Do Anti-Takeover Provisions Spur Corporate Innovation?

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ABSTRACT

We study the relation between antitakeover provisions (ATPs) and corporate innovation, and show that ATPs affect firm value through a novel "innovation channel." We find that firms with a larger number of ATPs are more innovative. To establish causality, we use a regression discontinuity approach relying on "locally" exogenous variation in the number of ATPs generated by governance proposal votes that pass or fail by a small voter margin, as well as an instrumental variable approach. The evidence suggests that ATPs spur innovation and thus allow long-run value creation by insulating managers from short-term pressures arising from the equity market.

Key words: anti-takeover provisions, innovation, firm value, patents

JEL classification: G34, G38, O31

1. Introduction

Starting with the pioneering paper of Gompers, Ishii, and Metrick (2003), there has been considerable debate in financial economics on the effect of anti-takeover provisions (ATPs) in corporate charters on various aspects of firm performance and thereby on shareholder value. Thus, while Gompers, Ishii, and Metrick (2003) show that firms with a larger number of ATPs have lower long-term stock returns, Core, Guay, and Rusticus (2006) question the above findings, arguing that there is no conclusive evidence indicating that ATPs affect actual firm performance. One possibility is that ATPs destroy shareholder value in a subset of firms, while they are value-neutral or even enhance value in others. The objective of this paper is to delve deeply into the above issue by focusing on a specific channel through which ATPs may affect firm value, namely, corporate innovation, and thereby to contribute to the above debate.

Innovation is a key corporate strategy for the long-run competitive advantage of firms. Unlike routine tasks such as mass production and marketing, innovation involves a long process that is full of uncertainties and with a high probability of failure (Holmstrom, 1989). Therefore, motivating innovation needs tolerance for failure in the short run and reward for success in the long run (Manso, 2011).[1] Another stream of the theoretical literature suggests that firms innovate more when managers are insulated from the pressures from short-term equity market investors. Stein (1988) argues that shareholders cannot properly evaluate a manager's investment in innovative long-run projects due to information asymmetry. Therefore, outside shareholders tend to undervalue the stocks of companies investing in innovative projects, which leads to a great exposure to hostile takeovers for the firm. To protect current shareholders against such expropriation, managers tend to invest less in innovation and put more effort in routine tasks that offer quicker and more certain returns. In a similar setting with asymmetric information, Chemmanur

[1] See also the theoretical model of Ferreira, Manso, and Silva (2012), who argue that insiders of private firms (which are less transparent to outside investors compared to public firms) are more tolerant of failures and thus more inclined to choose innovative projects, unlike the insiders of public firms, who choose more conventional (safer) projects that allow them to cash in early following the arrival of good news. Another important theoretical paper that deals with the relationship between the private versus public status of a firm and its innovative productivity is Spiegel and Tookes (2008), which predicts that firms will implement their most productive innovations when they are private firms and will go to the public markets only when more modest innovations remain.

and Jiao (2012) show that ATPs such as dual class share structures may encourage managers to undertake innovative long-term investments by insulating them from takeovers. [2]

Thus, the above literature suggests that corporate governance mechanisms such as ATPs that insulate managers from the threat of hostile takeovers may help to solve the conflicts between short-term pressures exerted by myopic public equity markets and innovation activities that may be in the long-run interest of the firm. However, an alternative view in the literature is that ATPs may in fact be value-reducing overall by entrenching firm managers through freeing them from the disciplining effect of the takeover market. In this paper, we address the above issue empirically by analyzing the effect of ATPs on corporate innovation and by examining how this effect of ATPs on innovation affects the firm's long-run equity value.

We develop our testable hypotheses based on two strands in the theoretical literature that produces contradictory predictions regarding how ATPs affect firm innovation. The theoretical literature discussed earlier implies that ATPs increase the productivity of firms in generating corporate innovation: we will refer to the above hypothesis from now on as the "long-term value creation" or "failure tolerance" hypothesis. Another strand in the theoretical literature produces the opposite implication regarding how ATPs affect a firm's innovation productivity. Moral hazard models suggest that managers who are not properly monitored will shirk or tend to invest suboptimally in routine tasks with quicker and more certain returns in order to enjoy private benefits, thus reducing firm value. The existence of hostile takeovers serves as an effective disciplining mechanism to mitigate the above moral hazard problem and encourage innovation, thus increasing firm value. In the above setting, the theoretical literature emerging from the seminal works of Grossman and Hart (1988) and Harris and Raviv (1988, 1989) imply that ATPs serve mainly to entrench incumbent firm management, thus reducing the effectiveness of equity

[2] Shleifer and Summers (1988) suggest that incumbent managers have less power over shareholders when takeover threats are high, leading them to have less of an incentive to invest effort and human capital in activities with only a long-run payoff (such as innovation). This is because incumbent managers fear that a hostile bidder will dismiss them after the takeover (when the innovation is completed), leaving them unable to enjoy the profits resulting from the innovation.

market discipline on them and consequently reducing corporate innovation (lowering firm value).[3] We refer to it as the "management entrenchment" hypothesis.

We test the above two competing hypotheses by examining two research questions in this paper. First, we study whether or not ATPs spur corporate innovation. Specifically, we want to understand if a firm's adopting more ATPs leads to a higher or a lower level of innovation output. We make use of the number of patents granted to a firm and the number of citations received by each patent as our measures of corporate innovation. Second, we examine how a firm's strategy of adopting a larger number of ATPs, potentially leading to higher productivity in innovation (if the long-term value creation hypothesis is supported) or lower productivity in innovation (if the management entrenchment hypothesis is supported), affects its valuation in the equity market.

Our baseline tests show that firms with a greater number of ATPs are significantly more innovative. For example, our baseline results suggest that a firm adopting one more ATP is associated with an increase in its patent counts by 9.0% and the number of citations per patent by 3.5% in three years. Our baseline results are robust to alternative subsamples, econometric models, and ATP measures.

While our baseline results suggest a positive relation between the number of ATPs and firm innovation output, one concern is that the number of ATPs a firm adopts is endogenous. The number of ATPs and innovation could be jointly determined, i.e., an omitted variables problem may seriously bias our results. There could also be reverse causality in which the level of expected future innovation affects the current number of ATPs. To establish causality, we use two different identification strategies. First, we use a regression discontinuity approach that relies on "locally" exogenous variation in the number of ATPs generated by governance proposal votes that pass or fail by a small margin of votes. This is a powerful and appealing identification strategy because for these close-call elections, passing is very close

[3] The above models consider a setting where the incumbent management of a firm (large shareholder) obtains not only cash flow or "security" benefits (arising from his equity ownership in the firm) but also private benefits from being in control; outside shareholders receive only security benefits. These models conclude that ATPs are value reducing, since they reduce the chance of takeovers by rival management teams who can increase the cash flows to current shareholders by managing the firm better than does the incumbent. Thus, under the above theories, ATPs are inefficient, and the only role of such provisions is to entrench existing management and reduce the chance of losing their benefits of control. See also Cary (1969) and Williamson (1975), who made earlier, more informal, arguments that ATPs act primarily to entrench incumbent management.

to an independent random event and therefore is likely uncorrelated with firm unobservable characteristics. Second, we construct instrumental variables by relying on two sources of plausibly exogenous variation, namely, the state-level anti-takeover laws and industry-specific hostile takeover intensity. We then undertake a two-stage least-square (2SLS) analysis using the above instrumental variables. Both identification strategies suggest a positive causal effect of ATPs on firm innovation.

Next, we look for further evidence of identification in the cross section by exploring the cross-sectional differences in the effect of ATPs on innovation. Specifically, we find that the positive effect of ATPs on firm innovation is more pronounced for firms that are subject to a larger degree of information asymmetry and that operate in more competitive product markets. We also find that the positive effect of ATPs on innovation is the strongest in the drug industry in which innovation is the most difficult to achieve (because of low success rates, large resources demanded, and a long innovation process), followed by the IT & chemical industry and other low-tech industries. All the above findings are consistent with the implications of the long-term value creation hypothesis that ATPs provide insulation for managers against pressures from short-term public market investors and allow managers to focus on investing in innovation. Therefore, ATPs are more valuable when information asymmetry is more severe and short-term pressures are higher.

Finally, we find that the number of ATPs contributes positively to firm value, but this is true only if the firm is involved in intensive innovation activity and has high innovation productivity. If, however, ATPs are adopted while firms are not conducting a significant extent of innovation, ATPs reduce firm value, which is consistent with the findings of the existing literature, especially Gompers, Ishii, and Metrick (2003). We further show that the positive effect of ATPs on firm value through innovation is more pronounced for firms with a larger degree of information asymmetry, operating in more competitive product markets, and being in the industries in which innovation is more difficult to achieve. This evidence is consistent with the implications of the long-term value creation (or the related failure tolerance) hypothesis. Overall, our results imply that the role of ATPs may be more nuanced than that indicated by the bulk of the literature so far: while adopting these ATPs is optimal (value-enhancing) for innovative firms, it is suboptimal (value-reducing) for firms that are not engaged in a significant extent of innovation.

The rest of the paper is organized as follows. In Section 2, we discuss related literature. We describe sample selection and report summary statistics in Section 3. Section 4 reports the empirical results regarding the effect of ATPs on innovation. Section 5 presents our results regarding the effect of ATPs on firm value through innovation. We conclude in Section 6.

2. Relation to the Existing Literature

Our paper contributes to two strands in the existing literature. The first literature is the one on corporate innovation. Recent empirical research testing the implications of Manso (2011) includes Ederer and Manso (2012), who conduct a controlled laboratory experiment, Azoulay, Graff Zivin, and Manso (2011), who exploit key differences across funding streams within the academic life sciences, and Tian and Wang (2012), who show that IPO firms financed by more failure-tolerant venture capital investors are more innovative. All studies provide supporting evidence for Manso's theory. Our paper contributes to this empirical literature providing support for the long-term value creation hypothesis by documenting that ATPs providing some insulation from the takeover market spur innovation in public firms.

The early literature examining the impact of anti-takeover amendments on R&D expenditures has provided mixed results. Meulbroek et al. (1990) show that firms decrease R&D expenditures after adopting anti-takeover amendments. However, Pugh et al. (1992) find evidence that R&D expenditures rise after amendment adoptions. Finally, Johnson and Rao (1997) do not find significant departures for R&D expenditures from industry norms after firms pass anti-takeover amendments. Different from these studies, we use patenting rather than R&D expenditures to capture firm innovation. One key advantage of this strategy is that patenting is an innovation output variable, which encompasses the successful usage of *all* (both observable and unobservable) innovation inputs. In contrast, R&D expenditures only capture one particular observable quantitative input and are sensitive to accounting norms such as whether R&D expenditures should be capitalized or expensed. In addition, information on R&D expenditures reported in the Compustat database is quite unreliable, which may introduce a significant measurement error problem.[4] Our strategy of using patenting to capture firm innovation significantly reduces the measurement error concern and has now become standard in the innovation literature (Aghion et al. 2005; Nanda and Rhodes-Kropf 2012; Hirshleifer, Low, and Teoh 2012; Seru 2012; He and Tian 2013).[5]

Two other recent papers examine research questions somewhat more closely related to ours. Atanassov (2013) uses the enactment of state antitakeover laws (specifically, the enactment of Business Combination laws) as a proxy for the decrease in the threat of hostile takeovers, and finds that state antitakeover laws stifle innovation. Sapra, Subramanian, and Subramanian (2013) develop a theoretical model and show a U-shaped relationship between innovation and takeover pressures. They also use the state-level antitakeover laws as the proxy for takeover. In contrast to the above two papers, we use state-level antitakeover laws only as a plausible variation that is related to firm-level ATPs to help identify causality. In other words, ours is the first paper that studies the relation between the number of ATPs at the firm level and corporate innovation. It is also worth noting that the broader conclusions that can be drawn from our paper regarding the relation between ATPs and innovation are *opposite* to that implied by the above two papers using state-level antitakeover laws.[6]

Our paper also contributes to the debate on the effect of ATPs on firm value and on long-term stock returns. Gompers, Ishii, and Metrick (2003) show that firms with a greater number of ATPs have lower stock returns. Bebchuk and Cohen (2005) find that staggered boards are associated with a reduction in firm value. Bebchuk, Cohen, and Ferrell (2009) show that six ATPs deserve most attention and they are associated with reductions in firm valuation and stock returns. Cremers and Ferrell (2012) use a new

[4] More than 50% of firms do not report R&D expenditures in their financial statements. However, the fact that a firm does not report its R&D expenditures does not necessarily mean that the firm is not engaging in innovation activities. Replacing missing values of R&D expenditures with zeros, a common practice in existing literature, introduces additional noise that may bias the coefficient estimates.

