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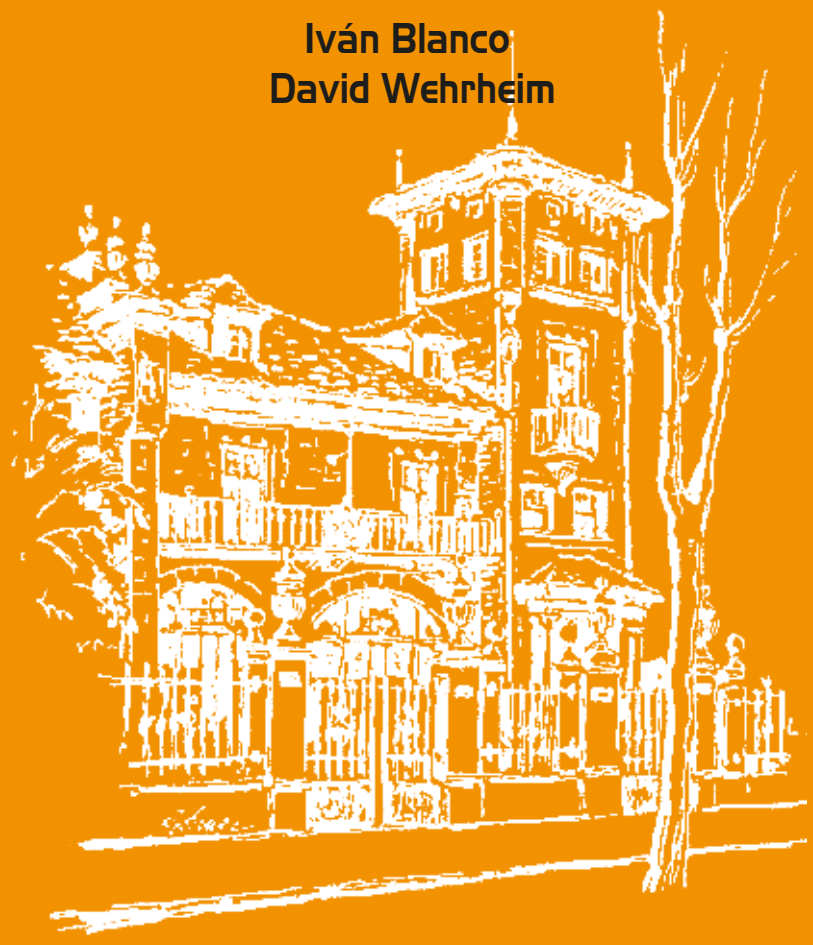
THREE ESSAYS IN FINANCIAL MARKETS. THE BRIGHT SIDE OF FINANCIAL DERIVATIVES: OPTIONS TRADING AND FIRM INNOVATION

Iván Blanco
David Wehrheim



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Iván Blanco is Assistant Professor in Finance at CUNEF. Ivan's current research interests include: (i) Feedback effects between financial markets and real economy, (ii) The intersection of asset pricing and corporate finance, (iii) Quantitative Investment & Trading and (iv) Mathematical & Quantitative Finance.

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Prior to joining academia, David spent several years in industry working in marketing and strategy positions.

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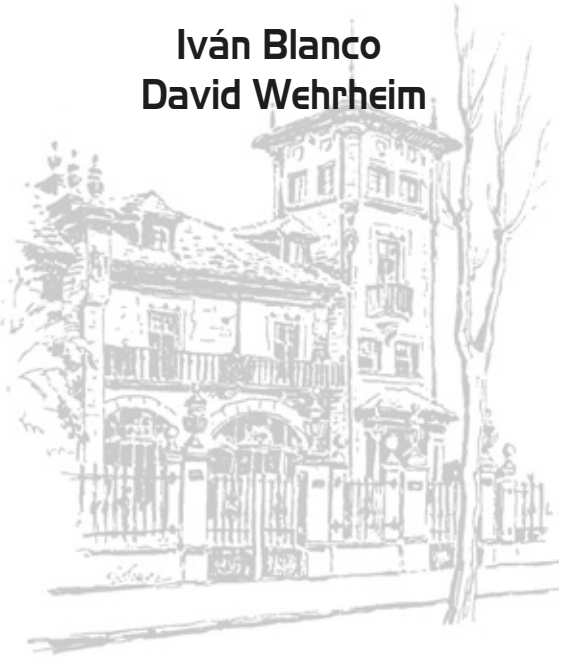

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- Y por último, la línea editorial, en la que se enmarcan estos Cuadernos de investigación, con el objetivo de poner a disposición de la sociedad en general, y de la comunidad académica y profesional en particular, el conocimiento generado en torno al Sector Financiero fruto de todas las acciones desarrolladas en el ámbito del Santander Financial Institute y especialmente los resultados de las Becas, Ayudas y Premios Tesis Doctorales.

ÍNDICE

INTRODUCTION

Innovation is the main driver of growth and the wealth of nations. As emphasized by Porter (1992, p. 65), "[t]o compete effectively in international markets, a nation's businesses must continuously innovate and upgrade their competitive advantages. Innovation and upgrading come from sustained investment in physical as well as intangible assets." Given the importance of innovation for competitiveness, it is a priority to understand those factors that determine incentives to innovate at the firm level. There has been much debate on the role of financial markets in promoting innovation. While developed capital markets can improve the efficiency of long-term resource allocation through their monitoring and disciplining mechanisms, the need to meet quarterly or annual financial objectives gives rise to adverse externalities that may impair firms' incentives to innovate (Holmström, 1989; Porter, 1992)[1].

In this paper, we focus on one cornerstone of public equity markets, namely, financial derivatives. Specifically, we study whether the volume of equity options written on the underlying asset encourages or impedes firm innovation. Since the beginning of the new century, the total equity options volume traded on U.S. exchanges has grown exponentially, from 676 million contracts in 2000 to over 3,727 million contracts in

Work on this paper was partly done while Wehrheim was visiting the Department of Management and Technology at Bocconi University. Wehrheim acknowledges financial support from the Spanish Ministry of Economics and Competition through project nº ECO2012-33427. The authors thank Alejandro Balbás, Emre Ekinci, Andrea Fosfuri, Marco Giarratana, Jose Marin, Eduardo Melero, Neus Palomeras, Rosa Rodríguez, Pablo Ruiz-Verdú and Marti G. Subrahmanyam, as well as conference participants at the Ratio Colloquium for Young Social Scientists (Stockholm, 2014), Barcelona GSE Summer Forum (2015), XXIII Finance Forum (Madrid, 2015), XXX Jornadas de Economía Industrial (Alicante, 2015), IP Statistics for Decision Makers (Vienna, 2015) and internal seminar participants at Universidad Carlos III de Madrid (2015) for useful comments on previous versions of this paper. All remaining errors are ours.

1. Laurence D. Fink, Chairman and Chief Executive Officer (CEO) of BlackRock, recently summed this up in a letter to Standard & Poor's 500 CEOs that BlackRock invests in (Business Insider, April 14, 2015): "Over the past several years at BlackRock, we have engaged extensively with companies, clients, regulators and others on the importance of taking a long-term approach to creating value. We have done so in response to the acute pressure, growing with every quarter, for companies to meet short-term financial goals at the expense of building long-term value. This pressure originates from a number of sources–the proliferation of activist shareholders seeking immediate returns, the ever-increasing velocity of capital, a media landscape defined by the 24/7 news cycle and a shrinking attention span, and public policy that fails to encourage truly long-term investment."

2015[2]. Unlike stock market listings, where firms apply, options listings are exogenous to firm decisions; they are made within exchanges. These exchanges are self-regulating institutions that are members of the Options Clearing Corporation (OCC), which operates under the jurisdiction of the Securities and Exchange Commission (SEC) (for exchange-listed options). Because the SEC plays an important role in determining the eligibility criteria for securities in options trading, this topic is of particular interest to policy makers[3].

