Heteroskedasticity-robust standard errors that account for autocorrelation at the firm level are reported in parentheses. Coefficients: ** Significant at 1%, * Significant at 5% level.

Table 3b - Differences in patenting

	(a) Top 1%	(b) Top 10%	(c) Cited	(d) Av. citations	(e) No cites
log(no. claims)	0.024**	0.104**	0.387**	0.160**	0.234**
	(0.003)	(0.007)	(0.008)	(0.009)	(0.011)
log(R&D)	0.010	0.020	0.024	0.039**	0.049
	(0.007)	(0.012)	(0.016)	(0.013)	(0.032)
log(Total assets)	0.033*	0.073**	0.078**	0.098**	0.125*
	(0.015)	(0.026)	(0.027)	(0.028)	(0.051)
Board size	0.007*	0.006	0.009	0.010	0.028*
	(0.003)	(0.005)	(0.006)	(0.006)	(0.012)
Independent board	0.042	0.025	0.165**	0.069	0.006
	(0.024)	(0.036)	(0.041)	(0.036)	(0.078)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	6676	6676	6676	6676	6676
R^2	0.325	0.556	0.887	0.626	0.613

Notes: All explanatory variables are lagged by one period. Board size is the number of board members. Independent board is a dummy that indicates firms that switched from a minority of independent board members to a majority of independent board members in 2001 or later. Highly cited patents (1%/10%) is the logarithm of the number of patents that fall into the highest percentile/centile of citations received within a given 3-digit patent class and application year. Cited patents is the logarithm of the number of patents that received at least one citation. Av. cites per patent is the logarithm of the average number of cites per patent. Patents without cites is the logarithm of the number of patents that received no citation. Heteroskedasticity-robust standard errors that account for autocorrelation at the firm level are reported in parentheses. Coefficients: ** Significant at 1%, * Significant at 5% level

Figure 11 - Quantile regression of citations



Notes: Figure 11 illustrates the effect of a change in board independence on patent citations. Coefficient size is estimated with quantile regressions. The grey area represents the 95% confidence band of the quantile regression estimates. The horizontal dashed lines are the OLS point estimate and the corresponding 95% confidence band.

sixth as high and not consistently significant. Taking also into account that the effect on the number of unsuccessful patents (no cites) is statistically insignificant and the effect on the average number of citations per patent is positive, it seems that firms focus more on moderately successful innovations.

Table 3b includes claims as a mediating variable, in line with the hypothesis that independent boards would encourage measurable but less risky innovation. Board independence now only correlates with patents that are cited at least once. Highly cited patents, patents without cites, and average citations are now insignificant, though their coefficients remain positive. Figure 11 illustrates results for a quantile regression on the log of citations, including claims as a control variable. The horizontal dashed lines are the OLS estimates and 95% confidence band for comparison. The evidence is consistent with independent boards encouraging more exploitation and less exploration.

8 Self-citations, age of cites

In this section, we run further regressions that aim to aid our understanding of the innovative search that companies pursue and whether the balance between exploration and exploitation shifted with increased board oversight. First, we calculate the number of citations that each patent makes to other patents. Increased backward citations could be interpreted as an indication for innovative search in relatively better-known and mature technological areas. Second, we take the number of times a given patent cites other patents owned by the same company. More self-cites could indicate constraining search within previously known areas of expertise while fewer self-citations could indicate a broadening of innovative search or efforts to explore areas that are new to the firm. We supplement these regressions with a similar model on the average age of the backward citations. The age of a particular citation is calculated as the time in years between the application of the citing patent and the year of application of the cited patent. We average those citation years over a given patent and then average over the whole patent portfolio of a given firm in a given year. Higher citation ages should indicate search in more mature technological areas, while citations to younger patents may indicate a switch to more recent technologies. Table 4 presents the corresponding results.

Table 4 - Self-citations, age of cites

	(a) Backward cites	(b) Self-cites	(c) Age of back-cites
log(R&D)	0.024	0.055	-0.001
	(0.057)	(0.035)	(0.012)
log(Total assets)	0.366**	0.182**	0.004
	(0.103)	(0.067)	(0.018)
Board size	0.005	0.033*	0.002
	(0.021)	(0.015)	(0.003)
Independent board	0.488**	0.372**	0.055*
	(0.130)	(0.079)	(0.025)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	4173	4173	4173
R^2	0.119	0.198	0.086

Notes: All explanatory variables are lagged by one period. Board size is the number of board members. Independent board is a dummy that indicates firms that switched from a minority of independent board members to a majority of independent board members in 2001 or later. Backward citations is the logarithm of the number patents that a given patent cites. Self-citations is the logarithm of the number patents that a given patent cites and that belong to the same firm. Av. age of back-cites is the logarithm of the average time in years between the year of application of the cited patent and the citing patent's application year. Heteroskedasticity-robust standard errors that account for autocorrelation at the firm level are reported in parentheses. Coefficients: ** Significant at 1%, * Significant at 5% level.