[5] Francis and Smith (1995) find that firms with either a high concentration of management ownership are more innovative. Aghion, Van Reenen, and Zingales (2013) show that institutional ownership matter for corporate innovation. Kortum and Lerner (2000) find that venture capital investments positively affect innovation.

[6] A contemporaneous work by Becker-Blease (2011) finds a positive association between the presence of governance provisions and corporate innovation for a sample of firms between 1984 and 1997. He further shows that coverage by state-level antitakeover legislations is typically unassociated or negatively associated with innovation. However, it is hard to draw causal inferences from his analysis, and he does not explore the valuation effect of ATPs through corporate innovation.

hand-collected dataset and find a robustly negative association between the number of ATPs and firm value over the 1978-2006 period. However, Core, Guay, and Rusticus (2006) question the above findings, arguing that there is no conclusive evidence suggesting that more ATPs lead to poorer stock returns. In contrast to the above papers, Chemmanur, Paeglis, and Simonyan (2011) show that firms with higher quality management teams tend to adopt a larger number of ATPs, and that firms with a combination of higher quality management teams and a larger number of ATPs outperform the other groups of firms in their sample. Our paper contributes to the above debate by showing a new channel, namely, corporate innovation, through which ATPs positively contribute to firm value. However, we also show that if ATPs are adopted by non-innovative firms (the vast majority of firms falls into this category), they are associated with a reduction in firm value. Thus, our evidence is consistent with the findings of Gompers, Ishii, and Metrick (2003) that ATPs lower subsequent stock returns, but sheds further light on their findings by distinguishing between the kind of firms in which ATPs reduce firm value and those in which they increase firm value.

3. Sample Selection and Summary Statistics

The sample examined in this paper includes 3,474 publicly traded firms with ATPs information available during the period of 1990-2006. We combine innovation data from the NBER Patent Citation database, ATPs and shareholder proposal vote information from the RiskMetrics, firms' balance sheet data from Compustat, analyst coverage data from I/B/E/S, and institutional ownership data from Thomson Financial *13f* institutional holdings database.

3.1. Measuring Innovation

The innovation variables are constructed from the latest version of the NBER Patent Citation database created by Hall, Jaffe, and Trajtenberg (2001), which contains updated patent and citation information from 1976 to 2006. The NBER Patent Citation database provides annual information regarding patent assignee names, the number of patents, the number of citations received by each patent, the technology class of the patent, the patent application year, and the patent grant year. As suggested by the innovation literature (e.g., Griliches, Pakes, and Hall 1987), the application year is more important than the grant year since it is closer to the time of the actual innovation. We then construct innovation variables based on the patent application year.

The NBER patent database is subject to two types of truncation problems. We follow the innovation literature to correct for the truncation problems in the NBER Patent Citation database. The first type of truncation problem is regarding patent counts, because the patents appear in the database only after they are granted and the lag between patent applications and patent grants is significant (about two years on average). As we approach the last few years for which there are patent data available (e.g., 2005 and 2006 in the database used in this paper), we observe a smaller number of patent applications that are eventually granted. This is because many patent applications filed during these years were still under review and had not been granted by 2006. Following Hall, Jaffe, and Trajtenberg (2001, 2005), we correct for the truncation bias in patent counts using the "weight factors" computed from the application-grant empirical distribution. The second type of truncation problem is regarding the citation counts, because patents keep receiving citations over a long period of time, but we observe at best only the citations received up to 2006. Following Hall, Jaffe, and Trajtenberg (2001, 2005), we correct the truncation in citation counts by estimating the shape of the citation-lag distribution.

The NBER patent database is unlikely to be subject to survivorship bias. An eventually granted patent application is counted and attributed to the applying firm at the time when the patent application is submitted even if the firm later gets acquired or goes bankrupt. In addition, patent citations attribute to a patent but not a firm. Hence, a patent assigned to an acquired or bankrupt firm can continue to receive citations for many years even after it goes out of existence.

We construct two measures for a firm's innovation output. The first measure is the truncation-adjusted patent count for a firm each year. Specifically, this variable counts the number of patent applications filed in a year that is eventually granted. One concern is that a simple count of patents may not distinguish breakthrough innovations from incremental technological discoveries. Griliches, Pakes, and Hall (1987) show that the distribution of patents' value is very skewed, i.e., most of the value is concentrated in a small number of patents. Therefore, we construct the second measure that intends to capture the importance of patents by counting the number of citations each patent receives in the subsequent years. To precisely capture the impact of patents, we exclude self-citations when we compute citations per patent. Given a firm's size and its innovation inputs, the number of patents captures its innovation quantity and the number of citations per patent captures its innovation quality.

Table 1 Panel A presents the firm-year summary statistics of the innovation variables. On average, a firm in our sample has 7.4 granted patents per year and each patent receives 2.4 non-self citations. Since the distributions of patent counts and citations per patent are highly right skewed, we use the natural logarithm of patent counts and citations per patent as the main innovation measures in our analysis. To avoid losing firm-year observations with zero patent or citation, we add one to the actual value when calculating the natural logarithm.

3.2. Measuring ATP and Control Variables

The number of ATPs a firm has in its charters and bylaws is collected from the RiskMetrics, which publishes an index compiled by Gompers, Ishii, and Metrick (2003). There have been eight publications (1990, 1993, 1995, 1998, 2000, 2002, 2004, and 2006). They include detailed information on the ATPs of approximately 1,500 firms in each of the eight publication years, with more firms added in recent publications. The index (defined as the G-index hereafter) counts how many ATPs the firm has, and consists of 24 different provisions in 5 categories.[7] Following Gompers, Ishii, and Metrick (2003), we assume that during the years between two consecutive publications firms have the same ATPs as in the previous publication year. Therefore, we replace the missing values of the G-index with the values reported in the previous publication year. Panel B of Table 1 reports the descriptive statistics of the ATP measures. On average, a firm has 8.9 ATPs each year. The median of the G-index is 9.

[7] See Gompers, Ishii, and Metrick (2003) for a detailed description of the individual provisions.

We also collect data from RiskMetrics about 9,082 shareholders' proposals from 1997 to 2006. Among them, we identify proposals that are related to changing the number of ATPs a firm has. RiskMetrics provides information on the meeting date, the percentage of votes in favor of the proposal, and the proponent. We distinguish shareholder proposals that intend to increase the number of ATPs from those that intend to decrease the number of ATPs.

Following the innovation literature, we control for a vector of firm and industry characteristics that may affect a firm's innovation productivity. In the baseline regressions, our control variables include firm size (measured by the natural logarithm of total assets), profitability (measured by ROA), investments in innovation (measured by R&D expenditure over total assets), asset tangibility (measured by net PPE scaled by total assets), leverage, capital expenditure, product market competition (measured by the Herfindahl index based on sales), growth opportunity (measured by Tobin's Q), financial constraints (measured by the Kaplan and Zingales (1997) five-variable KZ index), and institutional ownership. To capture possible non-linear relation between product market competition and innovation (Aghion et al. 2005), we also include the squared Herfindahl index in the baseline regressions. Detailed variable definitions are described in Appendix.

Panel B of Table 1 reports the descriptive statistics of the control variables. An average firm has total assets of $8.8 billion, ROA of 12.1%, leverage of 25.6%, Tobin's Q of 1.76, net PPE ratio of 58.8, and about 35% of equity shares held by institutional investors.

4. ATPs and Innovation

In this section, we first discuss our empirical design, report the results from the baseline regressions, and present a rich set of robustness checks in Section 4.1. We then discuss our identification strategies that help establish causality in Section 4.2. In Section 4.3, we explore the cross-sectional differences in ATPs' effect on innovation. Specifically, we examine how a firm's information environment, product market competition, and industry membership affect the effect of ATPs on innovation.

4.1. Baseline Results for Innovation

To examine the impact of ATPs on a firm's innovation output, we estimate the following empirical model in our baseline OLS regressions:

$$Ln(Innovation_{i,t+n}) = \alpha + \beta Gindex_{i,t} + \delta' Z_{i,t} + Year_t + Firm_i + u_{i,t} \qquad (1)$$

where *i* indexes firms, *t* indexes time, and *n* equals one, two, and three. *Ln(Innovation)* is the dependent variable and can be one of the following two measures: the natural logarithm of the number of patents filed by the firm, *Ln(Patent)*, and the natural logarithm of the number of citations received by each patent, *Ln(Cites/patent)*. *Z* is a vector of firm and industry characteristics that may affect a firm's innovation productivity discussed in Section 3.2. $Year_t$ captures fiscal year fixed effects. We control for time invariant unobservable firm characteristics by including firm fixed effects, $Firm_i$. Standard errors are clustered at the firm level.[8]

The reasons we include firm fixed effect in the baseline regressions are twofold. First, our paper's objective is to examine whether ATPs spur or stifle corporate innovation. Including firm fixed effects allows us to directly answer the question by examining if and how the variation of ATPs within a firm explains its contemporaneous as well as subsequent variation in innovation productivity. In other words, we can interpret β, the coefficient estimate of the G-index, as the impact of a firm's change in ATPs on its subsequent change in innovation productivity. Second, our empirical design may be subject to endogeneity concerns. Innovation output and the adoption of ATPs could be jointly determined by certain unobservable firm characteristics. Therefore, endogeneity in ATPs caused by omitted variables could bias the coefficient estimates. Firm fixed effects help mitigate this concern if the unobservable firm characteristics correlated with both ATPs and innovation output are constant over time.

Table 2 reports the baseline results. We estimate equation (1) with *Ln(Patent)* as the dependent variable and report the regression results in Panel A. The coefficient estimate of the G-index in column (1)

[8]Besides the pooled OLS regressions reported throughout the paper, we use a Tobit model that takes into consideration the non-negative nature of patent and citation data. We also run a Poisson regression when the dependent variable is the number of patents to take care of the discrete nature of patent counts. The baseline results are robust in the above alternative models.

is positive and significant at the 1% level, suggesting that a larger number of ATPs is positively related to the number of patents the firm generates in the following year. The economic effect of ATPs on innovation is large: a firm's decides to adopt one more ATP is associated with a 9.0% increase in its patent counts in the following year.

Since innovation process generally takes time longer than one year, we examine the impact of a firm's change in ATPs on its patenting in the subsequent years in columns (2) and (3), where the dependent variables are the natural logarithm of patent counts measured in two years (*t+2*) and in three years (*t+3*), respectively.[9] The coefficient estimates of the G-index are positive and significant at the 1% level in both two columns, suggesting that the number of ATPs is positively related to the firm's subsequent innovation productivity. More importantly, the magnitudes of the coefficient estimates are very much comparable to that in column (1) and remain stable over time (across various columns).