Did the significant rise in the volume of trading undermine innovative efforts or did it encourage firms to invest in innovation? We argue that for firms that are listed on options markets, greater trading activity is associated with an increased propensity to innovate. The literature suggests that active options markets alter incentives for market participants to gather private information that is especially relevant for long-term investments, and trading on such information makes stock prices more efficient (e.g., Cao, 1999; Chakravarty, Gulen, and Mayhew, 2004; Pan and Poteshman, 2006; Hu, 2014). If stock prices are more efficient, other types of (perhaps less-informed) investors learn more about the fundamental value of the firm, which reduces some of the asymmetric information problems connected to R&D. Because prices play an active role (i.e., managers learn from prices) when investment decisions are made, this should then provide firm management with more incentives to engage in value-enhancing innovative activities. The notion that informed agents in financial markets can ameliorate asymmetric information related to innovative activities is widely recognized in the literature (e.g., Hall and Lerner, 2010; Aghion, Van Reenen, and Zingales, 2013; He and Tian, 2013)[4].

In this paper, we focus on whether options trading spurs firm innovation in the context of R&D-intensive industries. We believe that these firms provide an ideal research setting for our study. For firms

2. See http://www.optionsclearing.com.
3. See Mayhew and Mihov (2004) for initial listing requirements.
4. If we believe that informed agents can reduce information asymmetries related to innovative activities and that the stock market is an efficient resource allocation mechanism, then the "prospective role" (Dow and Gorton, 1997) whereby stock prices provide managers with information relevant for investment decisions could generate the same prediction. Our focus on the disciplining role of stock prices (as in Holmström and Tirole, 1993) is a natural choice for understanding the role of options trading in innovation, although we consider the two approaches to be complementary.

that invest more heavily in R&D, innovation is a core component of their competitive strategy, but they might also be forced to make only partial disclosure and be subject to a larger degree of information asymmetry (Bhattacharya and Ritter, 1983; Anton and Yao, 2002). It follows that these firms are more likely to be undervalued by equity holders and have a greater exposure to hostile takeovers (Stein, 1988). Moreover, survey evidence obtained by Graham, Harvey, and Rajgopal (2005) shows that managers in technology-intensive industries are more prone to sacrifice long-term sustainability to meet desired short-term earnings targets, relative to managers in other industries, due to their personal wealth and career concerns. Those authors explain that meeting earnings benchmarks (particularly the earnings in the same quarter of the previous year) helps to maintain a firm's current stock price. Taken together, if the enhanced informational efficiency induced by options leads to better monitoring by reducing information asymmetries, making firms more willing to invest in innovation, we claim that this mechanism is particularly relevant for firms operating in R&D-intensive industries.

To test this conjecture, we assemble a rich and original data set containing time-varying information on standard measures of innovation based on U.S. patent data, R&D, options trading, governance, etc. To approximate the total annual dollar options volume, we use the approach proposed by Roll, Schwartz, and Subrahmanyam (2009). We run panel data regressions on a sample of 548 publicly traded U.S. firms during the period from 1996 to 2004. This sample consists of large firms that are active in five broadly defined high-tech sectors, where we observe high patenting propensities, and patents have been recognized as a meaningful indicator of innovation at the firm level (as explained in Section 3).

Our baseline test reveals a positive association between innovation and options trading. Options trading has a positive impact on R&D spending but a larger positive effect on the quality and/or productivity of R&D (i.e., citations per dollar of R&D invested). These results are robust to using alternative subsamples, alternative measures of innovation, the inclusion of a wide range of control variables, lagged explanatory variables, and several econometric models. While these findings are consistent with the beneficial effect of the production and aggregation of

information in options markets, we have concerns that our results could be biased if informed agents trade on the basis of unobservable characteristics that are correlated with options volume and innovation. We account for such selection issues by weighting sample observations using their propensity score of having high levels of options trading and by estimating two-stage least squares (2SLS) models using moneyness and open interest as instrumental variables. Overall, our identification tests suggest that the positive correlation between options trading and innovation is not simply driven by self-selection.

We extend these baseline results in two main directions. First, we examine the link between options trading and three measures of innovative direction: (i) a measure based on the diversity of patents applied for by the firm across technological classes, (ii) the Hall, Jaffe, and Trajtenberg (2001) measure of patent originality, and (iii) a measure of risk-taking behavior based on the standard deviation of citations received across patents. The results suggest that more active option markets are associated with a change in direction and not just an increase in R&D spending and productivity.

Second, we attempt to identify the underlying economic mechanism through which this link occurs. Our results could be explained by two hypotheses. On the one hand, the results could be driven by the reasoning that poorly governed managers prefer to avoid the difficult decisions and costly efforts associated with innovation and that the information conveyed by more active options markets "forces" managers to innovate if they are a priori reluctant to do so [i.e., managers prefer the quiet life as in Bertrand and Mullainathan (2003)]. On the other hand, the results could be consistent with the prediction that increased monitoring "shields" managers against those reputational consequences [i.e., career concerns as in Holmström (1989, 1999)] that are more likely to occur when managers invest in innovation. Potential consequences occur because innovation involves a high probability of failure, and the innovation process is unpredictable and idiosyncratic, with many future contingencies that are impossible to foresee. In line with recent evidence obtained by Aghion, Van Reenen, and Zingales (2013) in the context of institutional investors, we find strong support for the career concerns story. We show that the positive effect of options trading on innovation is more pronounced when product market competition is more intense,

when CEOs are less "entrenched," and for younger CEOs. Moreover, we provide evidence that the positive effect of more active options markets on innovation is magnified for firms that face a decline in profitability and remains substantial even after accounting for executive compensation schemes.

Although we follow standard procedures in using patent counts weighted by forward citations as a proxy for innovation, we must admit that one of the main limitations of our study is that we cannot completely exclude the possibility that our results may be partially driven by managerial signaling motives. This is because one common disadvantage in studies based on patents is that the latter are an indirect measure of innovation and contain no information on non-patentable inventions or inventions held in secrecy. We believe, however, that limiting our study to industries in which patenting represents the most important mechanism used by firms to protect their intellectual property for appropriability and/or strategic reasons mitigates such concerns.

While there is a growing literature that links a variety of financial market characteristics to innovation, to the best of our knowledge, such an analysis of the relationship between options trading and innovation has not previously been undertaken. Empirical studies have examined, for instance, the effect of institutional ownership on innovation (Aghion, Van Reenen, and Zingales, 2013), analyst coverage (He and Tian, 2013), credit supply (Amore, Schneider, and Žaldokas, 2013), stock liquidity (Fang, Tian, and Tice, 2014), leveraged buyouts (Lerner, Sorensen, and Strömberg, 2011), investors' failure tolerance (Tian and Wang, 2014), the decision to go public (Bernstein, 2015), and the development stage of financial markets (Hsu, Tian, and Xu, 2014). There is very little research on the role played by options (or more general financial derivatives) in the R&D process of publicly traded firms.

However, there is another paper that examines the possibility that active options markets are beneficial to the firm. Specifically, Roll, Schwartz, and Subrahmanyam (2009) find that options trading activity increases firm value through its impact on price informativeness. However, because greater informational efficiency tends to make an asset more valuable because it reduces the risk of investing in it, these results require further examination. Although several other studies also conclude that

resources are allocated more efficiently if prices convey more information, which in turn leads to greater firm value (e.g., Khanna, Slezak, and Bradley, 1994; Dow and Gorton, 1997; Subrahmanyam and Titman, 1999; Durnev, Morck, and Yeung, 2004; Chen, Goldstein, and Jiang, 2007), there is little empirical evidence of this effect on innovation. We view our study as complementary to Roll, Schwartz, and Subrahmanyam (2009) because we take option markets' effect on prices as given and aim to explain how this influences firms' incentives to innovate. Thus, the main contribution of our paper is to provide a direct link between options trading and the extent to which the firm allocates resources to innovation.

The remainder of the paper is organized as follows. Section 2 discusses the related literature in greater detail. Section 3 describes the sample, the measurement of variables, and descriptive statistics. In Section 4, we present our main results. In Section 5, we discuss the underlying mechanism through which options trading may affect innovation. Section 6 concludes the paper.

