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Bringing Innovation to Fruition: Insights From New Trademarks

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Abstract

We build a novel comprehensive data set of new product trademarks as an output measure of product development innovation. We show that risk-taking incentives in CEO compensation motivate this type of innovation and that this innovation improves firm performance. Using an exogenous shock to executive compensation, we find that reductions in stock option compensation cause reductions in new product development. We also find that firms undertaking new product development experience increases in future cash flow from operations and return on assets. These findings suggest the importance of product development innovation to firms and new trademarks as a novel innovation measure.

I. Introduction

The culmination of the innovation process is most often a new product or service, which is often filed as a new trademark with the United States Patent and Trademark Office (USPTO).[1] The academic literature on innovation has focused almost exclusively on scientific research and technological innovation, studying research and development (R&D) inputs and patent outputs. Both these measures

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capture primarily the earlier phases of high-technology innovation. In this study, we investigate product development innovation to evaluate the importance of this later phase of innovation. We analyze whether risk-taking incentives in CEO compensation motivate new product development and whether this innovative activity improves firm performance. To our knowledge, no academic study has examined these questions, due likely to the prior absence of a comprehensive data set measuring new product development.

To fill this gap in the literature, we build a novel comprehensive data set of new product trademarks by S&P 1500 companies over 20 years to capture firm-level product development innovation, and examine the incentives and consequences related to new product development. We use this data set to assess whether new product development is associated with increases in firm risk. We then test whether firms motivate the development of new products using risk-taking incentives in CEO compensation, specifically vega, the convexity of compensation with respect to firm value.[2] Finally, we examine whether new product development is associated with improvements in firm performance, namely cash flow from operations (CFO) and return on assets (ROA). Such evidence, on risk-taking incentives and improvements in performance, would validate the importance of product development innovation to firms.

In contrast to the academic literature, the corporate world and policy agencies appreciate the importance of product development innovation. In the corporate world, CEOs rank new product development high in importance for firm innovation, growth, and performance in several large surveys. For example, PricewaterhouseCooper's (PwC) annual global surveys report that CEOs rank new product development among the top agenda items to fuel firm growth, sometimes even above increasing market share, and they do so in "virtually all industries."[3] New products or services are necessary to penetrate new markets and maintain share in existing markets. The survey of over 45,000 companies by the Census Bureau and National Science Foundation's Business Research and Development and Innovation Survey (BRDIS) indicates that the percentage of firms ranking trademarks, output measures of product development innovation, as "very important" exceeds the percentage of firms ranking patents, output measures of scientific research,

Meeting, the AAA 2015 Managerial Accounting Section Midyear Meeting, the 2014 AAA Western Region Meeting, the 2015MIT Asia Conference, the 2016 Temple Conference on Convergence of Financial and Managerial Accounting, the 2015 UCI/UCLA/USC Conference, the 2015 Utah Winter Accounting Conference, and discussants Thomas Bourveau, Brian Cadman, Christo Karuna, Chen Li, Maria Loumioti, and Volkan Muslu. We gratefully acknowledge financial support from The Don Beall Center for Innovation and Entrepreneurship at the UCI Paul Merage School of Business.

[1]For brevity, we refer to new product(s) and/or new service(s) as new product(s) in the article.

[2]Previous studies provide evidence that managerial risk-taking can be motivated by incentives in the executive compensation structure. However, the importance of risk-taking compensation incentives in firms that undertake product development innovation has not been studied.

[3]See PricewaterhouseCoopers' 14th Annual Global CEO Survey (PwC (2011), Figure 5, p. 9) and 17th Annual Global Survey (PwC (2014)), sent to over 2,000 CEOs of top companies globally, with responses from over 1,300 CEOs.

and technological innovation as "very important" by double digits in several industries.[4,5]

With respect to policy agencies, the Organisation of Economic Cooperation and Development (OECD) defines innovation broadly as:

> … the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations (OECD/Eurostat (2005), p. 46, OECD (2010a), (2010b)).

Notably, this definition extends innovation to include "activities related to the development and implementation of product and process innovations … *that are not already included in R&D*" (emphasis added, OECD/Eurostat (2005), p. 98). Furthermore, page 114 of the OECD manual identifies trademarks, in addition to patents, as means of appropriating gains to innovation.

The innovation literature, employing R&D as inputs and/or patents as outputs, fails to capture innovation occurring in a large segment of companies. Some of the significant shortcomings from relying on R&D and/or patent data to measure innovation are highlighted by Koh and Reeb (2015) and Koh, Reeb, Sojli, Tham, and Wang (2022)).[6] More broadly, as noted above, R&D and patents relate to earlier phases of the innovation process, whereas trademarks represent its culmination. Studying only earlier and higher-tech innovation phases limits the analysis to a few industries and provides an incomplete understanding of innovation. Using a more

[4]https://ncses.nsf.gov/pubs/nsf18313/#& website explains BRDIS as "the primary source of information on research and development performed or funded by businesses within the United States." The sample contains for-profit companies with a U.S. presence and five or more employees engaged in the mining, utilities, construction, manufacturing, wholesale trade, retail trade, or services industries. Out of a population of 2 million eligible companies, over 6,000 with at least $1 million in R&D activity are sent the standard survey (BRDI-1), and about 40,000 other companies are sent a shorter survey (BRDI-1(S)) for a sample size of approximately 45,000 companies.

[5]Eleven industries with this gap are beverage and tobacco products (gap of 54.9%), finance and insurance (46.6%), food (45.9%), miscellaneous manufacturing (28.6%), wood products (25.0%), transportation and warehousing (23.2%), information (20.0%), machinery (17.4%), wholesale trade (16.2%), textile, apparel, and leather products (15.6%), and other nonmanufacturing (11.1%). In contrast, the importance of patents exceeding trademarks by double digits occurs in the following four industries: chemicals (gap of 20.4%), professional, scientific, and technical services (13.1%), electrical equipment, appliances, and components (12.3%), and computer and electronic products (10.9%). Aggregating across all industries, the gap is 1.2%, with 15.9% more firms rating trademarks as very "important" or "somewhat important" than firms rating patents as "very important" or "somewhat important." See Data Table 59 of the latest NSF (2015) survey (https://ncses.nsf.gov/pubs/nsf18313/#&).

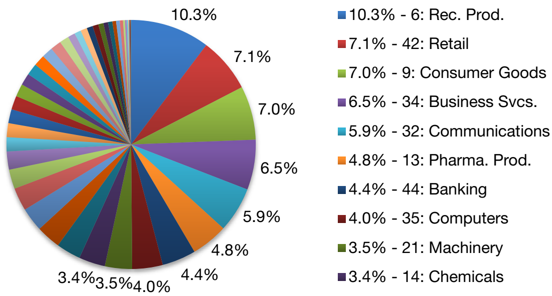
[6]Koh and Reeb (2015) and Koh et al. (2022) document the high rate of firms that do not report R&D expenditures. This is in part due to accounting rules. Expenditures on innovation activities are classified as R&D expense only under specific circumstances by generally accepted accounting principles (GAAP), and innovation-related expenditures are sometimes included in other expense items such as operating expense or selling, general, and administrative (SG&A) expense instead. Even among firms which seem to conduct research and development activities, many do not report R&D expense separately. In addition, many firms that report R&D expense do not file for patents. Koh et al. (2022) show that such missing/zero values are nonrandom and can induce bias into analyses. Trademarks can help partly fill this gap, by providing data on firm-level innovation activities, especially for firms that do not report R&D and/or do not file for patents.

FIGURE 1

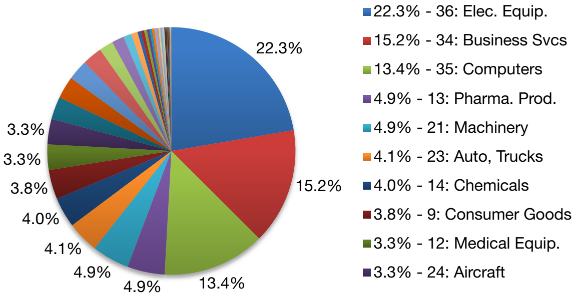
Distribution of New Product Trademarks and New Patents by Industry

Figure 1 presents the distribution by industry of new product trademarks (top figure) and new patents (bottom figure). The samples cover fiscal years 1993-2011 and include 70,465 new product trademarks by 2,293 distinct firms and 795,088 new patents by 1,711 distinct firms. Industry grouping is based on the Fama and French 48–industry classification.

Graph A. New Product Trademarks



Graph B. New Patents



comprehensive measure of innovation that applies across a large swath of firms provides a more complete understanding of the drivers and consequences of firm innovation efforts. Empirically, 56.4% of all S&P 1500 firms and 50.7% of S&P 1500 firms with product trademarks do not report R&D during our sample period. Additionally, 47.8% of all S&P 1500 firms and 46.6% of S&P 1500 firms with product trademarks do not register patents (see Figure 1). These statistics suggest that many new product trademarks are unrelated to R&D or patents, which confirms that these measures capture distinct underlying innovative activities.

To illustrate, certain major industries, such as financial services and alcoholic beverages, do not usually generate patents, despite extensive innovation. Their innovations include new financial securities, new ways of investing, and new banking and payment methods in the financial services industry as well as new containers and recipes in the beverage industry.[7] Furthermore, disruptive innovations need not originate from technological innovation but may result from business model innovation, often using existing technologies (Christensen, Raynor, and McDonald

[7]Alcoholic beverages are a low-patent industry, ranked 25th in patent intensity, but which has the second highest number of new product trademarks per firm year among the 48 major industries (Panel D of Table 1). As one example among others, Diageo PLC highlights its innovation department on its website (http://www.diageo.com/en/our-business).

(2015)). Two prominent examples are Uber, with its model of digitally connecting riders with drivers using existing technologies, and Netflix, with its highly innovative DVD-by-mail service (now superseded by streaming) which relied on straightforward technology and software. These two companies are undoubtedly innovative, but they belong in low-patent industries (transportation and entertainment, ranked 39th and 28th in patent intensity, respectively, out of 48, see Panel D of Table 1), and many of their innovations are trademarked rather than patented. Using patent-intensity measures would misclassify them as being less innovative than they truly are.

To compile our comprehensive data set, we obtain trademark information from the USPTO. Our sample consists of 105,582 firm-level U.S. trademark by S&P 1500 firms from fiscal years 1993– 2011. We distinguish between product development and marketing by classifying new trademarks as either new product trademarks or new marketing trademarks and focus on new product trademarks to capture firm-level product development innovation.[8] For firms with both patents and trademarks, trademarks may be an extension of having patents. Thus, for our main analyses, we report results for the full sample of firms as well as separately for firms in low- and high-patent industries. The low-patent sample can better isolate the effects of new product development in firms where product development innovation is economically important. The high-patent sample provides insights about the incremental importance of product development in the final phases of the innovation process to bring patented technologies to the market as new products. We define low-patent industries as those with fewer than 15 patents per firm year, on average (see Panel D of Table 1). Firms in these industries are important for the economy, representing 63.3% of the sales of all S&P 1500 firms in our sample. Additionally, these firms use significant amounts of option-based compensation, 23.8% of total CEO compensation on average, compared to an S&P 1500 average of 27.7%, suggesting that risk incentives matter for these firms, despite their low patent innovation.

We first examine whether new product development is associated with increases in firm risk, as predicted if they represent a risky innovative activity. We then examine the incentives that motivate product development innovation. Consistent with theoretical predictions of compensation models for the motivation of risky innovation, we find a statistically and economically significant positive relation between incentive convexity in CEO compensation structure and product trademark creation. An interquartile increase of our risk-taking incentives measure, ln(VEGA), increases product trademark creation by 9.0% for a firm producing one product trademark per year. We find that this risk-taking incentive effect is driven by firms in industries where product development innovation is of greater importance.

Next, we find that product development innovation is associated with improved future firm performance. Specifically, new product trademarks increase future CFO and ROA, with statistically and economically significant effects. An interquartile increase in the number of new product trademarks (equivalent to an

[8]For details, see Sections II.A and III.A as well as Appendix A. Additional details of the compilation procedure for the dataset are available upon request.

TABLE 1

Distribution of New Product Trademarks and Firm-Years

Panel A of Table 1 presents the distribution by year of the sample of 70,465 new product trademarks by 2,293 distinct firms and all firm-year observations (43,013 firm-year observations from 3,276 distinct firms). Panel B presents the distribution of new product trademarks in a year across all firms and firms with at least one new product trademark (i.e., "new product trademark sample"). Panel C presents selected summary statistics for firm-year observations in the new product trademark sample (14,077 firm-year observations from 2,293 distinct firms) and all firms (43,013 firm-year observations from 3,276 distinct firms), which includes the new product trademark sample. Panel C also presents comparisons and results of *t*-tests (Wilcoxon rank-sum tests) of mean (median) differences for each variable. Panel D presents the ranking of low- and high-patent industries, where low-patent (high-patent) industries have less (more) than 15 patents per firm year on average. Panel D shows the distribution by industry of all firm-year observations, the sample of new patents, and the sample of new product trademarks, as well as the average number of new patents per firm-year and new product trademarks per firm-year in each industry, along with the corresponding rank across all 48 industries. Ranks are from one (highest number per firm year) to 48 (lowest number per firm year). In all panels, the sample covers fiscal years 1993–2011. See Appendix B for variable definitions. Industry grouping is based on the Fama and French 48-industry classification. To mitigate the influence of outliers, all variables except NB_MONTHS are winsorized at the 1st and 99th percentiles.

Panel A. Distribution of New Product Trademarks and Firm-Years by Fiscal Year

	New Product Trademarks		All Firm-Years	
Year	*N*	%	*N*	%
1993	3,032	4.30	2,247	5.22
1994	3,136	4.45	2,348	5.46
1995	3,681	5.22	2,532	5.89
1996	4,089	5.80	2,600	6.04
1997	4,073	5.78	2,569	5.97
1998	3,956	5.61	2,555	5.94
1999	3,887	5.52	2,490	5.79
2000	4,008	5.69	2,392	5.56
2001	4,114	5.84	2,323	5.40
2002	3,975	5.64	2,323	5.40
2003	3,972	5.64	2,315	5.38
2004	3,837	5.44	2,287	5.32
2005	3,612	5.13	2,227	5.18
2006	4,063	5.77	2,153	5.00
2007	4,153	5.89	2,056	4.78
2008	3,788	5.38	1,977	4.60
2009	3,410	4.84	1,936	4.50
2010	3,171	4.50	1,878	4.37
2011	2,508	3.56	1,805	4.20
All Years	70,465	100.00	43,013	100.00

Panel B. New Product Trademarks Per Firm-Year

	No. of Firm-Years	Min	Q1	Mean	Median	Q3	P99	Max	Std. Dev.
All firms	43,013	0	0	1.6	0	1	21	496	8.0
New product trademark firms	14,077	1	1	5.0	2	5	40	496	13.3

Panel C. New Product Trademark Firm-Years Versus All Firm-Years

	Variable					
	New Product Trademark Firm-Years *N* = 14,077		All Firm-Years *N* = 43,013		Trademark Versus All *p*-Value of Difference	
	Mean	Median	Mean	Median	Mean	Median
TOTAL_ASSETS ($M)	14,619.0	1,751.5	7,377.5	1,082.1	<0.01	<0.01
MVE ($M)	9,658.2	1,911.1	4,614.1	998.4	<0.01	<0.01
SALES ($M)	6,603.9	1,580.4	3,438.8	813.2	<0.01	<0.01
ROA	0.0448	0.0501	0.0348	0.0428	<0.01	<0.01
TOBIN_Q	2.1079	1.5878	1.9404	1.4458	<0.01	<0.01
LEVERAGE (% of TOTAL_ASSETS)	0.5579	0.5572	0.5584	0.5553	0.85	0.74
R&D (% of SALES)	0.0476	0.0049	0.0477	0.0000	0.98	<0.01
NB_MONTHS	287.0	223.0	244.8	178.0	<0.01	<0.01
SALARY ($K)	725.57	685.00	633.98	582.10	<0.01	<0.01
BONUS ($K)	655.81	236.25	489.56	158.50	<0.01	<0.01
OPTION_GRANTS ($K)	2,283.70	753.85	1,549.37	420.26	<0.01	<0.01
STOCK_GRANTS ($K)	946.21	0.00	752.27	0.00	<0.01	<0.01
TOTAL_COMP ($K)	5,619.07	3,180.82	4,238.73	2,266.83	<0.01	<0.01
OPTION_COMP (% of TOTAL_COMP)	0.3160	0.2803	0.2773	0.2214	<0.01	<0.01
VEGA ($K)	168.87	65.33	112.38	40.08	<0.01	<0.01
DELTA ($K)	1,070.02	282.43	683.51	196.18	<0.01	<0.01

(continued on next page)

TABLE 1 (continued)