We control for a comprehensive set of firm characteristics that may affect a firm's innovation output. We find that firms that are larger, are more profitable, and have lower leverage are more innovative. A larger R&D spending, which can be viewed as a larger innovation input, is associated with more innovation output. Larger capital expenditures are also associated with higher innovation productivity. Further, consistent with the findings in Aghion, Van Reenen, and Zingales (2013), Institutional ownership is positively related to a firm's innovation output. However, industry competition does not appear to significantly affect firm innovation.

Table 2 Panel B reports the regression results estimating equation (1) with the dependent variable replaced with *Ln(Cites/Patent)*. The coefficient estimates of the G-index are positive and significant at either 1% or 5% level. For example, column (1) suggests that a firm's adopting one more ATP increases its citations per patent by 4.4% in the following year. Once again, we find firms that are more profitable, have lower financial constraints, have lower leverage, invest more in R&D, and have higher institutional ownership are more likely to generate high impact patents.

[9] In an untabulated analysis, we examine the impact of ATPs on innovation productivity in the contemporaneous year (*t*) and in four years (*t+4*), and the results are both quantitatively and qualitatively unchanged.

To check the robustness of our baseline results, we conduct a rich set of robustness tests. First, we focus on the subsample of firms that has at least one patent in the sample period. This test is due to the concern that our results may be driven by the large number of firm-year observations with zero patents. In an untabulated analysis, we continue to observe positive and significant coefficient estimates of the G-index in this subsample. For example, the coefficient estimate for the G-index is 0.129 (p-value < 0.001) in model (1) of Table 2 Panel A where $Ln(Patent_{t+1})$ is the dependent variable, and 0.047 (p-value = 0.015) in model (1) of Panel B where $Ln(Cites/Patent_{t+1})$ is the dependent variable. Not surprisingly, the magnitudes of the coefficient estimates of the G-index are larger than those estimated from the full sample because innovation is more relevant in this subsample.

Second, while we adjust the truncation problems of the NBER patent database following Hall, Jaffe, and Trajtenberg (2001, 2005), to further address the possible truncation bias, we cluster standard errors of the baseline regressions by both firm and year. In an untabulated analysis, the positive coefficient estimates of the G-index continue to be statistically significant, although the significance level drops to the 5% level.

Third, in addition to using the G-index as the continuous variable, we construct a dummy variable that equals one if the number of ATPs a firm has is higher than the sample median (i.e., 9) and zero otherwise. The baseline results are robust to this alternative empirical specification. For example, the coefficient estimate of the dummy variable is 0.313 (p-value < 0.001) in model (1) of Table 2 Panel A, and 0.172 (p-value <0.001) in model (1) of Panel B.

Finally, Bebchuk, Cohen, and Ferrell (2009) suggest that six provisions are most effective and are not influenced by the noise produced by the other ATPs.[10] Therefore, we define the index consisting of the six provisions as the E-index and re-estimate equation (1) with the main independent variable replaced with the E-index. In untabulated tests, the coefficient estimates of the E-index are positive and significant at the 1% level in all specifications.

[10] The six provisions are staggered boards, limits to bylaw amendments, limits to charter amendments, supermajority requirements for mergers, poison pills, and golden parachutes.

Overall, the results reported in this section suggest that a firm's adopting a larger number of ATPs is positively associated with its subsequent innovation output, i.e., the firm not only generates more patents, but also produces patents with larger impact. The findings are consistent with the long-term value creation hypothesis.

4.2. Identification

While our baseline results are consistent with the long-term value creation hypothesis, as discussed earlier, our empirical design may be subject to endogeneity concerns due to omitted variables. For example, high quality managers may tend to have a larger number of ATPs relative to low quality managers (Chemmanur, Paeglis, and Simonyan, 2011). High quality managers would also be more likely to engage in innovation activities and result in a larger innovation output. This will lead to the number of ATPs being positively correlated with the firm's innovation, even though a larger number of ATPs *per se* does not lead to higher innovation productivity. There could also be a concern about reverse causality: i.e., firms with greater expected future innovation may adopt a larger current number of ATPs.

Our strategy of including firm fixed effects in the baseline regressions partially mitigates the omitted variables concern if the unobservable firm characteristics are constant over time. However, if the unobservable characteristics are time-varying, including firm fixed effects is not adequate to control for the endogeneity problem. To establish causality, we use two different identification strategies.

First, we use a regression discontinuity approach that relies on the simple majority passing rule (50%) and explore the passage of ATP-related governance proposals. The regression discontinuity approach relies on "locally" exogenous variation in the number of ATPs generated by the ATP-related governance proposal votes that pass or fail by a small margin. It is a powerful identification strategy because, for close-call elections, passing the governance proposal (and thereby changing the number of ATPs) is very close to an independent random event and therefore is likely uncorrelated with firm characteristics, which helps us to identify the causal effect of ATPs on innovation.

We undertake the regression discontinuity design with an estimation of a polynomial model that uses all the firms with ATP-related governance proposal votes in the sample. We focus on a sample of governance proposal votes that were intended to reduce the number of a firm's ATPs. Specifically, we estimate the following model:

$$Ln(Innovation_{i,t+n}) = \alpha + \beta Pass_{i,t} + P_l(v_i, c) + P_r(v_i, c) + Year_t + Industry_j + \varepsilon_{i,t} \quad (2)$$

where i indexes firm, j indexes industry, and t indexes time, and n equals one, two, and three. $P_l\ (v_i,\ c)$ is a flexible polynomial function for observations on the left-hand side of the threshold c with different orders; $P_r\ (v_i,\ c)$ is a flexible polynomial function for observations on the right-hand side of the threshold c with different orders; v is the total vote share (percentage of votes in favor of the proposal). Because shareholder proposal elections win with a simple majority of support among the voters, c equals 50% in our setting. *Pass* is a dummy that equals one if the governance proposal passes and therefore the number of ATPs declines and zero otherwise. In this setting, β is the key variable of interest and its magnitude is estimated by the difference in these two smoothed functions at the cutoff, which captures the causal effect of passing an ATP-related governance proposal on firm innovation output one, two, and three years later. Note, however, that this coefficient should be interpreted locally in the immediate vicinity of the win threshold.

We present the results estimating equation (2) in Table 3, panel A. Following Cunat, Gine, and Guadalupe (2012), we report the results with polynomials of order four, but our results are qualitatively similar using other polynomial orders. In columns (1) – (3), the dependent variable is patent counts. The coefficient estimates of *Pass* are all negative and statistically significant in the first two columns, suggesting that passing a governance proposal that intends to reduce the number of a firm's ATPs leads to a decline in the firm's patent counts in subsequent years. In columns (4) – (6), we replace the dependent variable with patent citations. The coefficient estimates of *Pass* are all negative and statistically significant in the last two columns, suggesting that the passing of a governance proposal that reduces ATPs leads to a decline in a firm's post-vote patent quality.

In Panel B we present placebo tests in which we artificially create alternative thresholds to examine whether the passage of ATP-related governance proposals around these artificial thresholds is related to firms' post-vote innovation output. If the results reported in Panel A are spurious, we should observe similar findings around these artificial thresholds as well. We report the results assuming 25% and 75% are the "win" thresholds. In these placebo tests, the coefficient estimates of *Pass* are mixed and statistically insignificant.

In an untabulated analysis, we repeat the regression discontinuity test for governance proposals that intend to increase the number of a firm's ATPs. We generally observe positive and marginally significant coefficient estimates of *Pass*. Overall, we use a regression discontinuity approach that explores the "locally" exogenous variation in ATPs generated by governance proposal votes to establish causality. Our evidence is consistent with the long-term value creation hypothesis.

Next, we attempt to further establish causality using an instrumental variable approach. We use two sources of plausibly exogenous variation to identify the impact of ATPs on innovation. The first plausibly exogenous variation is state antitakeover laws. There has been a large literature in law and finance documenting the consequences of state antitakeover legislation (see Bertrand and Mullainathan (2003) for a detailed summary). State antitakeover laws constitute an important component of a firm's total defensive posture, and have been argued as substitutes for firm-level antitakeover defenses (Karpoff and Malatesta, 1989). Recent literature, however, finds that state antitakeover laws and firm-level ATPs tend to be complements instead (Field and Karpoff, 2002). To use this plausibly exogenous variation, following Field and Karpoff (2002), we construct our first instrument, *State Law*, that takes on a value of one if the state in which the firm is incorporated has any one of the five state antitakeover laws (e.g., freeze-out law, control share acquisition law, fair price law, cash-out law, and poison pill endorsement law) and zero otherwise. Our argument is that state antitakeover legislation does not directly affect a firm's innovation, but affects it only through its effect on the firm's adoption of ATPs.[11] Therefore, the instrument, *State Law*, reasonably satisfies the exclusion restriction.

The second plausibly exogenous variation is the intensity of past hostile takeovers within the industry. Hostile takeovers reduce firms' value and managers' private benefits. In response to past hostile takeover attempts, firms tend to adopt more ATPs to reduce their exposures to unwanted takeover attempts. We construct a variable, *Hostile Takeover Intensity*, by computing the number of hostile takeovers scaled by the total number of takeovers within the firm's 2-digit SIC industry during the past five years. We use it as the second instrument. There is little reason to believe that the intensity of an industry's hostile takeover in the past five years directly affects a firm's subsequent innovation productivity, and therefore it reasonably satisfies the exclusion restriction.

Since several state anti-takeover laws are part of the 24 ATPs in the G-index, we avoid a mechanical relation between state antitakeover laws and firm ATPs by constructing an adjusted G-index, *AdjG-index*, that exclude the state anti-takeover laws from the original G-index. To check the relevance of the instruments, we present the first-stage regression results with the *AdjG-index* as the dependent variable in Table 4. The main variables of interest are the two instruments. All other control variables are the same as those in the baseline regressions. Year and firm fixed effects are included and standard errors are clustered at the firm level.[12]

The coefficient estimate of the first instrument, *State Law*, is positive and significant at the 5% level, suggesting that the state antitakeover laws and firm-level ATPs are complements. The finding is consistent with Field and Karpoff (2002). The coefficient estimate of the second instrument, *Hostile Takeover Intensity*, is positive and significant at the 1% level, consistent with the intuition that firms adopt more ATPs in response to the increase in hostile takeover attempts in their industries.

[11] One concern is that state antitakeover laws may not be entirely exogenous because the enactment of these laws may have been influenced by lobbying, which in turn could be correlated with firm's innovation productivity. In other words, firms that expect a decrease in innovation that makes them vulnerable to a hostile takeover lobby for these antitakeover laws. However, this seems to be unlikely. Romano (1987) provides evidence that state antitakeover laws are almost always not promoted by a specific firm and are not the result of concerted pressure by a wide coalition of firms.

[12] Since our instruments are state- and industry-wise variables, respectively, in an untabulated analysis, we cluster standard errors at the state and industry level as well in the first-stage regressions. The levels of statistical significances of the two proposed instruments are unchanged.

While the above regression suggests that the instruments are valid, it is still possible to have biased estimates due to "weak instruments." We report *F*-statistics for the test of joint significance of the two proposed instruments. The value of the *F*-statistics is large, i.e., 40.97, which is larger than the critical values of the Stock-Yogo weak instrument test based on both 2SLS bias and 2SLS size. Therefore, we reject the null hypothesis that these instruments are weak. Therefore, the coefficient estimates and their corresponding standard errors reported in the second stage are likely to be unbiased and inferences based on them are reasonably valid.

