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Should Directors Have Term Limits? – Evidence from Corporate Innovation

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ABSTRACT This paper examines the effect that directors with extended tenure have on corporate innovation based on a sample of US firms from 1996 to 2006. Using the propensity-score matched-pair research design, I find that firms with a higher portion of outside directors enjoying extended tenure produce significantly fewer patents and that these patents receive fewer subsequent citations. These firms also have lower research and development (R&D) productivity and exploration intensity than their matched control firms, although I found no significant difference in their R&D investment intensity. Difference-in-differences tests based on director deaths and regulatory changes in the early 2000s suggest that the adverse effect of long director tenure on innovation performance is causal. I also find that the effect is mitigated when long-tenured directors have more years of overlap in service with CEOs, and when long-tenured directors are executives at other firms. Finally, I find that boards with extended tenure attenuate the contributions of innovation outputs to future firm value and performance. These findings shed new light on the debate over length of board tenure and provide another justification for imposing term limits on directors.

JEL Classification: G34; O31; O34

1. Introduction

The debate over imposing term limits on members of boards of directors has come under the spotlight again in light of recent evidence that the average length of board members' service in corporate America has risen significantly over the last decade. A 2013 GMI Ratings study showed that among Russell 3000 companies, 6457 independent directors – nearly 34% of the total – have served 10 years or longer, up from 18% in 2008 (Lublin, 2013).

Does length of director tenure matter? The question has significant practical and regulatory implications. A number of countries around the world either already have or are contemplating imposing term limits on independent directors.[1] Previous studies and policy debates on this issue have largely centered around the impact of extended tenure on directorial oversight of management and have offered mixed findings. One view is that directors with lengthy tenure are more prone to befriending managers, rendering them less effective at monitoring those managers' activities. Vafeas (2003), Byrd, Cooperman, and Wolfe (2010), and Niu and Berberich

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[1]Regulations in the UK, Australia, India, Hong Kong, Singapore, among other countries and regions, have imposed term limits on directors of between 9 and 10 years.

(2015) find empirical evidence consistent with this perspective. An opposing argument is that long-tenured directors acquire firm-specific knowledge and experience that ultimately results in greater commitment and competence in managerial oversight. Dou, Sahgal, and Zhang (2015) find supporting evidence that long director tenure is associated with tighter control and fewer agency problems.

While prior studies primarily focus on the monitoring role of directors, this study contributes to the debate over director tenure by examining how length of director tenure affects boards' advisory functions. In particular, I focus on corporate innovation, a critical driver of long-term corporate success. Providing advice and guidance on innovation activities is a key board function. Since directors monitor as well as advise firms, regulators should consider the impact on both of these directorial functions when deciding whether or not to impose term limits on the board of directors. This study sheds new light on the impact of director tenure on corporate innovation.

Ex ante, it is unclear whether extended director tenure has a positive or negative impact on corporate innovation performance. On the one hand, because innovation is a type of high-risk, long-term, and unpredictable investment that might not generate immediate financial returns, managers who are under board scrutiny may be prone to invest less (in some cases suboptimally) in such projects and put more effort into routine tasks that offer quicker and more certain returns (He & Tian, 2013). Consistent with this view, Faleye, Hoitash, and Hoitash (2011) find that intense monitoring promotes managerial myopia by weakening the CEO's perception of board support, which impedes investments in risky but value-enhancing ventures, such as corporate innovation. Overcoming such managerial myopia would require boards to offer CEOs the implicit assurance necessary to induce them to assume strategic risks, and to grant them a degree of autonomy (Faleye et al., 2011; Tushman & O'Reilly, 1997). A number of prior studies argue that directors develop congeniality with managers as the length of their service increases (e.g. Byrd et al., 2010; Niu & Berberich, 2015; Vafeas, 2003). As a result, they may be more inclined to trust CEOs' decisions to invest in long-term, risky innovation projects. Directors who have been with a firm for a long time may also be more tolerant of short-term failure, which has been shown to be an important factor in motivating innovation (Manso, 2011; Tian & Wang, 2014).

On the other hand, however, it is also possible that long-serving directors may hinder corporate innovation. A major criticism of long director tenure is that stagnant boards filled with directors with extended tenure fail to refresh themselves in a timely manner, can no longer keep current with technological developments, and grow unable to offer new insights into corporate issues. Prior management literature also notes that long executive tenure is often associated with rigidity and a commitment to established policies and practices that potentially kill the entrepreneurial spirit and hinder innovation (Marcus & Goodman, 1986; Tushman & O'Reilly, 1997). March and March (1977) find that executives with short tenure contribute fresh insights and are more willing to take risks that deviate from industry norms.

Given these contradictory findings, assessing the effect of long director tenure on corporate innovation is ultimately an empirical question. I examine five variables that capture various aspects of corporate innovation activities and performance: R&D investment intensity (a measure of input into innovation activities), the number of patents (a measure of quantity of innovation output), the number of citations received by each patent (a measure of quality of innovation output), the research quotient (a measure of R&D productivity), and the intensity of exploratory innovation (a measure of innovation type and strategy). I define an independent director with extended tenure as one who has served at least 10 years on a given board. Dou et al. (2015) argue that using an aggregate measure of board tenure, such as the median or average, masks the distribution of tenure among directors. To avoid this concern, I measure the extent to which a board has extended tenure, the key explanatory variable *PercentTenure10*, as the proportion of outside directors on the board with service exceeding 10 years. The decision to use 10 years as the threshold is consistent with regulations in the UK, Australia, India, Hong Kong, Singapore, and other countries and regions that have imposed term limits on directors of between 9 and 10 years (although I obtain quantitatively similar results when using 15 years as an alternative threshold).

Endogeneity is a common concern for corporate governance research. I use a research design, based on propensity score matching, to draw inferences about the relationship between extended director tenure and corporate innovation.[2] The general idea is to use propensity scores to generate matched pairs with maximum variation in the causal variable of interest while minimizing the variation in the controls. As Armstrong, Jagolinzer, and Larcker (2010) note, this approach can be applied to empirical studies in which the hypothesized causal variable is an endogenous choice by the managers or the board. This approach not only alleviates the endogeneity concern but is also more robust to concern of misspecification of the functional form of the underlying relationship between extended board tenure and corporate innovation performance.

Baseline results of an analysis of a sample of publicly listed US firms from the years 1996 to 2006 show that firms with a higher portion of directors with extended tenure produce significantly fewer patents and that these patents receive significantly fewer subsequent citations. Compared with their matched control peers, these firms also exhibit lower R&D productivity and exploratory innovation intensity. I do not find a significant relation between director tenure and corporate investments into R&D activities, however. Taken together, my findings suggest that long-tenured directors hinder corporate innovation. This happens not through a reduction in firms' R&D investments, but instead through the pursuit of different innovation strategies (also a decision influenced by the board). Firms with a higher portion of long-tenured directors tend to prefer an exploitative innovation strategy that emphasizes 'the refinement and extension of existing technologies and paradigms' (March, 1991), as opposed to an exploratory strategy that invests R&D resources in projects that require extensive new knowledge in the pursuit of breakthrough inventions.[3]

Although I employ the propensity-score matched-pair research design in an effort to mitigate endogeneity concerns, the baseline findings may still be subject to the concern that the association between extended board tenure and corporate innovation could be driven by unobservable characteristics that are related both to firms' board structures and to their innovation activities, which makes it difficult to draw causal inferences. To further attempt to establish causality, I use two different identification strategies that rely on plausibly exogenous shocks to the percentage of long-tenured directors at a given firm. The first strategy relies on changes in the percentage of long-tenured directors due to the deaths of such directors. I use a difference-in-differences (DiD) approach that strips out both time-series and cross-sectional differences. As detailed in Section 4.1, results of DiD analysis suggest that compared to firms that do not experience death of long-serving directors, firms that do experience such events incur a statistically and economically significant increase in patent quantity and quality, R&D productivity as well as exploratory intensity.

The second identification strategy relies on regulatory changes in the early 2000s surrounding the enactment of the Sarbanes–Oxley Act (SOX), which forced publicly listed firms to increase

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[2] I thank the referee for suggesting this research design.

[3] Compared with exploration innovation, exploitation innovation tends to have less impact and benefits, as evidenced by fewer patents and subsequent patent citations, as well as lower contributions of R&D investments to the firms' future revenues.

their board independence. Changes in board composition following the new regulations likely affect the percentage of long-tenured directors for some firms. I therefore exploit this plausibly exogenous shock to director tenure and examine (separately for increases and decreases in the percentages of long-tenured directors) the effect of long tenure on corporate innovation. The DiD analyses are generally consistent with the baseline results. As detailed in Section 4.2, results of the DiD analysis suggest that, compared to firms that do not experience an increase in the percentage of long-tenured directors, firms that do experience such event incur a statistically and economically significant decrease in patent quantity and quality, as well as in exploratory intensity. I find similar but opposite results for decreases in the percentage of long-tenured directors pursuant to regulatory changes.

Next, I explore cross-sectional heterogeneity in long-tenured directors on firms' innovation performance. Researchers have argued that overcoming managerial myopia and encouraging innovation requires the board to lend the CEO support (Faleye et al., 2011; Tushman & O'Reilly, 1997). I posit that long-tenured directors with more years of overlap in service with CEOs are more prone to befriending the CEOs and therefore more willing to support their investments in risky innovation projects. I therefore expect the adverse effect of long-tenured directors on corporate innovation to be attenuated when the long-tenured directors have longer relationships with their CEOs. My empirical findings provide support for this conjecture.

The second contextual variable that I examine is whether long-tenured directors simultaneously serve as executives in other corporations. As I mentioned above, a major criticism of long board tenure is that such boards fail to keep current with industrial developments and to bring fresh ideas to their advisory role, which may hinder corporate innovation performance. I conjecture that this is less of a concern for long-serving directors who are executives at other corporations because these directors are still at the 'frontline' of their fields of business. Consistent with this conjecture, I find that the adverse effect of long director tenure on innovation is reduced when such directors are also executives at other corporations. Evidence of the differential effects of long director tenure on corporate innovation along these dimensions also helps to alleviate endogeneity concerns to some extent and suggests that a causal relation is at least partially in effect.

Finally, to further assess the economic implications of extended board tenure on corporate innovation, I examine whether and how extended board tenure affects the relation between innovation and firm value (measured by Tobin's Q) and performance (measured by return on assets). The findings suggest that while innovation outputs (i.e. patents) have a significant positive impact on firms' future value and performance, the effect is significantly attenuated for firms with stagnant boards filled with long-serving directors.