Distribution of New Product Trademarks and Firm-Years

Panel D. Ranking of Low- and High-Patent Industries

Industry Code and Description	No. of Firm-Years	New Patents: No. (% of Total)	New Patents: Avg No. Per Firm-Year	New Patents: Rank	New Product Trademarks: No. (% of Total)	New Product Trademarks: Avg No. Per Firm-Year	New Product Trademarks: Rank
High-patent industries							
24: Aircraft	191	3.31	137.80	1	0.66	2.43	13
26: Defense	93	0.84	71.96	2	0.61	4.59	5
36: Electronic equipment	2,569	22.31	69.04	3	3.42	0.94	31
35: Computers	1,615	13.37	65.84	4	3.96	1.73	21
48: Miscellaneous	471	2.95	49.82	5	1.55	2.32	14
23: Automobiles and trucks	726	4.13	45.22	6	2.51	2.44	11
9: Consumer goods	713	3.83	42.69	7	6.99	6.91	3
14: Chemicals	1,021	3.95	30.79	8	3.52	2.43	12
38: Business supplies	674	2.57	30.31	9	2.35	2.46	10
34: Business services	4,305	15.19	28.05	10	6.50	1.06	30
21: Machinery	1,490	4.87	25.99	11	3.16	1.50	23
12: Medical equipment	1,049	3.32	25.20	12	3.18	2.14	17
13: Pharmaceutical products	1,543	4.88	25.15	13	4.76	2.17	16
22: Electrical equipment	541	1.59	23.37	14	1.52	1.98	18
32: Communications	1,014	2.90	22.71	15	5.88	4.08	6
1: Agriculture	139	0.32	18.38	16	0.25	1.29	25
37: Measuring and control equip.	826	1.85	17.82	17	1.40	1.20	27
25: Shipbuilding, railroad equip.	67	0.13	15.43	18	0.12	1.22	26
Low-patent industries							
30: Petroleum and natural gas	1,606	2.67	13.22	19	1.21	0.53	39
6: Recreational products	220	0.36	12.90	20	10.30	32.99	1
5: Tobacco products	71	0.10	11.75	21	0.56	5.58	4
17: Construction materials	739	1.06	11.36	22	0.95	0.90	33
39: Shipping containers	185	0.19	8.17	23	0.20	0.75	34
15: Rubber and plastic products	208	0.15	5.57	24	0.48	1.63	22
4: Alcoholic beverages	135	0.09	5.19	25	1.44	7.50	2
19: Steel works, and so on	811	0.44	4.31	26	0.85	0.73	35
10: Apparel	629	0.30	3.80	27	1.65	1.84	19
7: Entertainment	503	0.23	3.67	28	1.79	2.50	9
18: Construction	527	0.19	2.82	29	0.42	0.56	38
16: Textiles	236	0.08	2.55	30	0.76	2.27	15
2: Food products	777	0.25	2.52	31	2.99	2.71	8
28: Nonmetal and metal mining	146	0.03	1.77	32	0.09	0.42	41
20: Fabricated products	116	0.02	1.28	33	0.08	0.50	40
42: Retail	2,738	0.43	1.25	34	7.09	1.83	20
44: Banking	2,682	0.35	1.05	35	4.39	1.15	28
47: Trading	2,268	0.29	1.01	36	1.81	0.56	37
41: Wholesale	1,409	0.13	0.75	37	1.81	0.91	32
45: Insurance	1,923	0.15	0.62	38	3.09	1.13	29
40: Transportation	1,069	0.06	0.47	39	0.85	0.56	36
27: Precious metals	138	0.01	0.42	40	0.00	0.01	48
11: Healthcare	843	0.04	0.34	41	0.48	0.40	42
8: Printing and publishing	407	0.01	0.29	42	1.84	3.19	7
31: Utilities	2,085	0.05	0.19	43	0.78	0.26	45
3: Candy and soda	96	0.00	0.18	44	0.05	0.34	44
33: Personal services	460	0.01	0.12	45	0.23	0.36	43
43: Restaurants, hotels, motels	787	0.00	0.05	46	1.45	1.30	24
29: Coal	84	0.00	0.05	47	0.01	0.10	46
46: Real estate	68	0.00	0.01	48	0.01	0.09	47

increase of one new product trademark in a year) increases CFO by 0.13% (0.17%) and ROA by 0.24% (0.31%) in the 1 (2) subsequent year(s). In comparison, the sample median changes in 1 (2) subsequent year(s) are −0.07% (−0.15%) for CFO and 0.03% (−0.06%) for ROA, respectively. Additional analyses indicate that the association between product development innovation and improvements in future firm performance is driven by new product development that is deemed to be of higher quality.

All results are of similar magnitude and statistical significance when focusing on firms in low- and high-patent industries separately. Importantly, all results are incremental to the inclusion of new patents in all of our regressions. Overall, our findings suggest that, even after controlling for scientific research and technological innovation, CEOs respond to increased risk-taking compensation incentives with increased product development innovation and firms engaged in more product development innovation experience improvements in firm performance.

Since compensation is endogenous, instead of convex compensation schemes encouraging risky product development innovation, it could be that firms with strong product development opportunities select convex compensation schemes. Boards of directors may select such schemes, owing to a desire to incentivize managers to pursue these development opportunities. However, this possibility is also consistent with product development being a value-creating activity that boards of directors, on behalf of shareholders, seek to encourage. In other words, the reverse causality interpretation is consistent with product development innovation being an important source of value creation.

Nevertheless, we conduct an additional analysis to address whether option compensation drives trademark creation and examine an event that represents an exogenous shock to executive compensation. A revised accounting rule, SFAS 123 (R), required firms to include stock option compensation as an expense in the income statement in fiscal years beginning after June 15, 2005, raising the reporting costs of using stock options. This reduced many firms' use of option compensation for an exogenous reason unrelated to new product development. We use propensity-score matching to create matched pairs of firms that are similar along a wide set of firm characteristics but differ in how SFAS 123(R) affects them. We find that firms with top-tercile stock option compensation before SFAS 123(R) significantly reduce product trademark creation, relative to similar firms less affected by SFAS 123(R), consistent with risk-taking compensation incentives driving new product development.

Our study makes several contributions. We examine a central yet underexplored firm innovative activity, product development innovation, using product trademark creation. We validate that new product development is associated with increases in firm risk, consistent with representing a risky form of innovation. Our study provides the first evidence that CEO risk-taking incentives, specifically convexity of compensation, motivates product development innovation incrementally to motivating patent innovation. The effect is present for all firms, including those in both low- and high-patent industries. Our study generalizes Mao and Zhang's (2018) finding that risk-taking compensation incentives motivate patents in several ways. We show that risk-taking compensation incentives also motivate innovation beyond the patent innovation phase. Our results for firms in low-patent industries help explain the extensive use of executive risk-taking compensation incentives, even in firms with less scientific research and technological innovation. We also provide the first evidence that product development innovation is valuable to companies through improvements in firm performance, specifically cash flow from operations and return on assets.

Collectively, our findings provide insights into the structure of compensation contracts to motivate product development innovation, and the benefits of this innovation for future firm performance for all firms in the economy. Our evidence indicates that new product development is an important firm innovation activity that is distinct from patent innovation. We develop a novel measure of innovation, new product trademarks, capturing product development innovation. These two key contributions suggest that the scope of future innovation research be broadened to include a wider range of innovation activities, firms, and industries by using new trademark measures.

II. Data on New Product Development

A. New Product Trademarks as a Measure of New Product Development

While our study is not the first to make use of trademark data, our use of new product trademarks to construct a large-sample cross-industry measure of firm-level product development output is unique.[9] One key reason for the prior lack of a large-sample study of new product development, despite the practical and theoretical importance of product development as a component of innovation, is that firms rarely identify and report development expenditures to outsiders. Instead, product development expenditures are often combined with expenditures in R&D expense or pooled into other cost categories, with no consistency across firms.[10]

We considered several alternative data sources for obtaining measures of new products. Mukherjee, Singh, and Žaldokas (2017) identify new products from press releases. We explored a similar method, using media sources of new product announcements in Capital IQ. We also examined Gale Publishers' annual editions of "Brands and Their Companies" that list companies' brands. Unfortunately, both these sources capture only a subset of new products that firms self-select to publicize and/or firm-product pairs that attract media coverage. While these sources are adequate for examining disclosure-related issues, a more comprehensive sample is key for our research into the importance of new product innovation, independent of disclosure choices and media coverage. The USPTO trademark data also provide the advantage of including exact dates for when new products are introduced (more details are provided below).

Graham, Hancock, Marco, and Myers (2013) describe the USPTO Trademark Case Files Data set and associated institutional details to facilitate future research using the data. The USPTO provides details about trademark filing and registration and defines a trademark as: "*A trademark is a word, phrase, symbol, and/or design that identifies and distinguishes the source of the goods of one party from those of others.*"[11] A firm files for a new trademark when it has a new product (good or

[9]Research studies using trademarks are primarily focused on intellectual property law and litigation (see Beebe (2019)) for a review of research on trademark law, Port (2008) for an analysis of trademark litigation, and Heath and Mace (2020) for a study of changes to trademark legal protections) or marketing and brand value (Krasnikov, Mishra, and Orozco (2009), Block, Fisch, and Sandner (2014), and Ertekin, Sorescu, and Houston (2018)).

[10]For details, see Financial Accounting Standards Board (FASB (2004)) U.S. Generally Accepted Accounting Principles Codification 105-10-05-6 and 730-15-4.

[11]The USPTO also writes: "*A service mark is a word, phrase, symbol, and/or design that identifies and distinguishes the source of a service rather than goods. The term 'trademark' is often used to refer to both trademarks and service marks.*" Consistent with this, we use the term "trademark" to include marks for both goods and services.

service) or a new name, slogan, logo, drawing, or sound for an existing product. Examples include Microsoft Office, Microsoft Office XP, and Windows Phone registered by Microsoft Corp., Escort and Mustang registered by Ford Motor Co., and versions of Hot Wheels and Barbie toys and their individual logos registered by Mattel Inc.[12]

Thus, new trademarks capture the outputs of two types of activities. First, they capture product development of goods or services that are novel and distinct from those of competitors or a firm's own products. For example, The Coca Cola Company filed a trademark for Coke Zero to differentiate it from its main Coke product and protect the new product's name, and Yoplait S.A.S. filed a trademark for Yoplait Pro-Force Greek yogurt, a child-focused Greek yogurt, to differentiate it from its existing products and from other companies' Greek yogurts. Second, trademarks capture marketing innovations, such as those associated with logos and slogans from marketing campaigns of either new or existing products. In addition, registration requirements ensure that trademarks are tied to goods or services for sale, not hypothetical ones, and firms must provide a date for when the goods or services were first used in commerce.[13] Appendix A describes how we identify and separate new product trademarks from new marketing trademarks to allow us to focus on new product development in our study.[14]

Figure 1 illustrates the difference in industry concentration between new product trademarks and new patents. The intuition that patents are concentrated among a small set of high-tech industries is affirmed by the data. The top three patent-producing industries account for over 50% of new patents. In contrast, new product trademarks cover a wide range of industries, with the top three industries representing 24.4% of new product trademarks. Additionally, as we describe in Section III.B and illustrate in Panel D of Table 1, there are significant differences

[12]Because the cost of filing and registering a trademark is low and no proprietary information needs to be released, strategic considerations typically favor filing and registering trademarks. This makes trademarks a reliable and effective measure for product development innovation. The primary reason to not file a trademark is the lack of a sufficiently new, distinct, and important product (Dean (2017)). Despite the low cost, less brand-focused industries may not see value in trademarking. Partly for this reason, we include industry fixed effects in our analyses.

[13]Prior to a trademark registration, the USPTO requires the applicant to have "*used the mark in commerce in connection with all the goods/services listed.*" (A trademark application may be filed under the "use in commerce" basis, if the trademark has already been used in commerce, or the "intent to use" basis, if the trademark has not been used in commerce yet, in which case a "statement of use" must be submitted prior to registration (USPTO (2016))). This requirement makes it highly unlikely that firms file extraneous trademarks in case of future use or to block competitors from using them, the way they can register domain names. The USPTO's requirements are designed to ensure that any registered trademark is tied to an actual marketed good or service.

[14]There is a relatively high correlation between the number of new product trademarks and the number of new marketing trademarks, 0.59, given that new products are typically accompanied by new marketing. Our main results are robust if we examine all new trademarks, including new product and new marketing trademarks. New marketing trademarks are less risky than new product trademarks, and less likely to require high risk-taking incentives. We also repeat the analysis in Section III.C for new marketing trademarks instead of new product trademarks (untabulated for brevity). When partitioning firm-year observations into terciles based on the number of new marketing trademarks, we find no statistically significant relation between new marketing trademarks and future changes in stock return volatility.

in industries with higher levels of patent production (e.g., electronic equipment and computers) versus those with higher levels of product trademark creation (e.g., recreational products and food products), with only a few industries overlapping (e.g., automobiles and trucks and consumer goods). These statistics reinforce the intuition that trademarks capture a type of activity that is distinct from patents and is potentially particularly important for low-patent industries.

In sum, we employ new product trademarks in this study to capture product development innovation as a distinct activity from scientific and technological research efforts represented by patents. We investigate the incentives and consequences related to product development innovation while controlling for scientific research and technological innovation.

B. Related Evidence

Anecdotal statistics and limited research findings indicate that trademarks provide value. In particular, anecdotal evidence and business media reports suggest that trademarks are highly valuable. Companies spend considerable amounts defending trademarks in courts and often receive large awards in these cases. Interbrand lists the top 100 global brands (each protected by trademarks) and their estimated values. The mean (median) market value of the top global brands owned by U.S. companies is 149% (37%) of the associated companies' reported total assets.[15]

Despite the lack of large-sample academic studies examining the value of trademarks and focusing on product trademarks, three studies provide limited evidence suggesting that trademarks provide value. A study in marketing by Krasnikov et al. (2009)) focuses primarily on "brand association" measured as what we define as new marketing trademarks. Using a small sample of 89 to 108 firms over 10 years, they find that firm performance is positively associated with marketing trademarks. In the management literature, González-Pedraz and Mayordomo (2012) examine the stock market's valuation of trademarks in 16 major banks over 10 years. Finally, Chemmanur, Rajaiya, Tian, and Yu (2018) show that trademarks provide value to VC-backed private firms.

However, existing evidence is limited in scope and restricted to very specific foci. Thus, prior results may not generalize to the larger population of trademarks, firms, or industries. In contrast, our comprehensive sample covers all S&P 1500 companies over 20 years. Therefore, our findings generalize the economy and provide insight into whether product development innovation is an important economic activity for companies.

III. Sample Selection and Data Description

A. Sample Selection

We obtain data from the USPTO, Compustat Annual, and Compustat ExecuComp databases. We restrict our analysis to S&P 1500 firms with positive total assets

[15]Interbrand is a leading brand consultancy company. The lists of global brands are provided for years 2000 to 2019 and are available at https://www.interbrand.com/best-brands/.

and sales. The sample covers the 19 fiscal years from 1993 to 2011 and consists of 43,013 firm-year observations from 3,276 distinct firms.

Each trademark application goes through four steps: filing, examination by the USPTO, publication for opposition, and registration. After an application is filed, the USPTO examines the filing and determines whether the trademark is registrable. If it is, the trademark is published online in the Official Gazette, and the public may raise oppositions within 30 days. If no opposition is received, the USPTO proceeds with the registration. At this time, for applications filed under the "use in commerce" basis (i.e., the trademark has been used in commerce at the time of the filing), the USPTO directly approves the registration. For applications filed under the "intent to use" basis (i.e., the trademark has not yet been used in commerce at the time of the filing), the registration is not complete until the receipt of a "statement of use" or other equivalent forms. The average length of time between the filing date and the registration in our data is approximately 15 months.[16]

To compile a comprehensive sample of new trademarks, we first download from the USPTO's website (http://www.uspto.gov/products/catalog/trademarks.jsp) all trademark applications filed between Jan. 1, 1992, and Sept. 8, 2012, with at least one U.S. corporation in the list of owners. This step yields 2,653,464 trademark applications. We limit to new trademarks that are registered and owned by U.S. corporations, with no change in ownership between the filing and registration dates. This reduces the sample to 1,316,985 new trademarks. Using company names and locations, we manually merge the trademark data with data from the Compustat Annual and ExecuComp databases, focusing on S&P 1500 firms. To include trademark information for firms' subsidiaries, we employ the Orbis database to identify subsidiaries. This is particularly important, as many firms establish intellectual property holding companies in Delaware or Nevada to reduce corporate income tax (Simpson (2002)) and thus hold trademarks under the names of these holding companies rather than the corporate parent. Finally, we require trademark filing or "first use" dates to be within fiscal years 1993–2011, reducing the sample to 105,582 unique new trademarks by 2,456 distinct firms.[17]

To distinguish between product- and marketing-related trademarks, we classify each trademark as either a new product trademark or a new marketing trademark. Trademarks filed for logos (i.e., drawings), slogans (identified as trademarks with at least four words of text), or sounds capture marketing and are classified as new marketing trademarks. Conversely, trademarks filed for product names, service names, or brand names capture product development and are classified

[16]Detailed information regarding the process is available at https://www.uspto.gov/sites/default/files/documents/Basic-Facts-Booklet.pdf.

[17]In a trademark application, the "date of first use" refers to the date when the goods are first sold or transported or the services first rendered. In the case of trademarks filed as "use in commerce," the date of first use will be prior to the filing date. Because our intent is to capture the creation of the trademarked product, for each trademark, we employ the latest of the filing date and the date of first use to calculate the number of new trademarks created in a year. All results, interpretations, and inferences remain unchanged if we alternatively employ registration dates to determine the number of new product trademarks in a year. Relatedly, as an additional sample selection criterion, we exclude trademark applications where the date of first use is earlier than 36 months prior to the filing date. These observations may be due to data errors and/or may not accurately reflect the creation of the product.

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as new product trademarks. Appendix A discusses this distinction in more detail. We classify the 105,582 new trademarks into 70,465 new product trademarks and 35,117 new marketing trademarks, covering 2,293 and 2,169 distinct firms, respectively. In this study, we focus on new product trademarks. Therefore, the final sample of trademarks examined in this study consists of 70,465 new product trademarks from 2,293 distinct firms.[18]

B. New Product Trademark Data Description

Panel A of Table 1 presents the distribution by year of new product trademarks and firm-year observations in our sample (43,013 firm-year observations from 3,276 distinct firms). The distribution of new product trademarks generally comports with the findings of studies describing the entire population of trademarks (e.g., Graham et al. (2013), Myers (2013)). The number of new product trademarks increases annually from the start of the sample period of 1993 to 1997, after which it fluctuates. In contrast, the number of firm-year observations peaks in 1996 and then generally declines. Thus, the average number of new product trademarks per firm year in our sample generally increases over the sample period. We include year-fixed effects in our main tests to adjust for this time trend.