Table 5 reports the results from the second-stage regressions estimating equation (1) with the main variable of interest replaced with the fitted value of *AdjG-index* from the first-stage regression. Panel A presents the results with *Ln(Patent)* as the dependent variable. Consistent with the findings from the OLS regressions, the coefficient estimates of *AdjG-index* are positive and significant at the 1% or 5% levels in all columns, consistent with the implication of the long-term value creation hypothesis. Panel B reports the regression results with patent quality, *Ln(Cites/Patent)*, as the dependent variable. The coefficient estimates of *AdjG-index* are all positive and significant at the 1% level. Relative to the baseline OLS regressions reported in Table 2, we observe larger and more significant coefficient estimates.

In summary, the identification tests based on both the regression discontinuity approach and the instrumental variable approach reported in this section suggest that there is a positive causal effect of ATPs on firm innovation, consistent with the long-term value creation hypothesis.

4.3. Cross-Sectional Analysis

In this section, we look for further evidence of identification in the cross-section using cross-sectional variations in firms' information environment, product market competition, and industry membership to further explore the impact of ATPs on innovation. We first examine how heterogeneity in firms' information asymmetry affects the positive effect of ATPs on innovation in section 4.3.1. We then study how product market competition alters the marginal effect of ATPs on innovation in section 4.3.2.

Finally, we examine how a firm's industry membership affects the positive effect of ATPs on innovation in section 4.3.3.

4.3.1. Information Asymmetry

A key assumption in the model of Stein (1988) on which the long-term value creation hypothesis is based is the information asymmetry between firm insiders and outside investors. Due to information asymmetry, firm outsider investors cannot properly evaluate a firm manager's investment in long-term innovation and tend to undervalue the equity of companies undertaking innovative projects. Therefore, a natural implication of the long-term value creation hypothesis is that the value of ATPs that insulate managers from short-term investor pressures will be larger if there is a larger information gap between firm insiders and outsiders. Therefore, we expect that the positive effect of ATPs on innovation is more pronounced for firms with a larger degree of information asymmetry.

Following previous literature, we construct a measure for a firm's information asymmetry, *Dispersion*, which equals the average standard deviation of analyst earnings forecasts in a year. Firms with a higher standard deviation of analyst earnings forecasts are expected to have a larger extent of information asymmetry. We obtain analyst forecast information from the I/B/E/S database. We test the cross-sectional implication of the long-term value creation hypothesis by including an interaction term between *G-index* and *Dispersion* as well as *Dispersion* itself in equation (1). If the above conjecture is supported, we expect to observe a positive and significant estimate of the interaction term between *G-index* and *Dispersion*.

Table 6 Panel A reports the regression results with *Ln(Patent)* as the dependent variable. The coefficient estimates of the G-index are positive and significant at the 1% level in all columns, consistent with our baseline findings. The coefficient estimates of *G-index*Dispersion* are positive in all three columns and statistically significant at the 5% or 1% level in columns (2) and (3), suggesting that the positive effect of ATPs on firm innovation is more pronounced for firms with a larger degree of information asymmetry (a higher value of *Dispersion*). In Panel B, we replace the dependent variable with *Ln(Cites/Patent)*. The coefficient estimates of *G-index*Dispersion* are all positive and statistically significant. Similar to the interpretation of the evidence in Panel A, the results suggest that the positive effect of ATPs on patent quality is stronger for firms with a larger degree of information asymmetry between insiders and outsiders.

For robustness, we construct two alternative proxies for firm information asymmetry. The first one is a firm's analyst coverage, which equals the number of analysts following the firm in a year. Firms with larger analyst coverage are considered to have a lower degree of information asymmetry. The second measure is a firm's analyst earnings forecast error, which equals the ratio of the absolute difference between the forecasted and actual earnings per share over the absolute actual earnings per share in a year. Firms with a higher analyst forecast error can be expected to have a greater extent of information asymmetry. In an untabulated analysis, we replace *Dispersion* with these two alternative information asymmetry proxies, and the results are qualitatively unchanged.

Overall, our findings are consistent with the theoretical prediction of Stein (1988) and support the implication of the long-term value creation hypothesis: the effect of ATPs on firm innovation is more pronounced for firms with a larger degree of information asymmetry.

4.3.2. Product Market Competition

Product market competition increases a firm's pressure to keep competitive advantages over its rivals and make progress in generating profits in the short run to satisfy its equity market investors (see Aghion, Van Reenen, and Zingales (2013) for a similar argument.). If ATPs indeed provide a shield for managers against short-term investors such that they can focus on innovation, we then expect that the positive effect of ATPs on innovation is more pronounced when the firm is operating in a more competitive product market, i.e., the pressures are higher and the insulation provided by ATPs is more needed and valued.

We test the above conjecture by including an interaction term between *G-index* and *Herfindahl* in equation (1). The Herfindahl index has been widely used in the economics and finance literature as a proxy for product market competition. The Herfindahl index is calculated by summing up the square of each firm's market share (in sales) at the four-digit SIC level. The Herfindahl index ranges between 0 and 1 with an increase in its value indicating a decrease in market competition. If the above conjecture is supported, we expect to observe a negative and significant coefficient estimate of the interaction term between *G-index* and *Herfindahl*.

Table 7 Panel A reports the regression results with *Ln(Patent)* as the dependent variable. The coefficient estimates of the G-index are positive and significant at the 1% level in all columns, consistent with our baseline findings. On top of that, the coefficient estimates of *G-index***Herfindahl* are all negative and statistically significant in the first two columns. For example, based on the coefficient estimate reported in column (1), the marginal effect of *G-index* on patent counts increases from 5.8% (=0.100 - 0.042) to 10% if the firm is competing a monopoly industry instead of a perfect competitive industry. In columns (2) and (3) where patent counts in two years and three years are examined, we observe a similar pattern, suggesting that the positive effect of ATPs on innovation is more pronounced when the product market is more competitive.

Panel B of Table 7 reports the regression results with *Ln(Cites/Patent)* as the dependent variable. The coefficient estimates of *G-index***Herfindahl* are all negative, and statistically significant in the first two regressions. Similar to the interpretation of the findings in Panel A, the results suggest that the positive effect of ATPs on patent quality is stronger for firms that are operating in more competitive product markets.

4.3.3. Industry Membership

Different industries have different innovation potentials as well as different risks associated with innovation. If insulation from capital market pressures is important and needed because innovation activities involve substantial failure risk and may not show immediate progress in generating profits in the short run, a natural cross-sectional implication is that the effect of ATPs on innovation should be stronger in industries in which innovation is more difficult to achieve (see Tian and Wang (2012) for a similar argument). The innovation difficulty may come from large resources demanded, long process required, and low probability of success. For example, common knowledge suggests that developing a new drug is much more time consuming and resource demanding than developing new software. A new drug development process involves many steps requiring different levels of experimentation.[13] Thus, firms in these industries are subject to higher pressures from capital markets, and the value of ATPs being able to effectively insulate managers against capital market pressures is higher.

We estimate equation (1) industry by industry and compare the effect of ATPs on innovation across industries. Instead of relying on SIC codes or Fama-French industry classifications, we classify firm industries based on the technological nature of patents. Following Hall, Jaffe, and Trajtemberg (2005), we classify patents into three categories: (1) drugs; (2) IT and chemical; (3) low-tech. If a firm has no patent, then we classify it into one of the above three categories based on the type of patents that is most frequently produced by the firm's 3-digit SIC industry. For example, if a firm is in the industry with 3-digit SIC 283 and has no patent in the sample period, then it is classified into category (1) because most of the patents generated by the firm's industry are related to drugs.

Table 8 reports the regression results estimating equation (1) within each patent category (industry). Columns (1) through (3) present the results with $Ln(Patents_{t+1})$ as the dependent variable. In all three categories, the coefficient estimates of the G-index are positive and significant, being consistent with our baseline findings. More importantly, the coefficient estimate of the G-index for drug firms is 0.337, which is much larger than that in other industry firms, i.e., 0.100 in the IT & chemical firms and 0.061 in low-tech firms. The evidence is consistent with the intuition that firms in industries in which innovation is more difficult to achieve and the innovation process is longer need ATPs more to insulate managers against pressures from short-term investors. On the other hand, the effect of ATPs on innovation is smaller (but still positive and significant) for firms in industries in which innovation is relatively less resource demanding and time consuming.

[13] Existing studies suggest that the cost of developing a new drug varies from \$500 million to \$2 billion and the development horizon could be as long as dozens of years (see, e.g., Adams and Brantner, 2006).

Columns (4) through (6) present the results with *Ln(Cites/Patent$_{t+1}$)* as the dependent variable. We once again observe positive and significant coefficient estimates of the G-index. We also find a similar pattern for the coefficient estimates of the G-index across patent industries, i.e., the impact of ATPs on patent citations is the largest in drug firms and smaller in other industry firms. In an untabulated analysis, we repeat the same analysis for the innovation proxies measured in two and three years and find quantitatively similar results.

In summary, the cross-sectional analysis in Section 4.3 shows that the marginal impact of ATPs on innovation is stronger in firms in which the ATPs are more needed and valued. These findings provide further evidence supporting for the long-term value creation hypothesis and the identification of the positive effect of ATPs on firm innovation.

5. Analysis on Firm Value

Innovation enhances long-run competitive advantages of firms. Ultimately, the objective of undertaking innovation is to increase firm value. As we have discussed in this paper, adopting ATPs is one of strategies that the firm can use to insulate managers from short-term market pressures and enhance innovation. In this section, we first examine the impact of innovation on firm value attributable to the firm's number of ATPs in Section 5.1. We then link the effect of innovation on firm value attributable to its ATPs to the firm's information environment, product market competition, and industry membership in Section 5.2.

5.1. Baseline Results of Firm Value

Existing literature has shown that ATPs reduce firm value largely because of management entrenchment (see, e.g., Gompers, Ishii, and Metrick, 2003; Bebchuk and Cohen, 2005; Bebchuk, Cohen, and Ferrell, 2009; and Cremers and Ferrell, 2012). However, another stream of literature has suggested that ATPs do not necessarily reduce firm value (see, e.g., Core, Guay, and Rusticus, 2006). We approach the debate by estimating variations of the following model in this section:

$$Q_{i,t+n} = \alpha + \beta_1 \times Gindex_{i,t} + \beta_2 \times Gindex_{i,t} * Ln(Innovation_{i,t}) + \beta_3 \times Ln(Innovation_{i,t}) + \delta' Z_{i,t} + Year + Firm_i + u_{i,t} \qquad (3)$$

where i indexes firms, t indexes time, and n equals one, two, and three. Tobin's Q is the dependent variable. Similar to equation (1), we control for year and firm fixed effects to absorb any unobservable characteristics that vary only by year or by firm but cannot explain our results.

Table 9 Panel A reports the regression results estimating equation (3) with patent counts as the proxy for innovation. In column (1), we estimate a variation of equation (3) by excluding *Ln(Patent)* and the interaction term *Ln(Patent)*G-index* from the regression and control for industry instead of firm fixed effects. The purpose of this regression is to examine the direct effect of ATPs on firm value, which serves as a benchmark to which we are going to compare. Since industry fixed effects instead of firm fixed effects are included in the regression, the variation mainly comes from cross-section. Consistent with the findings of the existing literature, the coefficient estimate of ATPs in column (1) is negative and significant, suggesting that a larger number of ATPs overall reduces firm value.

In column (2), we add *Ln(Patent)* and *Ln(Patent)*G-index* to the regression. Once again, industry and year fixed effects are included in the regression. The coefficient estimate of the G-index is negative and significant at the 1% level, suggesting that the cross-sectional negative effect of ATPs on firm value in the following year is still present if firm produces no patent. The coefficient estimate of *Ln(Patent)* is negative but not significant, suggesting that cross-section variation in innovation is not related to cross-section variation in firm value. However, the coefficient estimate of *G-index*Ln(Patent)* is positive and significant at the 1% level, suggesting that the negative effect of ATPs on firm value is mitigated by innovation. This finding is consistent with the prediction of the long-term value creation hypothesis that if ATPs are adopted to insulate managers against capital market pressures so that managers can focus on long-run value creation activities such as innovation, then ATPs contribute positively to firm value.