This study contributes to the growing literature on board tenure. Prior studies and debates about board tenure predominantly focus on its impact on directorial monitoring and offer mixed results. Based on a sample of 93 publicly traded US banks, Byrd et al. (2010) find a positive association between director tenure and the compensation of CEOs with tenure of six years or more. Niu and Berberich (2015) find that long-serving directors with multiple directorships are less effective in carrying out their oversight responsibilities. In contrast, Dou et al. (2015) find that long-tenured directors are more committed. This commitment manifests in a higher likelihood of directors attending board meetings and becoming members of board committees. Firms with higher proportions of directors with extended tenures have lower CEO pay, higher CEO turnover-performance sensitivity, and a smaller likelihood of intentionally misreporting earnings. This paper sheds new light on the debate over board tenure by focusing on its impact on directors' advisory role. It finds that directors with extended tenure are less effective in advising on corporate innovation activities. However, it is worth noting that this study does not capture all costs and benefits associated with long director tenure, and does not speak to the optimality of imposing term limits on the boards. It focuses primarily on one downside associated with extended director tenure.

This study also contributes to the growing literature on drivers of innovation. This literature links various market and firm characteristics to innovation, but little is known about the role that board of directors plays in innovation activities (Balsmeier, Buchwald, & Stiebale, 2014).[4] Baysinger, Kosnik, and Turk (1991) document a positive relationship between the proportion of inside directors on the board and R&D spending. Coles, Daniel, and Naveen (2008) further find that R&D-intensive firms have a higher fraction of inside directors with firm-specific knowledge on the board, which is associated with higher firm value. More recently, Balsmeier et al. (2014) examine how outside directors on supervisory boards influence corporate innovation. Using a sample of German firms, they find that outside directors positively affect patenting productivity of innovative firms. Balsmeier, Mleming, and Manso (2015) use the regulatory change created by the SOX, and find that transition to independent boards results in greater but less creative patenting. While this research has focused almost exclusively on board independence, my study examines another important dimension of board structure and quality: board tenure and its impact on innovation performance.

The remainder of the paper proceeds as follows. Section 2 describes the data and presents descriptive statistics. Section 3 reports baseline empirical results. Section 4 provides two identification strategies. Section 5 provides cross-sectional analyses and several additional tests. Section 6 concludes the paper.

2. Sample Selection and Summary Statistics

2.1. Sample Selection

The sample includes publicly listed US firms during the period 1996–2006.[5] I collect firm-year patent information from the latest version of the National Bureau of Economic Research (NBER) Patent Citation database (see Hall, Jaffe, & Trajtenberg (2001) for details). This database provides annual information on patent assignee names, the number of patents, the number of citations received, and patents' application years as well grant years. I obtain data on firms' R&D investments and financial statement items from Compustat Industrial Annual Files. Data on research quotient, which is firm-specific output elasticity of R&D that represents the percentage increase in revenues from a 1% increase in R&D, are obtained from the ResearchQuotient database provided by Wharton Research Data Services.[6] I obtain board and director characteristics from the RiskMetrics database. After excluding observations with missing data, my final sample consists of 7706 firm-year observations.

[4]Prior studies have examined various market and firm characteristics that affect innovation, including the participation of venture capital (Kortum & Lerner, 2000; Tian & Wang, 2014), especially corporate venture capital (Chemmanur, Loutskina, & Tian, 2014), CEO overconfidence (Hirshleifer, Low, & Teoh, 2012), analyst coverage (He & Tian, 2013), private ownership (Ferreira, Manso, & Silva, 2014), involvement of institutional investors (Aghion, Van Reenen, & Zingales, 2013; Ferreira et al., 2014), conglomerate form (Seru, 2014), competition (Aghion, Bloom, Blundell, Griffith, & Howitt, 2005), stock liquidity (Fang et al., 2014), debtor-friendly legal environments (Acharya & Subramanian, 2009), stringent labor laws and lower union powers (Acharya, Baghai, & Subramanian, 2013; Bradley, Kim, & Tian, in press), and financial market development (Hsu, Tian, & Xu, 2014).

[5]The sample period starts in 1996 because it's the first year that director data become available in the RiskMetrics database. The sample period ends in 2006 due to availability of patent data from the NBER Patent Citation database at the time of this research.

[6]I tried to fill in missing values for research quotient whenever possible by doing the calculations myself.

2.2. *Variable Measurement*

2.2.1. *Measuring innovation*

I examine five variables that capture different aspects of firms' innovation activities and performances. The first variable is R&D intensity, which is commonly used as a measure of corporate investments in innovation projects (Faleye et al., 2011). The R&D budget is likely to be discussed and influenced directly by boards of directors. I measure R&D intensity as the ratio of R&D expenditures to total assets. As is conventional, I set this variable to zero when Compustat reports R&D as missing.[7] If long board service induces directors to be more willing to lend CEO support in assuming strategic risks, I expect long-tenured directors to be associated with higher R&D intensity. On the other hand, if long-tenured directors monitor managerial behavior more closely and/or are unable to keep up with latest industry trends and/or underestimate the importance of innovation in firms' future growth prospects, their presence may discourage investments in innovation projects.

Atanassov (2008) argues that R&D is principally an input into the innovation process and may not necessarily represent its outcome. I therefore employ two patent-based measures of innovation outcome that are less susceptible to this limitation. *NumPat* and *CitePat* gauge patent quantity and quality, respectively, and have been extensively examined in earlier innovation studies (e.g. Fang, Tian, & Tice, 2014; He & Tian, 2013). I define *NumPat* as the total number of patent applications a firm has filed in a given year and that are eventually granted.[8] I define *CitePat* as the total number of citations each patent receives in subsequent years. Following the existing innovation literature, to account for the long-term nature of the innovation process, my empirical tests relate firm characteristics in the current year to the above two patent-related variables three years ahead. I also adjust patent-related variables to address the truncation problems associated with the NBER patent database.[9] A first look at the distribution of the number of patents in the sample shows that the distribution is right skewed. That is, a significant number of firm-year observations have zero patents. To mitigate the right skewness problem, I use the natural logarithm of patent counts, *LnPatent*, and the natural logarithm of citations per patent, *LnCitePat*. To avoid losing firm-year observations with zero patents, I add the value one to the actual values when calculating the natural logarithm.

The next innovation variable that I examine is research quotient. This variable has certain advantages over patent-based measures of innovation outcome because a large number of firms investing in R&D do not patent their innovations (Cooper, Knott, & Yang, 2015).[10] Research

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[7]As a robustness check, I also reconduct the analyses using firm-year observations without missing R&D data. In the baseline analysis, the mean R&D intensity for the pooled treatment group (T) and control group (C) is 0.068 and 0.061, respectively. The difference is statistically insignificant, which is consistent with the results reported in Table 4 Panel A.

[8]The reason for using a patent's application year rather than its grant year is that previous studies (such as Griliches, Pakes, & Hall, 1988) have shown that the former is superior in capturing the actual time of innovation.

[9]The truncation problem arises because the patents appear in the NBER patent database only after they are granted. I observe a gradual decrease in the number of patent applications as I approach the last few years of my sample period. This observation is because the lag between a patent's application year and its grant year is significant (about two years on average) and many patent applications filed during these years were still under review and had not been granted by 2006. To adjust the truncation bias in patent counts, I supplement the NBER database with the Harvard Business School (HBS) patent database, which contains patents granted through 2010. To the extent that the patent application outcomes have been announced by 2010 for the patents filed by 2005 (the last year of my sample period), this approach largely mitigates the patent truncation concern. Neither the NBER nor the HBS patent database is likely to be affected by the survivorship bias. As long as a patent application is granted by the USPTO, it is attributed to the applying firm at the time of application even if the firm later gets acquired or goes bankrupt.

[10]I thank the referee for suggesting this variable.

quotient is also a proxy for the R&D productivity construct in endogenous growth theory (Lentz & Mortensen, 2008). A higher value of research quotient implies that the firm is able to generate greater financial gains from its R&D investments.

The last innovation variable that I examine is innovation strategy. The management literature has identified two generic types of innovation activity: *exploratory* innovation and *exploitative* innovation (Benner & Tushman, 2002; Levinthal & March, 1993). Exploration involves departure from existing knowledge and experimentation with new technologies or approaches. In contrast, exploitation pertains to 'the refinement and extension of existing technologies and paradigms' (March, 1991). I define exploratory innovation intensity according to the extent to which firms' new patents use new vs. existing knowledge. Firms' existing knowledge consists of its previous patent portfolio and the set of patents that have been cited by firms' patents filed over the past five years. A patent is categorized as exploratory if at least 80% of its citations are based on new knowledge. I then calculate the intensity of exploratory innovation as the number of exploratory patents a firm has filed in a given year divided by the number of all patents the firm filed in the same year. A higher value of exploration intensity suggests that firms' innovation strategies are more exploration-oriented.

Table 1. Sample distribution

Panel A: Sample distribution by year

Year	Number of obs.	Percentage of sample	Cumulative percentage
1996	620	8.05	8.05
1997	778	10.10	18.14
1998	718	9.32	27.46
1999	796	10.33	37.79
2000	762	9.89	47.68
2001	786	10.20	57.88
2002	686	8.90	66.78
2003	670	8.69	75.47
2004	650	8.43	83.91
2005	630	8.18	92.08
2006	610	7.92	100.00
Total	7706	100.00	100.00

Panel B: Sample distribution by industry

SIC code	Industry	Number of obs.	Percentage of sample	Cumulative percentage
36	Electronic & Other Electric Equipment	1042	13.52	13.52
28	Chemicals and Allied Products	969	12.57	26.10
35	Industrial and Commercial Machinery and Computer Equipment	830	10.77	36.87
73	Business Services	782	10.15	47.02
38	Instruments & Related Products	664	8.62	55.63
37	Transportation Equipment	402	5.22	60.85
49	Electric, Gas, and Sanitary Services	289	3.75	64.60
20	Food and Kindred Products	262	3.40	68.00
26	Paper and Allied Products	259	3.36	71.36
34	Fabricated Metal Products	219	2.84	74.20
–	Others	1988	25.80	100.00
Total		7706	100.00	100.00

Note: This table reports sample distribution by year and by industry, respectively.