Panel B of Table 1 reports the distribution of new product trademarks across firm-years. Sample firms with at least one new product trademark during our sample period (i.e., the "new product trademark" sample) have an average of five new product trademarks per firm year. The standard deviation of 13.3 across these firm years suggests substantial variation in product trademark creation across firm years.

Panel C of Table 1 reports a comparison of selected descriptive statistics for the new product trademark sample (14,077 firm-year observations from 2,293 distinct firms) with the full sample (43,013 firm-year observations from 3,276 distinct firms), and associated *t*-test (Wilcoxon rank-sum test) statistics of the mean (median) differences for each variable. The primary difference between new product trademark firms and all firms appears to be firm size, as captured by assets, market value of equity, and sales. However, new product trademarks are not simply a proxy for size. Some large firms have few or no trademarks. For example, 23.4% of firms in our sample with market capitalization over $1 billion have no new product trademark during our sample period. As discussed in Section II, this can occur in companies for which product branding is less important.[19] On other dimensions, including firm performance (return on assets) and investment opportunities (Tobin's Q), new product trademark firms differ from all firms, but the magnitudes of the differences seem economically small. For example, the difference between the mean ROA (Tobin's Q) for trademark firm-years and all firm-

[18]The number of observations included in each analysis varies with the data availability of the variables included in the analysis. Additional details are provided in the notes for each table. See Tables OA8 and OA9 in the Supplementary Material for a replication of the primary analyses, reported in Tables 3 and 5, using a constant sample with data availability for both analyses.

[19]We replicate our main results restricting to the subsample of firm-years with at least one new product trademark. Results are qualitatively similar.

TABLE 2

Descriptive Statistics and Correlation Coefficients

Table 2 presents selected descriptive statistics (Panel A) and correlation coefficients (Panel B) of the main analysis variables for all firm-year observations (43,013 firm-year observations from 3,276 distinct firms). The sample covers fiscal years 1993–2011. In Panel B, Pearson (Spearman) correlation coefficients are provided in the lower left (upper right). Bolded correlation coefficients are statistically significant (two-tailed *p*-values < 0.10). See Appendix B for variable definitions. Industry grouping is based on the Fama and French 48-industry classification. To mitigate the influence of outliers, all variables are winsorized by year and industry at the 1st and 99th percentiles.

Panel A. Descriptive Statistics

Variable	Q1	Mean	Median	Q3	Std. Dev.
ln(NB_TRADEMARKS)	0.0000	0.4465	0.0000	0.6931	0.7685
ln(NB_PATENTS)	0.0000	0.7977	0.0000	1.0986	1.4369
ln(VEGA)	2.5353	3.5460	3.7155	4.7769	1.7642
ln(DELTA)	4.2898	5.2914	5.2840	6.3017	1.6160
ln(TOTAL_COMP)	6.9796	7.7513	7.7286	8.5271	1.1804
CFO	0.0424	0.0900	0.0895	0.1446	0.1209
ROA	0.0110	0.0326	0.0428	0.0860	0.2260
SIZE	5.7740	7.0820	6.9867	8.3410	1.9474
TOBIN_Q	1.1037	2.0002	1.4458	2.1638	2.2631
LEVERAGE	0.3774	0.5713	0.5554	0.7192	1.0124
CASH	0.0207	0.1451	0.0677	0.2037	0.1793
AGE	4.4427	5.0358	5.1874	5.8464	1.1245
HHI_NORM	0.0276	0.0499	0.0383	0.0558	0.0527

Panel B. Pearson (Spearman) Correlation Coefficients in the Lower Left (Upper Right)

	A	B	C	D	E	F	G	H	I	J	K	L	M
A: ln(NB_TRADEMARKS)		**0.33**	**0.25**	**0.20**	**0.22**	**0.08**	**0.08**	**0.21**	**0.12**	**0.02**	**0.05**	**0.15**	**0.08**
B: ln(NB_PATENTS)	**0.39**		**0.24**	**0.14**	**0.20**	**0.08**	**0.09**	**0.10**	**0.23**	**−0.16**	**0.19**	**0.16**	**0.17**
C: ln(VEGA)	**0.26**	**0.28**		**0.55**	**0.67**	**0.10**	**0.08**	**0.48**	**0.12**	**0.11**	**0.03**	**0.16**	**0.05**
D: ln(DELTA)	**0.22**	**0.19**	**0.49**		**0.48**	**0.22**	**0.29**	**0.36**	**0.36**	**−0.02**	**0.09**	0.00	**0.06**
E: ln(TOTAL_COMP)	**0.24**	**0.24**	**0.61**	**0.43**		**0.08**	**0.08**	**0.59**	**0.06**	**0.19**	**0.02**	**0.18**	**0.06**
F: CFO	**0.07**	**0.06**	**0.09**	**0.21**	**0.09**		**0.64**	**−0.07**	**0.42**	**−0.28**	**0.12**	**0.01**	**0.07**
G: ROA	**0.04**	**0.02**	**0.08**	**0.25**	**0.06**	**0.40**		**−0.13**	**0.53**	**−0.38**	**0.13**	**−0.01**	**0.11**
H: SIZE	**0.27**	**0.22**	**0.44**	**0.37**	**0.55**	**0.06**	**0.07**		**−0.31**	**0.49**	**−0.30**	**0.42**	**−0.17**
I: TOBIN_Q	**0.04**	**0.10**	**0.05**	**0.27**	0.00	**0.05**	**−0.10**	**−0.23**		**−0.40**	**0.39**	**−0.19**	**0.17**
J: LEVERAGE	0.00	**−0.03**	**0.08**	**−0.04**	**0.02**	**−0.11**	**−0.29**	**0.06**	**0.31**		**−0.40**	**0.22**	**−0.20**
K: CASH	**−0.02**	**0.13**	0.00	**0.06**	**−0.06**	**−0.03**	**−0.05**	**−0.35**	**0.34**	**−0.10**		**−0.19**	**0.08**
L: AGE	**0.17**	**0.19**	**0.15**	0.00	**0.15**	**0.04**	**0.03**	**0.39**	**−0.18**	**0.06**	**−0.24**		**−0.04**
M: HHI_NORM	**0.13**	**0.15**	**0.02**	**0.02**	**0.03**	−0.01	−0.01	**−0.07**	**0.01**	0.00	0.00	**0.04**	

years is only 4.4% (7.4%) of the standard deviation of ROA (Tobin's Q) in the full sample (see Panel A of Table 2).

Moreover, there are meaningful differences in the structure of CEO compensation between the two samples that are relevant for our study. The CEOs of new product trademark firms receive higher annual compensation, with greater portions of their total compensation in the form of stock options. The mean and median fraction of stock options to total compensation are 31.6% and 28.0% for new product trademark firm-years versus 27.7% and 22.1% for all firm-years, respectively. Interestingly, the CEOs of new product trademark firms are offered greater risk-taking incentives in the form of higher convexity of incentives (vega) as well as greater pay-performance sensitivity (delta).

Finally, Panel D of Table 1 shows the industry distribution of patents and trademarks with the total percentage of new patents and new product trademarks in each industry as well as the average number of new patents and new product trademarks per firm year in each industry.[20] The industries are ranked by the

[20] We use USPTO patent data collected by Kogan, Papanikolaou, Seru, and Stoffman (2017). Our patent data consists of 795,088 new patents during our sample period, covering 14,254 firm years and 1,711 distinct firms.

average number of new patents per firm year, and industries with more than 15 patents per firm year are labeled as high-patent industries, while those with less than 15 patents per firm year are labeled as low-patent industries.[21] Firms in low-patent industries file approximately 2.55 patents per year on average, in contrast to an average of over 38.54 patents per year for firms in high-patent industries. New product trademarks span all 48 Fama and French industry groups. While the distribution of new trademarks across the 48 industries is uneven, there is little evidence of industry clustering. No single industry group represents more than 10.3% of the trademark sample. The largest industry group within new product trademarks is recreational products, representing 10.3% of the sample, followed by retail, consumer goods, business services, and communications, with more than 5% each. In contrast, patents are largely concentrated in a few industries. Electronic equipment accounts for 22.3% of patents, business services for 15.2%, and computers for 13.4%.

Most relevantly, the table shows the distributions of trademark- and patent-related industries. Several of the high-patent industries, such as electronic equipment, computers, and business services, produce few trademarks, while many high-trademark industries, such as recreational products, alcoholic beverages, and printing and publishing, produce few patents. Overall, the patent production per-firm ranking differs substantially from the trademark creation per-firm ranking. These differences in industry rankings by patent production and product trademark creation suggest that product development is particularly important in low-patent industries, given how little they pursue patent-related activities. Given the differences in the economic importance of product development activities between low- and high-patent industries, we perform our analyses for the sample of all firms as well as separately the samples of firms in low- and high-patent industries. Dividing the sample in this way provides an additional control for patent effects to facilitate cleaner attribution of the results to new product development.[22]

Table 2 presents descriptive statistics and correlation coefficients for the main variables used in our analyses. Panel A shows that the means of ln(NB_TRADEMARKS) and ln(NB_PATENTS) are 0.4465 and 0.7977, respectively. Untabulated, the mean numbers of new product trademarks and new patents are 1.6117 and 16.6579, respectively. The means (median) of ln(VEGA) and ln(DELTA) are 3.5460 (3.7155) and 5.2914 (5.2840), respectively. Overall, the distributions of these two variables comport with prior studies (e.g., Coles, Daniel, and Naveen (2006), Devers, McNamara, Wiseman, and Arrfelt (2008), and

[21]As sensitivity tests, we perform our main analyses with alternate low-/high-patent industry cutoffs of 5, 10, and 20 patents per firm year. The results are robust.

[22]In sensitivity analyses, we partition firms into low- and high-R&D industries, rather than low- and high-patent industries, using R&D spending as an alternate measure of research-related innovation. Low-R&D (below top 15) industries have an average firm-year R&D expense ranging from $0 million to $66.2 million, and high-R&D (top 15) industries have an average firm-year R&D expense ranging from $68.1 million to $551.0 million. As expected, given the high degree of overlap between industry-level patent and R&D intensity, results are similar for this alternative sample classification. We also conduct a similar analysis partitioning firms into a sample with zero (or unreported) R&D expense and a sample with positive reported R&D. Results are similar for this alternative classification as well.

Armstrong and Vashishtha (2012)).[23] The means (medians) of CFO and ROA are 9.00% (8.95%) and 3.26% (4.28%), respectively, as a percentage of average total assets. Panel B reports Pearson (Spearman) correlation coefficients in the lower left (upper right) diagonal. We find significantly positive correlations between CEO risk-taking incentives (ln(VEGA)) and new product trademarks (ln(NB_TRADEMARKS)). We also find statistically significant positive correlations of new product trademarks (ln(NB_TRADEMARKS)) with both CFO and ROA. The results of these univariate tests provide initial support that risk-taking incentives in CEO compensation encourage new product development, and that new product development is associated with positive future performance.

C. The Riskiness of New Product Development

Innovation is commonly viewed as a risky activity. While survey evidence and the OECD definition of innovation suggest that new product development is a form of innovation, there is no statistical evidence of whether it is risky. In comparison to developing fundamentally new technologies leading to patents, product development may seem less risky. Nevertheless, considerable uncertainty remains in the product development phase of the innovation process as well as uncertainty about the success of new products in the market. To examine whether new product development is risky, we relate new product trademarks to changes in firm risk. If new product development is a risky activity, we conjecture a positive relation between new product trademarks and firm risk.

We partition firm-year observations into terciles based on the number of new product trademarks in year t, NB_TRADEMARKS_t. We measure changes in firm risk using changes in stock return volatility between year t and $t+1$, $\Delta\text{RET\_VOL}_{[t;t+1]}$, calculated as RET_VOL_{t+1} minus RET_VOL_t, where RET_VOL is the annualized standard deviation of daily stock returns over the year. For each new product trademark tercile, we compute mean $\Delta\text{RET\_VOL}_{[t;t+1]}$ for firm-year observations in the sample of all firms as well as firms in low- and high-patent industries separately.

The tabulated results and graphical presentation of the relation are presented in Figure 2. All three samples generally show a positive relation between NB_TRADEMARKS and ΔRET_VOL. The relation is monotonically increasing for firms in low-patent industries, with mean ΔRET_VOL increasing from 0.0018 to 0.0057, to 0.0094, for low to mid, to high terciles of new product trademarks, respectively. For the other two samples, the change in firm volatility is greater for the high tercile, compared to the low and mid terciles, which have approximately similar magnitudes. The difference in mean ΔRET_VOL between the high and low terciles is statistically significant for all three samples; the differences are 0.0052, 0.0076, and 0.0051 (p-values =0.02, =0.02, and <0.09) for all firms, low-patent industry firms, and high-patent industry firms, respectively.

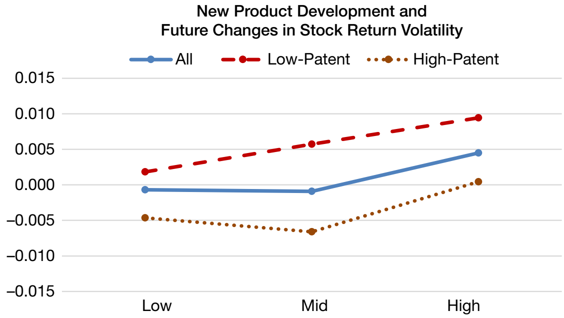
In sum, these results are consistent with our premise that new product development represents a risky innovative activity. These findings do not imply causality, which is unnecessary for our investigation. Evidence that firms with greater product

[23] We follow Core and Guay (2002) and Coles et al. (2006) to estimate VEGA and DELTA.

FIGURE 2

New Product Development and Firm Risk

Figure 2 and its companion table present mean future changes in stock return volatility between years t and $t+1$ for terciles formed on the number of new product trademarks in year t. The sample covers fiscal years 1993–2011. Results are presented for all firm-year observations (43,013 firm-year observations from 3,276 distinct firms) and firm-year observations in low-patent (high-patent) industries (23,966 and 19,047 firm-year observations from 1,899 and 1,549 distinct firms, respectively). Low-patent (high-patent) industries have less (more) than 15 patents per firm year on average (see Panel D of Table 1). Differences between the high and low NB_TRADEMARKS terciles and t-statistics are bolded. See Appendix B for variable definitions. To mitigate the influence of outliers, all variables are winsorized at the 1st and 99th percentiles.



NB_TRADEMARKS Tercile	Mean NB_TRADEMARKS	ΔRET_VOL$_{[t;t+1]}$ All	Low-Patent	High-Patent
Low	0.0	–0.0007	0.0018	–0.0046
Mid	1.3	–0.0009	0.0057	–0.0066
High	8.5 to 8.7	0.0045	0.0094	0.0004
High – Low		**0.0052**	**0.0076**	**0.0051**
(t-stat)		***(2.34)***	***(2.26)***	***(1.65)***

trademark creation experience higher firm risk validates that new product development is risky. Hence, to provide insights on the importance of product development innovation to firms, a natural next step includes investigating whether risk-taking incentives in CEO compensation motivate firms to undertake new product development.

IV. Motivating New Product Development with Incentives

A. Hypothesis and Research Design

In this section, we examine whether firms motivate new product development activity via CEO compensation. Given the evidence in Section III.C that new product development represents a risky innovative activity, for all firms as well as firms in low- and high-patent industries separately, we turn next to analyze whether risk-taking incentives are used in CEO compensation to motivate product development innovation by risk-averse managers.

Basic agency theory suggests that owners should tie managers' wealth to firm value to reduce agency conflicts (Jensen and Meckling (1976)). This is often done through equity-based pay, but a higher sensitivity of managerial wealth to stock price (delta) can *decrease* risky effort when managers are risk-averse (Smith and Stulz (1985), Lambert, Larcker, and Verrecchia (1991)) and therefore can discourage innovation, even if it is value-increasing in expectation. The academic literature also suggests that using instruments such as stock options, which include convex payoffs with respect to firm value, can help encourage risk-taking. For example, Smith and Stulz (1985) show that increasing the convexity of managers' wealth with respect to firm value increases the managers' willingness to make risky investments and decreases hedging. Hirshleifer and Suh (1992) conclude that stock option compensation should be higher when there are riskier desirable growth opportunities, due to the convexity that they induce.

Stock option compensation can also increase innovation incentives due to its multiyear vesting schedule, which provides long-term incentives. Cadman, Rusticus, and Sunder (2013) show that stock option grants to CEOs have mean and median vesting periods of 36 months, and Gopalan, Milbourn, Song, and Thakor (2014) demonstrate that vesting periods cluster around three to four years. In several models, the possibility of short-term failure associated with risky innovation reduces managers' willingness to innovate. Holmstrom and Costa (1986) and Hirshleifer and Thakor (1992) argue that long-term compensation helps insulate managers and induce them to innovate. Manso (2011) specifically focuses on structuring incentives to motivate innovation. He shows that the optimal incentives are tolerant of short-term failure and reward long-term success.

Evidence largely supports these theories.[24] Focusing on the horizon problem, Dechow and Sloan (1991) find that CEOs near the end of their tenure cut R&D spending but that stock and option holdings mitigate this effect.[25] Guay (1999) reports that stock return volatility increases with vega, the sensitivity of CEO wealth to an increase in stock volatility, which suggests vega as a good proxy for managerial risk-taking incentives. A large literature shows that vega is positively related to a wide set of managerial risky actions including risky exploration activities in the oil and gas industry (Rajgopal and Shevlin (2002)), high investments in R&D spending (Coles et al. (2006), Xue (2007)), and risk-increasing acquisitions by banks (Hagendorff and Vallascas (2011)). Gormley, Matsa, and Milbourn (2013) identify a sample of firms being subject to an exogenous shock of increased litigation risk from workers' exposure to chemicals that are newly classified as carcinogens to study the relation between vega and managerial risk-taking. They find that firms that reduce vega more tend to cut leverage and R&D, increase cash holdings, and make more diversifying acquisitions. Studies also show that vega is positively related to the risk of misreporting (Armstrong, Larcker, Ormazabal, and Taylor (2013)) and to higher audit fees (Chen, Gul, Veeraraghavan, and Zolotoy (2015), Kim, Li, and Li (2015)). Finally, Mao and Zhang (2018) provide evidence that CEOs' vega is positively associated with the number of patents and patent citations.