In column (3), we repeat the regression in column (2) but control for firm fixed effects instead of industry fixed effects, which examines how time-series variation in the number of ATPs within a firm affects firm value over time. The coefficient estimate of the G-index is negative and significant, suggesting that a firm's adopting more ATPs is negatively related to the firm's market value in the subsequent year if the firm is not innovative and generates no patent. The coefficient estimate of *Ln(Patent)* is positive and significant at the 1% level, suggesting that innovation increases firm value in the following year although the economic impact of patents is quite small. This finding is consistent with the existing literature that innovation increases firm value (e.g., Hall, Jaffe, and Trajtenberg, 2005). More importantly, the coefficient estimate of *G-index***Ln(Patent)* is positive and significant at the 1% level, suggesting that the negative effect of ATPs on firm value is largely mitigated by the firm's innovativeness. To be more concrete, the marginal effect of ATPs on firm value is initially negative but turns to be positive when the value of *Ln(Patent)* is greater than 3.8 (=0.013/0.004). This is equivalent to the number of patents being greater than 48, which is at the 93rd percentile of the full sample but slightly below the median for the subsample for firms with at least one patent. The evidence is consistent with the implications of the long-term value creation hypothesis that ATPs positively contribute to firm value through innovation (for the top 7% firms that are most innovative). However, for the vast majority of firms that are not innovative (i.e., the remaining 93% of firms), ATPs reduce firm value.

In columns (4) and (5), we estimate equation (3) with firm value in two years (*t+2*) and in three years (*t+3*) as the dependent variable, respectively. We continue to observe negative coefficient estimates of the G-index and positive and significant coefficients of the interaction term in columns (4) and (5).

Table 9 Panel B reports the regression results with the number of citations each patent receives as the proxy for innovation quality. The regressions are parallel to those reported in Panel A with model (1) of Panel A omitted. In column (1) where industry and year fixed effects are included, we find a similar negative effect of *G-index* on firm value. In columns (2) through (4), we control for firm and year fixed effects and find positive and significant coefficient estimates of *G-index***Ln(Cites/Patent)*.

One concern is that our results could be driven by a large number of firm-year observations with zero patents. We then re-run our firm value regressions estimating equation (3) in a subsample of firms that has at least one patent in the sample period. In an untabulated analysis, we find even stronger results. For example, the coefficient estimate of *G-index* in model (1) of Table 9 Panel A is -0.028 (p-value =

0.006), suggesting that a larger number of ATPs is associated with a reduction in firm value even for innovative firms (recall that this analysis is for firms that generate at least one patent in the sample period). The coefficient estimates of *G-index* and *G-index*Ln(Patent)* in model (3) of Table 9 Panel A are -0.029 (p-value = 0.010) and 0.004 (p-value < 0.001), respectively. Once again, the evidence suggests that the G-index positively contributes to firm value for the very innovative firms, but it destroys firm value for less innovative firms.

5.2. Cross-Sectional Analysis for Market Value

Based on the similar logic discussed in Section 4.3, we examine how the effect of ATPs on firm value through innovation varies in the cross-section. Section 5.2.1 explores the heterogeneity in firms' information environment. Section 5.2.2 examines the heterogeneity in product market competition. Section 5.2.3 studies the cross-sectional variation in firms' industry membership. For brevity, we only report the results with the number of patents as the proxy for innovation in this section. In un-tabulated analyses, we find qualitatively similar results for patent quality.

5.2.1. Information Asymmetry

The implication of the long-term value creation hypothesis is that if the firm is subject to a greater extent of information asymmetry, the value of insulating managers from short-term pressures provided by ATPs would be larger if the managers take the advantage and focus more on long-run innovation, which ultimately increases firm value. It implies that the effect of ATPs on firm value through innovation is larger for firms with a larger degree of information asymmetry.

To test the above implication, we split the sample based on the median value of our information asymmetry proxy, *Dispersion*, and estimate equation (3) in each of the subsample. If the conjecture is supported, we expect a larger coefficient estimate of the interaction term, *G-index*Ln(Patent)*, in the subsample in which *Dispersion* is above the median, i.e., the firm is subject to a larger degree of information asymmetry, than that in the subsample in which *Dispersion* is below the median.

We report the results in Table 10. In columns (1) and (2), Q_{t+1} is the dependent variable and we control for year and firm fixed effects. The coefficient estimates of *G-index*Ln(Patent)* are positive in both columns but statistically significant only in column (1) in which the *Dispersion* is above the sample median. The differences across the two subsamples are statistically significant. The above finding suggests that the positive effect of ATPs on firm value (through innovations) is mainly driven by firms with a larger degree of information asymmetry.

In columns (3) through (6), we repeat the regressions estimating equation (3) with firm value in two years (*t+2*) and in three years (*t+3*) as the dependent variable, respectively. The coefficient estimates of the interaction term are all positive but statistically significant only in the group of firms that are subject to a larger degree of information asymmetry.

5.2.2. Product Market Competition

The implication of the long-term value creation hypothesis is that if the firm is operating in a more competitive product market, the value of insulating managers from short-term pressures provided by ATPs would be larger if the managers take the advantage and focus more on the long-run innovation, which ultimately increases firm value. It implies that the effect of ATPs on firm value through innovation is larger for firms operating in more competitive product markets.

To test this conjecture, we split the sample based on whether the value of *Herfindahl* is above or below the sample median, and estimate equation (3) in each of the subsample. If the conjecture is supported, we expect a larger coefficient estimate of the interaction term, *G-index*Ln(Patent)*, in the subsample in which *Herfindahl* is below the median, i.e., the product market is more competitive, than that in the subsample in which *Herfindahl* is above the median.

We report the results Table 11. We show that the results are consistent with the conjecture that the effect of ATPs on firm value through innovation is more pronounced for firms operating in more competitive product markets. In columns (1) and (2), Q_{t+1} is the dependent variable and year and firm fixed effects are included. Similar to findings in Table 9 Panel A, the coefficient estimates of *G-*

*index*Ln(Patent)* are positive and significant in both columns. More importantly, the magnitude of the interaction term in column (2) in which *Herfindahl* is below the median is larger than that in column (1) in which *Herfindahl* is above the median. The differences across the two subsamples are statistically significant. The above finding suggests that the marginal effect of ATPs on firm value (through innovations) is stronger for firms that are operating in more competitive product markets.

In columns (3) through (6), we repeat the regressions estimating equation (3) with firm value in two years ($t+2$) and in three years ($t+3$) as the dependent variable, respectively. The coefficient estimates of the interaction term are all positive and significant. Meanwhile, the magnitudes of the coefficient estimate are larger in columns (4) and (6) than those in columns (3) and (5), consistent with the results reported in columns (1) and (2).

5.2.3. Industry Membership

The implication of the long-term value creation hypothesis regarding the firm's industry membership is that if the firm is in industries in which innovation is more difficult to achieve, the value of ATPs that protects mangers against short-term pressures is larger, which ultimately contributes more to firm value. We split the sample based on the same industry classification as in Section 4.3.3, and estimate equation (3) in each industry separately. If the implication of the long-term value creation hypothesis is supported, we expect a larger coefficient estimate of the interaction term in the drug industry than in other industries.

We report regression results in Table 12. The dependent variable is Q_{t+1}. The coefficient estimates of *G-index*Ln(Patent)* are positive and significant in all three columns, which is consistent with the findings reported in Table 9. More importantly, the coefficient estimate of the interaction term is 0.005 for drug firms (as reported in column (1)), which is more than twice larger than those for either IT & chemistry firms or low-tech firms. The differences in the coefficient estimates between the drug industry and the other industries are statistically significant. Overall, the evidence presented in Table 12 suggests that if the firm is in an industry in which innovation is more difficult to achieve, e.g., the drug industry, the marginal effect of ATPs on firm value through innovation is significantly larger than that for a firm in industries in which innovation is less difficult to achieve. In an untabulated analysis, we repeat the same analysis using *Ln(Cites/Patent)* as the innovation proxy and firm value measured in the subsequent years and find similar results.

In summary, the evidence reported in this section is consistent with the long-term value creation hypothesis that ATPs contribute positively to firm value through innovation for very innovative firms in which insulation against capital market pressures are more valued and needed. Such firms are characterized by a greater degree of information asymmetry, in more competitive product markets, and in industries in which innovation is more difficult to achieve.

6. Conclusion

We have studied the relation between ATPs and corporate innovation, and documented that one of the ways through which ATPs affect firm value is through this novel "innovation channel." We test two different hypotheses: the "long-term value creation" hypothesis and the "management entrenchment" hypothesis.

We find that firms with a larger number of ATPs are more innovative. To establish causality, we use a regression discontinuity approach that relies on "locally" exogenous variation in the number of ATPs generated by governance proposal votes that pass or fail by a small margin, as well as an instrumental variable approach. Our identification tests suggest that there appears a positive causal effect of ATPs on firm innovation. We also show that the number of ATPs contributes positively to firm value for firms involved in intensive innovation. However, for firms that are not conducting a significant extent of innovation, ATPs negatively affect firm value. Overall, our results imply that the role of ATPs is more nuanced than that understood from the existing literature: while adopting more ATPs is optimal for innovative firms, it is suboptimal for firms that are not engaged in a significant extent of innovation.

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Appendix: Variable Definitions and Data Sources

Innovation Variables (data source: NBER Patent Database)	
$Patents_{it}$	Number of patents firm *i* applied for in year *t*.
$Citations/Patent_{it}$	The number of citations per patent of firm *i* applied for in year *t*
ATPs Variables (data source: RiskMetrics)	
$G\text{-}index_{it}$	Firm *i*'s governance index based on 24 ATPs, taken from Gompers, Ishii, and Metrick (2003) in year *t*
$Pass_{it}$	A dummy that equals one if an ATP-related governance proposal passes and zero otherwise.
Firm Characteristics (data source: Compustat)	
$Assets_{it}$	Total assets of firm *i* in year *t* (in $million)
ROA_{it}	Operating income before depreciation to total assets ratio of firm *i* in year *t*
$R\&D/Assets_{it}$	Research and Development expenditure to total assets ratio of firm *i* in year *t*
$PPE/Assets_{it}$	Net property, plants and equipments to assets ratio of firm *i* in year *t*
$Leverage_{it}$	Total debt of firm *i* in year *t* divided by its total assets
$CapExp/Assets_{it}$	Capital expenditure to total assets ratio of firm *i* in year *t*
Herfindahl $Index_{it}$	Herfindahl index of firm *i*'s industry in year *t* constructed based on sales at 4-digit SIC industries
Tobin's Q_{it}	Market to book ratio of firm *i* in year *t*: (total assets + year end closing price*year end outstanding shares - book equity)/total assets
KZ $Index_{it}$	Firm *i*'s KZ index at year *t* is calculated as -1.002*Cash flow + 0.28*Q+3.18*Leverage–39.368*Dividends–1.315*Cash holdings
Inst. $Ownership_{it}$	Total percentage of firm *i*'s equity held by institutional investors in year *t* (Source: Thomson *13f* institutional holdings database)
$Dispersion_{it}$	Average standard deviation of analyst earnings forecast for firm *i* in year *t* (Source: I/B/E/S)
Instrumental Variables (data source: RiskMetrics and SDC)	
State Law_{i}	A dummy that equals one if the state in which the firm *i* is incorporated has any one of the five state antitakeover laws and zero otherwise
Hostile Takeover $Intensity_{it}$	The number of hostile takeovers within firm *i*'s 2-digit industry scaled by the total number of takeovers during the past five years in year *t*

Table 1: Summary Statistics

This table reports the summary statistics for variables constructed based on the sample of U.S. public firms from 1990 to 2006. Panel A reports the summary statistics of innovation variables. Panel B reports the summary statistics of anti-takeover provision variables as well as other control variables.