Table 2. Descriptive statistics and correlation matrix

Panel A: Summary statistics

Variable	Mean	SD	25th Percentile	Median	75th Percentile	Number of obs.
R&D	0.042	0.059	0.000	0.018	0.064	7706
LnPatent	1.663	1.841	0.000	1.099	2.890	7706
LnCitePat	1.474	1.675	0.000	0.000	2.686	7706
ResearchQuotient	0.104	0.037	0.080	0.101	0.124	7706
Explore	0.700	0.351	0.421	0.825	1.000	7706
PercentTenure10	0.260	0.250	0.000	0.200	0.385	7706
DirectorAge	59.340	4.456	56.857	59.645	62.000	7706
DirectorOwn	0.008	0.022	0.000	0.001	0.005	7706
NumComittee	2.348	1.811	1.000	2.000	3.000	7706
Size	7.566	1.617	6.403	7.412	8.622	7706
Leverage	0.220	0.167	0.069	0.217	0.333	7706
MTB	3.394	3.326	1.628	2.454	3.934	7706
ROA	0.038	0.109	0.016	0.051	0.088	7706
NumSeg	2.977	2.104	1.000	3.000	4.000	7706
FirmAge	27.450	15.886	13.000	26.000	42.000	7706
FirmAge^2	1005.794	941.074	169.000	676.000	1764.000	7706
CEOOwn	0.063	0.372	0.024	0.097	0.384	7706
CEOAge	55.993	7.361	51.000	56.000	61.000	7706
CEOTenure	6.533	7.364	2.000	4.000	9.000	7706
Duality	0.484	0.693	0.000	1.000	1.000	7706

Panel B: Correlation matrix

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	*R&D*	1																			
2	*ResearchQuotient*	0.16^{c}	1																		
3	*LnPatent*	0.35^{c}	0.02^{c}	1																	
4	*LnCitePat*	0.24^{b}	0.03^{c}	0.45^{c}	1																

5	*Explore*	0.00	0.04[b]	0.09[c]	0.36[c]	1															
6	*PercentTenure10*	−0.03[b]	−0.04[c]	−0.06[c]	−0.17[c]	−0.15[c]	1														
7	*DirectorAge*	−0.17[c]	−0.09[c]	−0.00	−0.10[c]	−0.00	0.19[c]	1													
8	*DirectorOwn*	0.00	0.04[b]	−0.07[c]	−0.09[c]	−0.05[c]	−0.03[c]	0.02[a]	1												
9	*NumCommittee*	−0.07[c]	−0.02	0.21[c]	0.14[c]	0.01	0.04[c]	0.08[c]	−0.11[c]	1											
10	*Size*	−0.03[c]	0.06[c]	0.39[c]	0.11[c]	−0.08[c]	0.03[c]	0.03[c]	−0.12[c]	0.34[c]	1										
11	*Leverage*	−0.32[c]	−0.09[c]	−0.09[c]	−0.02[a]	0.01	0.00	0.07[c]	−0.03[c]	0.13[c]	0.00	1									
12	*MTB*	0.22[c]	0.17[c]	0.18[c]	0.17[c]	0.02	0.01	−0.12[c]	0.01	0.08[c]	0.41[c]	−0.08[c]	1								
13	*ROA*	−0.26[c]	0.17[c]	0.03[c]	−0.01	0.04[c]	0.07[c]	0.05[c]	−0.02[b]	0.02	0.27[c]	−0.18[c]	0.18[c]	1							
14	*NumSeg*	−0.21[c]	−0.11[c]	0.11[c]	−0.15[c]	−0.14[c]	−0.09[c]	0.15[c]	0.03[c]	0.14[c]	0.20[c]	0.14[c]	−0.12[c]	−0.02[a]	1						
15	*FirmAge*	−0.34[c]	−0.16[c]	0.13[c]	−0.04[c]	0.02	0.17	0.28	−0.05[c]	0.23[c]	0.28[c]	0.21[c]	−0.06[c]	0.13[c]	0.34[c]	1					
16	*FirmAge*^{2}	−0.21[c]	−0.15[c]	0.16[c]	−0.04[c]	−0.01	0.14[c]	0.25[c]	−0.05[c]	0.25[c]	0.30[c]	0.21[c]	−0.04[c]	0.11[c]	0.35[c]	0.98[c]	1				
17	*CEOOwn*	−0.05[c]	−0.04[b]	0.09[c]	0.02	−0.05[c]	−0.12[c]	0.06[c]	−0.01	0.63[c]	0.20[c]	0.09[c]	0.05[c]	−0.01	0.12[c]	0.13[c]	0.15[c]	1			
18	*CEOAge*	−0.19[c]	−0.08[c]	−0.05[c]	−0.02[b]	0.07[c]	0.08[c]	0.41[c]	−0.03[c]	0.04[c]	0.01	0.07[c]	−0.09[c]	0.08[c]	0.09[c]	0.18[c]	0.16[c]	0.02[a]	1		
19	*CEOTenure*	0.02	−0.01	−0.06[c]	−0.02	0.02[a]	0.02[b]	0.08[c]	0.00	−0.11[c]	−0.05[c]	−0.05[c]	−0.02[a]	0.03[c]	−0.05[c]	−0.08[a]	−0.10[a]	−0.06[a]	0.37[a]	1	
20	*Duality*	−0.09[c]	−0.07[c]	0.02[b]	0.15[c]	0.12[c]	0.11[c]	0.05[c]	−0.05[c]	0.05[c]	−0.00	0.06[c]	0.01	0.08[c]	−0.03[c]	0.15[c]	0.13[c]	−0.01	0.06[c]	0.02	1

Notes: Pearson correlations are reported. Definitions of variables are provided in Appendix. This table reports descriptive statistics and correlation matrix of variables used in the baseline analyses.

[a]Significant at the 10% level.

[b]Significant at the 5% level.

[c] Significant at the 1% level.

2.2.2. *Measuring boards with extended tenure*

Dou et al. (2015) argue that using an aggregate measure of board tenure, like the median or average, masks the distribution of tenure among directors. I therefore measure boards with extended tenure, *PercentTenure10*, as the proportion of independent directors on the board with at least 10 years of service as of a given year. The choice of 10 years is consistent with industry practices and regulations. A growing number of countries have adopted tenure-related guidelines or restrictions for directors. In 2014, the Securities and Exchange Board of India announced changes to regulations, mandating that no person can serve as independent director on the board of the company for more than 10 years (Mampatta, 2014). In Hong Kong, an independent director is limited to a three-term, nine-year maximum tenure unless shareholders separately vote on a resolution permitting re-appointment.

2.3. Sample Description and Summary Statistics

Table 1, Panel A reports sample distribution by year. There does not appear to be strong clustering in the year distribution of the sample. Panel B reports the sample distribution by industry where industry classification is based on the two-digit SIC code. The largest sector is Electronic & Other Electric Equipment (SIC code 36), followed by Chemical & Allied Products (SIC code 28) and Industrial and Commercial Machinery and Computer Equipment (SIC code 35), respectively. Firms in those industries tend to be more active in innovation and patenting than those in other industries.

Table 2 provides descriptive statistics and correlation matrix of variables used in the baseline analyses. These variables are discussed in more detail in the next section and their definitions are reported in Appendix. To minimize the effect of outliers, I winsorize all continuous variables at the 1st and 99th percentiles. On average, a sample firm has a R&D intensity of 0.04, a natural logarithm of patents of 1.66, 1.47 citations per patent, a research quotient of 0.10, and an exploration intensity of 0.70. The average (median) percentage of directors with long tenure at each firm is 26% (20%), respectively. As for director characteristics, the average director is 59 years old, has an equity ownership of 0.8%, and serves on two committees. As for firm characteristics, an average firm has a natural logarithm of market value of 7.56, leverage ratio of 22%, market-to-book ratio of 3.4, return on asset of 0.04. 48.4% of sample firms have a CEO who also serves as the chairman of the board. The average CEO is 56 years old and has a tenure of 6.5 years.

Table 2, Panel B reports the correlation matrix among variables used in the baseline analyses. The main independent variable *PercentTenure10* has a significant negative relation with R&D intensity, number of patents, citations per patent, research quotient, and exploration intensity, which suggests a negative impact of long director tenure on corporate innovation. Since univariate correlation analysis does not take into account the effects of the other correlated variables, however, I consider the evidence to be suggestive and rely on subsequent analyses to draw inferences.

3. Baseline Empirical Results

As with other corporate governance studies, my examination of the relation between board tenure and corporate innovation is subject to significant endogeneity concerns. For this reason, I employ a propensity-score matched-pair research design. As Armstrong et al. (2010) note, this approach can be applied to empirical studies in which the hypothesized causal variable is an endogenous choice by the mangers or the board. The general idea is to use propensity scores to generate matched pairs with maximum variation in the causal variable of interest while minimizing the variation in the controls. This approach helps alleviate endogeneity concerns, and is more robust than ordinary least squares to concerns about misspecifications of the functional form of the underlying relationship between extended board tenure and corporate innovation performance.

At a high level, the propensity-score matched-pair research design involves five steps. First, I estimate an ordered logistic propensity score model, which is the probability that a firm has a certain percentage of long-tenured directors conditional on a set of firm and board characteristics. Second, I form matched pairs by identifying the pairings that result in observations with minimum difference in propensity scores but maximum difference in actual percentage of long-tenured directors. Third, I examine the covariate balance between the treatment and control groups and remove the most dissimilar matched pairs (if necessary) to better control for potentially confounding factors. Fourth, I compare innovation variables between treatment observations and their matched control observations and assess whether they are significantly different. Fifth, I estimate the sensitivity of the results to potential hidden bias by relaxing the assumption that matched observations have an equal probability of receiving a certain level of treatment (Rosenbaum, 2002).

The first step involves modeling the determinants of the proportion of long tenure directors in a given firm. Vafeas (2003) examines the relation between length of board tenure and outside director independence, and finds that director age, director ownership, and number of committee memberships are significant variables in distinguishing between directors in the various board tenure categories. I include these variables in the propensity score estimation. Linck, Netter, and Yang (2008) examine determines of board structure and find that size (measured by the natural logarithm of market value of equity), leverage (measured by total debt to total assets ratio), business diversity (measured by the natural logarithm of business segments), firm age (measured by the number of years since the firm first appeared in Compustat), firm age squared, market-to-book ratio (measured by the market-to-book ratio of equity), profitability (measured by return-on-assets ratio), CEO ownership (measured by the percent of shares held by the CEO), CEO age, CEO tenure (measured by the number of years the CEO has been in this position), and CEO duality (a dummy that equals one if the CEO is also the chairman of the board) are significant determinants of board structure. I therefore include these firm and management characteristics as additional determinants in the propensity score estimation. Finally, to control for industry effect, I require treatment and control firms to be in the same four-digit SIC industry category.

I estimate the following ordered logistic propensity score model, annually, for firms in my sample:

$$\begin{aligned} Pr(TenureQuint) = {} & \alpha_{\mathrm{k}} + \beta_1 DirectorAge_i + \beta_2 DirectorOwn_i + \beta_3 NumComittee_i \\ & + \beta_4 Size_i + \beta_5 Leverage_i + \beta_6 MTB_i + \beta_7 ROA_i + \beta_8 NumSeg_i \\ & + \beta_9 FirmAge_i + \beta_{10} FirmAge^2{}_i + \beta_{11} CEOOwn_i + \beta_{12} CEOAge \\ & + \beta_{13} CEOTenure + \beta_{14} Duality + \varepsilon_i. \end{aligned} \tag{1}$$

I provide detailed variable definitions in Appendix. The independent variables in Equation (1) are measured in the year prior to tenure length measurement. Table 3, Panel A reports the aggregated estimates of the annual ordered logistic propensity score regression of the percentage of long-tenured directors. *TenureQuint* is a dichotomous variable that equals one if the percentage of long-tenured directors falls within the kth quintile and equals zero otherwise. Column (1) reports the average coefficient estimate across year-specific estimations from 1996 to 2006. Column (2) reports an aggregate z-statistic, which is calculated as the sum of the individual annual z-statistics divided by the square root of the number of years over which Equation (1) is estimated (i.e. 11 years). Columns (3) and (4) report the number of years for which the year-specific coefficient is positive and negative, respectively. The results are generally consistent with prior research. I find that the percentage of long-tenured directors is higher for higher director age, ownership, number of committee memberships, firm size, market-to-book ratio, firm age, CEO ownership, and tenure. In contrast, director tenure appears shorter for firms with higher leverage, for loss firms, and for firms with lower diversity and CEO age. Finally, the pseudo-R^2 is 20.4%, suggesting that propensity score model has reasonable explanatory power.