Based on these discussions, we hypothesize that new product development increases with risk-taking incentives in the CEO's compensation. The hypothesis, stated in alternative form, is:

[24]Datta, Iskandar-Datta, and Raman (2001) find that executives with higher stock option compensation complete riskier acquisitions. Lerner and Wulf (2007) focus on the head of R&D department and show that long-term incentives, in the form of stock option compensation or restricted stock, increase the number, originality, and citations of patents. Francis, Hasan, and Sharma (2011) find that patent innovation increases with stock option compensation. Currim, Lim, and Kim (2012) show that increases in stock and stock option compensation increase R&D and advertising spending. Baranchuk, Kieschnick, and Moussawi (2014) find that CEO incentive compensation, comprised largely of option compensation, is positively associated with post-IPO patent production at newly public firms.

[25]Relatedly, Tian and Wang (2014) find that IPO firms backed by more failure-tolerant venture capital investors have significantly more patents and patent citations.

Hypothesis 1. Risk-taking incentives in CEO compensation are positively associated with new product development,

where the measure of CEO risk-taking incentives is vega, the convexity of the relation between CEO wealth and stock price, and the measure of new product development is new product trademarks. We test this hypothesis for all firms as well as firms in low- and high-patent industries separately. We expect Hypothesis 1 to hold for firms in low-patent industries, where new product development is the primary form of risky innovation. However, the prediction is less clear for high-patent industries. High-patent industries may focus increased innovative efforts on even riskier scientific research and technological innovation (captured by patents), rather than new product development. They may concurrently increase, maintain, or even shift away from product development, as long as overall risky innovation increases. However, controlling for patent innovation, we expect an increase in product development innovation for all firms as well as firms in both low- and high-patent industries if product development innovation matters for firms.

We estimate OLS regressions of the number of new product trademarks on risk-taking incentives for firm i in year t, using the following model:

$$(1)\quad \begin{aligned} \ln(\text{NB\_TRADEMARKS})_{i,t} = {} & \alpha + \beta_1 \ln(\text{VEGA})_{i,t-1} + \beta_2 \ln(\text{DELTA})_{i,t-1} \\ & + \beta_3 \ln(\text{NB\_PATENTS})_{i,t} + \beta_4 \ln(\text{TOTAL\_COMP})_{i,t-1} \\ & + \beta_5 \text{SIZE}_{i,t-1} + \beta_6 \text{ROA}_{i,t-1} + \beta_7 \text{CASH}_{i,t-1} \\ & + \beta_8 \text{TOBIN\_Q}_{i,t-1} + \beta_9 \text{LEVERAGE}_{i,t-1} \\ & + \sum \chi_j \text{Year}_j + \sum \delta_k \text{Industry}_k + \varepsilon_{i,t}, \end{aligned}$$

where the dependent variable, ln(NB_TRADEMARKS), is the natural logarithm of one plus the number of new product trademarks in year t. Our main independent variable, ln(VEGA), is the natural logarithm of one plus the CEO's sensitivity to stock return volatility, measured as the dollar change in the CEO's option portfolio for a 0.01 change in annualized standard deviation of stock returns in year $t-1$.[26,27] We predict positive and significant values for β_1.[28]

[26]Several papers suggest that unvested stock options are likely to provide longer-run incentives that are appropriate for risky innovation (Devers et al. (2008), Erkens (2011), and Souder and Bromiley (2012)). Executives who hold relatively large amounts of unvested stock options are less concerned about current stock price performance since a higher stock price is beneficial only after the options become exercisable (Souder and Bromiley (2012)). Thus, these executives are more likely to undertake risky investments, which potentially generate long-term value and result in high future stock price, but which may depress short-term stock price as the company experiences the costs and risks associated with the initial investments. Consequently, we estimate equation (1) using ln(UNVESTED_OPTIONS), the natural logarithm of one plus the CEO's unvested stock option holdings measured using the Black-Scholes value of unvested stock options held at year-end, as an alternative CEO risk incentive measure. The results (untabulated) are qualitatively similar to our tabulated results.

[27]Given that CEO incentives might affect the decision of when to file the trademark, we alternatively use the date of first use for all new product trademarks. Results (untabulated) are similar to the results tabulated.

[28]We also estimate a negative binomial model using NB_TRADEMARKS as the dependent variable and results (untabulated) are robust.

To control for risk-taking incentives targeted for motivating CEOs to invest in scientific research and technological innovation, particularly for high-tech firms, we include ln(NB_PATENTS), the natural logarithm of one plus the number of new patents in the same year as the new product trademarks, in equation (1), to control for patent creation concurrent with the new product development.[29] Thus, any effect documented for product development innovation is incremental to the effect for patent-related innovation. Moreover, we include the following control variables for other possible determinants of new product development: ln(DELTA), capturing the sensitivity of compensation to stock price[30]; ln(TOTAL_COMP), the natural logarithm of the CEO's annual total compensation, measured as the sum of salary, bonus, other annual compensation, value of restricted stock granted, value of new stock options granted during the year, long-term incentive payouts, and all other compensation; SIZE, the natural logarithm of total assets; ROA, return on assets, measured as earnings before extraordinary items and discontinued operations divided by average total assets; CASH, cash and cash equivalents divided by total assets; TOBIN_Q, the market value of total assets divided by the book value of total assets; LEVERAGE, total liabilities divided by total assets; as well as year and industry fixed effects. Finally, we cluster standard errors by firm and report results of two-tailed tests.[31]

B. Empirical Evidence for Motivating New Product Development with Incentives

Table 3 presents the results, where models I, II, and III include all firms, firms in low-patent industries, and firms in high-patent industries, respectively. In all three models, ln(NB_PATENTS), SIZE, and TOBIN_Q are significantly positively related to future new product trademarks, while ln(DELTA), ln(TOTAL_COMP), and LEVERAGE are not significantly related to future new product trademarks. Thus, overall, larger firms and those with greater patent creation and growth opportunities tend to undertake more product development innovation.

Focusing on Hypothesis 1, we find a significantly positive relation between ln(VEGA) and future new product trademarks, with p-values <0.01, =0.03, and =0.02, respectively, for models I, II, and III. The magnitude of the coefficient estimate in model I suggests that holding all else equal and controlling for concurrent patent creation, an interquartile increase of ln(VEGA) increases product

[29]Results (tabulated in Table OA4 in the Supplementary Material) are similar if we control for patent citations instead. Results (tabulated in Table OA6 in the Supplementary Material) are also similar if we control alternatively for patents over years $t-3$ through t to control for any lags in the conversion of new patents into new product trademarks.

[30]Including ln(DELTA) as a control variable allows us also to study vega and delta's potentially different effects on new product development. While delta creates an incentive for profitable investment, it may discourage higher-risk innovation efforts and encourage lower-risk efforts, as shown by Coles et al. (2006).

[31]Our results throughout the study are robust if we cluster standard errors by firm and year. However, the time effect is negligible in our data. The standard errors clustered by both firm and year for our variables of interest are either almost indistinguishable or slightly smaller than the standard errors clustered by firm. Consequently, and following Petersen (2009), clustering standard errors by both firm and year is unnecessary.

TABLE 3

CEO Incentives and New Product Development

Table 3 presents the results of the regression shown below. The sample covers fiscal years 1993–2011. t-statistics estimated using Huber–White robust standard errors clustered by firm are in parentheses below coefficient estimates. Bolded coefficient estimates and t-statistics are statistically significant (two-tailed p-values < 0.10). Year and industry-fixed effects are included but not reported for brevity. Model I presents the results for all firm-year observations (43,013 firm-year observations from 3,276 distinct firms) and model II (III) presents the results for the sample of firm-year observations in low-patent (high-patent) industries (23,966 and 19,047 firm-year observations from 1,899 and 1,549 distinct firms, respectively). Low-patent (high-patent) industries have less (more) than 15 patents per firm year on average (see Panel D of Table 1). In model I (II) [III], the sample decreases to 29,553 (16,597) [12,956] firm-year observations from 3,154 (1,807) [1,473] distinct firms after requiring data for the compensation variables (ln(VEGA), ln(DELTA) and ln(TOTAL_COMP)) and lastly to 29,451 (16,554) [12,897] firm-year observations from 3,152 (1,806) [1,472] distinct firms due to control variable data availability. See Appendix B for variable definitions. Industry grouping is based on the Fama and French 48-industry classification. To mitigate the influence of outliers, all variables are winsorized by year and industry at the 1st and 99th percentiles.

$$\begin{aligned}\ln(\text{NB\_TRADEMARKS})_{i,t} = {} & \alpha + \beta_1 \ln(\text{VEGA})_{i,t-1} + \beta_2 \ln(\text{DELTA})_{i,t-1} + \beta_3 \ln(\text{NB\_PATENTS})_{i,t} + \beta_4 \ln(\text{TOTAL\_COMP})_{i,t-1} \\ & + \beta_5 \text{SIZE}_{i,t-1} + \beta_6 \text{ROA}_{i,t-1} + \beta_7 \text{CASH}_{i,t-1} + \beta_8 \text{TOBIN\_Q}_{i,t-1} + \beta_9 \text{LEVERAGE}_{i,t-1} \\ & + \sum \chi_j \text{Year}_j + \sum \delta_k \text{Industry}_k + \varepsilon_{i,t}.\end{aligned}$$

	Expected Sign	All I	Low-Patent II	High-Patent III
$\ln(\text{VEGA})_{t-1}$	+	**0.0198**	**0.0159**	**0.0256**
		(3.23)	**(2.22)**	**(2.26)**
$\ln(\text{DELTA})_{t-1}$	?	0.0001	0.0056	−0.0155
		(0.02)	(0.57)	(−1.33)
$\ln(\text{NB\_PATENTS})_{t}$	+	**0.1437**	**0.1896**	**0.1379**
		(11.98)	**(7.66)**	**(10.48)**
$\ln(\text{TOTAL\_COMP})_{t-1}$	?	0.0091	0.0142	−0.0040
		(1.03)	(1.44)	(−0.27)
SIZE_{t-1}	+	**0.1354**	**0.1425**	**0.1295**
		(11.86)	**(9.76)**	**(7.00)**
ROA_{t-1}	?	**0.2346**	0.1703	**0.2234**
		(3.66)	(1.28)	**(3.01)**
CASH_{t-1}	?	0.0338	**0.3187**	**−0.1630**
		(0.52)	**(2.78)**	**(−2.16)**
TOBIN_Q_{t-1}	+	**0.0293**	**0.0567**	**0.0267**
		(5.25)	**(3.96)**	**(4.67)**
LEVERAGE_{t-1}	–	−0.0105	0.0495	−0.0508
		(−0.22)	(0.69)	(−0.82)
Year fixed effects			Included	
Industry fixed effects			Included	
No. of obs.		29,451	16,554	12,897
Adj. R^2 (%)		29.76	29.38	28.85

trademark creation by 9.0% for a firm producing one product trademark per year.[32] In model II (III), this effect is 7.6% (10.9%) for firms in low-patent (high-patent) industries. Moreover, in all three models, the ln(DELTA) coefficient is statistically insignificant, consistent with Coles et al. (2006), and consistent with the evidence in Section III.C that new product development represents a risky innovative activity. This suggests that the riskiness of new product development is high enough that

[32]An alternate method to derive economic significance is to examine the underlying distributions of the variables rather than the distributions of the logged variables. Using this approach, as used by Fang, Tian, and Tice (2014)) and Chang, Fu, Low, and Zhang (2015), we find that an interquartile increase in VEGA (vs. an interquartile increase in ln(VEGA)) increases product trademark creation by 24.6% of its mean. To illustrate, because $d[\ln(1+y)]/d[\ln(1+x)] = [(1+x)/(1+y)]dy/dx$, one can derive the relation between dy and dx directly as $dy = d[\ln(1+y)]/d[\ln(1+x)] \times [(1+y)/(1+x)]dx$. Applying this to our data, if we increase VEGA from its first quartile, 11.5, to its third quartile, 114.9, so that $dx = 103.4$, the change in NB_TRADEMARKS from its mean value of 2.0 is equal to $0.0198 \times [(1+2.0)/(1+11.5)] \times 103.4 = 0.49$, which is 24.6% of the mean value of NB_TRADEMARKS.

performance incentives, such as stock, are insufficient to motivate additional activity for typically risk-averse CEOs, without additional risk-taking incentives.[33] To explore further the riskiness of product development innovation and its relation to risk-taking compensation incentives, we partition the sample based upon the extent to which the firm creates product trademarks in new product categories. We find similar results in both subsamples, untabulated for brevity. In sum, whether the firm is largely creating new products in its existing product categories or extending into new product categories, we find that risk-taking incentives are important to motivate new product development.[34]

Overall, the findings in Table 3 support Hypothesis 1 and suggest that, when firms provide risk-taking incentives in the form of higher convexity of incentives, they pursue more product development innovation. Importantly, these results hold after controlling for concurrent patent innovation. Thus, risk-taking incentives are motivating CEOs to innovate through new product development, incremental to innovating in fundamental science and technology.

C. Importance of New Product Development

The results reported in Section IV.B indicate that risk-taking incentives motivate CEOs to increase product development innovation for all firms, low-patent industry firms, and high-patent industry firms. However, we would expect these risk-taking incentive effects on new product development to be stronger in industries where product development innovation is more important to firm success. We exploit trademark-related data to develop two measures of the importance of new product development at the industry level. We then examine whether the

[33]Our results are robust to several alternative specifications. First, the results in all three models are almost indistinguishable if we exclude ln(DELTA) as a control variable. Second, our results are similar if we substitute ln(VEGA) with VEGA in models I and II and if we scale VEGA or ln(VEGA) by CEO wealth (measured following Coles, Daniel, and Naveen (2013)) in models I and III. Third, to explore whether a potential nonlinearity in the relation between firm size and new product innovation affects results, we include the squared term of firm size as an additional independent variable in equation (1). We find a significant negative (positive) relation between (the squared term of) firm size and the number of new product trademarks. More importantly, with the inclusion of this square term, our results tabulated in Table 3 are qualitatively similar and even stronger in magnitude and significance. Fourth, to address any possible nonlinearity issues and to ensure that firms with either no trademark or large numbers of trademarks are not affecting our results, we replicate our analyses using the following distinct alternative specifications: i) using quintile rankings (by year and industry) of the number of new product trademarks as the dependent variable, ii) excluding firm-year observations with no new product trademark (i.e., 28,936 firm-years covering 3,078 firms), and iii) excluding firm-year observations with more than 10 new product trademarks (i.e., 1,406 firm-years covering 314 firms). The results are qualitatively similar to our tabulated results in all three models.

[34]Trademarks are classified into 45 product/service categories, called “classes.” The USPTO also defines related classes, called “coordinated classes,” which identify classes that are expected to relate to one another (e.g., chemicals and pharmaceuticals). We partition firm-year observations based on whether the percentage of similarity with past product trademarks for the same firm in the prior 5 years is above or below the median. We find a similar association between CEO risk-taking incentives and future new product development in each subsample: the ln(VEGA) coefficient estimate is significantly positive for the low-similarity subsample (coefficient = 0.0241; p-value = 0.02) as well as the high-similarity subsample (coefficient = 0.0255; p-value = 0.08), and these two coefficient estimates do not differ significantly.

incentive effects of vega vary with respect to the importance of product development innovation.

For the first measure of new product development importance, we use data from the 2015 Census Bureau and National Science Foundation's BRDIS survey, mentioned in the introduction and conducted with over 45,000 companies, in which firms rank trademarks in terms of importance.[35] We define IMPORTANCE_SURVEY as an indicator variable equal to 1 if the firm is in an industry where the percentage of firms ranking trademarks as "very important" or "somewhat important" is above the median and 0 otherwise. For the second measure, we use new product trademark data to examine the revealed importance of new product development in each industry, as measured by new product trademark intensity. We define IMPORTANCE_INTENSITY as an indicator variable equal to 1 if the firm is in an industry where the number of new product trademarks per firm year is above the median and 0 otherwise.

Using both definitions of IMPORTANCE, we augment equation (1) with the indicator variable IMPORTANCE and more relevantly the interaction terms ln(VEGA) × IMPORTANCE and ln(DELTA) × IMPORTANCE to examine whether the effects of CEO risk-taking incentives on new product development vary with respect to the importance of new product development to a firm's industry. The results are reported in Table 4, with models I–III and models IV–VI presenting the results with IMPORTANCE_SURVEY and IMPORTANCE_INTENSITY, respectively. The coefficient on ln(VEGA) × IMPORTANCE_SURVEY is positive and statistically significant for all firms and firms in low-patent industries, and the coefficient on ln(VEGA) × IMPORTANCE_INTENSITY is positive and statistically significant for all firms as well as firms in low- and high-patent industries. Overall, as predicted, the results indicate a stronger risk-taking incentive effect on new product development for industries where product development innovation is more important.