All results presented in Table 4 point out that firms with more independent boards tend to narrow their innovative search towards known and mature technological areas.

In the next section we provide complementary findings.

9 Classes and inventors

We now look at the classes in which patents are filed and the inventors employed by the firm. Specifically, we calculate the number of patents that are filed in classes previously unknown to the firm. Unknown patent classes are defined as those in which a given firm has not applied for any patent beforehand. The counter part is the number of patents applied for in known classes. A more sophisticated measure of whether firms stay or deviate from known research areas is the technological proximity between the patents filed in year t and the existing patent portfolio held by the same firm up to year t-1 We calculate this measure according to Jaffe (1986). It can formally be written as:

$$P_{it} = \sum_{k=1}^{K} f_{ikt} f_{ikt_{-1}} / \left(\sum_{k=1}^{K} f_{ikt}^2 * \sum_{k=1}^{K} f_{ikt_{-1}}^2 \right)^{\frac{1}{2}}$$

where f_{ikt} is the fraction of firm i's patents that belong to patent class k at time t, and $f_{ikt_{-1}}$ is the fraction of firm i's patent portfolio up to t-1 that belongs to patent class k. P_{it}ranges between 0 and 1. The highest possible value indicates that the patents filed in year t are distributed across patent classes in the exact same way as the portfolio of all patents of the same firm up to the previous year. Positive coefficients in a regression would thus indicate a more narrow innovation trajectory within known areas.

Moreover, we took advantage of the recent disambiguation of inventors mentioned on each patent document (see Li et al., 2014). Knowing the inventors of each patent allows us to calculate whether firms are more likely to rely on their own, previously successful staff of inventors or whether firms rather hire new inventors or fund their younger colleagues. Therefore, we identified the first time each inventor is mentioned on a patent document of the same firm, or in the whole patent database since 1975, respectively. From there we calculated for each inventor the number of years between the first appearance with the same firm (in the patent database) and the year of the given patent application. Inventors that appear for the first time received 0 years. Then we averaged these years over a given patent and then over all patents applied for by a given firm in a given year.

Table 5 presents the corresponding regression results. As can be seen, independent boards have an insignificant effect on exploration of new classes but a strong and significantly positive effect on search in previously patented classes. These results are consistent with the Jaffe measure as well. Finally, firms with more independent boards are more likely to patent inventions by inventors employed longer by the firm and inventors whose first patent is older as well.

Table 5 - Classes and Inventors

	(a) New class	(b) Old class	(c) Tech. prox.	(d) Inv. tenure	(e) Inv. Age
log(R&D)	-0.003	0.027	-0.018	0.001	-0.031
	(0.017)	(0.032)	(0.011)	(0.022)	(0.026)
log(Total assets)	0.073*	0.229**	0.042*	0.024	0.094*
	(0.030)	(0.056)	(0.017)	(0.035)	(0.040)
Board size	0.006	0.028*	0.009*	0.010	-0.004
	(0.007)	(0.013)	(0.004)	(0.007)	(0.008)
Independent board	0.063	0.310**	0.065**	0.095*	0.143**
	(0.044)	(0.078)	(0.024)	(0.043)	(0.051)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	5835	5835	5835	5835	5835
R^2	0.085	0.210	0.007	0.105	0.095

Notes: All explanatory variables are lagged by one period. Board size is the number of board members. Independent board is a dummy that indicates firms that switched from a minority of independent board members to a majority of independent board members in 2001 or later. Patents in new/old classes is the number of patents that are filed in classes where the given firm has filed no/at least one other patent beforehand. Technological proximity is the technological proximity between the patents filed in year t to the existing patent portfolio held by the same firm up to year t-1, and is calculated according to Jaffe (1986). Av. tenure of inventors is the average time in years since each inventor that appears on a patent filed in year t appeared on another patent applied for by the same firm the first time. Av. age of inventors is the average time in years since each inventor that appears on a patent filed in year t appeared on the first other patent after 1975, irrespective of the assignee. The latter two variables are set to zero if an inventor appears for the first time in the patent database. Heteroskedasticity-robust standard errors that account for autocorrelation at the firm level are reported in parentheses. Coefficients: ** Significant at 1%, * Significant at 5% level.