The second step is to identify matched control firms. Since I use director tenure quintiles as treatment, matching becomes an optimization problem of minimizing a function of the aggregate distances between the propensity scores of the matched pairs. Following Armstrong et al. (2010), I use the nonbipartite matching algorithm developed in Lu, Zanutoo, Hornik, and Rosenbaum (2001) and simultaneously minimize the difference between propensity scores and maximize the

Table 3. Propensity score estimation

Panel A: Propensity score estimation

Dependent variable = *TenureQuint*	Average coeff. (1)	Aggregate z-stats (2)	Years with positive coeff. (3)	Years with negative coeff. (4)
DirectorAge	0.097	17.509	11	0
DirectorOwn	8.412	9.077	11	0
NumComitttee	0.142	3.667	10	1
Size	0.053	3.479	10	1
Leverage	−0.257	−2.141	2	9
MTB	0.025	2.201	9	2
ROA	−0.106	−0.151	5	6
NumSeg	−0.022	−2.331	3	8
FirmAge	0.063	9.938	9	2
FirmAge^2	−0.001	−5.988	2	9
CEOOwn	1.379	4.373	10	1
CEOAge	−0.019	−6.054	1	10
CEOTenure	0.019	6.193	9	2
Duality	−0.012	−0.020	5	6
Intercept TenureQuint 1→ 2	7.791	18.048	11	0
Intercept TenureQuint 2→ 3	9.001	24.947	11	0
Intercept TenureQuint 3→ 4	9.843	25.106	11	0
Intercept TenureQuint 4→ 5	10.931	33.742	11	0
Number of Obs.	7706			
Pseudo-R^2	0.204			

Panel B: Matched-pair frequencies for director tenure quintiles

	Treatment (director tenure quintile)					
Control	1	2	3	4	5	Total
1	0	485	349	34	15	883
2		0	623	240	162	1025
3			0	606	202	808
4				0	847	847
5					0	0
Total	0	485	972	880	1226	3563

Panel C: Covariate balance between the matched pairs

	Mean treatment	Mean control	Differences	T-statistics
DirectorAge	58.811	58.970	−0.159	−1.080
DirectorOwn	0.005	0.005	0.000	0.786

(*Continued*).

Table 3. Continued

	Mean treatment	Mean control	Differences	*T*-statistics
NumComittee	1.020	1.019	0.001	0.069
Size	7.496	7.539	−0.043	−0.822
Leverage	0.233	0.238	−0.005	−0.721
MTB	3.672	3.807	−0.135	−1.117
ROA	0.049	0.047	0.002	0.487
NumSeg	2.412	2.477	−0.065	−1.090
FirmAge	26.986	27.301	−0.315	−0.659
FirmAge^2	953.91	977.12	−23.210	−0.866
CEOOwn	0.031	0.032	−0.001	−0.626
CEOAge	56.210	56.439	−0.229	−0.972
CEOTenure	6.558	6.667	−0.109	−0.442
Duality	0.462	0.478	−0.016	−0.548

Notes: This table reports the propensity score estimation results and covariance balance between the matched pairs. Panel A reports the results of propensity score estimation using conditional ordered logistic regression. *TenureQuint* is a dichotomous variable that equals one if the percentage of long-tenured directors falls within the *k*th quintile and equals zero otherwise. Column (1) reports the average coefficient estimate across year-specific estimation from 1996 to 2006. Column (2) reports an aggregate *z*-statistic, which is calculated as the sum of the individual annual *z*-statistics divided by the square root of the number of years over which Equation (1) is estimated. Columns (3) and (4) report the number of years for which the year-specific coefficient is positive and negative, respectively. Panel B reports the matched-pair frequencies for director tenure quintiles. Panel C reports the covariate balance between the matched pairs. Definitions of other variables are provided in Appendix.

difference between percentage of long-tenured directors.[11] Table 3, Panel B reports the distribution of matched pairs according to their pairwise director tenure quintiles. The matching process results in 3563 matched pairs. The diagonal elements are all zero, since I preclude matches with identical director tenure quintiles. Most matched pairs lie immediately off the diagonal, whereas the difference in the quintile rank of percentage of long-tenured directors between the treatment and control is one. Panel C of Table 3 reports the mean value of each matching variable for the treatment and control groups, as well as the difference between them. None of the matching variable difference is statistically significant, suggesting that the treatment firms and their matched control firms are similar along observable dimensions except for at the level of director tenure.

Table 4 presents the baseline results for the relationship between long director tenure and corporate innovation performance. The dependent variable is R&D intensity in Panel A, number of patents and citations per patent in Panel B, research quotient and exploratory innovation intensity in Panel C, respectively. For each panel, I present the results in two ways. First, I present results based on each possible pairing of director tenure quintile. Since there are five tenure levels and I preclude matched pairs from having identical levels of director tenure, I obtain a total of 10 possible combinations for each pair. This the finest level of aggregation. I report the mean value of innovation variable for each quintile for the treatment and control observations, and assess the significance of their differences. The second way to present the results is to pool all the treatment and control observations and look for differences in innovation variables between these two groups. The results of non-experimental empirical studies are susceptible to hidden bias caused by the omission of a correlated omitted variable. I therefore use a bounding approach, as outlined by Rosenbaum (2002) and Diprete and Gangl (2004), to assess the sensitivity of my inferences to any potential hidden bias that might exist and report the boundary values (where applicable). Finally, I also report the mean value of *TenurePercent10* for each quintile for the treatment and control firms.

[11] See Armstrong et al. (2010) and Lu et al. (2001) for a detailed discussion of the nonbipartite matching algorithm.

Table 4. Board with extended tenure and innovation – baseline analysis

Panel A: R&D investments

TenureQuint		*R&D*					
T	C	T	C	*p*	Γ	$\text{PercentTenure10}_{\text{T}}$	$\text{PercentTenure10}_{\text{C}}$
5	4	0.041	0.039	0.769		0.563	0.412
5	3	0.049	0.052	0.899			
5	2	0.066	0.052	0.624			
5	1	0.014	0.045	0.851			
4	3	0.031	0.028	0.641		0.452	0.340
4	2	0.047	0.061	0.627			
4	1	0.054	0.046	0.763			
3	2	0.044	0.049	0.736		0.328	0.221
3	1	0.064	0.046	0.222			
2	1	0.047	0.046	0.945		0.272	0.125
Pooled	Pooled	0.048	0.044	0.857			

Panel B: Number of patents and citations per patent

TenureQuint		*Lnpatent*						*LnCitePat*					
T	C	T	C	p	Γ	Percent $\text{Tenure10}_{\text{T}}$	Percent $\text{Tenure10}_{\text{C}}$	T	C	p	Γ	Percent $\text{Tenure10}_{\text{T}}$	Percent $\text{Tenure10}_{\text{C}}$
5	4	1.153	1.552	0.074	1.84	0.563	0.412	1.386	1.605	0.048	2.64	0.563	0.412
5	3	0.939	1.718	0.012	4.93			1.623	2.023	0.022	3.95		
5	2	1.028	1.984	0.004	3.75			1.683	1.506	0.051	3.02		
5	1	1.283	2.175	0.009	3.04			1.702	1.836	0.062	2.10		
4	3	1.433	1.645	0.093	1.03	0.452	0.340	1.814	1.823	0.839		0.452	0.340
4	2	1.632	1.941	0.091	1.26			1.893	2.288	0.022	3.87		
4	1	1.547	2.252	0.039	3.87			1.432	1.995	0.005	4.15		
3	2	1.759	2.122	0.088	2.30	0.328	0.221	1.819	1.825	0.894		0.328	0.221
3	1	1.736	2.487	0.032	2.57			1.657	2.372	0.006	3.94		
2	1	1.802	2.440	0.034	2.98	0.272	0.125	1.954	2.493	0.003	2.95	0.272	0.125
Pooled	Pooled	1.587	2.130	0.008	3.36			1.630	2.097	0.024	3.12		

Panel C: Productivity and type of innovation

TenureQuint		*ResearchQuotient*						*Explore*					
T	C	T	C	p	Γ	Percent $\text{Tenure10}_{\text{T}}$	Percent $\text{Tenure10}_{\text{C}}$	T	C	p	Γ	Percent $\text{Tenure10}_{\text{T}}$	Percent $\text{Tenure10}_{\text{C}}$
5	4	0.080	0.111	0.022	2.49	0.563	0.412	0.769	0.902	0.031	1.93	0.563	0.412
5	3	0.063	0.107	0.019	2.84			0.805	0.790	0.585			
5	2	0.067	0.127	0.003	4.02			0.768	0.881	0.040	1.84		
5	1	0.111	0.146	0.035	2.53			0.720	0.942	0.012	2.37		
4	3	0.099	0.097	0.476		0.452	0.340	0.704	0.714	0.017	2.64	0.452	0.340
4	2	0.108	0.118	0.073	1.63			0.833	0.894	0.085	1.79		
4	1	0.094	0.125	0.028	1.50			0.825	0.897	0.082	1.66		
3	2	0.084	0.129	0.015	3.62	0.328	0.221	0.722	0.942	0.020	2.02	0.328	0.221
3	1	0.102	0.131	0.046	1.74			0.892	0.893	0.906			
2	1	0.124	0.148	0.052	2.00	0.272	0.125	0.886	1.000	0.049	2.74	0.272	0.125
Pooled	Pooled	0.094	0.132	0.028	2.58			0.762	0.904	0.047	2.24		

Notes: This table reports the effect of long-tenured directors on corporate innovation performance based on the propensity score matching method. T represents treatment group and C represents control group. *TenureQuint* is a dichotomous variable that equals one if the percentage of long-tenured directors falls within the *k*th quintile and equals zero otherwise. Each cell reports the mean value of innovation variable for firms in the *k*th quintile. *t*-Test are used to assess the significance of difference between innovation performance between treatment and control groups and *p*-values are reported. Γ values quantify the amount of hidden bias necessary to alter the statistical significance ($p = .10$) that results from the assumption that two observations with identical propensity scores have an equal probability of receiving treatment. PercentTenure10_T and PercentTenure10_C are the mean value of percentage of long-tenured directors computed for the treatment and control matched observations reported in each cell. PercentTenure10_T and PercentTenure10_C are reported only when the difference in quintile between treatment and control firms equals 1, since this reflects the minimum director tenure distance and there is sufficient sample size for tests of mean differences.