D. CEO Characteristics

We consider how risk-taking incentives to motivate product development innovation vary with two CEO characteristics, specifically CEO tenure and whether the CEO is the firm founder. We predict CEO risk-taking incentives are likely to be less important to motivate product development innovation when the CEO has been with a firm for longer and/or when the CEO is the founder of the firm. In these situations, we anticipate that CEOs will likely engage in risk-taking activities, regardless of incentives. These predictions comport with past empirical evidence that longer-tenured CEOs and founder CEOs respond more to intrinsic incentives for risk-taking, compared to pecuniary incentives.[36] We define CEO_LGTENURE

[35]See footnotes 4 and 5 for descriptions of the survey and data.

[36]Fahlenbrach (2009) finds that founder CEOs invest more in R&D, and Lee, Kim, and Bae (2020) find that founder CEOs produce more innovation, suggesting greater risk-taking activities. Wowak, Mannor, and Wowak (2015) document a weaker relation between stock option compensation and product safety recall (interpreted as an outcome of excessive risk-taking) for longer-tenured CEOs and founder CEOs. The authors explain that such CEOs are motivated more by the intrinsic desire to see their firm succeed than from pecuniary incentives.

as an indicator variable equal to 1 if the CEO's tenure is strictly above the median and 0 otherwise. We define CEO_FOUNDER as an indicator variable equal to 1 if the CEO is the founder of the firm and 0 otherwise. We augment equation (1) with each of these CEO characteristic indicator variables and their interactions with ln(VEGA) and ln(DELTA). Results are reported in Panel B of Table 4.

We find that the coefficient on ln(VEGA) is significantly positive in all models, while the coefficients on ln(VEGA) × CEO_LGTENURE and ln(VEGA) × CEO_FOUNDER are both negative and statistically significant for all firms and firms in high-patent industries. These results suggest that, in low-patent industries, where product development innovation is a primary focus, risk-taking incentives motivate all CEOs to pursue product development innovation.

TABLE 4

CEO Incentives and New Product Development: The Importance of New Product Development and CEO Characteristics

Table 4 presents the results of the regression shown below. The sample covers fiscal years 1993–2011. *t*-statistics estimated using Huber–White robust standard errors clustered by firm are in parentheses below coefficient estimates. Bolded coefficient estimates and *t*-statistics are statistically significant (two-tailed *p*-values < 0.10). Control variables as well as year and industry fixed effects are included but not reported for brevity. In Panel A, models I–III, IMPORTANCE_SURVEY is an indicator variable equal to 1 (0) if the firm is in an industry where the percentage of firms ranking trademarks as "very important" or "somewhat important," in the 2015 survey by the Census Bureau and National Science Foundation's BRDIS, is above (below) the median. In Panel A, models IV–VI, IMPORTANCE_INTENSITY is an indicator variable equal to 1 (0) if the firm is in an industry where the product development intensity (i.e., the number of new product trademarks per firm year) is above (below) the median. In Panel B, models I–III, CEO_LGTENURE is an indicator variable equal to 1 if the CEO's tenure is strictly above the median, 0 otherwise. In Panel B, models IV–VI, CEO_FOUNDER is an indicator variable equal to 1 if the CEO is the founder of the firm, 0 otherwise. In both panels, models I and IV present the results for all firm-year observations (43,013 firm-year observations from 3,276 distinct firms), and models II and V (III and VI) present the results for the sample of firm-year observations in low-patent (high-patent) industries (23,966 and 19,047 firm-year observations from 1,899 and 1,549 distinct firms, respectively). Low-patent (high-patent) industries have less (more) than 15 patents per firm year on average (see Panel D of Table 1). In Panel A, the sample is the same as in Table 3. In Panel B, the sample is the Table 3 sample after also requiring data for the CEO characteristic variables, resulting in 26,859 and 28,114 (14,898 and 15,767) [11,961 and 12,347] firm-year observations from 3,026 and 3,051 (1,721 and 1,743) [1,420 and 1,424] distinct firms in models I and IV (II and V) [III and VI], respectively. See Appendix B for variable definitions. Industry grouping is based on the Fama and French 48-industry classification. To mitigate the influence of outliers, all nonindicator variables are winsorized by year and industry at the 1st and 99th percentiles.

$$\begin{aligned}\ln(\text{NB\_TRADEMARKS})_{i,t} = {} & \alpha + \beta_1 \ln(\text{VEGA})_{i,t-1} \times \text{Indicator} + \beta_2 \ln(\text{VEGA})_{i,t-1} + \beta_3 \ln(\text{DELTA})_{i,t-1} \times \text{Indicator} \\ & + \beta_4 \ln(\text{DELTA})_{i,t-1} + \beta_5 \text{Indicator} + \beta_6 \ln(\text{NB\_PATENTS})_{i,t} + \beta_7 \ln(\text{TOTAL\_COMP})_{I,t-1} \\ & + \beta_8 \text{SIZE}_{I,t-1} + \beta_9 \text{ROA}_{I,t-1} + \beta_{10} \text{CASH}_{I,t-1} + \beta_{11} \text{TOBIN\_Q}_{I,t-1} + \beta_{12} \text{LEVERAGE}_{i,t-1} \\ & + \sum \chi_j \text{Year}_j + \sum \delta_k \text{Industry}_k + \varepsilon_{i,t}.\end{aligned}$$

Panel A. Importance of New Product Development

		Importance of New Product Development *Indicator* = IMPORTANCE_SURVEY			*Importance of New Product Development* *Indicator* = IMPORTANCE_INTENSITY		
	Expected Sign	All I	Low-Patent II	High-Patent III	All IV	Low-Patent V	High-Patent VI
$\ln(\text{VEGA})_{t-1}$ × IMPORTANCE	+	**0.0218** **(1.82)**	**0.0345** **(2.34)**	0.0051 (0.23)	**0.0452** **(3.59)**	**0.0623** **(3.47)**	**0.0515** **(2.70)**
$\ln(\text{VEGA})_{t-1}$	?	0.0082 (1.03)	0.0011 (0.12)	0.0202 (1.20)	0.0014 (0.22)	−0.0035 (−0.51)	−0.0034 (−0.23)
$\ln(\text{DELTA})_{t-1}$ × IMPORTANCE	?	−0.0137 (−1.05)	0.0112 (0.66)	−0.0246 (−1.23)	0.0060 (0.43)	**0.0352** **(1.76)**	−0.0102 (−0.51)
$\ln(\text{DELTA})_{t-1}$	?	0.0071 (0.76)	0.0019 (0.15)	−0.0019 (−0.13)	−0.0012 (−0.15)	−0.0020 (−0.21)	−0.0111 (−0.67)
Control variables			Included			Included	
Year fixed effects			Included			Included	
Industry fixed effects			Included			Included	
No. of obs.		29,451	16,554	12,897	29,451	16,554	12,897
No. of IMPORTANCE = 1		15,890	7,275	8,615	12,566	4,782	7,784
Adj. R^2 (%)		29.84	29.59	29.17	30.00	30.10	29.04

(continued on next page)

TABLE 4 (continued)

CEO Incentives and New Product Development: The Importance of New Product Development and CEO Characteristics

Panel B. CEO Characteristics

		CEO Characteristic Indicator = CEO_LGTENURE			*CEO Characteristic Indicator* = CEO_FOUNDER		
	Expected Sign	All I	Low-Patent II	High-Patent III	All IV	Low-Patent V	High-Patent VI
$\ln(\text{VEGA})_{t-1} \times \text{CEO\_CHAR}_{t-1}$	–	**−0.0164** **(−1.87)**	0.0003 (0.03)	**−0.0357** **(−2.46)**	**−0.0291** **(−2.54)**	−0.0145 (−0.94)	**−0.0363** **(−2.05)**
$\ln(\text{VEGA})_{t-1}$	+	**0.0280** **(3.50)**	**0.0173** **(1.82)**	**0.0410** **(2.85)**	**0.0253** **(3.33)**	**0.0186** **(2.13)**	**0.0326** **(2.29)**
$\ln(\text{DELTA})_{t-1} \times \text{CEO\_CHAR}_{t-1}$	?	0.0167 (1.55)	0.0150 (1.07)	0.0171 (1.09)	−0.0097 (−0.65)	0.0023 (0.11)	−0.0285 (−1.53)
$\ln(\text{DELTA})_{t-1}$	?	−0.0060 (−0.65)	−0.0030 (−0.27)	−0.0179 (−1.18)	0.0096 (1.03)	0.0077 (0.67)	0.0060 (0.39)
Control variables			Included			Included	
Year fixed effects			Included			Included	
Industry fixed effects			Included			Included	
No. of obs.		26,859	14,898	11,961	28,114	15,767	12,347
No. of CEO_CHAR = 1		12,270	6,960	5,310	6,837	3,684	3,153
Adj. R^2 (%)		29.93	30.04	28.88	30.27	29.87	29.43

However, in high-patent industry firms (and all firms in general), risk-taking incentives are not as important to motivate new product development when CEOs have a relatively longer tenure or are founders of the firm. These findings are consistent with longer-tenured CEOs and founder CEOs identifying more strongly with the firm and/or having substantial wealth, weakening the effects of pecuniary incentives. Such CEOs place a strong weight on choosing the appropriate level of risk to maximize firm value without the need for risk-taking incentives.

E. Supplementary Analyses

In supplementary analyses, we examine whether risk-taking incentives are associated with high-quality new product development. Trademarks do not protect a product indefinitely. Instead, firms must file documents and show evidence of the product in use between the fifth and sixth years after initial trademark registration to maintain legal protection. Since only trademarks representing higher-quality products are likely to be maintained, trademark maintenance provides a trademark-specific ex-post indicator of the quality of the new product development. For each firm year, we define an indicator variable, HIGH_QUALITY_t, which equals one if the registration of at least 1 of the new product trademarks in year t is maintained in the future and 0 otherwise. We estimate a logistic regression, using a model similar to equation (1) and replacing the dependent variable with HIGH_QUALITY_t, to estimate whether the probability of creating high-quality new product development increases with CEO risk-taking incentives. The results are tabulated in Table OA1 in the Supplementary Material. We find a significantly positive relation between ln(VEGA) and high-quality new product development for all firms and firms in low-patent industries. The coefficient estimates are 0.0419 and 0.0443, with p-values =0.02 and =0.07, respectively in models I and II. The relation is insignificant for high-patent industries. Together with the results presented in Table 3, this suggests that risk-taking incentives motivate higher product development innovation in low-patent and high-patent industries, and particularly motivate high-quality product development innovation in low-patent industries, for which product development innovation is a primary focus. The result for high-patent industries may also be due to technological innovation; maintenance of trademarks past 5 or 6 years may be less relevant in industries with rapid technological change.

To empirically establish whether the trademark creation effect we document in Table 3 is incremental to any R&D, capital expenditure, and advertising spending effects of incentive compensation, we estimate equation (1) including the following additional control variables: R&D expense (set as 0 when missing) divided by total sales, capital expenditures divided by average total assets, and advertising expense (set as 0 when missing) divided by total sales. The results are qualitatively similar and tabulated in Table OA2 in the Supplementary Material. The coefficient estimates are 0.0167, 0.0126, and 0.0245, with p-values <0.01, $=0.09$, and $=0.03$, respectively in models I–III. These results suggest that risk-taking incentives directly affect product development creation, working incrementally to input effects of R&D, capital expenditures, and advertising. Thus, when provided with greater risk-taking incentives, CEOs are not only increasing product development innovation but also improving the efficiency of product development innovation investments.

While we include many control variables as well as year and industry-fixed effects in our main regressions and conduct numerous robustness tests, we do not include firm fixed effects. Consequently, our results can be driven by both across-firm and within-firm variation. Both of these are of interest to us. However, we conduct an additional analysis to examine whether our main results are robust when focusing on within-firm variation. We estimate equation (1) including firm and year fixed effects and clustering standard errors by firm. The coefficients on our incentive measure then capture the variation in compensation and product development creation within firms over time. The results, tabulated in Table OA3 in the Supplementary Material, show that the coefficient on ln(VEGA) is positive and statistically significant for models I and II (p-value $=0.02$ and <0.01, respectively). The magnitudes of the coefficients are similar as well, at 64.6% and 127.7% for the corresponding magnitudes reported in Table 3 for models I and II, respectively. Thus, our main findings appear to be driven largely by within-firm variation. Furthermore, these supplementary results support the conclusion that our main findings are not likely to be driven by alternative explanations, including potential endogeneity or firm characteristics. We further explore possible endogeneity in Section VI, exploiting an exogenous shock to CEO compensation.

Together, the results presented throughout Section IV suggest that boards of directors interested in motivating CEOs to develop new products are more likely to succeed if they structure CEO compensation to have stronger risk-taking incentives, rather than simply increasing total compensation. This also suggests that one of the ways in which CEOs respond to these incentives is increasing new product development. Our findings hold for a wide range of firms in the economy, including firms in low-patent industries where product development innovation is a primary focus and firms in high-patent industries where scientific research and technological innovation are primary focuses. We find, in untabulated tests, that the coefficient estimates on the incentive measure, ln(VEGA), do not differ significantly between low- and high-patent industries. These results suggest that CEO risk-taking incentives are equally important for driving product development innovation for all types of firms.

V. New Product Development and Changes in Future Firm Performance

A. Hypothesis and Research Design

To examine the consequence of new product development on future firm performance, we estimate how changes in future firm performance, measured as cash flow from operations (CFO) and return on assets (ROA), vary with current product development innovation. For low-patent industries, new product development is the primary form of innovation. For high-patent industries, a common way to monetize patent innovations is through the creation of new products as part of the next phase of the innovation process. In both cases, we expect that firms undertake the innovation to add value to the firm. Thus, we hypothesize a positive relation between new product development and changes in firm performance for all types of firm. The hypothesis, stated in an alternative form, is:

Hypothesis 2. New product development is positively associated with changes in firm performance,

where the firm performance measures are cash flow from operations and return on assets and the measure of new product development is new product trademarks. Product innovations, however, may not be associated with improvements in firm performance because the new products may be unsuccessful on the market, may cannibalize sales of existing products, or the related expenditures may be too high, relative to the new revenues generated.

We test Hypothesis 2 for all firms as well as firms in low- and high-patent industries separately, by estimating the following OLS regressions, using subscripts i for firm and t for year:

$$
\begin{aligned}
(2)\quad \Delta\text{PERFORMANCE}_{i,[t;t+k]} = {} & \alpha + \beta_1 \ln\left(\text{NB\_TRADEMARKS}\right)_{i,t} \\
& + \beta_2 \ln\left(\text{NB\_PATENTS}\right)_{i,t} + \beta_3 \text{SIZE}_{i,t} \\
& + \beta_4 \text{TOBIN\_Q}_{i,t} + \beta_5 \text{LEVERAGE}_{i,t} \\
& + \beta_6 \text{AGE}_{i,t} + \beta_7 \text{HHI\_NORM}_{i,t} + \sum \chi_j \text{Year}_j \\
& + \sum \delta_k \text{Industry}_k + \varepsilon_{i,[t;t+k]},
\end{aligned}
$$

where the dependent variable, ΔPERFORMANCE, is change in PERFORMANCE, measured as PERFORMANCE in year $t+1$ or year $t+2$ minus PERFORMANCE in year t, and PERFORMANCE is alternatively i) CFO, cash flow from operations divided by average total assets, or ii) ROA, return on assets, measured as earnings before extraordinary items and discontinued operations divided by average total assets. We examine firm performance for 2 subsequent years, as the performance benefits of product development innovation may take time to manifest (e.g., a new product may take time to gain traction in the market). Our main independent variable, ln(NB_TRADEMARKS), is the natural logarithm of one plus the number of new product trademarks in year t. Similar to equation (1), we estimate equation (2) on all firms as well as firms in low- and high-patent industries separately. If new product trademarks are positively associated with changes in firm performance, β_1 should be positive and significant for both ΔCFO and ΔROA.

We include ln(NB_PATENTS), the natural logarithm of one plus the number of new patents in the same year as the product trademarks, to control for patent creation concurrent to the new product development.[37] In addition, we include the following control variables for possible determinants of future firm performance: SIZE, the natural logarithm of total assets; TOBIN_Q, the market value of total assets divided by the book value of total assets; LEVERAGE, total liabilities divided by total assets; AGE, the natural logarithm of one plus the number of months since the firm first appeared on CRSP; HHI_NORM, the Herfindahl–Hirschman Index, measured as the sum of squares of the market shares of all firms in the industry, normalized to range between 0 and 1; as well as year and industry fixed effects. Finally, we cluster standard errors by firm and report results of two-tailed tests.

B. Empirical Evidence for New Product Development and Changes in Firm Performance

Table 5 presents the results. Consistent with the presentation of the Table 3 results, we first present results for all firms, in Panel A, and then for firms in low- and high-patent industries, in models I–IV and V–VIII of Panel B, respectively. Moreover, for each sample, the first two columns present the $t+1$ and $t+2$ results with future changes in CFO as the dependent variable and the next two columns present the results with future changes in ROA. For all firms, in Panel A, models I and II, we find a significantly positive relation between ln(NB_TRADEMARKS) and ΔCFO, with p-values < 0.01 for both models. In models III and IV, we similarly find a significantly positive relation between ln(NB_TRADEMARKS) and ΔROA, with p-values < 0.01 for both models. These results provide evidence that, for all firms, the number of new product trademarks in a year is significantly associated with improvements in CFO and ROA in the subsequent 2 years.

Importantly, these findings hold after controlling for concurrent patent innovation as well as several other firm performance drivers, such as growth opportunities and firm characteristics. Thus, the performance impact of product development innovation is incremental to that of research and technological innovation.[38] On economic magnitude, an interquartile increase in product trademark

[37]As with equation (1), we alternatively control for patent citations, and results (tabulated in Table OA5 in the Supplementary Material) are similar.