RELATED LITERATURE

Our paper borrows from different strands of the literature. Our starting point is the recognition that options stimulate informed trades and that the informational benefit of options depends on the trading volume. Almost 40 years ago, Ross (1976) was the first to argue that options trading can convey important information in a market with information asymmetry by expanding the contingencies that are covered by traded securities. Apart from reducing information asymmetry, Black (1975) notes that informed traders could use options markets as an alternative venue for trading because option contracts provide higher leverage. Easley, O'Hara, and Srinivas (1998) argue that options can be more attractive for informed traders because the availability of multiple contracts confronts uninformed traders with substantial challenges. In a similar vein, Cao (1999) suggests that agents with private information should be able to trade more effectively on their information in the presence of options, thereby improving price informativeness. Moreover, options are a mechanism for trading on information about future equity volatility, which allows investors with information about stock price volatility to benefit from options (Ni, Pan, and Poteshman, 2008). These notions are further supported by Chakravarty, Gulen, and Mayhew (2004) and Pan and Poteshman (2006), who find that options order flows contain information about the future direction of the underlying asset. More recently, Hu (2014) shows that an options-induced imbalance significantly predicts future stock returns. Taken together, these works provide strong support for the conjecture that informational efficiency may be greater in the presence of options.

A firm's informational benefit from options, however, should depend on the volume of options traded, beyond the presence of an options market on the firm's stock per se (as in Roll, Schwartz, and Subrahmanyam, 2009). For example, due to the maxim that "liquidity attracts liquidity," informed agents would be more willing to trade on their private information in markets with high trading volume because they are able to camouflage their trades (Kyle, 1985; Glosten and Milgrom, 1985). In

contrast, if informed traders perceive a low-liquidity options market, they optimally desist from trading, and this belief becomes self-fulfilling (Admati and Pfleiderer, 1988; Chowdhry and Nanda, 1991). It follows that the enhancement of the benefit from listing should be directly related to whether the market for the listed options has sufficient volume because then informed traders would be more active.

Second, our paper builds on the literature that interacts information production (i.e., price informativeness) with investment decisions in firms. The idea that the production and aggregation of information as a consequence of trading between speculators and investors can be useful for the provision of incentives in firms is a relatively recent one. Specifically, Holmström and Tirole (1993) and Faure-Grimaud and Gromb (2004) examine the role of price informativeness in disciplining managers and providing incentives to insiders to engage in value-increasing activities. Dow and Gorton (1997) show that, in equilibrium, the information contained in stock prices can be used to guide investment decisions because managers are compensated based on future stock prices. Subrahmanyam and Titman (1999) study a setting in which investors may obtain information unavailable to firm insiders that is useful in making investment decisions. They show that if such information is freely available to outsiders, the firm chooses to go public. Empirically, for example, Durnev, Morck, and Yeung (2004) show that U.S. industries and firms exhibiting larger firm-specific return variation make better capital budgeting decisions. The findings in Chen, Goldstein, and Jiang (2007) suggest that firm managers learn from private information concerning their own firms' fundamentals contained in stock prices by incorporating stock price information into corporate investment decisions. Foucault and Gehrig (2008) show that cross-listing enables firms to obtain more precise information on the value of their growth opportunities, which allows managers to make better investment decisions. Finally, Ferreira, Ferreira, and Raposo (2011) provide evidence that if prices are more efficient, the stock market is able to play a monitoring role that can reinforce internal and external monitoring mechanisms, although the sign of this relationship is ambiguous (i.e., they can interact as either complements or substitutes).

Our particular focus is on how the enhanced informational efficiency induced by options affects managerial incentives to invest in innovation. Stein (1989) shows that even in rational capital markets, firms take actions to improve current earnings at the expense of lower future earnings in an attempt to misguide the market. Shleifer and Vishny (1990) offer a different argument that leads to the same conclusion. Because arbitrage is cheaper for short-term assets than for long-term assets, the latter must be more mispriced in equilibrium for net returns to be equal. It follows that managers may forgo investment opportunities in long-term projects because the uncertainty of these assets can take a long time to disappear. The empirical literature offers evidence consistent with managerial short-termism in publicly traded firms. For example, Asker, Farre-Mensa, and Ljungqvist (2015) find that compared to unlisted firms, listed firms tend to invest less and their investment levels are less sensitive to changes in investment opportunities. Bushee (1998) shows that firms are more prone to cut R&D in response to a decline in earnings when a very large proportion of institutional owners are investors that often trade in and out of individual stocks.

Based on the streams of literature reviewed above, we argue that a potential solution to the distortion of innovative investment due to agency problems is active options markets. The intuition is the following. In the presence of option market participants who engage in monitoring, informed agents move the stock price toward the fundamental value and thus cause it to more closely reflect the effort exerted by the manager to enhance long-term risky investment decisions. Because other financial market participants (especially firm investors) may have difficulties in properly evaluating managerial investment decisions in innovation (Stein, 1988), they can use stock prices as a signal of whether informed traders agree or disagree with the allocation of corporate resources and can decide whether to take action (as in Edmans and Manso, 2011). For example, if investors discover that the manager is good despite bad public information, they will be more willing to retain their shares because they will expect higher returns. Alternatively, they can directly use the threat of disciplinary trading and sell more given the discovery of negative information, causing the stock price to decline.

DATA AND METHODS

We examine the effect of options trading on innovation in the context of publicly traded U.S. firms in the following five industries: (i) pharmaceuticals (Standard Industrial Classification [SIC] code 283), (ii) industrial and commercial machinery and computer equipment (35), (iii) electronics and communications (36), (iv) transportation equipment (37), and (v) instruments and related products (38). A trade-off made in the design of our study was to limit the sample to these five industries and not to consider the entire manufacturing universe. We ensured that these industries represent a broad spectrum[5]. Nevertheless, we exercised caution in selecting these specific industries for several reasons. First, R&D has been and continues to be vital for the long-run competitive advantage of firms operating in these industries. In fact, these sectors have the highest ratio between R&D expenditure and net sales among all industries (OECD, 2013). Second, these industries also form an apt context because of how they protect and document their inventions. Patenting (on which our dependent variables are based) is an important mechanism to protect intellectual property (Levin, Klevorick, Nelson, Winter, Gilbert, and Griliches, 1987) and firms tend to patent most patentable inventions. In particular, Mansfield (1986) shows that our sample industries are characterized by high patenting propensities relative to most other industries. Third, patents are a meaningful measure of innovation in these industries. The association between patents and technological innovation is likely to be stronger in industries in which patents provide firms with fairly strong protection of their intellectual property[6]. Acs, Anselin, and Varga (2002) conclude that the measure of patented inventions provides a fairly good, although not perfect, representation of innovative activity in these five industries. Therefore, patents have been extensively used in earlier research to understand the innovation processes of firms within these industries (e.g., Katila and Shane, 2005; Coad and Rao, 2008; Rothaermel and Alexandre, 2009).

5. In 2004, these industries collectively included approximately 35% of all publicly traded U.S. manufacturing firms drawn from the Compustat database.

6. Strictly speaking, patents are inventions. As Freeman and Soete (1997, p. 22) note, they represent "[...] an idea, a sketch or a model for a new improved device, product, process or system. Such inventions may often (not always) be patented but they do not necessarily lead to technical innovations."

We use firm-level data on innovation and options trading from several data sources. Our starting point is the Compustat universe, which contains detailed information on all U.S. publicly listed firms since the mid-1950s. We identified all firms traded on NYSE, Amex, or Nasdaq with accounting data available between 1996 and 2004. To mitigate backfilling bias, we require firms to be listed on Compustat for three years before including them in the sample. Our main Compustat items are sales (SALE); a capital-labor ratio constructed from the net stock of property, plant, and equipment (PPENT) and the number of employees (EMP); and R&D expenditure (XRD). R&D is used to create R&D capital stocks, calculated using a perpetual inventory method with a 15% depreciation rate following the method described in Hall, Jaffe, and Trajtenberg (2005).

Firm-level patent data are obtained from the latest version of the National Bureau of Economic Research (NBER) Patent Citation database, which contains approximately three million patents granted by the United States Patent and Trademark Office (USPTO) and citation information from 1976 to the end of 2006 (Hall, Jaffe, and Trajtenberg, 2001; Jaffe and Trajtenberg, 2002)[7]. We use patents that are ultimately granted, dated by the year of application, which approximates the year when the invention was completed because the patent system provides incentives to file quickly. To match Compustat firms with U.S. patent assignee codes, we begin with the name-matching tool of Bessen (2009) and then search by hand for variations on the names in our panel. Our sample ends in 2004 because many patent applications filed in the later years (i.e., 2005 and 2006) might still be under revision (Hall, Jaffe, and Trajtenberg, 2001).