The results presented in Table 4, Panel A show that long director tenure does not have a significant relation with corporate R&D intensity. There are no instances of statistically lower level R&D intensity for treatment observations relative to control observations for any comparison. It is also worth noting that a comparison of mean values of *TenurePercent10* exhibits a declining trend from top to the bottom row, which provides assurance that my classification of firms into quintiles based on percentage of long-tenured directors is correct. Panel B presents the comparison between treatment and control groups on number of patents and citations per patent. In almost all cases (except for two cells), the mean values of number of patents and citations per patent for the treatment group are significantly lower than for the matched control group, suggesting a negative effect of long director tenure on quantity and quality of patents obtained by the firm. I assess the sensitivity of observed statistically significant results by estimating and reporting the boundary Γ values that quantify the amount of hidden bias necessary to alter the statistical significance ($p = .10$) that results from the assumption that two observations with identical propensity scores have an equal probability of receiving treatment. Larger Γ values suggest that the observed results are less sensitive to hidden bias. Most of my results are robust and not highly sensitive to hidden bias. Panel C presents comparison of research quotient and exploratory innovation intensity between the treatment and control groups. I obtain similar findings as in Panel B. For most cells, research quotient and exploration intensity for treatment observations are significantly smaller than for matched control observations.

Taken together, the empirical findings based on the propensity-score matched-pair design suggest that long-tenured directors hinder corporate innovation. It seems that the adverse effect is not driven by lower R&D investment intensity, but rather driven by a greater inclination for an exploitation-oriented innovation strategy that emphasizes making small incremental changes to current products and/or services, as opposed to exploratory innovation strategies that requires extensive new knowledge and pursue of breakthrough inventions. The observed negative relation between long director tenure and exploration intensity is consistent with the criticism that boards filled with directors having extended tenure may fail to keep current with industrial or technological developments and are less capable of offering new ideas on corporate issues, including innovation. As a result, firms with a high percentage of long-serving directors may be more prone to stay with their current innovation paths and opt for exploitation strategies that emphasize profiting from currently successful approaches and making incremental improvements to existing technologies and/or products. Table 2, Panel B shows that exploration intensity has a significant positive relation with patent quantity and quality, as well as with research quotient. In contrast, exploitation innovation strategies likely lead to fewer patents, and these patents tend to have lower impact, as evidenced by fewer subsequent patent citations received and lower contributions of R&D investments to firms' future revenues.

4. Identification

The baseline results reported in the last section suggest a negative relation between extended board tenure and corporate innovation. The use of the propensity score matching method alleviates the concern of endogeneity to some extent. In this section, I attempt to further establish causality by using two identification strategies that rely on two plausible quasi-natural experiments: sudden deaths of long-tenured directors and regulatory changes in the early 2000s that increased board independence. Both quasi-natural experiments directly affect the percentage of long-tenured directors, but are plausibly exogenous to firms' innovation performance.

4.1. *Sudden Deaths of Long-Tenured Directors*

In this section, I explore the impact of long-serving directors on corporate innovation by examining how corporate innovation performance changes surrounding a reduction in the percentage of long-serving directors due to their sudden deaths using a DiD approach. Identification with multiple shocks avoids a common difficulty faced by studies with a single shock, namely, the existence of potential omitted variables coinciding with the shock that directly affect firm innovation performance. To implement the DiD approach, I need first to identify the treatment and control group. To identify the treatment group, I first identify directors who satisfy two conditions: (1) left their positions due to death during the sample period up to year *t*, and (2) have served on the board for at least 10 years before death, so that they are defined year by year. Deaths of long-tenured directors change the percentage of long-tenured directors (*PercentTenure10*) for the treatment firm.

Following the methodology of Nguyen and Nielsen (2010), I searched Factiva, Lexis-Nexis, and Edgar Online using keyword search terms for directors (board member, director, etc.) and death (passed away, died, deceased, etc.) to identify directors who experienced death during the sample period (i.e. between 1996 and 2006). I only retained deaths that were likely to be exogenous to corporate innovation performance, that is, deaths caused by illness (cancer, heart attack, stroke, etc.), accident, or murder. I rule out other causes, such as suicide. Table 5, Panel A reports the distribution of deaths of long-tenured directors by year. I identified a total of 201 incidents, where year 2004 has the highest number (32) and year 2002 has the lowest number (9). Panel B reports the cause of death. 108 director deaths are due to cancer, heart attack, stroke, complications from surgery or specified diseases, 56 are due to accident or murder; 37 are due to other illnesses, but lack an exact, specified cause.

For a firm to be classified into the treatment group, I also need it to have non-missing matching variables (to be discussed below) for year -1 (one year before the death of a long-tenured director) and non-missing innovation variables (patents, citations, research quotient, exploration intensity, and research intensity) for at least four years before and after the event (year -4, -3, -2, -1, $+1$, $+2$, $+3$, $+4$, respectively). The choice of a nine-year window (from year -4 to year $+4$) reflects the fact that innovation is a long-term corporate initiative and any meaningful changes in innovation outputs surrounding the events may not be readily observed within a narrow window.

I then proceed to construct a control group of firms that are matched to the treatment firms on all important observable characteristics prior to the events, but that do not experience reductions in their percentage of long-tenured directors due to director death. My matching procedure relies on a nearest-neighbor matching of propensity scores, originally developed by Rosenbaum and Rubin (1983) and also adopted in recent literature (Lemmon & Roberts, 2010).[12] I first run a probit regression of a dummy variable that equals one if a particular firm-year belongs to the treatment group (and zero otherwise) on a comprehensive list of observable characteristics, including all the independent variables in my baseline regression, as well as year dummies and SIC industry dummies to capture any time-invariant or industry-specific differences. Further, to ensure that the parallel trends assumption is satisfied, I also match firms on pre-event innovation growth variables, all computed over the four-year period before event.[13]

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[12]See for example, Rosenbaum and Rubin (1983) and Lemmon and Roberts (2010) for a more detailed discussion of the matching method and cautionary notes. I used random forest as an alternative matching algorithm based on Wager and Athey (2015), and results remain qualitatively unchanged.

[13]I match firms on the pre-event four-year averages of innovation variables because many of these variables have values of zero, which makes it difficult to calculate meaningful percentage growth measures. Therefore, to satisfy the parallel

Table 5. DiD analysis – evidence from death of long-tenured directors

Panel A: Deaths of long-tenured directors by year

	Number of long-tenured director	Percentage
1996	17	8.46
1997	10	4.98
1998	14	6.97
1999	20	9.95
2000	13	6.47
2001	11	5.47
2002	9	4.48
2003	20	9.95
2004	32	15.92
2005	27	13.43
2006	28	13.93
Total	201	100.00

Panel B: Cause of deaths

	Number
Illness (Cancer, heart attack, stroke, complications from surgery or specified diseases)	108
Accident or murder	56
Death due to other illness, but unspecified cause	37
Total	201

Panel C: Pre-match propensity score regression and post-match diagnostic regression

	Pre-match Dummy = 1 if in treatment group	Post-match = 0 if in control group
PatGrowth	−0.023**	−0.004
	(0.010)	(0.009)
CiteGrowth	0.008*	−0.001
	(0.005)	(0.000)
RQGrowth	−0.048	−0.021
	(0.036)	(0.019)
ExploreGrowth	0.401**	0.038
	(0.200)	(0.269)
RDGrowth	0.029	0.008
	(0.042)	(0.025)
DirectorAge	0.005**	−0.005
	(0.002)	(0.015)
DirectorOwn	1.294	1.594
	(1.343)	(2.231)
NumComittee	0.246**	0.123
	(0.097)	(0.128)
Size	0.105***	0.079
	(0.032)	(0.054)
Leverage	0.159	0.106
	(0.249)	(0.322)
MTB	0.213	0.540
	(2.463)	(2.699)
ROA	−0.526**	−0.430
	(0.270)	(0.322)
NumSeg	−0.005	−0.001
	(0.176)	(0.022)
FirmAge	0.025**	0.025
	(0.012)	(0.017)
FirmAge^2	−0.001**	−0.001
	(0.000)	(0.001)
CEOOwn	0.376	0.180
	(0.741)	(1.068)

(*Continued*).

Table 5. Continued

Panel C: Pre-match propensity score regression and post-match diagnostic regression

	Pre-match Dummy = 1 if in treatment group	Post-match = 0 if in control group
CEOAge	0.013*	0.015
	(0.006)	(0.010)
CEOTenure	0.002	0.003
	(0.006)	(0.007)
Duality	0.028	0.031
	(0.036)	(0.038)
Constant	−12.145***	−4.927**
	(0.671)	(2.480)
Year and Industry Fixed Effects	Included	Included
Observations	7238	373
Pseudo R^2	0.200	0.031
P-value of Chi-sq	0.003	0.999

Panel D: Estimated propensity score distributions

Propensity Scores	No. of Obs.	Mean	SD	Min	P5	P50	P95	Max
Treatment	132	0.08	0.09	0.00	0.01	0.05	0.26	0.38
Control	241	0.05	0.07	0.00	0.01	0.04	0.22	0.35
Difference		0.03	0.02	0.00	0.00	0.01	0.04	0.03

Panel E: DiD test results

	Mean treatment difference (after – before) (1)	Mean control difference (after –before) (2)	Mean DiD estimator (treat – control) (3)	*Z*-statistics for DiD estimator (4)
RD_4yr_avg	0.003	0.001	0.002	0.222
	(0.005)	(0.007)	(0.009)	
Patent_4yr_avg	3.072	2.210	1.862**	2.019
	(0.845)	(0.681)	(0.922)	
CitePerPat_4yr_avg	1.927	0.845	1.082*	1.831
	(0.468)	(0.570)	(0.591)	
RQ_4yr_avg	0.043	0.018	0.025**	2.083
	(0.011)	(0.013)	(0.012)	
Explore80_4yr_avg	0.004	−0.003	0.007*	1.750
	(0.003)	(0.003)	(0.004)	

Notes: This table reports diagnostics and results of the DiD tests on how changes in the percentage of long-tenured directors due to director death affect firm innovation. A one-to-four propensity matching method is used. Panel A presents the distribution of death of long-tenured directors by year. Panel B presents the distribution of long-tenured directors by cause of death. Panel C presents parameter estimates from the probit model used in estimating the propensity scores for the treatment and control groups. The 'Pre-Match' column contains the parameter estimates of the probit model estimated using the sample prior to matching. These estimates are then used to generate the propensity scores for matching. The 'Post-Match' column contains the parameter estimates of the probit model estimated using the subsample of matched treatment-control pairs after matching. Definitions of variables are listed in Appendix. Panel D reports estimated propensity score distributions. Panel E reports the DiD test results. *RD_4yr_avg* is firm *i*'s average research and development intensity in the four-year window before or after the event year. *Patent_4yr_avg* is firm *i*'s average number of patents in the four-year window before or after the event year. *CitePerPat_4yr_avg* is firm *i*'s average number of citations per patent in the four-year window before or after the event year. *RQ_4yr_avg* is firm *i*'s average research quotient in the four-year window before or after the event year. *Explore_4yr_avg* is firm *i*'s average exploration intensity in the four-year window before or after the event year. Ordinary standard errors are given in parentheses below the mean differences in innovation outputs and bootstrapped standard errors for the two-sample *t*-tests with unequal variance are given below the DiD $t-$stats.