10 Discussion and conclusion

We presented a model whereby shareholders appoint a board of directors and hire a manager. We considered a less independent and assumedly more friendly board, whose beliefs matched the manager; in this case, the firm explores new strategies if the manager is sufficiently optimistic. A less friendly board makes the manager less likely to explore new strategies, because the manager fears a lack of control over the choice of strategy.

Evidence to support this model comes from regulatory changes which made boards more independent. Following the model predictions, firms whose boards become more independent are less likely to explore new technologies and more likely to exploit previously successful areas of expertise. Consistent with an increase in patents, patent claims, and citations, firms with more independent boards appear to work harder in less risky areas. The number of claims mediates the increase in patenting and citations, especially in the tails of the citation distribution. Firms with more independent boards work in older and more familiar areas of technology. They are also more likely to patent work by inventors with a longer tenure within the firm and also inventors who have been patenting longer in general.

These more nuanced measures of search and exploration enable greater insight into the search and innovation process and highlight the importance of differentiating between greater effort and incremental output vs. breakthrough inventions. Further work will seek to establish the impact of exploration and exploitation on the novelty and technical and financial value of the firm's inventions.

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11 Appendix

Proof of Proposition 1: Under a friendly board, the manager proposes a new strategy when she believes that its payoff is higher than the conventional strategy. Because the board and manager share similar beliefs, such proposal will be approved by the board.

There are two action plans to consider: exploring the new strategy in the first period and switching to the conventional strategy in case of failure or exploring the new strategy in both periods.

For an agent with belief μ, exploring the new strategy and switching in case of failure is better than exploiting the conventional strategy iff

$$\begin{aligned} f(\mu)S + (1-f(\mu))F + f(\mu)\Bigg(f\left(\frac{\mu q_H}{\mu q_H + (1-\mu)q_L}\right)(q_H S + (1-q_H)F) \\ + \left(1 - f\left(\frac{\mu q_H}{\mu q_H + (1-\mu)q_L}\right)\right)(q_L S + (1-q_L)F)\Bigg) + \\ (1-f(\mu))(pS + (1-p)F) \\ \geq 2(pS + (1-p)F) \end{aligned} \tag{4}$$

where $f(x) = xq_H + (1-x)q_L$. Equation (6) is equivalent to:

$$\mu \geq \frac{(1+q_L)(p-q_L)}{(1+q_L+q_H-p)(q_H-q_L)} \tag{5}$$

Exploring the new strategy in both periods regardless of outcomes is better than exploiting the conventional strategy iff

$$2(f(\mu)S + (1-f(\mu))F) \geq 2(pS + (1-p)F). \tag{6}$$

In (6), we use the fact that by Bayes' rules beliefs follow a martingale. Equation (6) is equivalent to:

$$\mu \geq \frac{p-q_L}{q_H-q_L} \tag{7}$$

Condition (5) is more stringent than (7). ■

Proof of Proposition 2: From the proof of Proposition 1, if an agent believes that exploring the new strategy in both periods regardless of output dominates exploiting the conventional strategy, then the agent also believes that exploring in the first period and switching to exploitation in case of failure also dominates exploiting the conventional strategy. Therefore, a manager who believes that exploring in both periods is optimal will propose the new strategy as long as the board approves exploration at least in the first period. This gives rise to condition (2).

However, if the manager is only optimistic to implement exploration in the first period but switch to exploitation in case of failure in the second period, he does not propose the new strategy if the board is optimistic to the point of wanting to implement exploration of the new strategy in both periods. This gives rise to condition (3). ■

Proof of Proposition 3: If the manager is optimistic relative to shareholders about innovation ($\mu_M > \mu_S$), an independent board with $\mu_B = \mu_S$ induces the manager to propose any project with

$$\mu_M \geq \frac{(1+q_L)(p-q_L)}{(1+q_L+q_H-p)(q_H-q_L)}$$

as long as the project is profitable to shareholders:

$$\mu_S \geq \frac{(1+q_L)(p-q_L)}{(1+q_L+q_H-p)(q_H-q_L)}$$

If the manager is pessimistic relative to shareholders about innovation ($\mu_M < \mu_S$), we know from Proposition 2 that the manager may be reluctant to propose the new strategy if an independent board is likely to force him to stick to the new strategy even after failure. A friendly board ($\mu_M = \mu_S$) solves this problem, inducing the manager to propose a new strategy as long as

$$\mu_M \geq \frac{(1+q_L)(p-q_L)}{(1+q_L+q_H-p)(q_H-q_L)}.$$

Because shareholders are more optimistic than the manager about innovation, they always want to implement exploration under the above conditions. ■