For data on options trading, we use OptionMetrics. This database contains information on the daily number of contracts traded for each individual put and call option on U.S. publicly listed equities, along with daily closing bid and ask prices from 1996 onwards. The sample is selected to include firms with positive options volume to maintain comparability, as firms without options listings tend to be small (Mayhew and Mihov, 2004) with different structural relationships between innovation and the right-hand variables[8]. To approximate the total annual dollar options volume, we use the approach in Roll, Schwartz, and Subrahmanyam (2009). Specifically,

7. See https://sites.google.com/site/patentdataproject.
8. For example, Acs and Audretsch (1988) show that small firms spend disproportionately less on R&D, but they appear to benefit more from R&D investments, suggesting they are more efficient at R&D than their larger counterparts.

for each stock, we first multiply the total trade in each option by the end-of-day quote midpoint for that option and then aggregate this number annually across all trading days and all options listed on the stock.

To calculate other control variables and the variables used for exploring underlying mechanisms, we collect institutional ownership information from Thomson Reuters' CDA/Spectrum Institutional Holdings data set (SEC Form 13F), corporate governance information from the RiskMetrics database, analyst coverage data from the Institutional Brokers' Estimate System (I/B/E/S) database, CEO age and compensation from ExecuComp, stock price information from the Center for Research in Security Prices (CRSP), intraday trades and quotes for constructing stock illiquidity measures from the Trade and Quote (TAQ) database, and information on each firm's alliances and joint ventures from the Securities Data Company (SDC) Platinum database. These data sets do not overlap perfectly; thus, our baseline regressions run from 1996, the first year for which options trading data are available, to 2004, the last year when we can realistically construct innovation measures based on patent data. Although the exact number of observations depends on the specific regression, the baseline sample for which we estimate the equations contains 3,271 observations of 548 firms[9].

Dependent variables

Our primary measure of innovation is a *future* citation-weighted count of U.S. patents. We prefer patents weighted by citations as an indicator of innovative "output" over simple counts because patent citations can better reflect the technological and economic "importance" or "value of the underlying invention (Trajtenberg, 1990; Albert, Avery, Narin, and McAllister, 1991). Specifically, the use of patent citations exploits the fact that patent applications must acknowledge "prior art," in which light they need to meet the requirements for patentability, i.e., U.S. patent law ree quires an invention to be novel, non-trivial, and susceptible to industrial application for a patent to be granted (35 U.S. Code §102)[10]. These citations

9. Our sample faces another restriction from the overall Compustat database. Because our preferred regressions use firm fixed effects, we condition our sample on firms that received at least one citation and had at least two years of non-missing data for all variables between 1996 and 2004. Thus, we drop firms from the Compustat/USPTO match that patented prior to 1996 but not in the 1996–2004 period, and of those that did patent, we drop those that did not receive citations.
10. See https://www.uspto.gov/web/offices/pac/mpep/mpep-9015-appx-l.html.

serve an important legal function because they can delimit the scope of the property rights awarded to the inventor. U.S. patent applicants are legally required to disclose any knowledge upon which their inventions are based. This prior art is typically referenced through citations provided by patent applicants (inventors or their lawyers) and patent examiners. Because of this important legal function, the economics of innovation literature has frequently used the number of forward citations received by a patent as an indirect measure of its value (e.g., Pakes and Griliches, 1980; Harhoff, Narin, Scherer, and Vopel, 1999; Aghion, Bloom, Blundell, Griffith, and Howitt, 2005; Hall, Jaffe, and Trajtenberg, 2005; Aghion, Van Reenen, and Zingales, 2013). To control for the fact that citation counts are inherently truncated, we employ three strategies. First, we estimate until 2004, allowing for a two-year window of forward citations for the last cohort of patents in the data. Second, we include a full set of time dummies, which accounts for the fact that patents taken out later in the panel have less time to be cited than patents taken out earlier in the panel. Third, we also perform our estimations using simple unweighted patent counts[11]. We consider several additional innovation metrics. First, we use R&D expenditure as a measure of innovation inputs. Because more than 50% of firms in the entire Compustat database do not report R&D expenditures, we follow common practice in the literature by replacing missing values with zeros, although we obtain similar results when we drop these observations or interpolate over any gaps of three years or less[12]. Second, given that self-citations may differ from other citations in various ways (Hall, Jaffe, and Trajtenberg, 2005), we weight patents by the number of non-self forward citations. Finally, in a series of extensions, we examine changes in the direction of innovative efforts. To proxy for the direction of a firm's activities in its innovative process, we use the diversity of activities (i.e., the dispersion of the firm's patent portfolio across technological classes), originality-weighted patent counts (i.e., the dispersion of backward citations across technological classes), and a measure of risk-taking (i.e., the standard deviation of forward citations across patents).

It is important to note, however, that using patent data to measure innovation also has limitations. In particular, not all firms patent their

11. We also experimented with adjusted citations, taking into account systematic differences in the number of citations each patent receives across application year and technological class (Hall, Jaffe, and Trajtenberg, 2001). This delivers very similar results to the unadjusted citation results presented here.

12. Note that the fact that a firm does not report R&D expenditures in its financial statement does not necessarily imply that the firm is not engaging in R&D. Because this information is public, a firm could decline to report for strategic reasons.

inventions because some inventions do not meet the patentability criteria, and others are not patented for strategic reasons. Moreover, firms differ in their patenting propensity, and the degree to which these factors are problematic varies substantially across industries (e.g., Levin, Klevorick, Nelson, Winter, Gilbert, and Griliches, 1987; Cohen and Levin, 1989; Griliches, 1990). We believe that limiting our study to specific industries in which patents are a meaningful indicator of technological activities reduces such concerns because other factors that may affect patent propensity are relatively stable within such a context (Cohen and Levin, 1989; Griliches, 1990). Because firms may differ in their patenting propensity for unobserved reasons even in R&D-intensive industries, we treat this problem as one of unobserved heterogeneity across industries and firms and control for such variations in our statistical analysis[13].

Descriptive statistics

Table 1 provides summary statistics of the main variables used in this study[14]. Our sample firms are large: $494 million in net sales at the median and 2,400 employees. On average, a firm in our sample has 62 granted patents per year and subsequently receives 294 citations for its patents, which is comparable to previous studies (e.g., Aghion, Van Reenen, and Zingales, 2013). The citation series is highly skewed, with a median of 15. Due to the right-skewed distribution of cite-weighted patents, we use the natural logarithm as the main innovation measure in our analysis. To avoid losing firm-year observations, we add one to the actual values when calculating the natural logarithm. The options volume measure has a mean value of $157 million and a median value of $8.5 million. Regarding the other variables, an average firm invests $287 million in R&D, approximately 51% of shareholders are institutional investors, the average firm's return on assets is 9%, and 22.5 years have passed since its inclusion in Compustat.

13. For example, one concern might be that our analysis includes firms in "complex" (i.e., SIC codes 35, 36, 37, and 38) and "discrete" industries (i.e., pharmaceuticals; SIC code 283) in the sense proposed by Cohen, Nelson, and Walsh (2000). The authors define complex (discrete) industries as those in which a given technology is protected by many (few) patents. One might therefore observe a lower number of patents generated by firms in discrete industries, but this does not necessarily imply that these firms are less innovative. Moreover, one may argue that our industry classification is too broad to isolate, for example, the role of highly innovative biotechnology companies within the pharmaceutical industry. We account for this potential bias in our regressions by using the most detailed industry classification available (i.e., four-digit SIC code).

14. Descriptive statistics for all other variables used throughout the course of our study are in the Internet Appendix, Table A16.

Table I. Descriptive statistics.