*** Significant at the 1% level.

** Significant at the 5% level.

* Significant at the 10% level.

I report the probit model estimates in the first column of Panel C in Table 5, labeled 'Pre-Match'. The results suggest that the specification has substantial explanatory power for the choice variable, as evidenced by a pseudo-R^2 of 12.4% and a very small p-value for a Chi-square test of the overall model fitness. I then use the predicted probabilities, or propensity scores, from this probit estimation and perform a nearest-neighbor match with replacement. That is, I match each treatment firm with four control firms with the closest propensity scores. Since I allow for replacement, a control firm may be matched to more than one treatment firm. This process results in 132 treatment firms and 241 control firms.

The success of the DiD approach hinges on the 'parallel trends' assumption, which means that in the absence of treatment, the observed DiD estimator is zero. To be precise, the parallel trends assumption does not require the level of outcome variables (innovation variables in my setting) to be identical across the treatment and control firms or across the two regimes, because these distinctions are differenced out in the estimation. Instead, this assumption requires similar trends in the innovation variables during the pre-event regime for both the treatment and control groups. To check if the parallel trends assumption is satisfied, I conduct a number of diagnostic tests to verify that the assumption is indeed satisfied. In the first test, I re-run the probit model restricted to the matched sample and present the probit estimates in column (2) of Table 5, Panel C, labeled 'Post-Match'. None of the independent variables is statistically significant. In particular, the coefficient estimates of pre-shock innovation growth variables are not statistically significant, suggesting no observable different trends of innovation outcomes between the two groups of firms pre-event. Also, the coefficient estimates in column (2) are much smaller in magnitude than the ones in column (1), suggesting that the results in column (2) are not simply an artifact of a decline in degrees of freedom due to the drop in sample size. In addition, the pseudo-R^2 drops dramatically from 12.4% prior to the matching to 3.1% post the matching, and a Chi-square test for the overall model fitness shows that I cannot reject the null hypothesis that all of the coefficient estimates of independent variables are zero (with a p-value of .999).

In my second diagnostic test, I check the difference between the propensity scores of the treatment firms and the scores of their matched control firms. Panel D of Table 6 suggests that the difference is quite trivial. For example, the maximum difference between the two matched firms' propensity scores is only 0.03, while the median difference is 0.

Table 5, Panel E reports the results from the DiD analysis. I report summary measures beginning with the average difference between post-event period and the pre-event period for the treatment and control firms. For example, the first role of column (1) shows the average change in R&D intensity for treatment firms. I compute this estimate by first calculating the four-year average R&D intensity for the post-event era and then subtracting the four-year average intensity for the pre-event era for each firm. This difference is then averaged over treatment firms. A similar procedure is conducted for the matched control firms. I also report the standard error for each average in parentheses. In columns (3) and (4), I report the DiD estimates and the corresponding t-statistics of the null hypothesis that these estimates are zero, respectively, as well as bootstrapped standard errors for the DiD estimates in parentheses in column (3).

As shown in column (1), firms that experienced a reduction in the percentage of long-tenured directors due to director death on average experience an increase of 0.003 in research intensity, 3.072 in patents, 1.927 in citations per patent, 0.043 in research quotient, and 0.004 in exploration intensity in the post-event period (i.e. in the four years after the event). In column (2), control firms experience an increase of 0.001 in research intensity, 2.210 in patents, 0.845 in citations

trends assumption, I match firms on both the numerator and denominator of a hypothetical 'percentage growth rate' for innovation outputs.

Table 6. DiD analysis –evidence from regulatory changes

Panel A: Changes in the percentage of long-tenured directors for treatment firms

	Mean	Median	SD	Obs.
Increase	0.177	0.125	0.166	174
Decrease	−0.105	−0.098	0.117	253

Panel B: Differences in observables

	Increase in percentage of long-tenured directors			
	Treatment	Control	Differences	*T*-statistics
PatGrowth	−1.475	−1.021	−0.454	−0.489
CiteGrowth	−1.579	−1.645	0.066	0.234
RQGrowth	−0.283	−0.244	−0.039	−0.673
ExploreGrowth	−0.041	−0.029	−0.012	−0.467
RDGrowth	−0.001	0.001	−0.002	−0.128
DirectorAge	58.819	57.640	1.179	0.692
DirectorOwn	0.014	0.012	0.002	0.124
NumComittee	1.625	1.483	0.142	0.259
Size	7.379	7.038	0.341	0.259
Leverage	0.269	0.294	−0.025	−0.670
MTB	3.021	3.103	−0.082	−0.294
ROA	−0.178	−0.149	−0.029	−0.162
NumSeg	3.149	3.058	0.091	0.486
FirmAge	26.119	27.032	−0.913	−0.396
FirmAge^2	906.467	928.032	−21.565	−0.402
CEOOwn	0.062	0.064	−0.002	−0.230
CEOAge	55.136	55.837	−0.701	−0.837
CEOTenure	6.699	6.724	−0.025	−0.285
Duality	0.325	0.346	−0.021	−0.730

	Decrease in percentage of long-tenured directors			
	Treatment	Control	Differences	T-statistics
PatGrowth	0.834	1.035	−0.201	−0.630
CiteGrowth	0.440	0.783	−0.343	−1.094
RQGrowth	0.186	0.194	−0.008	−0.118
ExploreGrowth	0.025	0.038	−0.013	−0.487
RDGrowth	0.001	0.001	0.000	0.008
DirectorAge	59.123	59.746	−0.623	−0.573
DirectorOwn	0.011	0.009	0.002	0.009
NumComittee	1.600	1.583	0.017	0.010
Size	7.870	7.448	0.422	0.426
Leverage	0.189	0.206	−0.017	−0.395
MTB	3.100	2.936	0.164	0.623
ROA	0.042	0.034	0.008	0.102
NumSeg	3.000	2.852	0.148	0.857
FirmAge	27.222	26.847	0.375	0.194
FirmAge^2	942.929	920.292	22.637	0.511
CEOOwn	0.095	0.074	0.021	1.294
CEOAge	56.614	56.038	0.576	0.683
CEOTenure	7.926	7.503	0.423	1.024
Duality	0.428	0.395	0.033	0.848

(*Continued*).

Table 6. Continued

Panel C: Estimated propensity score distributions

Propensity scores	Increase in percentage of long-tenured directors				Decrease in percentage of long-tenured directors			
	No. of obs.	Mean	SD	P50	No. of obs.	Mean	SD	P50
Treatment	174	0.16	0.13	0.27	253	0.14	0.14	0.33
Control	307	0.12	0.12	0.23	575	0.12	0.15	0.30
Difference		0.04	0.01	0.04		0.02	−0.01	0.03

Panel D: DiD test results – Increase in percentage of long-tenured directors

Increase in percentage of long-tenured directors	Mean treatment difference (after – before) (1)	Mean control difference (after – before) (2)	Mean DiD estimator (treat – control) (3)	*Z*-statistics for DiD estimator (4)
RD_4yr_avg	−0.002	−0.001	−0.001	−0.143
	(0.005)	(0.006)	(0.007)	
Patent_4yr_avg	3.034	4.492	−1.458	−1.992**
	(0.678)	(0.642)	(0.732)	
CitePerPat_4yr_avg	1.049	2.058	−1.009	−1.834*
	(0.504)	(0.526)	(0.550)	
RQ_4yr_avg	0.128	0.133	−0.005	−0.278
	(0.017)	(0.015)	(0.018)	
Explore_4yr_avg	−0.005	0.006	−0.011	−2.200**
	(0.004)	(0.005)	(0.005)	

Panel E: DiD test results – Decrease in percentage of long-tenured directors

Increase in percentage of long-tenured directors	Mean treatment difference (after – before) (1)	Mean control difference (after – before) (2)	Mean DiD estimator (treat – control) (3)	*Z*-statistics for DiD estimator (4)
RD_4yr_avg	0.001	0.002	−0.001	−0.125
	(0.005)	(0.007)	(0.008)	
Patent_4yr_avg	2.523	−0.029	2.552	2.601***
	(0.703)	(0.681)	(0.981)	
CitePerPat_4yr_avg	2.469	1.052	1.417	1.990**
	(0.673)	(0.694)	(0.712)	
RQ_4yr_avg	0.048	0.021	0.027	1.687*
	(0.016)	(0.013)	(0.016)	
Explore_4yr_avg	0.005	−0.003	0.008	1.143
	(0.006)	(0.005)	(0.007)	

Notes: This table reports diagnostics and results of the DiD tests on how changes in the percentage of long-tenured directors due to regulatory changes in the early 2000s affect firm innovation. A one-to-four propensity matching method is used. Panel A presents the distribution of changes in the percentage of long-tenured directors surrounding the first time that a treatment firm is forced to switch to an independent board following the passage of new regulations. Panel B reports the univariate comparisons between the treatment and control firms' characteristics and their corresponding *t*-statistics. Definitions of variables are listed in Appendix. Panel C reports the distribution of estimated propensity scores for the treatment firm-years, control firm-years, and the difference in estimated propensity scores. Panel D reports the DiD test results based on increase and decrease in the percentage of long-tenured directors, respectively. *RD_4yr_avg* is firm *i*'s average research and development intensity in the four-year window before or after the event year. *Patent_4yr_avg* is firm *i*'s average number of patents in the four-year window before or after the event year. *CitePerPat_4yr_avg* is firm *i*'s average number of citations per patent in the four-year window before or after the event year. *RQ_4yr_avg* is firm *i*'s average research quotient in the four-year window before or after the event year. *Explore_4yr_avg* is firm *i*'s average exploration intensity in the four-year window before or after the event year. Ordinary standard errors are given in parentheses below the mean differences in innovation outputs and bootstrapped standard errors for the two-sample *t*-tests with unequal variance are given below the DiD *t*-stats.

*** Significant at the 1% level.

** Significant at the 5% level.

* Significant at the 10% level.

per patent, and 0.018 in research quotient, as well as a decrease of 0.003 in exploration intensity in the same period.

The DiD estimate for the number of patents *Patent_4yr_avg* is 2.019, and significant at the 5% level. I obtain significant results for citations per patent, research quotient, and exploration intensity. The magnitude of the DiD estimate suggests that compared to firms that do not experience death of long-serving directors, firms that do experience such events on average generate approximately 1.8 more patents per year over four years after the event. Each patent has 1.1 more citations. Research productivity (research quotient) increases by 0.025, which implies that firms enjoy an approximately 0.03% additional increase in revenues for a marginal 1% increase in R&D. Such firms on average incur a 0.007 increase in the intensity of exploratory patents, which implies that the number of exploratory patents in the portfolio increases by 0.7% each year. I do not, however, find a significant difference in R&D intensity between treatment and control firms. These findings are consistent with the baseline results.