Panel A: Innovation Variables

Variable	Mean	Median	Std. Dev.	N
Patents	7.40	0	36.74	36,159
Cites/Patent	2.42	0	10.43	36,159

Panel B: Independent Variables

Variable	Mean	Median	Std. Dev.	N
G-index	8.93	9	2.75	36,159
Assets (Billion)	8.77	1.20	46.20	33,233
ROA (%)	12.14	6.22	10.13	32,300
R&D/Assets (%)	1.65	0	7.11	36,159
PPE/Assets (%)	58.82	51.81	40.47	29,890
Leverage (%)	25.59	23.51	20.34	32,956
CapExp/Assets (%)	5.88	4.53	5.67	30,436
Herfindahl Index	0.21	0.09	0.27	36,159
Tobin’s Q	1.76	1.35	1.37	32,545
KZ Index	0.90	0.84	6.96	27,080
Inst. Ownership (%)	35.29	35.23	33.45	36,159
Analyst Dispersion (%)	8.89	4.50	13.58	22,129

Table 2: Baseline Regressions

This table reports the baseline regressions estimating equation (1). The dependent variable is the natural logarithm of the number of patents in a year in Panel A and the natural logarithm of the number of citations per patent in a year in Panel B. The variable of interest is the G-index. Other independent variables include the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, Tobin's Q, the KZ index, and institutional ownership. Coefficient estimates and standard errors clustered by firm are reported. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Ln(Patent)			**Panel B: Ln(Cites/Patent)**		
Dependent Variable	Ln($Patent_{t+1}$)	Ln($Patent_{t+2}$)	Ln($Patent_{t+3}$)	Ln(Cites/ $Patent_{t+1}$)	Ln(Cites/ $Patent_{t+2}$)	Ln(Cites/ $Patent_{t+3}$)
	(1)	(2)	(3)	(1)	(2)	(3)
G-index	0.090***	0.087***	0.090***	0.044***	0.038***	0.035**
	(0.025)	(0.025)	(0.028)	(0.014)	(0.015)	(0.016)
Ln(Assets)	0.296***	0.181***	0.058	0.053	-0.001	-0.036
	(0.065)	(0.067)	(0.071)	(0.037)	(0.038)	(0.041)
ROA	0.599***	1.062***	1.356***	0.525***	0.752***	0.676***
	(0.183)	(0.224)	(0.283)	(0.134)	(0.147)	(0.163)
R&D/Assets	1.276***	1.763***	2.147***	0.887***	1.110***	1.052***
	(0.376)	(0.370)	(0.401)	(0.206)	(0.194)	(0.213)
PPE/Assets	0.351**	0.250	0.323*	0.089	0.094	0.170
	(0.143)	(0.160)	(0.177)	(0.090)	(0.100)	(0.110)
Leverage	-0.399***	-0.319**	-0.297**	-0.196***	-0.186**	-0.180**
	(0.114)	(0.127)	(0.144)	(0.071)	(0.079)	(0.088)
CapExp/Assets	1.134***	1.464***	1.367***	0.729***	0.784***	0.689***
	(0.381)	(0.422)	(0.483)	(0.231)	(0.253)	(0.257)
Herfindahl	0.102	-0.019	-0.126	0.045	-0.076	-0.116
	(0.174)	(0.188)	(0.219)	(0.108)	(0.116)	(0.128)
Herfindahl Sq.	-0.201	-0.074	0.006	-0.127	-0.025	0.016
	(0.247)	(0.267)	(0.304)	(0.150)	(0.162)	(0.182)
Tobin's Q	0.075***	0.049**	-0.009	0.004	-0.016	-0.036***
	(0.023)	(0.023)	(0.023)	(0.012)	(0.012)	(0.012)
KZ Index	0.002***	0.002***	0.003***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Inst. Ownership	0.284***	0.340***	0.389***	0.208***	0.210***	0.143*
	(0.102)	(0.123)	(0.148)	(0.059)	(0.070)	(0.084)
Constant	-1.490***	-2.926***	-2.043***	0.320	-0.688**	-0.358
	(0.491)	(0.592)	(0.620)	(0.274)	(0.333)	(0.360)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,204	18,663	17,018	20,204	18,663	17,018
R^2	0.800	0.787	0.778	0.671	0.657	0.645

Table 3: Regression Discontinuity Approach

This table reports regressions discontinuity results. Panel A reports the results form estimating a polynomial model in the vote share of order four surrounding the threshold of 50% as specified in equation (2). Panel B reports placebo test results from estimating a polynomial model in the vote share of order four surrounding artificial thresholds of 25% and 75%. The variable of interest is the Pass dummy. Coefficient estimates and standard errors clustered by firm are reported. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Threshold value = 50%

Dependent Variable	$Ln(Patent_{t+1})$	$Ln(Patent_{t+2})$	$Ln(Patent_{t+3})$	$Ln(Cites/Patent_{t+1})$	$Ln(Cites/Patent_{t+2})$	$Ln(Cites/Patent_{t+3})$
	(1)	(2)	(3)	(4)	(5)	(6)
Pass	-1.542***	-1.222**	-0.811	-0.016	-0.212**	-0.192***
	(0.576)	(0.581)	(0.693)	(0.149)	(0.098)	(0.074)
Ind./Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	793	696	595	793	696	595
R^2	0.398	0.382	0.325	0.174	0.170	0.206

Panel B: Placebo Test
Threshold value = 25%

Dependent Variable	$Ln(Patent_{t+1})$	$Ln(Patent_{t+2})$	$Ln(Patent_{t+3})$	$Ln(Cites/Patent_{t+1})$	$Ln(Cites/Patent_{t+2})$	$Ln(Cites/Patent_{t+3})$
	(1)	(2)	(3)	(4)	(5)	(6)
Pass	-2.441	-2.424	-2.584	-0.492	-0.366	-0.350
	(2.537)	(2.470)	(2.440)	(0.720)	(0.677)	(0.492)
Ind./Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	793	696	595	793	696	595
R^2	0.397	0.380	0.322	0.185	0.171	0.203

Threshold value = 75%

Dependent Variable	$Ln(Patent_{t+1})$	$Ln(Patent_{t+2})$	$Ln(Patent_{t+3})$	$Ln(Cites/Patent_{t+1})$	$Ln(Cites/Patent_{t+2})$	$Ln(Cites/Patent_{t+3})$
	(1)	(2)	(3)	(4)	(5)	(6)
Pass	0.078	-0.595	-0.320	-0.086	0.002	0.177
	(0.450)	(0.493)	(0.589)	(0.128)	(0.135)	(0.119)
Ind./Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	793	696	595	793	696	595
R^2	0.398	0.382	0.325	0.174	0.170	0.206

Table 4: 2SLS Regressions --1st Stage Regression

This table reports the first-stage regression for the 2SLS regressions. The dependent variable is the firm's adjusted G-index in a year. The instruments are *State Law* is a dummy that equals one if the state in which the firm is incorporated has any one of the five state anti-takeover laws. *Hostile Takeover Intensity* equals the number of hostile takeovers within the firm's same 2-digit industry over the previous five years. Other independent variables include the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, Tobin's Q, the KZ index, and institutional ownership. Coefficient estimates and standard errors clustered by firm are reported. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable		AdjG-index
State Law	z_1	0.575**
		(0.238)
Hostile Takeover Intensity	z_2	0.017***
		(0.005)
Ln(Assets)		0.223***
		(0.040)
ROA		0.154
		(0.313)
R&D/Assets		-0.066
		(0.544)
PPE/Assets		0.978***
		(0.170)
Leverage		0.180
		(0.190)
CapExp/Assets		-2.057***
		(0.759)
Herfindahl		0.787**
		(0.391)
Herfindahl Sq.		-0.602
		(0.471)
Tobin's Q		-0.081***
		(0.030)
KZ Index		0.001
		(0.001)
Inst. Ownership		0.569***
		(0.158)
Constant		2.150**
		(0.956)
Year Fixed-effects		Yes
Firm Fixed-effects		Yes
$F(z_1 = z_2 = 0)$		40.97***
Observations		21,646
R^2		0.123

Table 5: 2SLS Regressions – 2nd Stage Regressions

This table reports the second-stage regressions for the 2SLS regressions. The dependent variable is the natural logarithm of the number of patents in a year in Panel A and the natural logarithm of the number of citations per patent in a year in Panel B. The variable of interest is the fitted values of *AdjG-index* obtained from the 1st stage regressions. Other independent variables include the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, Tobin's Q, the KZ index, and institutional ownership. Coefficient estimates and standard errors clustered by firm are reported. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Ln(Patent)			**Panel B: Ln(Cites/Patent)**		
Dependent Variable	Ln($Patent_{t+1}$)	Ln($Patent_{t+2}$)	Ln($Patent_{t+3}$)	Ln(Cites/ $Patent_{t+1}$)	Ln(Cites/ $Patent_{t+2}$)	Ln(Cites/ $Patent_{t+3}$)
	(1)	(2)	(3)	(1)	(2)	(3)
AdjG-index	0.396***	0.417***	0.353**	0.260***	0.310***	0.340***
	(0.136)	(0.147)	(0.168)	(0.084)	(0.106)	(0.100)
Ln(Assets)	0.220***	0.101	-0.005	0.001	-0.171***	-0.106**
	(0.072)	(0.075)	(0.082)	(0.041)	(0.050)	(0.046)
ROA	0.530***	0.989***	1.289***	0.485***	0.501***	0.631***
	(0.184)	(0.225)	(0.286)	(0.134)	(0.172)	(0.164)
R&D/Assets	1.294***	1.783***	2.161***	0.904***	0.670*	1.086***
	(0.379)	(0.373)	(0.403)	(0.206)	(0.379)	(0.213)
PPE/Assets	-0.046	-0.174	-0.042	-0.173	-0.196	-0.180
	(0.202)	(0.222)	(0.246)	(0.124)	(0.165)	(0.155)
Leverage	-0.463***	-0.386***	-0.354**	-0.239***	-0.219**	-0.238***
	(0.116)	(0.130)	(0.148)	(0.073)	(0.105)	(0.090)
CapExp/Assets	1.934***	2.312***	2.091***	1.256***	1.045***	1.388***
	(0.476)	(0.527)	(0.601)	(0.284)	(0.375)	(0.324)
Herfindahl	-0.211	-0.347	-0.402	-0.162	-0.243	-0.388**
	(0.202)	(0.217)	(0.259)	(0.127)	(0.162)	(0.151)
Herfindahl Sq.	0.031	0.171	0.208	0.030	0.136	0.225
	(0.257)	(0.278)	(0.322)	(0.158)	(0.208)	(0.191)
Tobin's Q	0.108***	0.084***	0.020	0.026*	-0.025	-0.007
	(0.026)	(0.027)	(0.027)	(0.015)	(0.015)	(0.014)
KZ Index	0.001	0.001**	0.002**	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Inst. Ownership	0.059	0.100	0.185	0.059	-0.051	-0.057
	(0.136)	(0.156)	(0.182)	(0.077)	(0.120)	(0.104)
Constant	-2.767***	-4.218***	-0.907	-0.629	-0.986	-0.436
	(0.796)	(0.902)	(0.927)	(0.487)	(0.628)	(0.569)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,204	18,663	17,018	20,204	15,479	17,018
R^2	0.800	0.787	0.778	0.671	0.635	0.646