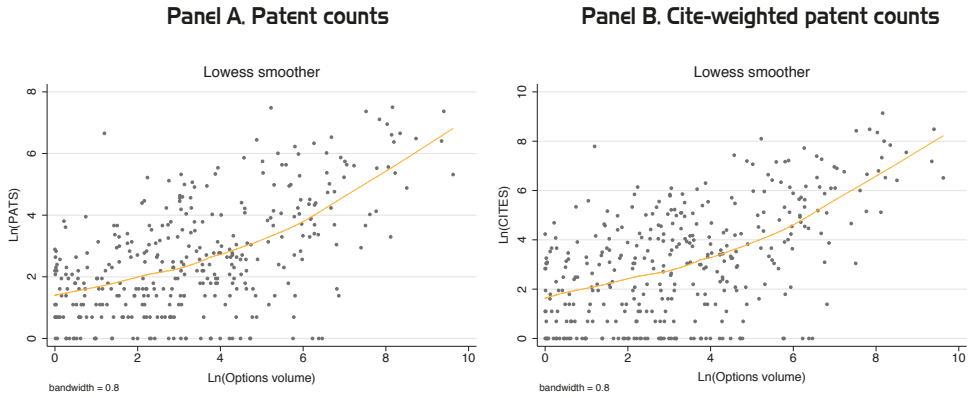
This table reports summary statistics for variables constructed based on the sample of U.S. publicly traded high-tech firms with positive options volume from 1996 to 2004.

	Mean	*StdDev*	*Min*	*Median*	*Max*	*Observations*	*Source*
Cite-weighted patents	294	1,181	0	15	18,950	3,271	USPTO
Patents	62.4	185	0	7	2,355	3,271	USPTO
Non-self cite-weighted patents	233	906	0	12	17,188	3,271	USPTO
Originality-weighted patents	30.8	89.3	0	4.0	1,158	3,245	USPTO
Std. dev. of patent citations	4.9	6.0	0	2.8	66.5	2,382	USPTO
Innovative diversity	0.62	0.21	0	0.67	0.94	1,526	USPTO
Options volume (in $m)	157	700	0.0002	8.5	15,135	3,271	Option-Metrics
Moneyness	0.29	0.17	0.06	0.25	2.4	3,271	Option-Metrics
Institutional ownership (in %)	50.7	27.5	0	56.8	100	3,271	CDA/Spec-trum 13F
Fixed capital (in $m)	1,013	3,913	0.04	105	84,101	3,271	Compustat
Employees (in 000s)	15.2	34.8	0.01	2.4	372	3,271	Compustat
Sales (in $m)	3,968	11,841	0.004	494	171,652	3,271	Compustat
Firm age	22.5	15.5	3	16	55	3,271	Compustat
R&D (in $m)	287	811	0	39.4	12,183	3,271	Compustat
1 - Lerner index	0.86	0.04	0.76	0.87	0.96	3,271	Compustat
Profits/Assets	0.09	0.17	−1.4	0.12	0.62	3,271	Compustat
CEO age	55.6	7.6	32	56	89	1,996	ExecuComp
CEO vega (in $000s)	158	292	0	73.7	4,578	1,845	ExecuComp
CEO delta (in $000s)	762	1,695	0	295	34,647	1,845	ExecuComp
Governance index	9.0	2.7	2	9	16	921	RiskMetrics and Gompers et al. (2003)

As a preamble to our main analysis, we provide the results of non-parametric regressions that consider the relationship between our innovation measures and options trading. Fig. 1 presents the results. In both panels, we show a line for the local linear regression estimated by the lowest smoother with a bandwidth of 0.8. Panel A displays the non-parametric relationship between the natural logarithm of (one plus) the number of

patents granted (unweighted patent counts) and the natural logarithm of options volume. Panel B replicates the graph but uses our primary measure of innovation, the natural logarithm of (one plus) forward citation-weighted patent counts. As can be seen, the correlation between innovation and options trading is clearly positive and appears to be monotonically increasing across options volume.

Fig. I. Non-parametric regressions of innovation and options volume.



This figure depicts a non-parametric (local linear) regression of firms' unweighted patent counts (*PATS*) and annual options volume (Panel A) and patents weighted by the number of forward citations (*CITES*) and annual options volume (Panel B). The graph is from 2000, the middle of our sample period.

Specification

Our main econometric models focus on the relationship between future cite-weighted measures of innovative activity and options trading. We estimate the following model using ordinary least squares (OLS):

$$Yi,t = \alpha + \beta Oi,t + \gamma Zi,t + \delta t + \lambda i + \varepsilon i,t \qquad (1)$$

where i indexes firms and t indexes time. The dependent variable, Yi,t, is the natural logarithm of (one plus) the number of cite-weighted patents. The options trading measure, Oi,t, is measured for firm i over its fiscal year t as the logarithmic transformation of the options volume, although similar results are also obtained using the untransformed variable. Because both innovation and options activity are in logarithmic form, the coefficient on O gives us the elasticity of innovation to

options trading. δt are time dummies that account for intertemporal variation that may affect the relationship between options trading and innovation and λi is a firm fixed effect that controls for unobserved time-invariant firm heterogeneity. Because innovation metrics are likely to be autocorrelated over time, all of our models will allow the standard errors to have arbitrary heteroskedasticity and autocorrelation (i.e., clustering standard errors by firm). The vector Zi,t contains a range of control variables. Specifically, in our main regressions, we condition on firm size (*Sales*), capital-labor ratio (K/L), and deflated *R&D stock*, as suggested by the literature on patent production functions (e.g., Pakes and Griliches, 1980; Hausman, Hall, and Griliches, 1984). The model of Aghion, Van Reenen, and Zingales (2013) shows that innovative activities are affected by institutional ownership; we include the percentage of shares held by institutional investors (*InstOwn*). We also control for a firm's *Age* in the baseline model, measured as the number of years since the inclusion of the firm in Compustat.

When a firm's *R&D stock* is included in Z, we can interpret the equation as a "production function" that relates past R&D investments to innovative outputs. It follows that in this specification, β gives us the effect of options trading activity on the productivity of R&D, measured by forward cite-weighted patent counts per R&D dollar invested. Note that we also estimate models that omit the R&D stock from Z, and hence, β indicates the combined impact of changes in R&D stocks and innovative productivity.

Finally, λi, the fixed effects term, is introduced into the models using the "pre-sample mean scaling" estimator of Blundell, Griffith, and Van Reenen (1999). Essentially, we exploit the fact that we have a long pre-sample history of a firm's innovative activities and construct pre-sample averages of the dependent variables[15]. This initial condition can proxy for unobserved heterogeneity if the first moments of the variables are stationary. Monte Carlo simulations show that this pre-sample mean scaling estimator performs well compared to alternative econometric estimators for dynamic panel data models with a long panel for innovations but only a short panel for the explanatory regressors.

15. We estimate from 1996 and use the information on patenting between 1976 and 1995 to construct the pre-sample means.

EMPIRICAL RESULTS

Table 2 presents our first set of regression results. Columns 1 through 4 report the OLS estimates with the dependent variable *Ln(1+CITES)*: the natural logarithm of (one plus) the number of citation-weighted patents for issued patents applied for in year *t*. Due to the count-based nature of citation and patent data, we also use count-based regression models, such as the Negative Binomial (NB). Columns 5 through 8 report NB regressions. Across all the columns of Table 2, the coefficient estimates on *Ln(Optvol)* are positive (ranging between 0.118 and 0.244) and both economically and statistically significant. For example, the coefficient of 0.118 in column 4 suggests that a 200% increase in the dollar volume of options traded (e.g., from the median of $8.5 million to $25.5 million) is associated with a 24% increase in cite-weighted patents (e.g., from the median of 15 to 19)[16].

We begin in column 1 with OLS regressions of *Ln(1+CITES)* on options trading with controls for *InstOwn*, *Ln(K/L)*, *Ln(Sales)*, *Ln(Age)*, four-digit industry dummies, and time dummies. Consistent with the bivariate relationships in Fig. 1, there is a positive and significant association beg tween innovation and options volume. Column 2 includes the controls for fixed effects (which are highly significant), and these substantially reduce the coefficient on *Ln(Optvol)* from 0.232 to 0.148. In columns 1 and 2, the options volume coefficient measures the combined impact of changes in R&D productivity (more innovative output per dollar of R&D invested) and innovative intensity (greater spending on innovation). In column 3, we add the natural logarithm of each firm's deflated R&D stock, and hence the equation becomes a production function, where β indicates the innovative premium of options trading per dollar of R&D. As expected, the coefficient on *Ln(R&D stock)* shows a very robust positive association with patent citations. The coefficient on options volume also declines by approximately 32%, from 0.232 to 0.158, indicating that the main effect of options trading operates by impacting R&D productivity rather than by stimulating more R&D spending. Column 4

16. In the sample period between 1996 and 2004, the trading volume for our firms rose by 188%, and thus 200% is a reasonable change to consider.

presents the full model, which includes the controls for fixed effects. As before, this reduces the options volume coefficient from 0.158 to 0.118[17]. The final four columns of Table 2 repeat the main OLS specifications but use NB models. Our findings are similar.