4.2. Regulatory Changes in the Early 2000s

My second identification strategy relies upon regulatory changes in the early 2000s that forced publicly listed firms to increase board independence. Pursuant to the recommendations of the Blue Ribbon Committee (BRC) in 1999, the Securities and Exchange Commission (SEC) approved new rules that required public firms to move to a fully independent audit committee with the next re-election or replacement of audit committee members. This rule was written into US law in 2002 as a part of the SOX. It was followed by subsequent New York Stock Exchange and Nasdaq regulations that imposed even stricter requirements on board composition. In addition to having an audit committee composed of merely independent directors, both stock exchanges forced firms to have a majority of independent directors as board members.

These regulations forced publicly traded firms who did not have majority independent directors prior to the new regulations to enhance their board independence. Figure 1 illustrates the fraction of independent boards for my sample firms during the sample period. It shows an increase in board independence from 1996 to 2006, especially around the early 2000s. Figure 1 resembles a pattern that has been documented in other studies for differing sets of public firms (e.g. Duchin, Matsusaka, & Oguzhan, 2010; Linck et al., 2008). Changes in board composition induced by the regulatory changes in the early 2000s likely affect the percentage of long-tenured directors on a given corporate board. I therefore exploit this plausibly exogenous

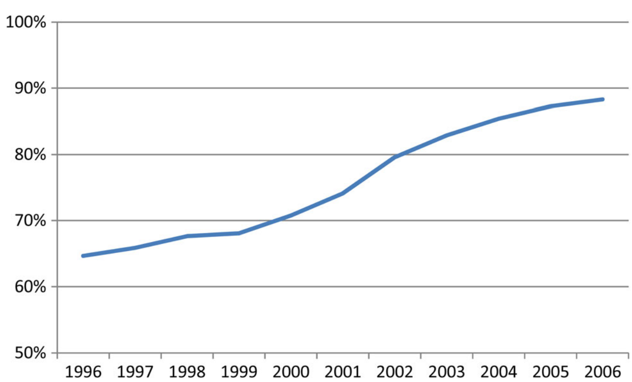

Figure 1. Fraction of independent boards. This graph depicts the fraction of independent boards for sample firms used in this study over the period of 1996 and 2006.

shock to director tenure in an attempt to establish causality between long board tenure and firm innovation performance.[14]

In line with Duchin et al. (2010), I define a firm as a treatment firm if it switched to an independent board after 2000 and had an audit committee that contains 100% independent board members. The latter requirement helps to screen out potential voluntary switches, increasing the amount of truly exogenous increases in the number of independent board members and making my main variable of interest less likely to be confounded by endogenous choice. The event year is the first year the firm switched to an independent board in the post-2000 period. All firms that already satisfied the requirements (and therefore did not need to change their board composition) serve as potential control firms.

Table 6, Panel A presents changes in the percentage of long-tenured directors (for increases and decreases separately) surrounding the event year. After requiring the treatment firms to have non-missing matching variables for year -1 (one year before the compliance year) and non-missing innovation variables for at least four years before the after the event, I identified a total of 427 firms who experienced a change in the percentage of long-tenured directors, among which 174 are increases and 253 are decreases. Average increase (and decrease) in the percentage of long-tenured directors is 0.177 (and -0.105) respectively surrounding the event year.

To identify the causal effect on the change in corporate innovation performance surrounding compliance events, I conduct DiD tests separately for increases and decreases in the percentage of long-tenured directors due to regulatory changes. The procedure is similar to Section 5.1. Table 6, Panel B reports the univariate comparisons between the treatment and control firms' characteristics and their corresponding *t*-statistics, for increases and decreases in percentage of long-tenured directors, respectively. As shown, none of the observed differences between the treatment and control firms' characteristics is statistically significant in the pre-regulatory change regime. As an alternative diagnostic check, in Table 6, Panel C, I report the difference between the propensity scores of the treatment firms and the scores of their matched control firms. Results suggest that the difference is quite trivial.

Table 6, Panel D reports the results of the DiD analysis based on treatment firms that experience an increase in the percentage of long-tenured directors due to regulatory changes. The magnitude of the DiD estimate suggests that, compared to firms that do not experience an increase in the percentage of long-tenured directors, firms that do experience such event on average generate approximately 1.4 fewer patents per year over four years after the event. Each patent has 1 less citation. The number of exploratory patents in the portfolio increases by 1.1% each year. The differences in research quotient and research intensity between treatment and control firms are also negative, although statistically insignificant.

Table 6, Panel E reports the DiD results using treatment firms that experience a decrease in the percentage of long-tenured directors due to regulatory changes. The results are generally the opposite of those in Panel D. The magnitude of the DiD estimate suggests that compared to firms that do not experience a decrease in the percentage of long-serving directors, firms that do experience such events on average generate approximately 2.6 more patents per year over four years after the event. Each patent has 1.4 more citations. These firms also enjoy an

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[14]This identification strategy offers at least three advantages over identification based on sudden deaths of directors. First, the number of firms that are affected by the regulatory changes is larger than the number of firms who experience director death. Second, regulation-induced changes in board composition can potentially lead to changes in the percentage of long-tenured directors in both directions (i.e. increase and decrease) whereas deaths only result in a decrease of percentage of long-tenured directors. Third, regulations affect more directors at a given firm whereas director deaths only affect a small group of directors. I thank the referee for suggesting this identification strategy and for pointing out the advantages of this identification over the sudden deaths of directors.

additional 0.03% increase in revenues for a marginal 1% increase in R&D. Research intensity and exploration intensity exhibit no significant change, however.

Taken together, findings of the two identification tests suggest that extended board tenure has a negative effect on corporate innovation performance, and the relation appears causal.

5. Additional Analyses

5.1. Cross-sectional Tests

The baseline results using the propensity-score matching approach and the two identification tests help alleviate the endogeneity concern and suggest a negative causal relation between extended board tenure and corporate innovation performance. In this section, I examine how the effect varies in the cross-section.

Researchers have argued that overcoming managerial myopia and encouraging innovation requires boards to be supportive (Faleye et al., 2011; Tushman & O'Reilly, 1997). Directors with a greater number of years of overlap in service with their CEOs may establish greater trust and friendship with them, and therefore become more willing to lend support to the CEO for pursuing risky but value-enhancing projects. I therefore expect the adverse effect of long-tenured directors on corporate innovation to be attenuated when long-tenured directors have longer relationships with CEOs.

I report the results in Table 7. Panel A presents the distribution of the number of years of overlap between long-tenured directors and CEOs where the average overlap is 6.9 years. I then partition the sample firms into two subsamples based on whether the overlap is above or below the sample median, and conduct baseline analyses separately for each subsample. Results are reported in Panel B of Table 7. Consistent with my conjecture, the differences in innovation variables between treatment and control observations appear to be less pronounced for the subsample of firms with higher levels of overlap between long-tenured directors and CEOs.

The second contextual variable that I examine is whether the long-tenured director is an executive at other corporations. I argue that long-tenured directors may hinder corporate innovation at least partially because they fail to keep current with industrial or technological developments and bring fresh ideas when performing their advising role. I conjecture that this is less of a problem for directors who are executives in other corporations and therefore are still active in the business arena. I test this conjecture and report evidence in Table 8. Panel A presents the distribution of the percentage of long-tenured directors who are executives at other firms. I then partition the sample based on whether a firm has at least one long-tenured director who is also an executive at other firms, and conduct propensity score matching analysis separately for each subsample. Each firm is matched with a control firm using the same approach as in Equation (1). Results are reported in Panel B of Table 9. Consistent with my conjecture, I find that the adverse effect of long director tenure on innovation is reduced when such directors are executives at other firms.

Overall, findings in this section suggest that the adverse effect of long director tenure on corporate innovation is attenuated for directors who have longer relationships with CEOs and for directors who are executives at other firms. Evidence of the differential effects of long board tenure on innovation activities along these dimensions alleviates endogeneity concerns to some extent and suggests that a causal effect is at least partially at play.

5.2. Long-Tenured Directors on Audit Committees

The effect of long-tenured directors on corporate innovation is also likely to differ by which committees such directors sit on. If long-tenured directors mostly concentrate on the audit committee,

Table 7. Cross-sectional analysis – years of overlap with CEO

Panel A: Distribution of number of years of overlap between long-tenured directors and CEO

	Mean	Median	SD
Years of overlap	6.968	5	6.659

Panel B: Analysis for firms with high overlap and low overlap

Subsample with high overlap

	Treatment	Control	*p*
RD	0.047	0.043	0.512
LnPatent	1.755	1.946	0.063
LnCitePat	1.593	1.865	0.042
RQ	0.095	0.114	0.074
Explore	0.083	0.086	0.734

Subsample with low overlap

	Treatment	Control	*p*
RD	0.042	0.039	0.445
LnPatent	1.649	2.130	<0.001
LnCitePat	1.685	1.882	0.056
RQ	0.089	0.121	0.043
Explore	0.076	0.089	0.073

Notes: This table reports the moderating effect of director's trust and friendship with CEO on the effect of extended tenure on corporate innovation. Director's trust and friendship with CEO is measured by the year of overlap between director and the CEO. Panel A presents the distribution of number of years of overlap between long-tenured directors and the CEO. *High Overlap* equals 1 if the number of years of overlaps is above the sample median. *Low Overlap* equals 1 if the number of years of overlaps is below the sample median. In Panel B, Each firm is matched with a control firm using the same approach as in Equation (1). Average value of innovation variables for the treatment and control firms are reported. *t*-Test is used to test for the mean difference and *p*-values are reported.

they are unlikely to have a significant impact on innovation performance. To test this conjecture, I construct a new variable *AuditCommiteePercentTenure10*, which is calculated as the number of long-tenured independent directors who are also audit committee members divided by the total number of independent directors. As reported in Table 9, Panel A, the average value of *AuditCommiteePercentTenure10* is 0.118, with a standard deviation of 0.143. In Panel B, I repeat the baseline analyses where *PercentTenure10* is replaced by *AuditCommiteePercentTenure10.* Consistent with my conjecture, comparisons of treatment and control groups show that none of the innovation variables differ significantly across the two groups.