[38]Because new patents may take longer than two years before they can be monetized to result in increases in firm performance, we control for ln(NB_PATENTS) measured over years $t-3$ through t, as an alternative variable to control for patent innovation. The results, tabulated in Table OA7 in the Supplementary Material, are either similar or stronger than the results presented in Table 5. We find a

creation, which is equivalent to an increase of one new product trademark in year t, increases $\Delta CFO_{[t;t+1]}$ ($\Delta CFO_{[t;t+2]}$) by 0.13% (0.17%) of average total assets and $\Delta ROA_{[t;t+1]}$ ($\Delta ROA_{[t;t+2]}$) by 0.24% (0.31%) of average total assets. These improvements in future performance are economically meaningful when compared to median changes in CFO and ROA for $t + 1$ ($t + 2$) for all firms, which are −0.07% and 0.03% (−0.15% and −0.06%) of average total assets, respectively.[39]

TABLE 5

New Product Development and Changes to Firm Performance

$$\Delta \mathrm{PERFORMANCE}_{i,[t;t+k]} = \alpha + \beta_1 \ln(\mathrm{NB\_TRADEMARKS})_{i,t} + \beta_2 \ln(\mathrm{NB\_PATENTS})_{i,t} + \beta_3 \mathrm{SIZE}_{i,t} + \beta_4 \mathrm{TOBIN\_Q}_{i,t} + \beta_5 \mathrm{LEVERAGE}_{i,t} + \beta_6 \mathrm{AGE}_{i,t} + \beta_7 \mathrm{HHI\_NORM}_{i,t} + \sum \chi_j \mathrm{Year}_j + \sum \delta_k \mathrm{Industry}_k + \varepsilon_{i,[t;t+k]}$$

Table 5 presents the results of the regression shown below. The sample covers fiscal years 1993–2011. t-statistics estimated using Huber–White robust standard errors clustered by firm are in parentheses below coefficient estimates. Bolded coefficient estimates and t-statistics are statistically significant (two-tailed p-values < 0.10). Year and industry-fixed effects are included but not reported for brevity. Panel A presents the results for all firm-year observations (43,013 firm-year observations from 3,276 distinct firms). Panel B, models I–IV (V–VIII) present the results for the sample of firm-year observations in low-patent (high-patent) industries (23,966 and 19,047 firm-year observations from 1,899 and 1,549 distinct firms, respectively). Low-patent (high-patent) industries have less (more) than 15 patents per firm year on average (see Panel D of Table 1). In Panel A, models I and II (models III and IV) and Panel B, models I, II, V, and VI (models III, IV, VII, and VIII), the dependent variable is ΔCFO (ΔROA). In Panel A, models I and III (models II and IV) and Panel B, models I, III, V, and VII (models II, IV, VI, and VIII), the dependent variable is changes between year t and year $t+1$ ($t+2$). The sample decreases to 39,096 (37,598) [40,398] {38,843} firm-year observations from 3,194 (3,126) [3,251] {3,189} distinct firms in Panel A, model I (II) [III] {IV}, 21,351 (20,588) [22,624] {21,803} firm-year observations from 1,827 (1,781) [1,884] {1,844} distinct firms in Panel B, model I (II) [III] {IV}, and 17,745 (17,010) [17,774] {17,040} firm-year observations from 1,535 (1,499) [1,536] {1,500} distinct firms in Panel B, model V (VI) [VII] {VIII} after requiring data for the dependent variable (ΔCFO or ΔROA) and lastly to 37,888 (36,428) [39,168] {37,652} firm-year observations from 3,183 (3,108) [3,241] {3,172} distinct firms in Panel A, model I (II) [III] {IV}, 20,650 (19,914) [21,901] {21,108} firm-year observations from 1,822 (1,775) [1,880] {1,839} distinct firms in Panel B, model I (II) [III] {IV}, and 17,238 (16,514) [17,267] {16,544} firm-year observations from 1,524 (1,483) [1,525] {1,484} distinct firms in Panel B, model V (VI) [VII] {VIII} due to control variable data availability. See Appendix B for variable definitions. Industry grouping is based on the Fama and French 48-industry classification. To mitigate the influence of outliers, all variables are winsorized by year and industry at the 1st and 99th percentiles.

Panel A. All Firms

		ΔCFO		ΔROA	
		$t+1$	$t+2$	$t+1$	$t+2$
	Expected Sign	I	II	III	IV
$\ln(\mathrm{NB\_TRADEMARKS})_t$	+	**0.0018**	**0.0025**	**0.0035**	**0.0045**
		(3.91)	**(3.85)**	**(3.03)**	**(3.45)**
$\ln(\mathrm{NB\_PATENTS})_t$	+	0.0004	**0.0017**	**0.0017**	**0.0033**
		(1.28)	**(3.76)**	**(2.23)**	**(2.54)**
SIZE_t	?	**−0.0025**	**−0.0056**	**−0.0050**	**−0.0079**
		(−7.36)	**(−9.35)**	**(−1.89)**	**(−1.80)**
$\mathrm{TOBIN\_Q}_t$	+	−0.0001	**−0.0014**	**−0.0058**	**−0.0063**
		(−0.01)	**(−1.83)**	**(−2.80)**	**(−3.10)**
$\mathrm{LEVERAGE}_t$	–	**0.0182**	**0.0486**	−0.0373	0.0337
		(11.17)	**(6.02)**	(−1.19)	(0.51)
AGE_t	?	**−0.0012**	**−0.0019**	**0.0028**	0.0014
		(−3.20)	**(−3.33)**	**(2.43)**	(1.04)
$\mathrm{HHI\_NORM}_t$	?	−0.0080	−0.0231	−0.0228	−0.0557
		(−0.56)	(−1.02)	(−1.26)	(−1.27)
Year fixed effects			Included		
Industry fixed effects			Included		
No. of obs.		37,888	36,428	39,168	37,652
Adj. R^2 (%)		1.54	2.11	1.81	1.46

(continued on next page)

positive and significant relation between product trademark creation and changes in firm performance in all panels and models.

[39]A related question is whether improvements in future firm performance are arising from CEO risk-taking compensation incentives through their effect on product development innovation. In untabulated

TABLE 5 (continued)

New Product Development and Changes to Firm Performance

Panel B. Firms in Low- and High-Patent Industries

		Low-Patent				High-Patent			
		ΔCFO		ΔROA		ΔCFO		ΔROA	
		$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$
	Expected Sign	I	II	III	IV	V	VI	VII	VIII
ln(NB_TRADEMARKS)$_t$	+	**0.0015** **(2.73)**	**0.0025** **(3.28)**	0.0017 (1.54)	**0.0037** **(2.32)**	**0.0023** **(3.12)**	**0.0029** **(2.78)**	**0.0049** **(2.61)**	**0.0052** **(2.80)**
ln(NB_PATENTS)$_t$	+	0.0002 (0.39)	**0.0019** **(3.03)**	**0.0024** **(3.68)**	**0.0050** **(3.83)**	**0.0012** **(2.87)**	**0.0034** **(5.20)**	**0.0047** **(2.98)**	**0.0058** **(2.32)**
SIZE$_t$	?	−0.0006 (−1.21)	**−0.0022** **(−3.36)**	−0.0035 (−1.62)	−0.0049 (−1.45)	**−0.0045** **(−6.69)**	**−0.0096** **(−9.64)**	**−0.0112** **(−2.33)**	**−0.0135** **(−1.78)**
TOBIN_Q$_t$	+	**−0.0034** **(−2.90)**	**−0.0068** **(−4.15)**	−0.0016 (−0.42)	**−0.0112** **(−1.85)**	0.0005 (0.98)	−0.0005 (−0.68)	**−0.0057** **(−2.36)**	**−0.0050** **(−2.44)**
LEVERAGE$_t$	−	0.0008 (0.09)	0.0139 (1.41)	0.0378 (0.87)	0.0363 (0.55)	**0.0195** **(10.95)**	**0.0665** **(8.41)**	**−0.0472** **(−1.70)**	0.0296 (0.30)
AGE$_t$	?	**−0.0017** **(−3.93)**	**−0.0022** **(−3.31)**	**0.0024** **(2.38)**	0.0020 (1.51)	−0.0008 (−1.24)	**−0.0021** **(−2.20)**	0.0036 (1.63)	0.0005 (0.22)
HHI_NORM$_t$	?	−0.0178 (−0.93)	−0.0383 (−1.18)	0.0093 (0.34)	−0.0474 (−0.59)	0.0055 (0.25)	0.0069 (0.24)	−0.0482 (−1.56)	−0.0381 (−0.93)
Year fixed effects		Included				Included			
Industry fixed effects		Included				Included			
No. of obs.		20,650	19,914	21,901	21,108	17,238	16,514	17,267	16,544
Adj. R^2 (%)		0.95	1.95	2.15	3.48	2.67	3.47	2.43	1.50

Results of improvements in future firm performance are also present for the separate samples of firms in low- and high-patent industries. In Panel B, models I–IV, we find a significantly positive relation between ln(NB_TRADEMARKS) and ΔCFO for both years and ΔROA in year $t+2$, with p-values <0.01, <0.01, and =0.02, respectively. Thus, firms in low-patent industries experience significant improvements in cash flow from operations in each of the 2 subsequent years and significant improvements in return on assets in the second year, consistent with benefits of new product development. In models V–VIII, we find a significantly positive relation between ln(NB_TRADEMARKS) and both ΔCFO and ΔROA for both years, with p-values < 0.01 in all models. On economic magnitude, controlling for concurrent patent innovation, for a low-patent industry firm, an interquartile increase in product trademark creation, equivalent to an increase of one new product trademark, increases $\Delta CFO_{[t;t+1]}$ ($\Delta CFO_{[t;t+2]}$) by 0.10% (0.17%) of average total assets, and $\Delta ROA_{[t;t+2]}$ by 0.26%. For a high-patent industry firm, an interquartile increase in product trademark creation increases $\Delta CFO_{[t;t+1]}$ and $\Delta ROA_{[t;t+1]}$

analyses, we estimate structural equations models to estimate the direct and indirect effects of lagged ln(VEGA) on future ΔCFO and ΔROA. For the indirect effect via the new product development channel, we estimate the association between ln(VEGA)$_{t-1}$ and $\Delta PERFORMANCE_{[t;t+k]}$ through ln(NB_TRADEMARKS)$_t$. We find a statistically significant positive indirect relation between ln(VEGA)$_{t-1}$ and $\Delta PERFORMANCE_{[t;t+k]}$ through ln(NB_TRADEMARKS)$_t$, for both CFO and ROA in years $t+1$ and $t+2$. Interestingly, we also find a statistically insignificant direct relation between ln(VEGA)$_{t-1}$ and $\Delta PERFORMANCE_{[t;t+k]}$ (for CFO and ROA in years $t+1$ and $t+2$). In our setting, these findings suggest that the total effect of CEO risk-taking compensation incentives on improvements in future firm performance is primarily derived from the product development innovation channel.

($\Delta CFO_{[t;t+2]}$ and $\Delta ROA_{[t;t+2]}$) by 0.25% and 0.53% (0.32% and 0.57%) of average total assets, respectively.

Overall, the findings in Table 5 support Hypothesis 2 and suggest that product development innovation is positively associated with changes in firm performance, even after controlling for patent innovation. Both firms in low- and high-patent industries experience these significant improvements in firm performance. In fact, we find, in untabulated tests, that the coefficient estimates on ln(NB_TRADEMARKS) do not differ significantly between low- and high-patent industries for both ΔCFO and ΔROA as the dependent variables. These results suggest that product development innovation is associated with improvements in firm performance for all types of firms, even after controlling for patent innovation. In other words, product development innovation is incrementally important, beyond any underlying technological innovation that may go into new products.

C. High-Quality New Product Development and Changes in Firm Performance

We conduct a cross-sectional analysis to further investigate how new product development is associated with the firm performance improvements documented in Section V.B. As discussed in Section IV.E, trademarks do not protect a product indefinitely. Firms must take action, filing documents and evidence, to maintain legal protection. Trademark maintenance provides a trademark-specific ex-post indicator of trademark quality. To examine the effect of high-quality new product development on changes in future firm performance, we use the indicator variable, $HIGH\_QUALITY_t$, defined in Section IV.E, which equals 1 if the registration of at least one of the new product trademarks in year t is maintained in the future and 0 otherwise. We then augment equation (2) with HIGH_QUALITY and the interaction term ln(NB_TRADEMARKS) × HIGH_QUALITY to examine whether the firm performance effects of new product development vary with quality.

The results are reported in Panel A of Table 6 for all firms and Panel B for firms in low- and high-patent industries separately. In all models, we find insignificant coefficients on ln(NB_TRADEMARKS). However, the coefficients on ln(NB_TRADEMARKS) × HIGH_QUALITY are positive and statistically significant in three of the four models in Panel A and for all four models for the low-patent industry sample in Panel B. Thus, for all firms and low-patent industry firms, it is specifically the subset of new product development that is deemed higher quality that is associated with improvements in future firm performance. This demonstrates that it is product development innovation, not other correlated factors, that drives the improvements in future firm performance. For high-patent industry firms, neither the individual coefficients on ln(NB_TRADEMARKS) nor ln(NB_TRADEMARKS) × HIGH_QUALITY are significant. Thus, for firms for which product development innovation is not a primary form of innovation, the results suggest that it is the combination of both types of new product trademarks – those that are subsequently maintained and those that are not – that contributes to firm performance improvements.

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TABLE 6

High-Quality New Product Development and Changes to Firm Performance

Table 6 presents the results of the regression shown below. The sample covers fiscal years 1993–2011. t-statistics estimated using Huber–White robust standard errors clustered by firm are in parentheses below coefficient estimates. Bolded coefficient estimates and t-statistics are statistically significant (two-tailed p-values < 0.10). Control variables as well as year and industry fixed effects are included but not reported for brevity. Panel A presents the results for all firm-year observations (43,013 firm-year observations from 3,276 distinct firms). Panel B, models I–IV (V–VIII) present the results for the sample of firm-year observations in low-patent (high-patent) industries (23,966 and 19,047 firm-year observations from 1,899 and 1,549 distinct firms, respectively). Low-patent (high-patent) industries have less (more) than 15 patents per firm year on average (see Panel D of Table 1). In Panel A, models I and II (models III and IV) and Panel B, models I, II, V, and VI (models III, IV, VII, and VIII), the dependent variable is ΔCFO (ΔROA). In Panel A, models I and III (models II and IV) and Panel B, models I, III, V, and VII (models II, IV, VI, and VIII), the dependent variable is changes between year t and year $t+1$ ($t+2$). In Panels A and B, the samples are the same as in Panels A and B of Table 5, respectively. See Appendix B for variable definitions. Industry grouping is based on the Fama and French 48-industry classification. To mitigate the influence of outliers, all nonindicator variables are winsorized by year and industry at the 1st and 99th percentiles.

$$\begin{aligned}\Delta\text{PERFORMANCE}_{i,[t;t+k]} = {} & \alpha + \beta_1 \ln(\text{NB\_TRADEMARKS})_{i,t} \times \text{HIGH\_QUALITY}_{i,t} + \beta_2 \ln(\text{NB\_TRADEMARKS})_{i,t} \\ & + \beta_3 \text{HIGH\_QUALITY}_{i,t} + \beta_4 \ln(\text{NB\_PATENTS})_{i,t} + \beta_5 \text{SIZE}_{i,t} + \beta_6 \text{TOBIN\_Q}_{i,t} + \beta_7 \text{LEVERAGE}_{i,t} \\ & + \beta_8 \text{AGE}_{i,t} + \beta_9 \text{HHI\_NORM}_{i,t} + \sum \chi_j \text{Year}_j + \sum \delta_k \text{Industry}_k + \varepsilon_{i,[t;t+k]}.\end{aligned}$$

Panel A. All Firms

		ΔCFO		ΔROA	
		$t+1$	$t+2$	$t+1$	$t+2$
	Expected Sign	I	II	III	IV
ln(NB_TRADEMARKS)$_t$ × HIGH_QUALITY$_t$	+	**0.0031**	**0.0039**	**0.0049**	0.0036
		(1.92)	**(1.87)**	**(1.77)**	(0.85)
ln(NB_TRADEMARKS)$_t$	?	−0.0003	−0.0023	0.0002	−0.0013
		(−0.21)	(−1.27)	(0.07)	(−0.50)
Control variables		Included			
Year fixed effects		Included			
Industry fixed effects		Included			
No. of obs.		37,888	36,428	39,168	37,652
No. of HIGH_QUALITY = 1		9,301	9,032	9,524	9,251
Adj. R^2 (%)		1.55	2.13	1.82	1.46

Panel B. Firms in Low- and High-Patent Industries

		Low-Patent				High-Patent			
		ΔCFO		ΔROA		ΔCFO		ΔROA	
		$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$
	Expected Sign	I	II	III	IV	V	VI	VII	VIII
ln(NB_TRADEMARKS)$_t$ × HIGH_QUALITY$_t$	+	**0.0052**	**0.0061**	**0.0053**	**0.0097**	0.0015	0.0026	0.0077	0.0006
		(2.72)	**(2.61)**	**(2.22)**	**(1.98)**	(0.59)	(0.79)	(1.38)	(0.08)
ln(NB_TRADEMARKS)$_t$	?	−0.0016	−0.0028	−0.0012	−0.0031	0.0010	−0.0018	−0.0006	−0.0007
		(−0.99)	(−1.42)	(−0.66)	(−1.51)	(0.45)	(−0.60)	(−0.15)	(−0.15)
Control variables		Included				Included			
Year fixed effects		Included				Included			
Industry fixed effects		Included				Included			
No. of obs.		20,650	19,914	21,901	21,108	17,238	16,514	17,267	16,544
No. of HIGH_QUALITY = 1		4,047	3,945	4,267	4,156	5,254	5,087	5,257	5,095
Adj. R^2 (%)		0.97	1.99	2.16	3.52	2.67	3.49	2.44	1.51