Table 6: Information Asymmetry

This table reports the regressions examining the impact of information asymmetry. The dependent variable is the natural logarithm of the number of patents in a year. Independent variables include the G-index, an interaction between the G-index and analyst forecast dispersion, analyst forecast dispersion, natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, Tobin's Q, the KZ index, and institutional ownership. Standard errors are clustered by firm. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Ln(Patent)			Panel B: Ln(Cites/Patent)		
Dependent Variable	Ln($Patent_{t+1}$)	Ln($Patent_{t+2}$)	Ln($Patent_{t+3}$)	Ln(Cites/ $Patent_{t+1}$)	Ln(Cites/ $Patent_{t+2}$)	Ln(Cites/ $Patent_{t+3}$)
	(1)	(2)	(3)	(1)	(2)	(3)
G-index	0.126***	0.115***	0.109***	0.049***	0.044**	0.030**
	(0.032)	(0.033)	(0.038)	(0.017)	(0.018)	(0.012)
G-index	0.000	0.042**	0.053***	0.004*	0.017*	0.034***
*Dispersion	(0.002)	(0.018)	(0.020)	(0.002)	(0.011)	(0.012)
Dispersion	-0.004	-0.244**	-0.319***	-0.032	-0.113*	-0.213***
	(0.018)	(0.102)	(0.114)	(0.020)	(0.063)	(0.068)
Ln(Assets)	0.639***	0.487***	0.326***	0.176***	0.103*	0.077
	(0.095)	(0.103)	(0.118)	(0.055)	(0.060)	(0.066)
ROA	0.614*	1.416***	2.062***	0.764***	0.923***	0.889***
	(0.333)	(0.367)	(0.449)	(0.191)	(0.201)	(0.222)
R&D/Assets	4.779***	5.389***	5.411***	2.153***	2.145***	2.042***
	(1.022)	(1.225)	(1.335)	(0.552)	(0.583)	(0.665)
PPE/Assets	0.659***	0.494**	0.598**	0.179	0.233	0.326*
	(0.222)	(0.251)	(0.279)	(0.129)	(0.152)	(0.167)
Leverage	-0.386*	-0.264	-0.154	-0.081	-0.090	-0.141
	(0.218)	(0.243)	(0.280)	(0.128)	(0.142)	(0.160)
CapExp/Assets	0.909*	1.374**	1.197*	0.577**	0.750**	0.553*
	(0.497)	(0.575)	(0.680)	(0.293)	(0.323)	(0.335)
Herfindahl	0.029	-0.102	-0.401	-0.027	-0.179	-0.225
	(0.227)	(0.247)	(0.291)	(0.131)	(0.143)	(0.158)
Herfindahl Sq.	-0.169	0.051	0.384	-0.074	0.084	0.185
	(0.341)	(0.373)	(0.427)	(0.190)	(0.209)	(0.235)
Tobin's Q	0.109***	0.075***	0.006	0.013	-0.007	-0.030**
	(0.025)	(0.028)	(0.027)	(0.016)	(0.014)	(0.014)
KZ Index	0.003*	0.004**	0.003	0.001	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Inst. Ownership	0.053	0.260*	0.529**	0.098	0.209**	0.230**
	(0.128)	(0.158)	(0.209)	(0.073)	(0.091)	(0.114)
Constant	-3.988***	-2.989***	-1.954**	-0.444	-0.006	0.229
	(0.732)	(0.786)	(0.879)	(0.403)	(0.453)	(0.499)
Year & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,309	13,935	12,502	15,309	13,935	12,502
R^2	0.812	0.801	0.794	0.687	0.678	0.667

Table 7: Product Market Competition

This table reports the regressions examining the impact of product market competition The dependent variable is the natural logarithm of the number of patents in a year in Panel A and the natural logarithm of the number of citations per patent in a year in Panel B. An interaction term between the G-index and the Herfindahl index is included in each panel. Other independent variables include the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, Tobin's Q, the KZ index, and institutional ownership. Coefficient estimates and standard errors clustered by firm are reported. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Ln(Patent)			**Panel B: Ln(Cites/Patent)**		
Dependent Variable	$Ln(Patent_{t+1})$	$Ln(Patent_{t+2})$	$Ln(Patent_{t+3})$	$Ln(Cites/Patent_{t+1})$	$Ln(Cites/Patent_{t+2})$	$Ln(Cites/Patent_{t+3})$
	(1)	(2)	(3)	(1)	(2)	(3)
G-index	0.100***	0.097***	0.091***	0.051***	0.046***	0.038***
	(0.014)	(0.015)	(0.017)	(0.008)	(0.009)	(0.009)
G-index *Herfindahl	-0.042**	-0.039**	-0.006	-0.027**	-0.030**	-0.013
	(0.018)	(0.019)	(0.021)	(0.012)	(0.013)	(0.013)
Ln(Assets)	0.296***	0.181***	0.058	0.053***	-0.001	-0.036*
	(0.034)	(0.036)	(0.039)	(0.019)	(0.020)	(0.021)
ROA	0.598***	1.062***	1.356***	0.525***	0.753***	0.676***
	(0.123)	(0.149)	(0.182)	(0.108)	(0.109)	(0.105)
R&D/Assets	1.273***	1.763***	2.147***	0.885***	1.110***	1.052***
	(0.272)	(0.266)	(0.279)	(0.155)	(0.146)	(0.142)
PPE/Assets	0.351***	0.250***	0.323***	0.089*	0.094*	0.170***
	(0.085)	(0.094)	(0.099)	(0.050)	(0.053)	(0.056)
Leverage	-0.399***	-0.320***	-0.297***	-0.196***	-0.187***	-0.181***
	(0.069)	(0.076)	(0.085)	(0.046)	(0.049)	(0.051)
CapExp/Assets	1.141***	1.472***	1.369***	0.734***	0.789***	0.692***
	(0.259)	(0.284)	(0.310)	(0.180)	(0.185)	(0.184)
Herfindahl	0.473**	0.326	-0.071	0.283**	0.192	-0.001
	(0.197)	(0.211)	(0.230)	(0.134)	(0.138)	(0.144)
Herfindahl Sq.	-0.196	-0.070	0.007	-0.124	-0.022	0.017
	(0.158)	(0.170)	(0.184)	(0.100)	(0.104)	(0.108)
Tobin's Q	0.076***	0.049***	-0.009	0.005	-0.016*	-0.036***
	(0.015)	(0.015)	(0.016)	(0.009)	(0.009)	(0.009)
KZ Index	0.002***	0.002***	0.003***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Inst. Ownership	0.282***	0.338***	0.388***	0.206***	0.208***	0.142***
	(0.062)	(0.071)	(0.084)	(0.037)	(0.041)	(0.047)
Constant	-1.577***	-3.006***	-2.056***	0.264*	-0.751***	-0.385**
	(0.270)	(0.328)	(0.341)	(0.153)	(0.179)	(0.189)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,204	18,663	17,018	20,204	18,663	17,018
R^2	0.800	0.787	0.778	0.671	0.657	0.645

Table 8: Industry Analysis

This table reports the regressions estimating equation (1) based on patent industries. The dependent variable is the natural logarithm of the number of patents in a year in columns (1) – (3) and the natural logarithm of the number of citations per patent in a year in columns (4) – (6). The patent categories are based on the classification in Hall, Jaffe, and Trajtemberg (2005). The variable of interest is the G-index. Other independent variables include the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, Tobin's Q, the KZ index, and institutional ownership. Coefficient estimates and standard errors clustered by firm are reported. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	$Ln(Patent_{t+1})$			$Ln(Cites/Patent_{t+1})$		
	Drugs	IT & Chemical	Low-Tech	Drugs	IT & Chemical	Low-Tech
	(1)	(2)	(3)	(4)	(5)	(6)
G-index	0.337***	0.100**	0.061***	0.067**	0.043*	0.044***
	(0.121)	(0.042)	(0.015)	(0.030)	(0.022)	(0.016)
Ln(Assets)	-0.201	0.573***	0.310***	-0.166***	0.162***	0.074
	(0.149)	(0.102)	(0.039)	(0.058)	(0.050)	(0.045)
ROA	0.617	-0.306	0.076	0.197	0.122	0.295
	(0.388)	(0.323)	(0.231)	(0.233)	(0.192)	(0.180)
R&D/Assets	0.341	4.537***	-0.267	0.139	2.822***	1.316
	(0.561)	(1.356)	(1.327)	(0.280)	(0.786)	(1.054)
PPE/Assets	0.721	0.745***	0.288***	-0.187	0.270**	0.046
	(0.709)	(0.231)	(0.097)	(0.227)	(0.121)	(0.104)
Leverage	0.133	-0.456***	-0.339***	0.025	-0.317***	-0.131
	(0.401)	(0.158)	(0.091)	(0.141)	(0.111)	(0.096)
CapExp/Assets	1.170	0.485	1.318***	1.279*	0.388	0.564*
	(1.358)	(0.536)	(0.339)	(0.687)	(0.351)	(0.333)
Herfindahl	-0.094	0.133	0.312*	-0.578*	0.263	0.073
	(0.475)	(0.269)	(0.159)	(0.298)	(0.167)	(0.143)
Herfindahl Sq.	0.389	-0.432	-0.389**	0.402	-0.478**	-0.122
	(0.620)	(0.378)	(0.196)	(0.355)	(0.230)	(0.207)
Tobin's Q	0.048	0.091***	0.045**	0.024	0.030*	-0.015
	(0.049)	(0.029)	(0.022)	(0.017)	(0.017)	(0.016)
KZ Index	0.003	0.001***	0.003	0.006**	0.001***	0.000
	(0.008)	(0.000)	(0.004)	(0.003)	(0.000)	(0.003)
Inst. Ownership	0.875***	0.150	0.195***	0.675***	0.126	0.154**
	(0.308)	(0.144)	(0.074)	(0.123)	(0.081)	(0.072)
Constant	-2.719	-3.395***	-1.489***	0.177	-0.454	0.038
	(1.745)	(0.841)	(0.303)	(0.538)	(0.402)	(0.345)
Year Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,808	8,062	11,776	1,808	8,062	11,776
R^2	0.842	0.844	0.827	0.785	0.753	0.709

Table 9: Regressions for Firm Value

Panel A: Ln(Patent)

This table reports the baseline regressions estimating equation (3). The dependent variable is Tobin's *Q*. The main independent variable is the interaction between the G-index and the natural logarithm of the number of patents. Other independent variables include the natural logarithm of the number of patents, the G-index, the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, the KZ index, and institutional ownership. Standard errors are clustered by firm. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	Q_{t+1} (1)	Q_{t+1} (2)	Q_{t+1} (3)	Q_{t+2} (4)	Q_{t+3} (5)
G-index	-0.017**	-0.024***	-0.013*	-0.009	-0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
G-index*Ln(Patent)		0.005***	0.004***	0.004***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Ln(Patent)		-0.000	0.000***	0.000***	0.000**
		(0.000)	(0.000)	(0.000)	(0.000)
Ln(Assets)	-0.047***	-0.078***	-0.447***	-0.430***	-0.350***
	(0.016)	(0.019)	(0.036)	(0.032)	(0.033)
ROA	4.091***	4.013***	1.774***	0.972***	0.355
	(0.821)	(0.823)	(0.493)	(0.257)	(0.224)
R&D/Assets	6.765***	6.559***	2.010***	0.629	-0.272
	(1.135)	(1.120)	(0.756)	(0.538)	(0.433)
PPE/Assets	-0.411***	-0.424***	0.007	0.097	-0.085
	(0.071)	(0.071)	(0.083)	(0.069)	(0.071)
Leverage	0.012	0.051	0.365**	0.433***	0.504***
	(0.226)	(0.227)	(0.156)	(0.126)	(0.117)
CapExp/Assets	1.677**	1.602*	-0.235	-0.593*	-0.436
	(0.846)	(0.832)	(0.301)	(0.327)	(0.314)
Herfindahl	0.117	0.095	0.062	0.011	0.079
	(0.132)	(0.132)	(0.100)	(0.100)	(0.099)
Herfindahl Sq.	-0.139	-0.120	-0.044	-0.015	-0.084
	(0.143)	(0.142)	(0.105)	(0.110)	(0.111)
KZ Index	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Inst. Ownership	0.104	0.097	0.162***	0.106***	0.065
	(0.066)	(0.066)	(0.038)	(0.039)	(0.046)
Constant	1.802***	2.032***	4.361***	4.326***	4.070***
	(0.376)	(0.361)	(0.271)	(0.244)	(0.241)
Year Fixed-effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed-effects	Yes	Yes	-	-	-
Firm Fixed-effects	-	-	Yes	Yes	Yes
Observations	19,064	19,064	19,064	16,737	14,529
R^2	0.276	0.280	0.689	0.707	0.720