5.3. Innovation and Future Firm Performance: The Moderating Role of Extended Director Tenure

In this section, I examine the impact of firm innovation outputs on future value and performance and the moderating role of extended board tenure. For knowledge-intensive firms, intellectual property assets are important intangible assets that create a sustained competitive advantage and

Table 8. Cross-sectional analysis – long-tenured directors who are executives at other firms

Panel A: Distribution of percentage of long-tenured directors who are executives at other firms

	Mean	Median	SD
Percentage of long-tenured directors who are executives at other firms	0.150	0	0.250

Panel B: Analysis for firms with and without long-tenured directors who are executives at other firms

Subsample with long-tenured directors who are executives

	Treatment	Control	*p*
RD	0.035	0.040	0.642
LnPatent	1.754	1.995	0.078
LnCitePat	1.756	1.684	0.156
RQ	0.122	0.132	0.064
Explore	0.086	0.075	0732

Subsample without long-tenured directors who are executives

	Treatment	Control	*p*
RD	0.040	0.036	0.757
LnPatent	1.684	2.103	0.013
LnCitePat	1.739	1.996	0.056
RQ	0.079	0.114	0.025
Explore	0.078	0.090	0.084

Notes: This table reports the moderating effect of the presence of long-tenured directors who are executives at other firms on the effect of extended tenure on corporate innovation. Panel A presents the distribution of percentage of directors with extended tenure who are also executives at other firms. In Panel B, I partition the sample based on whether a firm has at least one long-tenured director who is also an executive at other firms, and conduct propensity score matching analysis separately for each subsample. Each firm is matched with a control firm using the same approach as in Equation (1). Average value of innovation variables for the treatment and control firms are reported. *t*-Test is used to test for the mean difference and *p*-values are reported.

future economic benefits.[15] The value relevance literature in accounting also suggests that financial statements omit salient firm information and documents important contributions of intangible assets to firm valuation (Cohen, Holder-Webb, Nath, & Wood, 2012). Barth, Clement, Foster, and Kasznik (1998), for example, find that brands are important intangible assets and are major drivers of firms' equity values. Lev and Sougiannis (1996) find that R&D investments positively affect firm valuation. Hirschey, Richardson, and Scholz (2001), Lerner (1994), and Kaplan, Sensoy, and Stromberg (2009), among others, similarly provide empirical evidence that patents are important non-financial drivers of value creation and have a significant positive impact on firm value.

[15]Several high-profile intellectual property-based transactions provide good anecdotes. For example, Google purchased Motorola Mobility for $12.5 billion, primarily to obtain 14,600 granted patents and 6700 pending patents. Similarly, Nortel Network's patent portfolio was purchased for $4.5 billion by several companies, including Apple, Microsoft, and Research in Motion.

Table 9. Additional analysis – long-tenured directors on audit committee

Panel A: Distribution of long-tenured directors on the audit committee

	Mean	Median	SD
AuditCommiteePercentTenure10	0.118	0	0.143

Panel B: Long-tenured audit committee members and innovation

	Treatment	Control	*p*
RD	0.038	0.031	0.583
LnPatent	1.920	1.696	0.294
LnCitePat	1.752	1.893	0.658
RQ	0.114	0.125	0.549
Explore	0.076	0.080	0.774

Notes: This table reports the relation between long-tenured audit committee members on corporate innovation. Panel A presents the distribution of the percentage of audit committee members with at least 10 years of service. Panel B reports the relation between long-tenured audit committee members and corporate innovation based on the propensity score matching approach as in Equation (1). Average value of innovation variables for the treatment and control firms are reported. *t*-Test is used to test for the mean difference and *p*-values are reported.

I postulate that if stale boards have an adverse impact on corporate innovation productivity and quality, innovation outputs at these firms may have lower future economic benefits. I examine Tobin's Q and return on assets (ROA), respectively, two commonly used measures of firm performance in the analyses of relationship between governance and performance (Hermalin & Weisbach, 2003; John & Senbet, 1998). I use the following model to test this conjecture:

$$\begin{aligned} TobinQ_{i,t+3}(ROA_{i,t+3}) = {} & \alpha + \beta LnPatent_{i,t} + \beta_2 LnPatent_{i,t} \times PercentTenure10_{i,t} \\ & + \beta_3 PercentTenure10_{i,t} + \lambda' Control_{i,t} + Year_t + Industry_j + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where i indexes firm, j indexes industry, and t indexes time. The main variable of interest is *PercentTenure10*. *Control* is a vector of firm characteristics that could affect firms' future performances. *Year* and *Industry* capture year and industry fixed effects, respectively. To account for the long-term nature of innovation activities and the possibility that it may take several years for a firm to materialize financial benefits from innovation outputs, I link innovation outputs in year t to Tobin's Q and ROA in year $t + 3$. I cluster standard errors at the firm level.

Table 10 reports the regression results estimating Equation (2). The dependent variable is Tobin's Q in column (1). The coefficient estimate on the key variable number of patents *LnPatent* is positive and significant at the 1% level, suggesting that firm innovation outputs positively contribute to future firm value. Coefficient on board tenure is insignificant, suggesting that board tenure does not have a direct impact on future firm value when *LnPatent* equals 0. In contrast, the coefficient on the interaction term *LnPatent* × *PercentTenure10* is significantly negative at the 5% level, suggesting that the contribution of innovation outputs to future firm value is smaller at firms with longer tenured boards.

The dependent variable is three-year-ahead ROA in column (2). The coefficient estimate on the key variable number of patents *LnPatent* is positive and significant at the 5% level, suggesting that firm innovation outputs positively contribute to future firm profitability. While I do not find that board tenure has direct impact on future ROA conditional on *LnPatent* being equal to 0, the coefficient on the interaction term $LnPatent_{i,t} \times PercentTenure10$ is significantly negative at the 5% level, suggesting that the contribution of innovation outputs to future profitability is smaller at firms with longer tenured boards.

Table 10. Innovation, future firm performance and the moderating effect of boards with extended tenure

	TobinQ ($t + 3$)	*ROA* ($t + 3$)
Dependent Variable =	(1)	(2)
LnPatent	0.302***	0.040**
	(0.113)	(0.021)
PercentTenure10 × *LnPatent*	– 0.092**	– 0.012**
	(0.046)	(0.006)
PercentTenure10	0.176	0.027
	(0.129)	(0.021)
Size	0.257***	0.010***
	(0.256)	(0.003)
ROA	0.311	0.219***
	(0.626)	(0.058)
Leverage	– 1.041***	– 0.046*
	(0.210)	(0.024)
Capex	0.421	– 0.046
	(0.676)	(0.097)
R&DAssets	4.565***	0.399
	(0.828)	(0.276)
PPEAssets	– 0.617***	0.006
	(0.106)	(0.016)
Constant	0.375	– 0.045**
	(0.241)	(0.022)
Year and Industry Fixed Effects	Included	Included
Adjusted R^2	0.34	0.30
Observations	7012	7431

Notes: This table reports regression estimates of future firm value and performance on innovation outputs and the moderating effect of boards with extended tenure. *TobinQ*($t + 3$) is firm's market-to-book ratio during fiscal year $t + 3$, calculated as [market value of equity (#199 × #25) plus book value of assets (#6) minus book value of equity (#60) minus balance sheet deferred taxes (#74, set to 0 if missing)] divided by book value of assets (#6). Capex is capital expenditure (#128) scaled by book value of total assets (#6) measured at the end of fiscal year t; *PPEAssets* is property, plant & equipment (net, #8) divided by book value of total assets (#6) measured at the end of fiscal year t. Definitions of other variables are provided in Appendix. Year and industry fixed effects are included in all regressions but the coefficients are not reported. Robust standard errors clustered by firm are displayed in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

6. Concluding Remarks

In this paper, I examine the effect of extended director tenure on corporate innovation performance based on a sample of US firms from 1996 to 2006. Using a propensity-score matched-pair research design, I find that firms with a higher portion of independent directors with extended tenure (i.e. with board service exceeding 10 years) produce significantly fewer patents and these patents receive fewer subsequent citations. These firms also have lower research and development (R&D) productivity and exploration intensity than their matched control firms, although I find no significant difference in their R&D investment. DiD tests based on director deaths and regulatory changes in the early 2000s suggest that the adverse effect of long director tenure on innovation performance appears causal. I also find that the effect is mitigated when the long-tenured director has a longer relationship with the CEO and when the long-tenured director is an executive at other firms. Finally, boards with extended tenure attenuate the contribution of innovation outputs to future firm value and performance.

This paper's empirical findings provide new insights on the debate over director tenure. Most prior arguments have centered around its impact on the monitoring role of directors and whether long tenure compromises director independence. I provide a new perspective by examining the impact of long tenure on directors' advisory role as reflected in corporate innovation activities and performance. My findings suggest that long-serving directors are less effective in advising management on innovation activities. My evidence also suggests that the adverse effect does not seem to occur through a reduction in R&D investments, but rather through the choice of a more conservative and exploitation-orientated innovation approach. This study's findings have regulatory implications and provide a potential justification for limiting directors' terms of service. Future research can expand the analysis to other aspects of the advisory role (e.g. merger and acquisition activity) that may be affected by extended director tenure.

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Appendix. Variable definition

This appendix presents definitions of variables used in the baseline analysis.

Variable	Definition
R&D	Research and development intensity, defined as search and development expenditure (#46) divided by book value of total assets (#6) measured at the end of fiscal year *t*;
LnPatent	Natural logarithm of one plus firm *i*'s total number of patents filed (and eventually granted) in year $t + 3$;
LnCitePat	Natural logarithm of one plus firm *i*'s total number of citations received on the firm's patents filed (and eventually granted) scaled by the number of patents filed (and eventually granted) in year $t + 3$;
ResearchQuotient	Firm-specific output elasticity of R&D that represents the percentage increase in revenues from a 1% increase in R&D in year *t;*
Explore	Number of exploratory patents filed in year $t + 3$ divided by the number of all patents filed by the firm in the same year. A patent is classified as exploratory if at least 80% of its citations are based on new knowledge;
PercentTenure10	Percentage of independent directors who have served at least 10 years (inclusive) on the board of directors of a firm as of year *t*;
DirectorAge	Average director age in a firm in year *t*;
DirectorOwn	Percentage of firm's shares held by directors in year *t*;
NumComittee	Average number of committee memberships held by directors in a firm in year *t*;
Size	Firm size, defined as the natural logarithm of book value of market value of equity (#199 $\times$ #25) measured at the end of fiscal year *t*;
Leverage	Leverage ratio, defined as book value of debt (#9 + #34) divided by book value of total assets (#6) measured at the end of fiscal year *t*;
MTB	Market-to-book ratio during fiscal year *t*, calculated as [market value of equity (#199 $\times$ #25) plus book value of assets (#6) minus book value of equity (#60) minus balance sheet deferred taxes (#74, set to 0 if missing)] divided by book value of assets (#6);
ROA	Return on assets ratio, calculated as operating income before depreciation (#13) divided by book value of total assets (#6), measured at the end of fiscal year *t*;
NumSeg	Firm's number of business segments in year *t*;
FirmAge	Number of years since the firm first appeared on Compustat as of year *t*;
$FirmAge^2$	Square term of firm age;
CEOOwn	Percentage of firm shares held by the CEO as of year *t*;
CEOAge	CEO age as of year *t*;
CEOTenure	Number of years that the CEO has been holding the current position as of year *t*;
Duality	A dummy variable equals 1 if the CEO is also the chairman of the board in year *t*, and 0 otherwise;