VI. Exogenous Shock in CEO Incentives and Supplementary Analyses

A. CEO Incentives and New Product Development Around SFAS 123(R): Research Design

Given the persistence in many firm characteristics, our results may be due to an unobserved factor that drives both product development innovation and incentive compensation, or there could be reverse causality whereby new product development opportunities cause convex compensation. While our inclusion of firm fixed effects in additional analyses, described in Section IV.D, partially addresses this issue, to the extent that certain firms tend to have higher product development opportunities, reverse causality remains a possibility. To better understand the direction of causality, we use a change in the accounting rules for stock option compensation, the adoption of SFAS 123(R) in 2005, as an exogenous shock to the use of option-based pay.[40]

Prior to SFAS 123(R), firms provided footnote disclosures of the fair value of stock option grants during the period but only recognized the "intrinsic value" of these grants as an expense on the income statement. Because the strike price of stock options is typically set at the stock price on the grant date, the intrinsic value is typically 0. For fiscal years beginning after June 15, 2005, SFAS 123(R) requires firms to recognize the "fair value" of stock option grants as an expense on the income statement. Consequently, the financial reporting cost of using stock options, in terms of the impact on reported net income, increased considerably with the implementation of SFAS 123(R). Prior research documents a noticeable decrease in the use of stock option compensation after the adoption of SFAS 123(R). Consistent with prior findings and our expectations, option compensation in our sample decreases considerably the following adoption. In our sample, the mean (median) OPTION_COMP, the CEO's annual stock option compensation, measured as the value of new stock options granted as a fraction of total compensation, decreases significantly from 36.5% (35.0%) of total compensation to 19.0% (15.3%) in the three years before and after the implementation of SFAS 123(R), respectively.[41] The decrease in option compensation around SFAS 123(R) is notable when compared to the general increase throughout the 1990s, and the relative stability in the years before and after SFAS 123(R).[42]

We implement propensity-score matching for a difference-in-differences research design, following Fang et al. (2014)). Ideally, we would select a treatment sample that is affected by the exogenous shock and a control sample that is not. We do not have these ideal samples because the accounting rule change applies to all publicly traded firms with stock options. However, some firms are more strongly affected by the revised accounting standard than others, and we exploit this variation in our test. Because the exogenous shock of SFAS 123(R) increases the financial reporting cost of stock option compensation, firms with more CEO compensation in the form of stock options are more strongly affected by SFAS 123(R) and approximate the ideal treatment sample. Firms that are otherwise similar but have a smaller fraction of CEO compensation in the form of stock

[40]Several studies have similarly used SFAS 123(R) as an exogenous shock to stock option compensation to study the effects of CEO incentives on firm policy, including the work of Brown and Lee (2010), Hayes, Lemmon, and Qiu (2012), Skantz (2012), Bakke, Mahmudi, Fernando, and Salas (2016), Mao and Zhang (2018), and Ferri and Li (2020).

[41]OPTION_COMP is measured using the ExecuComp variables option_awards_blk_value (i.e., the Black-Scholes value of stock options granted during the year) prior to 2006 and option_awards_fv (i.e., the grant-date fair value of stock options granted during the year) starting from 2006, scaled by total compensation.

[42]We focus on changes in OPTION_COMP since SFAS 123(R) most directly affects the use of option compensation. We would expect similar incentive effects for option compensation as for vega. A decrease (increase) in option compensation should cause a decrease (increase) in risk-taking from the CEO, including pursuit of risky product development innovation.

options are less affected by SFAS 123(R) and approximate the ideal control sample. Effects within the control sample act as a benchmark for time trends in option compensation and product development innovation to better capture the incremental effects of the SFAS 123(R) shock to the treatment sample.

We designate 2002–2004 (2007–2009) as the pre-(post-) SFAS 123(R) period. We begin with the sample of 635 distinct firms with at least one new product trademark in both subperiods and nonmissing OPTION_COMP. We then sort them into terciles based on mean OPTION_COMP from the pre-event period. As expected, treatment firms are the most affected by SFAS 123(R), with a decrease of mean OPTION_COMP of 57.9% of total compensation between the pre- and post-SFAS 123(R) periods. In comparison, control firms experience an increase of mean OPTION_COMP of 40.7% of total compensation over the same period. Firms in our treatment sample experience a decrease in product trademark creation after SFAS 123(R), from a total of 14.76 new product trademarks in the pre-SFAS 123 (R) period to 13.29 (10.0% decrease) in the post-period. In comparison, firms in the control sample experience an increase, from 14.74 to 17.55 (19.0% increase). These univariate statistics provide prima facie evidence of a drop in new product development following the implementation of SFAS 123(R) for firms with large amounts of stock option compensation in the pre-SFAS 123(R) period.

Using propensity scores for the likelihood of high OPTION_COMP, we match the top-tercile treatment sample firms with firms in the bottom-tercile control sample. The probit model to obtain propensity scores for the 212 and 211 firms in the treatment and control samples, respectively, is as follows. The dependent variable equals 1 (0) if the firm is a treatment (control) firm. The independent variables are 3-year averages of pre-SFAS 123(R) new product trademarks, new patents, total compensation, assets, return on assets, and analyst coverage, as well as new product trademark growth over the pre-SFAS 123(R) period, and industry fixed effects using the Fama and French 12-industry classification. Results are untabulated for brevity. The probit model has a Pseudo R^2 of 47.00% and p-value of χ^2 smaller than 0.01, indicating a good fit.

Each firm in the treatment sample is matched to the firm from the control sample with the closest propensity score calculated from the probit model.[43] We then apply caliper matching to ensure a proper match between the two samples. The final matched sample consists of 50 treatment-control pairs. The post-matching treatment-control firm differences in mean and median propensity scores are 0.0004 and 0.0009, respectively, while these differences pre-matching are 0.5270 and 0.7374, respectively. This suggests that the treatment and control samples are well-matched. However, they differ in option compensation, suggesting that the samples correctly capture a difference in the likely effect of SFAS 123(R). We also check for any post-matching differences between treatment and control firms on individual matching variables. The t-test statistics confirm that treatment and control firms do not differ along the characteristics on which they are matched.[44]

[43]We match with replacement as it gives rise to better matches, less bias, and imposes lower sample size requirements compared to matching without replacement (Roberts and Whited (2013), DeFond, Erkens, and Zhang (2017)).

[44]Table OA10 in the Supplementary Material presents additional propensity-score-matching diagnostics. Moreover, we conduct diagnostic tests to examine whether the parallel trends assumption holds for our treatment and control samples. First, the difference in the pre-event product trademark growth

We estimate the following equation for the difference-in-differences test for firm i:

$$
\begin{aligned}
(3)\quad \ln(\text{NB\_TRADEMARKS})_{i,\text{Pre/Post123R}} = {} & \alpha + \beta_1 \text{TREATMENT}_i \times \text{POST\_123R}_i \\
& + \beta_2 \text{TREATMENT}_i + \beta_3 \text{POST\_123R}_i \\
& + \beta_4 \ln(\text{NB\_PATENTS})_{i,\text{Pre123R}} \\
& + \beta_5 \ln(\text{TOTAL\_COMP})_{i,\text{Pre123R}} \\
& + \beta_6 \text{SIZE}_{i,\text{Pre123R}} + \beta_7 \text{ROA}_{i,\text{Pre123R}} \\
& + \beta_8 \text{TOBIN\_Q}_{i,\text{Pre123R}} \\
& + \beta_9 \text{LEVERAGE}_{i,\text{Pre123R}} + \varepsilon_{i,\text{Pre/Post123R}},
\end{aligned}
$$

where ln(NB_TRADEMARKS)$_{Pre/Post123R}$ is the 3-year average of the natural logarithm of one plus the number of new product trademarks in a year, measured in the pre- or post-SFAS 123(R) period; TREATMENT is an indicator variable equal to 1 (0) if the firm is in the treatment (control) sample; and POST_123R is an indicator variable equal to 1 (0) if the observation is measured in the post-(pre-) SFAS 123(R) period. We also include, as control variables, the 3-year averages of the variables ln(NB_PATENTS), ln(TOTAL_COMP), SIZE, ROA, TOBIN_Q, and LEVERAGE, measured over the pre-SFAS 123(R) period.[45] Our variable of interest is the interaction between TREATMENT and POST_123R. If treatment firms experience a larger decrease in new product development after the adoption of SFAS 123(R) than control firms do, β_1 will be significantly negative. We cluster standard errors by firm to account for the fact that the matching was performed with replacement.

Finally, we check the parallel trends assumption for the difference-in-differences test following (Bertrand and Mullainathan (2003)). We examine the years before and after the adoption of SFAS 123(R) in the following difference-in-differences equation:

$$
\begin{aligned}
(4)\quad \ln(\text{NB\_TRADEMARKS})_{i,\text{Pre/Post123R}} = {} & \alpha + \beta_1 \text{TREATMENT}_i \times \text{BEFORE}_i^{-2} \\
& + \beta_2 \text{TREATMENT}_i \times \text{BEFORE}_i^{-1} + \beta_3 \text{TREATMENT}_i \times \text{AFTER}_i^{1} \\
& + \beta_4 \text{TREATMENT}_i \times \text{AFTER}_i^{2+} + \beta_5 \text{TREATMENT}_i + \beta_6 \text{BEFORE}_i^{-2} \\
& + \beta_7 \text{BEFORE}_i^{-1} + \beta_8 \text{AFTER}_i^{1} + \beta_9 \text{AFTER}_i^{2+} + \beta_{10} \ln(\text{NB\_PATENTS})_{i,\text{Pre123R}} \\
& + \beta_{11} \ln(\text{TOTAL\_COMP})_{i,\text{Pre123R}} + \beta_{12} \text{SIZE}_{i,\text{Pre123R}} + \beta_{13} \text{ROA}_{i,\text{Pre123R}} \\
& + \beta_{14} \text{TOBIN\_Q}_{i,\text{Pre123R}} + \beta_{15} \text{LEVERAGE}_{i,\text{Pre123R}} + \varepsilon_{i,\text{Pre/Post123R}},
\end{aligned}
$$

between the matched treatment-control pairs is economically and statistically insignificant (treatment-control difference = 0.66; t-statistic = 0.77; p-value = 0.44). Second, we construct a new variable TREND, which takes the value of zero for the year of 2002, one for 2003, and two for 2004, and estimate a regression model in the pre-event period, regressing ln(NB_TRADEMARKS) on the indicator variables TREATMENT, TREND, and the interaction term TREATMENT × TREND. The coefficient on TREATMENT × TREND is statistically insignificant (coefficient = −0.0468; t-statistic = −0.77; p-value = 0.44), which indicates that there are no differential time trends between the treatment and control samples.

[45]In sensitivity analyses, we find that our difference-in-differences results presented in Panel A of Table 7 remain unchanged if we include or exclude any of the control variables included in equation (3).

where BEFORE^{-2}, BEFORE^{-1}, AFTER^{1}, and AFTER^{2+} are indicator variables for each of the years in the pre- and post-SFAS 123(R) periods.

B. CEO Incentives and New Product Development Around SFAS 123(R): Empirical Evidence

Panel A of Table 7 presents the results of the difference-in-differences test of equation (3) for the effect of the exogenous shock from SFAS 123(R). In the post-SFAS 123(R) period, control firms experience an increase in product development creation, with a statistically significant coefficient on POST_123R. The results show a significantly negative coefficient on TREATMENT × POST_123R of −0.2577 (p-value = 0.05), indicating that treatment firms experience a significantly negative change in new product development due to the adoption of SFAS 123(R). The economic magnitude is large as well, consistent with the univariate statistics described above. The coefficient estimate implies that a firm in the matched treatment sample with median pre-SFAS 123(R) product development produces roughly 18.8% fewer product trademarks after SFAS 123(R) than it would have without the SFAS 123(R) effect.

Together with the results presented in Section V.B, the reduction in new product development translates into decreases in future performance. Specifically, the 18.8% decrease in new product trademarks corresponds to decreases in CFO and ROA of −0.05% and −0.09% (−0.06% and −0.12%), of average total assets, in the 1 (2) subsequent year(s), respectively. These drops in future performance range from 11.0% to 47.1% of the magnitudes of the corresponding median changes in CFO and ROA for matched treatment firms in the pre-SFAS 123(R) period. Results are also similar if we control for restricted stock use.[46]

For valid inferences from the difference-in-differences test, we need to check that the parallel trends assumption in the pretreatment period holds. To that end, we estimate equation (4). Results are presented in Panel B of Table 7. Neither of the coefficients on TREATMENT × BEFORE^{-2} and TREATMENT × BEFORE^{-1} are significant, indicating no difference in ln(NB_TRADEMARKS) between the treatment and control samples in the pre-SFAS 123(R) period. This confirms that pre-SFAS 123(R) trends are not driving differences between the treatment and control groups. In contrast, the coefficients on TREATMENT × AFTER^{1} and TREATMENT × AFTER^{2+} are both significantly negative, consistent with SFAS 123(R) causing a decrease in new product development. These results indicate that the decrease in stock option compensation from the exogenous shock, the implementation of SFAS 123(R), is followed by a relative drop in product development

[46]SFAS 123(R) adoption also triggered a general re-weighting of compensation components, leading some firms to increase the use of restricted stock as an alternative to stock options. In particular, in our sample firms, restricted stock represents an average of 8.4% of total CEO compensation before SFAS 123(R) and 14.1% afterward. Restricted stock grants during our sample period generally have time-based vesting schedules, with no performance-based vesting criteria, so they do not provide any convexity of incentives. However, as a robustness test, we include the fraction of total CEO compensation in the form of restricted stock as a control variable in the difference-in-differences regression in equation (3). The results (untabulated) are almost indistinguishable to the results in Panel A of Table 7.

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innovation for firms most affected by the shock, compared to a matched control sample. Thus, option compensation has a causal effect on new product development.

These findings supplement the evidence in Mao and Zhang (2018) of a shift following SFAS 123(R) away from higher-risk explorative innovation toward lower-risk exploitative innovation. If patent innovation is more likely associated with the former and product development innovation with the latter, one might predict that firms would pursue more of the lower-risk product development innovation. However, our result of a *drop* in new product development after the implementation of SFAS 123(R) is inconsistent with this conjecture. Instead, our

TABLE 7

CEO Stock Option Compensation and New Product Development Around SFAS 123(R): Difference-in-Differences Analysis with Propensity Score Matching

Table 7 presents the results of a difference-in-differences regression of CEO stock option compensation and product trademark filing around the adoption of SFAS 123(R). The 3-year pre-SFAS 123(R) period corresponds to fiscal years 2002–2004 for ln(NB_TRADEMARKS) and ln(NB_PATENTS), and 2001–2003 for all other variables. For ln(NB_TRADEMARKS), the 3-year post-SFAS 123(R) period corresponds to fiscal years 2007–2009. The sample consists of 635 distinct firms, with at least one new product trademark in both the pre- and post-SFAS 123(R) periods and nonmissing mean OPTION_COMP in the pre-SFAS 123(R) period. We sort the 635 firms into terciles based on mean pre-SFAS 123(R) OPTION_COMP and retain the 211 (212) firms in the bottom (top) tercile with the smallest (largest) mean pre-SFAS 123(R) OPTION_COMP. We then use propensity score matching to construct matched treatment-control pairs where firms in the bottom (top) tercile with the smallest (largest) mean pre-SFAS 123(R) OPTION_COMP are the control (treatment) sample. We apply a combination of nearest-neighbor matching and caliper matching, resulting in 50 treatment-control pairs. In Panel A, for each firm, we calculate the average of each variable over the 3-year pre- and post-SFAS 123(R) periods, resulting in 200 observations. In Panel B, we apply the method of Bertrand and Mullainathan (2003) to verify the parallel trend assumption. For this method, we include indicator variables for each of the 3 years of the pre- and post-SFAS 123(R) periods, increasing the possible number of observations to 600. Due to lack of data for certain firm years, 12 observations are lost, resulting in 588 observations. In this panel, control variables are included but not reported for brevity. *t*-statistics estimated using Huber–White robust standard errors clustered by firm are in parentheses below coefficient estimates. Bolded coefficient estimates and *t*-statistics are statistically significant (two-tailed *p*-values < 0.10). See Appendix B for variable definitions. To mitigate the influence of outliers, all nonindicator variables are winsorized at the 1st and 99th percentiles.