Panel B: Ln(Cites/Patent)

This table reports the baseline regressions estimating equation (3). The dependent variable is Tobin's *Q*. The main independent variable is the interaction between the G-index and the natural logarithm of the number of patents. Other independent variables include the natural logarithm of the number of citations per patent, the G-index, the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, the KZ index, and institutional ownership. Standard errors are clustered by firm. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	Q_{t+1} (1)	Q_{t+1} (2)	Q_{t+2} (3)	Q_{t+3} (4)
G-index	-0.021***	-0.009	-0.003	-0.006
	(0.007)	(0.007)	(0.007)	(0.012)
G-index*Ln(Cites/Patent) (e-05)	0.283	0.563***	0.580***	0.475***
	(0.198)	(0.265)	(0.244)	(0.202)
Ln(Cites/Patent)	0.020	0.020**	0.003	0.003
	(0.024)	(0.009)	(0.011)	(0.009)
Ln(Assets)	-0.053***	-0.443***	-0.425***	-0.425***
	(0.020)	(0.036)	(0.055)	(0.031)
ROA	4.229***	1.768***	0.964**	0.964***
	(0.781)	(0.492)	(0.440)	(0.257)
R&D/Assets	7.039***	2.010***	0.634	0.634
	(1.062)	(0.756)	(0.813)	(0.539)
PPE/Assets	-0.458***	0.011	0.099	0.099
	(0.054)	(0.082)	(0.105)	(0.069)
Leverage	0.032	0.358**	0.420*	0.420***
	(0.208)	(0.156)	(0.238)	(0.125)
CapExp/Assets	1.873**	-0.257	-0.610**	-0.610*
	(0.749)	(0.302)	(0.257)	(0.327)
Herfindahl	0.047	0.069	0.020	0.020
	(0.144)	(0.100)	(0.122)	(0.100)
Herfindahl Sq.	-0.115	-0.063	-0.035	-0.035
	(0.156)	(0.105)	(0.158)	(0.110)
KZ Index	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Inst. Ownership	0.024	0.162***	0.105*	0.105***
	(0.067)	(0.038)	(0.059)	(0.039)
Constant	1.813***	4.319***	4.292***	4.292***
	(0.197)	(0.270)	(0.414)	(0.243)
Year Fixed-effects	Yes	Yes	Yes	Yes
Industry Fixed-effects	Yes	-	-	-
Firm Fixed-effects	-	Yes	Yes	Yes
Observations	19,064	19,064	16,737	14,529
R^2	0.240	0.689	0.707	0.720

Table 10: Regressions for Firm Value and Information Asymmetry

This table reports the baseline regressions estimating equation (3). The dependent variable is Tobin's Q. The main independent variable is the interaction between the G-index and the natural logarithm of the number of patents. Other independent variables include the natural logarithm of the number of patents, the G-index, the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, the KZ index, and institutional ownership, year dummies, and firm dummies. Standard errors are clustered by firm. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	Q_{t+1}		Q_{t+2}		Q_{t+3}	
	Dispersion >Median	Dispersion < Median	Dispersion >Median	Dispersion < Median	Dispersion >Median	Dispersion < Median
	(1)	(2)	(3)	(4)	(5)	(6)
G-index	0.025	-0.024*	0.021	-0.022	0.013	-0.011
	(0.029)	(0.014)	(0.028)	(0.013)	(0.028)	(0.012)
G-index*Ln(Patent)	0.006***	0.001	0.006***	0.001	0.007***	-0.000
	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Ln(Patent)	0.000**	0.000***	0.000	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Assets)	-0.602***	-0.417***	-0.641***	-0.393***	-0.561***	-0.214***
	(0.100)	(0.068)	(0.094)	(0.069)	(0.120)	(0.074)
ROA	6.216***	1.033***	3.153***	0.040	1.533*	-0.034
	(0.679)	(0.320)	(0.631)	(0.396)	(0.792)	(0.288)
R&D/Assets	5.941**	5.054***	3.563*	1.402	1.475	1.125
	(2.673)	(1.555)	(2.032)	(1.251)	(1.490)	(1.082)
PPE/Assets	-0.568**	-0.063	0.025	0.039	0.206	0.042
	(0.274)	(0.125)	(0.313)	(0.113)	(0.393)	(0.111)
Leverage	-0.237	-0.025	0.383	0.315	0.682	0.361
	(0.360)	(0.211)	(0.429)	(0.269)	(0.424)	(0.274)
CapExp/Assets	-1.153*	-0.183	-1.177*	-0.168	-1.529**	-0.077
	(0.644)	(0.287)	(0.712)	(0.299)	(0.667)	(0.282)
Herfindahl	0.071	0.024	-0.125	-0.004	-0.077	0.045
	(0.230)	(0.137)	(0.259)	(0.145)	(0.265)	(0.145)
Herfindahl Sq.	0.006	0.032	0.106	0.036	0.063	-0.119
	(0.295)	(0.184)	(0.368)	(0.198)	(0.374)	(0.188)
KZ Index	0.012*	0.008	0.008***	0.001	0.006**	0.012
	(0.007)	(0.008)	(0.003)	(0.003)	(0.002)	(0.034)
Inst. Ownership	0.379***	-0.020	0.331**	-0.157	0.075	-0.254*
	(0.135)	(0.081)	(0.166)	(0.099)	(0.247)	(0.133)
Constant	4.663***	4.909***	6.056***	4.865***	5.053***	3.391***
	(0.789)	(0.607)	(0.811)	(0.575)	(0.774)	(0.608)
Year Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,207	7,226	6,293	6,180	5,415	5,244
R^2	0.744	0.741	0.760	0.753	0.757	0.802

Table 11: Regressions for Firm Value and Product Market Competition

This table reports the baseline regressions estimating equation (3). The dependent variable is Tobin's *Q*. The main independent variable is the interaction between the G-index and the natural logarithm of the number of patents. Other independent variables include the natural logarithm of the number of patents, the G-index, the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, the KZ index, and institutional ownership, year dummies, and firm dummies. Standard errors are clustered by firm. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	Q_{t+1}		Q_{t+2}		Q_{t+3}	
	Herfindahl >Median	Herfindahl < Median	Herfindahl >Median	Herfindahl < Median	Herfindahl >Median	Herfindahl < Median
	(1)	(2)	(3)	(4)	(5)	(6)
G-index	-0.014	-0.010	-0.008	-0.016	-0.006	-0.022
	(0.015)	(0.017)	(0.014)	(0.017)	(0.016)	(0.015)
G-index*Ln(Patent)	0.003**	0.005***	0.002*	0.005**	0.003*	0.005*
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Ln(Patent)	0.000*	0.000	0.000***	0.000***	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Assets)	-0.456***	-0.387***	-0.397***	-0.396***	-0.388***	-0.303***
	(0.095)	(0.069)	(0.063)	(0.079)	(0.076)	(0.078)
ROA	1.136	2.224***	1.545***	0.549	0.325	0.027
	(1.158)	(0.463)	(0.540)	(0.462)	(0.641)	(0.309)
R&D/Assets	1.112	4.714***	1.203*	1.231	-0.755	-0.501
	(1.554)	(1.408)	(0.703)	(1.988)	(0.969)	(1.513)
PPE/Assets	-0.099	-0.004	0.023	-0.020	-0.287**	0.035
	(0.192)	(0.112)	(0.143)	(0.142)	(0.145)	(0.132)
Leverage	0.413	0.413*	0.447*	0.459	0.716**	0.441**
	(0.481)	(0.213)	(0.248)	(0.297)	(0.292)	(0.221)
CapExp/Assets	0.013	-0.326	-0.464	-0.670*	0.197	-0.837*
	(0.564)	(0.438)	(0.545)	(0.394)	(0.970)	(0.485)
Herfindahl	-0.425	-0.835	-0.386	-0.480	-0.357	-0.900
	(0.372)	(1.070)	(0.386)	(1.094)	(0.390)	(1.301)
Herfindahl Sq.	0.368	6.783	0.310	4.000	0.280	4.536
	(0.296)	(8.577)	(0.315)	(8.198)	(0.322)	(9.940)
KZ Index	0.002	-0.002***	0.003	-0.002***	-0.001	-0.001*
	(0.005)	(0.001)	(0.002)	(0.000)	(0.004)	(0.001)
Inst. Ownership	0.202**	0.123*	0.048	0.134*	0.064	0.018
	(0.084)	(0.073)	(0.084)	(0.072)	(0.104)	(0.085)
Constant	5.225***	4.295***	4.683***	4.301***	4.452***	4.187***
	(0.827)	(0.625)	(0.524)	(0.628)	(0.520)	(0.624)
Year Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,532	9,532	8,368	8,369	7,265	7,264
R^2	0.723	0.750	0.750	0.745	0.750	0.751

Table 12: Regression for Firm Value and Industry Analysis

This table reports the baseline regressions estimating equation (3). The dependent variable is Tobin's *Q*. The main independent variable is the interaction between the G-index and the natural logarithm of the number of patents. Other independent variables include the natural logarithm of the number of patents, the G-index, the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, the KZ index, and institutional ownership, year dummies, and firm dummies. Standard errors are clustered by firm. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	Q_{t+1}		
	Drugs (1)	IT & Chemical (2)	Low-Tech (3)
G-index	-0.131**	-0.002	-0.001
	(0.054)	(0.013)	(0.007)
G-index*Ln(Patent)	0.005*	0.002**	0.002**
	(0.003)	(0.001)	(0.001)
Ln(Patent)	0.000**	0.000***	0.000*
	(0.000)	(0.000)	(0.000)
Ln(Assets)	-0.730***	-0.391***	-0.351***
	(0.177)	(0.045)	(0.040)
ROA	1.047	2.934***	0.837
	(1.024)	(0.313)	(0.682)
R&D/Assets	1.010	5.216***	6.101**
	(1.093)	(1.312)	(2.985)
PPE/Assets	1.532	-0.045	-0.149*
	(0.937)	(0.102)	(0.087)
Leverage	-0.296	0.166	0.770***
	(0.451)	(0.133)	(0.232)
CapExp/Assets	-1.894	-0.126	-0.089
	(1.349)	(0.348)	(0.503)
Herfindahl	0.623	-0.031	0.093
	(0.566)	(0.180)	(0.105)
Herfindahl Sq.	-0.620	0.101	-0.130
	(0.567)	(0.199)	(0.115)
KZ Index	0.022	-0.001	-0.022*
	(0.016)	(0.001)	(0.013)
Inst. Ownership	0.085	0.163**	0.151***
	(0.200)	(0.068)	(0.037)
Constant	8.312***	4.181***	3.592***
	(1.535)	(0.386)	(0.306)
Year Fixed-effects	Yes	Yes	Yes
Firm Fixed-effects	Yes	Yes	Yes
Observations	1,521	6,997	10,546
R^2	0.651	0.689	0.732