Table 2. Innovation and options volume

This table presents estimates of OLS and NB panel regressions of firms' patents weighted by the number of forward citations (*CITES*) on options volume (*Optvol*) and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies and time dummies. The time period is 1996-2004 (with citations up to 2006); fixed effects are based on including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Method	*OLS*				*NB*			
Dependent var.	*Ln(1+CITES)*				*CITES*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Optvol)	0.232***	0.148***	0.158***	0.118***	0.244***	0.157***	0.163***	0.121***
	(0.027)	(0.022)	(0.025)	(0.022)	(0.026)	(0.022)	(0.026)	(0.021)
InstOwn	–0.229	–0.139	–0.046	–0.048	–0.211	–0.127	0.093	0.064
	(0.200)	(0.165)	(0.178)	(0.158)	(0.228)	(0.188)	(0.206)	(0.177)
Ln(K/L)	0.065	–0.004	0.102*	0.026	0.224**	0.075	0.260***	0.110
	(0.070)	(0.056)	(0.061)	(0.053)	(0.097)	(0.074)	(0.083)	(0.067)
Ln(Sales)	0.395***	0.266***	0.141***	0.140***	0.399***	0.293***	0.159***	0.142***
	(0.046)	(0.036)	(0.053)	(0.041)	(0.044)	(0.035)	(0.048)	(0.040)
Ln(Age)	0.115	–0.037	–0.051	–0.109	–0.062	–0.136	–0.266***	–0.213**
	(0.106)	(0.087)	(0.096)	(0.083)	(0.109)	(0.098)	(0.101)	(0.094)
Ln(R&D stock)			0.462***	0.262***			0.486***	0.302***
			(0.058)	(0.046)			(0.047)	(0.042)
Firm fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3,271	3,271	3,271	3,271	3,271	3,271	3,271	3,271

17. The results are similar if we replace the Blundell, Griffith, and Van Reenen (1999) controls for fixed effects with the Hausman, Hall, and Griliches (1984) approach. For example, in an identical specification to our main model incolumn 4, the coefficient (standard error) on *Ln(Optvol)* is 0.091 (0.034).

Alternative innovation measures

In Table 3, we ask whether our results are driven by greater innovation output (more patents) or greater innovation input (more R&D expenditure) and whether our results are robust to the exclusion of self-citations. We find support for all three effects.

Columns 1 and 2 report the regression results from replacing the dependent variable of cite-weighted patents with raw patent counts. We observe a pattern for the coefficient of options trading activity that is very similar to that in our baseline models (i.e., columns 3 and 4 of Table 2). We observe a positive and significant coefficient estimate of *Ln(Optvol)* that declines substantially after we introduce time-invariant, firm-specific innovation determinants into the regressions. The effect, however, remains economically and statistically significant. For example, the coefficient estimate in column 2 implies that an increase in options volume of 200% leads to roughly two additional patents filed by the median firm in our sample. Given that the median firm files for seven patents, this is a significant increase.

The middle two columns examine the association between options trading activity and R&D investment. We remove the deflated *R&D stock* from this specification because we are interested in inputs and rely instead on a conditional fixed-effects estimator. In columns 3 and 4, we find that options volume has a significant and positive association with firm R&D investment, although the magnitude of this effect becomes smaller than that for cite-weighted patents after we add fixed effects. Thus, focusing on R&D as the only measure of firm innovativeness may underestimate the importance of options trading.

Columns 5 and 6 of Table 3 show that the coefficient estimates on *Ln(Optvol)* continue to be positive and significant at the 1% level when we remove self-citations and re-estimate Eq. (1) with the dependent variable replaced by the number of patents weighted by non-self citations. We find this last result important because the interpretation that our results are driven primarily by pure managerial signaling behavior (as opposed to pushing the firm toward more innovation) is difficult to reconcile with our finding that firms with higher levels of options trading activity generate more forward citations in general and receive more

forward citations from other firms in particular (e.g., compared with an increase in patenting).

Table 3. Alternative innovation measures and options volume

This table presents estimates of OLS regressions of firms' unweighted patent counts (*PATS*), R&D expenditure *(XRD)*, and patents weighted by the number of non-self forward citations *(NS CITES)* on options volume (*Optvol*) and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of time dummies. The time period is 1996-2004 (with non-self citations up to 2006); *BGV* fixed effects controls use the Blundell, Griffith, and Van Reenen (1999) pre-sample mean scaling estimator. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+PATS)*		*Ln(1+XRD)*		*Ln(1+NS CITES)*	
Method: OLS	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.176***	0.158***	0.268***	0.102***	0.198***	0.157***
	(0.029)	(0.024)	(0.029)	(0.014)	(0.032)	(0.028)
InstOwn	-0.273*	-0.213	-0.283*	0.017	-0.025	-0.045
	(0.154)	(0.140)	(0.162)	(0.102)	(0.167)	(0.149)
Ln(K/L)	0.101**	0.043	-0.060	0.080**	0.094*	0.032
	(0.051)	(0.044)	(0.062)	(0.031)	(0.056)	(0.052)
Ln(Sales)	0.144***	0.118***	0.516***	0.240***	0.133***	0.130***
	(0.046)	(0.033)	(0.041)	(0.034)	(0.049)	(0.039)
Ln(Age)	0.010	-0.028	0.087	0.605***	-0.022	-0.094
	(0.079)	(0.069)	(0.078)	(0.151)	(0.091)	(0.080)
Ln(R&D stock)	0.432***	0.205***			0.431***	0.255***
	(0.056)	(0.043)			(0.056)	(0.045)
SIC four-digit dummies	Yes	Yes	Yes	n/a	Yes	Yes
Firm fixed effects	No	BGV	No	Yes	No	BGV
Observations	3,271	3,271	3,271	3,271	3,271	3,271

Robustness checks

We conduct a rich set of basic robustness tests for our baseline results and discuss the details of these tests in the Internet Appendix[18]. To summarize, we find that the positive effect of options trading activity on innovation continues to increase monotonically, is preserved in the two subperiods during and after the Internet bubble, is robust to alternative proxies for R&D inputs, lagged options volume, and alternative econometric models that address the right-skewed and non-negative nature of patent data.

To provide additional insights, we conduct several tests related to our main prediction. To save space, these results are tabulated in the Internet Appendix. First, we assess whether our results are robust to the inclusion of additional (financial) control variables. Although our approach is to condition on a wide range of firm characteristics (and fixed effects), one could object that this does not adequately control for observable omitted variables. For example, there may be concerns that our regressions omit the variable of a firm's market value, which is correlated with the number of citations (Hall, Jaffe, and Trajtenberg, 2005). Given that fundamentals that increase a firm's value may also increase innovation and because informed traders may be more likely to trade firms with higher growth opportunities, this may produce a spurious upward bias in the coefficient on options volume[19]. Similarly, He and Tian (2013) and Fang, Tian, and Tice (2014) show that analyst coverage and stock liquidity are important determinants of firm innovation. To address such concerns, in the Internet Appendix, Table A8, we augment our main specification by including stock illiquidity (*Illiquidity*), leverage (*Leverage*), stock market-based firm value (*Tobin's Q*), return on assets (*ROA*), capital expenditures (*Capex*), and analyst coverage (*Analyst coverage*). However, the coefficients on *Ln(Optvol)* continue to be positive and significant at the 1% level, and the magnitude of the coefficient declines only slightly from the baseline model (i.e., from 0.118 to 0.110)[20].

18. The Internet Appendix may be found in the online version of this article.
19. The correlation between *Tobin's Q* and *Ln(Optvol)* is positive (0.262) and significant at the 1% level.
20. In unreported results, we also consider return volatility, measured by the annualized standard deviation of daily returns. However, and consistent with the notion in Roll, Schwartz, and Subrahmanyam (2009), the return volatility variable is not significant. For example, in an identical specification to column 1 in Table A8 in the Internet Appendix, the coefficient (standard error) on return volatility is 0.017 (0.012), while the coefficient on *Ln(Optvol)* remains positive and significant at the 1% level, with the magnitude of the estimate almost identical to that reported above.