Panel A. Main Analysis

$$\begin{aligned}\ln(\text{NB\_TRADEMARKS})_{i,\text{Pre/Post123R}} = {} & \alpha + \beta_1 \text{TREATMENT}_i \times \text{POST\_123R}_i + \beta_2 \text{TREATMENT}_i + \beta_3 \text{POST\_123R}_i \\ & + \beta_4 \ln(\text{NB\_PATENTS})_{i,\text{Pre123R}} + \beta_5 \ln(\text{TOTAL\_COMP})_{i,\text{Pre123R}} + \beta_6 \text{SIZE}_{i,\text{Pre123R}} \\ & + \beta_7 \text{ROA}_{i,\text{Pre123R}} + \beta_8 \text{TOBIN\_Q}_{i,\text{Pre123R}} + \beta_9 \text{LEVERAGE}_{i,\text{Pre123R}} + \varepsilon_{i,\text{Pre/Post123R}}\end{aligned}$$

Variable	Expected Sign	Coefficient (*t*-Stat)
TREATMENT × POST_123R	–	**−0.2577** **(−1.95)**
TREATMENT	?	0.1937 (0.85)
POST_123R	?	**0.2854** **(2.80)**
ln(NB_PATENTS)$_{\text{Pre123R}}$	+	0.0708 (1.06)
ln(TOTAL_COMP)$_{\text{Pre123R}}$	?	0.2734 (1.51)
SIZE$_{\text{Pre123R}}$	+	0.0836 (0.75)
ROA$_{\text{Pre123R}}$	?	0.6295 (1.43)
TOBIN_Q$_{\text{Pre123R}}$	+	0.1301 (1.38)
LEVERAGE$_{\text{Pre123R}}$	–	0.4715 (0.87)
Intercept	?	**−2.3908** **(−2.53)**
No. of obs.		200
Adj. R^2 (%)		30.74

(continued on next page)

TABLE 7 (continued)

CEO Stock Option Compensation and New Product Development Around SFAS 123(R): Difference-in-Differences Analysis with Propensity Score Matching

Panel B. Analysis Applying the Method of Bertrand and Mullainathan (2003)

$$\begin{aligned}\ln(\text{NB\_TRADEMARKS})_{i,\text{Pre/Post123R}} = {} & \alpha + \beta_1 \text{TREATMENT}_i \times \text{BEFORE}_i^{-2} + \beta_2 \text{TREATMENT}_i \times \text{BEFORE}_i^{-1} \\ & + \beta_3 \text{TREATMENT}_i \times \text{AFTER}_i^{1} + \beta_4 \text{TREATMENT}_i \times \text{AFTER}_i^{2+} + \beta_5 \text{TREATMENT}_i \\ & + \beta_6 \text{BEFORE}_i^{-2} + \beta_7 \text{BEFORE}_i^{-1} + \beta_8 \text{AFTER}_i^{1} + \beta_9 \text{AFTER}_i^{2+} \\ & + \beta_{10} \ln(\text{NB\_PATENTS})_{i,\text{Pre123R}} + \beta_{11} \ln(\text{TOTAL\_COMP})_{i,\mathit{Pre123R}} \\ & + \beta_{12} \text{SIZE}_{i,\text{Pre123R}} + \beta_{13} \text{ROA}_{i,\text{Pre123R}} + \beta_{14} \text{TOBIN\_Q}_{i,\text{Pre123R}} \\ & + \beta_{15} \text{LEVERAGE}_{i,\text{Pre123R}} + \varepsilon_{i,\text{Pre/Post123R}}\end{aligned}$$

Variable	Expected Sign	Coefficient (*t*-Stat)
TREATMENT × BEFORE^{-2}	?	−0.1531 (−1.11)
TREATMENT × BEFORE^{-1}	?	−0.0936 (−0.77)
TREATMENT × AFTER^{1}	–	**−0.3881** **(−2.33)**
TREATMENT × AFTER^{2+}	–	**−0.3347** **(−2.25)**
TREATMENT	?	0.2668 (1.16)
BEFORE^{-2}	?	**0.5400** **(5.46)**
BEFORE^{-1}	?	**0.6697** **(6.81)**
AFTER^{1}	?	**0.8178** **(6.09)**
AFTER^{2+}	?	**0.6348** **(5.80)**
Intercept	?	**−2.8031** **(2.96)**
Control variables		Included
No. of obs.		588
Adj. R^2 (%)		29.05

evidence suggests that product development innovation is also highly risky and that risk-taking compensation incentives have an even stronger effect on overall firm innovation than previously documented.

C. Non-CEO Employee Incentives

Our focus on CEO compensation is motivated by the importance of CEO leadership in driving firm-wide product development. However, non-CEO executives can also contribute to innovation. Lerner and Wulf (2007) show that compensating non-CEO executives, in particular, those involved with R&D, with long-term or risk-taking incentives contributes to greater technological innovation, measured by more patents and patent citations, within higher-tech firms with standalone R&D divisions. We examine the effects of non-CEO executive option-based compensation on product development innovation. In line with the development of Hypothesis 1, we predict a positive association between risk-taking incentives of non-CEO executives (in the form of long-term payout incentives and convex incentives) and new product development.

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To test this prediction, we replace ln(VEGA) and ln(DELTA) in equation (1) with ln(VEGA) and ln(DELTA) based on non-CEO executives, ln(NONCEO_VEGA) and ln(NONCEO_DELTA). Consistent with our predictions, the coefficient on ln(NONCEO_VEGA) is significantly positive for all firms as well as firms in low- and high-patent industries separately (*p*-value < 0.01 for all three samples of firms). The coefficient on ln(NONCEO_DELTA) is negative yet statistically insignificant. These results (untabulated) are consistent with non-CEO executives contributing to product development innovation when faced with higher risk-taking incentives.

We would also expect incentives in nonexecutive rank-and-file employee compensation to affect product development innovation. Hochberg and Lindsey (2010) and Chang et al. (2015) show that nonexecutive employee incentives have a significant impact on overall firm performance. However, there are very limited data on nonexecutive compensation. We encourage future research to investigate this topic further.[47]

VII. Conclusion

CEO surveys have suggested that the development of new products and services is one of the most important operating decisions of managers, and governmental agencies (such as the OECD) have called for the inclusion of new product development in the definition of innovation. Despite its importance, product development activities are not reported separately by firms. Furthermore, product development innovation is rarely studied, perhaps because of the absence of large sample data of new products.

To fill this gap in the literature, we compile a large novel data set of new product trademarks as a measure of product development innovation. Using this measure, we study risk-taking compensation incentives for new product development as well as the associated improvements in firm performance. We find that the convexity of CEO compensation incentives is positively associated with greater new product development, even after controlling for patent innovation. These findings suggest that providing risk-taking incentives to CEOs promotes product innovation, independent of patent innovation. We also examine changes in firm performance following product development innovation. We find that new product development is significantly positively related with improvements in firm performance, measured using cash flow from operations and return on assets, consistent with product development innovation contributing to improvements in firm performance.

All these findings hold for all firms as well as for low- and high-patent industries separately. Examining firms in low-patent industries allows us to further isolate effects related to new product development and to provide insight into firms

[47]Following Bergman and Jenter (2007), we construct an estimate of stock options granted to nonexecutive employees, by combining total option compensation and executive option compensation data, to examine whether nonexecutive employee stock options are related to product trademark creation. The results (untabulated) are consistent with nonexecutive employee option compensation contributing to product development innovation. However, due to data availability in ExecuComp, the sample period for this test ends in 2006. This pilot study result suggests that the topic is worthy of further investigation.

for which product development is potentially more economically important. These results also help explain the use of stock option compensation in low-patent industries, which are traditionally considered less risky or less innovative; they simply pursue a different form of innovation than that captured by patent or R&D-related measures. Examining firms in high-patent industries, for which product development captures the final phases of a longer innovation process, allows us to provide insight into firms bringing patented technologies to the market in the form of new products. Our results are of similar magnitude and significance across both low- and high-patent industries, indicating the importance of product development innovation to all firms.

In an additional analysis, we exploit SFAS 123(R) as an exogenous shock to the use of stock options. Using a difference-in-differences design around this event, with propensity-score-matched samples, we find that firms most strongly affected by SFAS 123(R) experience a significant and substantial decrease in new product development in comparison to firms that are least affected. The result that an exogenous shock to compensation structure is followed by a change in new product development provides evidence on causality, indicating that stock option compensation helps drive product development innovation.

Previous innovation studies have focused almost exclusively on scientific research and technological innovation in high-patent industries. Thus, little is known about the value of product development innovation and what motivates it. This evidence is important, especially due to the broad presence of new product development in all industries. Our study qualitatively changes our understanding of innovation in a broad range of firms in the economy, especially low-patent industries. Indeed, based on prior research, one might conclude that low-patent industries, with extremely low levels of patent creation and R&D, do not innovate and that their use of risk-taking incentives is for noninnovation-related purposes. Our study also shows the importance of motivating product development innovation in high-patent industries, as new product development is associated with improvements in firm performance, even in these industries and after controlling for patent innovation.

Overall, our study provides insight into the design of compensation contracts to motivate product development innovation and the value of new product development, for firms in both low- and high-patent industries. We hope that this study encourages future research on product development and trademarks, both as an important firm activity and as an important and distinct dimension of innovation. Further examination of product development innovation would contribute to better incentivizing and monitoring managers, driving firm performance, valuing firms, and allocating resources more efficiently across firms, to encourage innovation and economic growth.

Appendix A. New Trademarks as Measures of New Product Development and Marketing

In Appendix A, we provide examples of trademarked products, logos, and slogans, and describe our methodology for identifying new product trademarks and marketing trademarks.

First, consider General Mills' Yoplait Pro-Force Greek yogurt. This new product was innovative for the company and market – tailoring the relatively new high-protein Greek yogurt product to children and teenagers who have traditionally favored the sweeter traditional yogurts (Zacks Equity Research (2013)). No previous product had attempted to tailor a Greek yogurt for this market. However, the new product was not technologically innovative. In general, the Food Products industry, a low-patent industry, tends to create new products by applying existing technologies in new and creative ways (e.g., unique new recipes, using organic rather than nonorganic ingredients), rather than developing new cutting-edge technology. Based on our search, General Mills and Yoplait did not file any new patents related specifically to the production of Greek yogurt or high-protein yogurt around the launch of Yoplait's new product. Most likely, they relied on their existing production methods. However, Yoplait registered two trademarks, for "Yoplait Pro-Force" and "Pro-Force," to protect its new product line. Thus, the trademarks capture the output of product development efforts, and can be viewed as innovation using a broad definition of the term.

Second, consider Apple Inc.'s iPhone, launched in 2007. Apple, a high-patent firm, develops new products, similar to General Mills. But unlike General Mills, Apple engages in significant amounts of engineering-related research to develop new technologies which it uses in these products. The iPhone in particular was technologically innovative. Prior to 2007, Apple had only 17 patents related to cell phones. By 2012, it had nearly 1,300, almost all filed after the 2007 launch of the initial iPhone (Gaze and Roderick (2012)). While some patents may never be related to products, these patents were turned into a product for sale, in the form of the iPhone. The trademark process resulted in a single trademark for the iPhone itself, with additional trademarks over time for variations in the logo, and for related products or marketing phrases, like "Made for iPod, iPad, iPhone" and "Works with iPhone." We were able to find a total of 15 active trademarks registered by Apple Inc. for the iPhone. Thus, the iPhone encompasses both research and product development.

Thus, new product development occurs whenever companies develop new products. The riskiness of this activity is likely to vary, but just as with Yoplait's Pro-Force yogurt, even low-technology new product development is likely to involve some risk. For example, Yoplait could not be certain that the product would be successful, and it had to divert certain limited resources, such as shelf space, to the new product and away from established products. In addition, product development innovation can occur either separate from, or in conjunction with, patent-related innovation. In low-patent industries, it is more likely to occur as the primary form of innovative activity, whereas in high-patent industries it is more likely that scientific research and technological innovation play a large role.

In addition, trademarks can capture marketing activity. While many trademarks represent product names, usually indicating new products, many trademarks are related to new marketing campaigns for existing products. For example, the following three images were registered by The Coca-Cola Company in 1976, 1992, and 2005, respectively.

While these trademarks represent investments in the firm's marketing of the Fanta product, they do not represent new product development.[48] Marketing functions are often separated from product development in organizations, and factors that contribute to the pursuit and success of these separate activities likely also differ. Consequently, for our analyses, separating new trademarks resulting from product development and new trademarks from marketing is appropriate.

We classify all images (20.3% of our sample trademarks) as marketing related. Similarly, we classify "sound marks," such as the MGM roaring of the lion and the THX sound at movies, as marketing related (0.02% of our sample trademarks). Finally, while companies often trademark logos such as the Fanta logos shown in this appendix, they often also include a "Word mark" for the product name. In the case of Fanta, The Coca-Cola Company has a trademark for the word "Fanta," which was originally registered in 1955 and which is still active, in addition to the changing image marks. "Word marks" tend to include both product names and slogans used for marketing. To illustrate this distinction, the following table provides examples for well-known companies:

Company	Product Trademarks	Marketing Trademarks (e.g., Slogans)
McDonald's Corp.	Big Mac; Big N' Tasty; McDouble	I'm Lovin' It; What We're Made Of
The Coca-Cola Co.	Fanta; Sprite; Cherry Coke	The Coca-Cola Side of Life; Coca-Cola Refresh Your Flow
Citigroup Inc.	Citi Retail Services; Citi Treasury Diagnostics; C-Tracks	Citibank Deals About Town; Endless Points. Endless Potential; Every Step of the Way

In order to categorize word marks as either product or marketing trademarks, we examine 500 randomly chosen trademarks, and hand-code them as product or marketing trademarks based upon searches for the given words or phrases. As expected, longer phrases are more likely to be marketing-focused, while shorter phrases are more likely to represent product names. In particular, we find that for trademarks of four words, slightly more than 50% are related to marketing. The percentage is even higher for longer phrases. For trademarks of three words, the percentage is approximately 25%, and less than 7% (2.5%) for two-word (one-word) trademarks. Thus, we use the number of words in the word mark to separate marketing- from product-focused word-based trademarks, where trademarks with at least four words of text are classified as marketing trademarks, and trademarks with three words or less of text are classified as product trademarks. While this partition is not error-free, it provides a reasonable rule for categorizing the 105,582 unique trademarks in our sample, while minimizing classification errors. The categorization results in 70,465, or 66.7%, of the trademarks being classified as product trademarks, while 35,117, or 33.3%, are classified as marketing trademarks.

[48]While we were unable to find definitive sources, a reading of dozens of news articles related to Fanta suggests that the 1992 and 2005 logo changes were not associated with any significant changes in the taste, color, or general packaging (e.g., cans and bottles) of the Fanta product. The 1992 logo change corresponded to a significant overseas marketing effort for Fanta, particularly in the former Soviet Union and Eastern Bloc countries. The 2005 logo change corresponded to a reintroduction of the Fanta product in the U.S. market in the early 2000s, with a large associated marketing effort. We were unable to find relevant information regarding the 1976 logo change.

Appendix B. Variable Definitions

AFTER^1 (AFTER^{2+}): Indicator variable equal to 1 for the fiscal year(s) 2007 (2008 or 2009), and 0 otherwise.

AGE: Natural logarithm of 1 plus the number of months since the firm first appeared on CRSP.

BEFORE^{-1} (BEFORE^{-2}): Indicator variable equal to 1 for the fiscal year 2004 (2003), and 0 otherwise.

BONUS: CEO's annual bonus (in $K).

CASH: Cash and cash equivalents divided by total assets.

CEO_FOUNDER: Indicator variable is equal to 1 if the CEO is the founder of the firm, and 0 otherwise.

CEO_LGTENURE: Indicator variable is equal to 1 if the CEO's tenure is strictly above the median, and 0 otherwise.

CFO: Cash flow from operations divided by average total assets.

ΔCFO: Change in CFO, measured as CFO in year $t+1$ or $t+2$ minus CFO in year t.

ΔRET_VOL: Change in RET_VOL, measured as RET_VOL in year $t+1$ or $t+2$ minus RET_VOL in year t.

ΔROA: Change in ROA, measured as ROA in year $t+1$ or $t+2$ minus ROA in year t.

DELTA: CEO's pay-performance sensitivity, measured as the dollar change in the CEO's wealth for a 1% change in stock price.

HHI_NORM: Herfindahl-Hirschman Index, measured as the sum of squares of the market shares of all firms in the industry, normalized to range between 0 and 1. Industry grouping is based on the Fama and French 48-industry classification.

HIGH_QUALITY: Indicator variable equal to 1 if the registration of at least one of the new product trademarks in the year is maintained in the future, and 0 otherwise.

IMPORTANCE_INTENSITY: Indicator variable equal to 1 (0) if the firm is in an industry where the product development intensity (i.e., number of new product trademarks per firm-year) is above (below) the median.

IMPORTANCE_SURVEY: Indicator variable equal to 1 (0) if the firm is in an industry where the percentage of firms ranking trademarks as "very important" or "somewhat important," in the 2015 survey by the Census Bureau and National Science Foundation's BRDIS, is above (below) the median.

LEVERAGE: Total liabilities divided by total assets.

ln(DELTA): Natural logarithm of 1 plus DELTA.

ln(NB_PATENTS): Natural logarithm of 1 plus the number of new patents in the year.

ln(NB_TRADEMARKS): Natural logarithm of 1 plus NB_TRADEMARKS.

ln(TOTAL_COMP): Natural logarithm of TOTAL_COMP.

ln(VEGA): Natural logarithm of 1 plus VEGA.

MVE: Market value of common equity (in $M).

NB_MONTHS: Number of months since the firm first appeared on CRSP.

NB_TRADEMARKS: Number of new product trademarks in the year, using the latest of the filing date and the date of first use for each trademark.

OPTION_COMP: CEO's annual stock option compensation, measured as the value of new stock options granted as a fraction of total compensation.

OPTION_GRANTS: Value of new stock options granted to the CEO during the year (in $K).

PERFORMANCE: Variable representing CFO or ROA.

POST_123R: Indicator variable equal to 1 (0) if the observation is in the post-(pre-) SFAS 123(R) period.

R&D: Research and development (R&D) expense divided by total sales (set as 0 when R&D expense is missing in Compustat).

RET_VOL: Annualized standard deviation of daily stock returns over the year.

ROA: Return on assets, measured as earnings before extraordinary items and discontinued operations divided by average total assets.

SALARY: CEO's annual base salary (in $K).

SALES: Total sales (in $M).

SIZE: Natural logarithm of total assets (in $M).

STOCK_GRANTS: Value of the stock-related awards (e.g., restricted stock, restricted stock units, phantom stock, phantom stock units, and common stock equivalent units) granted to the CEO during the year (in $K).

TOBIN_Q: Market value of total assets divided by the book value of total assets.

TOTAL_ASSETS: Total assets (in $M).

TOTAL_COMP: CEO's annual total compensation, measured as the sum of salary, bonus, other annual compensation, value of restricted stock granted, value of new stock options granted during the year, long-term incentive payouts, and all other compensation (in $K).

TREATMENT: Indicator variable equal to 1 (0) if the firm is in the treatment (control) sample.

VEGA: CEO's sensitivity to stock return volatility, measured as the dollar change in the CEO's option portfolio for a 0.01 change in standard deviation of stock returns.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001260.

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