Another concern might be that our results are affected by firms' external knowledge-sourcing behavior. Because of the increased complexity of the technological and scientific developments in our focal industries, firms cannot rely solely on internal R&D; they need to (and do) source knowledge externally to enhance the performance of their innovation process (Cassiman and Veugelers, 2006). Simultaneously, when prices are more efficient, managers can extract more information from the market, thereby allowing them to better assess the quality and potential outcomes of external knowledge acquisition activities[21]. To account for this, we include three alternative variables in our set of controls. Specifically, we use the *frequency* with which firms engage in R&D collaborations (i.e., the number of alliances and joint ventures reported in SDC), the *intensity* with which firms have sourced external knowledge (i.e., the number of jointly owned patents divided by the total number of patents), and the *acquisition* of innovative target firms (i.e., acquisition expenditure normalized by total assets). We report the results in the Internet Appendix, Table A9. We find that the coefficients on *Ln(Optvol)* continue to be of a very similar magnitude to those in column 4 of Table 2 (except when controlling for collaboration frequency because we only consider firms that have some information in SDC) and continue to be significant at the 1% level. Overall, this serves as reassurance that our findings are primarily related to internal R&D investment decisions.

Third, we argue that information asymmetries between the firm and market participants are especially challenging in R&D-intensive industries (which is one reason that this is our sample of interest). This is because the nature of firms' core activities is knowledge-based and highly opaque, and the fact that there could be a substantial cost of revealing information to their competitors reduces the quality of the signal they can send about their innovative activities (Bhattacharya and Ritter, 1983; Anton and Yao, 2002). Thus, if what we are capturing is related to the informational benefit from options to a firm in reducing asymmetric information problems related to R&D, then this should be more important for firms that are active in R&D-intensive industries, relative to cases in which such problems are less (or not at all) present.

21. Prior studies provide evidence consistent with this argument. For example, Luo (2005) finds that the positive correlation between announcement date return and the completion of mergers can be attributed to insiders' learning from outsiders after controlling for common information.

To reveal this, we begin by identifying firms with positive options volume and non-missing data on all other variables that operate in non-R&D-intensive industries, defined as those that are located in the OECD classification (based on R&D intensities) of low-tech industries (OECD, 2011)[22]. As these firms are very different from our focal firms, we then apply a matching procedure that relies on a nearest-neighbor matching of propensity scores (estimated as a function of all firm characteristics, including fixed effects). After restricting the sample to the common support, we are left with a panel of 1,453 firm-years in both groups. In column 1 of Table A10 in the Internet Appendix, we estimate our main specification on the matched sample, adding a dummy variable for R&D-intensive firms (= 1;0 = non-R&D-intensive). The coefficient on *Ln(Optvol)* remains positive (0.120) and statistically significant at the 1% level, while the coefficient on the dummy is also positive (1.219) and significant at the 5% level. In column 2, we add the interaction of this dummy variable with options volume. The estimates show that the interaction term, *Ln(Optvol) x Dummy for high-tech*, is 0.186 and highly significant, as expected. Most interesting, however, the coefficient on *Ln(Optvol)* goes toward zero (0.004) and becomes insignificant once the interaction term is included. Taken literally, this indicates that there is no effect of options trading activity on innovation in non-R&D-intensive industries, which is broadly consistent with the story we present. For robustness, we also split the sample. In column 3, in R&D-intensive industries, the coefficient on options volume is large, positive, and significant at the 1% level, whereas in column 4, in non-R&D-intensive industries, the coefficient is smaller and insignificant (0.144 versus 0.070)[23].

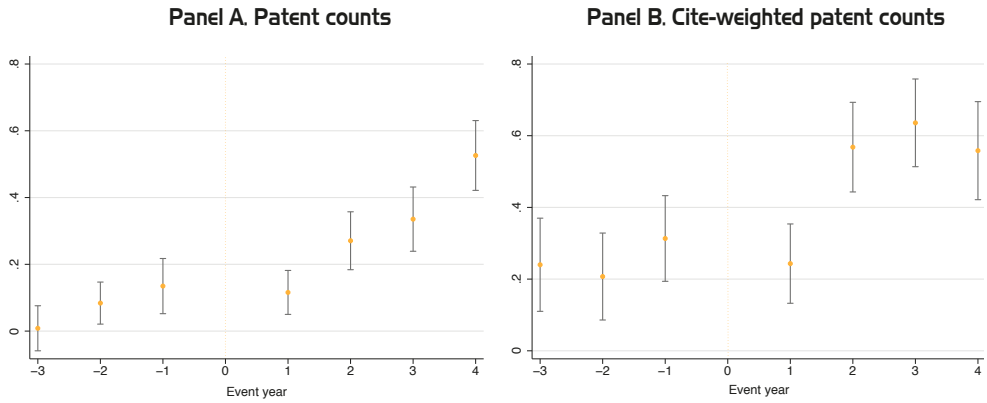
22. According to industrial codes of the International Standard Industrial Classification of All Economic Activities (ISIC Rev.3), OECD (2011) classifies manufacturing industries into four subgroups, high-technology, medium high- technology, medium low-technology, and low-technology, based on the technology intensity and level of R&D used in these industries.

23. Clearly, as detailed in Section 3, this approach has the problem that patent and citation data are a less reliable indicator of innovation in low-tech industries. To address this, we experimented with different subsamples of non- R&D-intensive firms such as including low- and/or medium low-tech industries and focusing only on those firms that have nonzero citations in more than 25% or 50% of the years they appear in our sample. Our finding, however, remains unaltered in all these tests. For example, re-performing the analysis using a matched sample of firms in low-tech industries that receive citations in more than 50% of the years yields the following results: we estimate a coefficient on the interaction term of 0.240 (standard error = 0.061) and a coefficient on options volume of –0.054 (standard error = 0.052) on this subsample of 2,192 observations. If we split this subsample into R&D- and non-R&D-intensive industries, the coefficient on *Ln(Optvol)* is large and significant only for firms in R&D-intensive industries (i.e., a coefficient of 0.130 with a standard error of 0.053 versus a coefficient 0.023 with a standard error of 0.056).

Finally, we perform a small event study that examines the effect of initial option listings on firms' innovation performance. To do so, we focus on the subsample of firms that appear for at least two years before and after the listing event. After excluding firms with multiple listings, we are left with a set of 93 events during the period between 1998 and 2002. Next, we proceed to construct a dummy variable, *Post*, that equals one for the post-event period and zero for the pre-event period. In column 1 of Table A11 in the Internet Appendix, we augment Eq. (1) by including *Post*. The within-firm estimator is 0.370 and significant at the 5% level. In terms of economic significance, this suggests that option listing is associated with a 37% increase in patent citations in subsequent periods. In our second diagnostic test, we examine the dynamics of innovation in the years around the listing event. We use a window of eight years and include in our main specification a set of dummy variables for the three years prior to the year when the firm was listed and four years after the firm was listed (year zero is the omitted category). Fig. 2 presents the results. Panel A depicts the within-firm changes in the raw number of patents and Panel B shows the changes in cite-weighted patents. In both figures, we find that there is little effect in the first year after listing, but in the following years innovation increases substantially by approximately 64% (measured by cite-weighted patents) with respect to the listing year.

Two conclusions emerge from this analysis. First, it mitigates concerns that options trading is endogenous due to reverse causality. This is a particular concern when studying innovation output because it is difficult to address by lagging the explanatory variable. Even if innovation is regressed on lagged options volume (as is done in the Internet Appendix, Table A3), it may be that lagged innovation causes lagged options volume and also causes current innovation. Because we only consider the first listing (based on the data available to us), it cannot be caused by past listings. Second, the phenomenon of such delayed effects is consistent with the starting point of our theory, i.e., that the benefit from options is related to whether the market for the listed option has sufficient volume because trading volume requires time to build.

Fig. 2. Innovation around the option listing event



This figure presents within-firm changes in (Panel A) unweighted patent counts (*PATS*) and (Panel B) patents weighted by the number of forward citations (*CITES*) in the years around the option listing event. The estimates are taken from the regressions reported in columns 2 and 4 of Table A11 in the Internet Appendix.

Innovative direction

We now employ alternative outcome variables to explore the idea that our baseline results are not simply driven by greater R&D productivity (more citations per R&D dollar) but are rather associated with different resource allocation decisions (or innovative directions). To perform such a test, we use three different measures of the direction of firms' innovative efforts: (i) an originality index regarding knowledge inputs, (ii) a measure of risk-taking behavior, and (iii) a proxy for innovative diversity. The results are reported in Table 4. As before, all models are estimated via fixed effects OLS panel regression using the pre-sample mean of the dependent variables. We lose some observations in these specifications because in the fixed effects estimator, we require a firm to have at least some information on the dependent variables in the 1996-2004 and pre-sample periods.

In column 1, the outcome variable is an originality-weighted patent count. Originality, as defined in Hall, Jaffe, and Trajtenberg (2001), is essentially one minus a Herfindahl index of the concentration of backward patent citations across two-digit technological classes. We find that the coefficient estimate on *Ln(Optvol)* is positive and significant at

the 1% level, suggesting that firms with more options trading activity make use of a more diverse set of knowledge[24]. In the next column, we use a measure of risk-taking behavior, i.e., the standard deviation of forward citations received across patents. The results show that there is a positive and meaningful relationship between *Ln(Optvol)* and *Ln(1+SD CITES)*[25]. In column 3, we introduce the diversity of innovation activities, defined as one minus the Herfindahl index of the number of patents across classes. The patent portfolio includes all patents of a given firm over a three-year period. To control for the fact that some firms are engaged in so little innovation that it may not be meaningful to speak of a diverse (or concentrated) technological direction, we define a minimum threshold of five patents to filter out such low-innovation firms[26]. As shown, the estimate on *Ln(Optvol)* is positive and significant at the 10% level, suggesting that firms with more options trading activity file for a more diverse set of patents[27].

Taken together, the results in Table 4 reveal that options trading appears to evoke a change in the direction of innovative efforts and not merely increase the amount of R&D or patenting; on average, firms with more trading activity produce a more diverse and original set of activities and are characterized by an increasing willingness to take risk in their innovation process. We find these results especially intriguing because, intuitively, one may conjecture that the disciplinary feature of financial markets is to force managers to refrain from engaging in overly risky projects and to abandon creativity and diversity for efficiency purposes. We take these results as a starting point to explore the question of why this is the case in Section 5.

24. The coefficient on options volume continues to be positive and significant when we use NB (coefficient of 0.157 with a standard error of 0.024) and Poisson (coefficient of 0.114 with a standard error of 0.050) specifications.

25. Our findings are similar if we use the untransformed variable: the coefficient (standard error) on *Ln(Optvol)* is 0.319 (0.085) in column 2 of Table 4 when *Ln(1+SD CITES)* is replaced by *SD CITES*.

26. We also consider alternate cut-off points of ten, 20, and 50 patents and obtain similar results.

27. For robustness purposes, we apply an alternative modeling approach that accounts for the bounded nature of the dependent variable. Specifically, we employ a double-truncated Tobit model and find similar results for the coefficient on options trading (i.e., the coefficient is 0.008 with a standard error of 0.004).

Table 4. Innovation direction and options volume

This table presents estimates of OLS panel regressions of firms' patents weighted by originality (*ORIG.*), the standard deviation of forward citations across firms' patents (*SD CITES*), and innovative diversity *(DIVERSITY)* on options volume (*Optvol*) and other firm-level control variables. See Hall, Jaffe, and Trajtenberg (2001) for a definition of originality. Diversity is defined as one minus the Herfindahl index of the number of patents across two-digit technological classes. Firms in columns: 542 in column 1, 455 in column 2, and 362 in column 3. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+ORIG.)*	*Ln(1+SD CITES)*	*DIVERSITY*
Method: OLS	(1)	(2)	(3)
Ln(Optvol)	0.154***	0.039***	0.007*
	(0.022)	(0.010)	(0.004)
InstOwn	–0.140	0.104**	0.028
	(0.127)	(0.052)	(0.023)
Ln(K/L)	0.032	–0.022	0.005
	(0.037)	(0.024)	(0.010)
Ln(Sales)	0.086***	0.010	0.027***
	(0.030)	(0.012)	(0.007)
Ln(Age)	–0.026	–0.082***	0.018
	(0.060)	(0.029)	(0.013)
Ln(R&D stock)	0.159***	0.041***	–0.003
	(0.040)	(0.012)	(0.006)
Observations	3,245	2,382	1,526

Endogeneity of options trading

In this subsection, we address concerns that informed traders select firms on the basis of characteristics that are observable to the traders but not observable for us. For example, informed investors might decide to trade options on stocks when they anticipate an increase in innovation. Another problem might be that our measure of options trading activity is noisy. This is because intraday execution prices are not available over

the long sample period. Although this is mitigated by annual averaging, we are likely to underestimate the effect of options[28].

We address these issues in a number of ways. First, we use matching estimators to calculate the average effect of having high levels of options volume on innovation. Second, we consider moneyness and open interest as two plausible exogenous instrumental variables and perform 2SLS estimations of the regressions in Table 2. Third, we test in Section 5 whether our results are consistent with additional predictions and empirical findings concerning the environment in which options trading should have differential effects on innovation[29].

Propensity score matching

We begin with propensity score matching (PSM) to determine whether firms with high trading activity would have innovated at a lower rate had they not had high trading activity. In the application that follows, we define a high (low) trading activity firm as a firm with options volume above (below) the yearly median in a given three-digit SIC industry. The PSM technique is based on the likelihood that an observation would be a high trading activity firm conditional on observables (Rosenbaum and Rubin, 1983, 1984). We use a probit specification to estimate the probabilities of being a high trading activity firm (= 1;0 = otherwise) on a comprehensive list of observable characteristics, including all the independent variables (including the additional controls), as well as fixed effects. We then use the predicted probabilities, or propensity scores (stratified by industry and year), from this probit estimation and perform the matching. As our main matching procedure, we use nearest-neighbor matching that allows each treated firm to be matched with multiple controls (i.e., four, although our results are robust to any number of matches between one and five), running the procedure with replacement. However, to ensure

28. Another issue might be that different types of options provide different signals. Although we could employ additional data to examine the breakdown of call and put options with different times to maturity, there are no clear hypotheses. As Roll, Schwartz, and Subrahmanyam (2009) note, while it may be the case that managers are more likely to act on "good news" than on "bad news," calls and puts can be bought and sold freely. Thus, in the absence of information on the signed order imbalance (data we unfortunately lack), disaggregating calls and puts cannot be unambiguously linked to managerial investment decisions.

29. An interesting context for the purpose of our study would be the use of a difference-in-differences estimator that relies on the exogenous variation in options trading generated by short selling bans or constraints imposed by regulators during the 2007 – 2009 crisis. Unfortunately, we lack data on patenting during and after the crisis period.

that the results are not sensitive to our choice of matching estimator, we also provide evidence from kernel and radius matching.

Table 5 reports the average treatment effect estimates. The average selection bias (not tabulated) across all specifications ranges from 3.4% to 4.7%, which means that the results are reliable. Our findings are in line with those obtained in the previous panel regressions. For example, the results in columns 1 and 2 suggest that firms with high trading activity produce 70% more patents that subsequently generate 72% more citations per dollar of R&D than firms with low options volume, all significant at the 1% level. Overall, this suggests that the non-random assignment of high levels of options trading to more innovative firms (at least based on observables) does not explain our findings.

Table 5. Propensity score matching

This table presents estimates of differences in firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) between the treatment group (high levels of options volume) and the control group (low levels of options volume). The matched sample is constructed using nearest-neighbor (Panel A), kernel (Panel B), and radius (Panel C) score matching with scores given by a probit model in which the dependent variable is a dummy variable that equals one if a firm has an options volume above the yearly median in a given three-digit industry. The propensity score is estimated using the following firm characteristics: *InstOwn*, *Ln(K/L)*, *Ln(Sales)*, *Ln(Age)*, *Ln(R&D stock)*, *Illiquidity*, *Leverage*, *Tobin's Q*, *ROA*, *Capex*, *Ln(Analyst coverage)*, and fixed effects. Firms in columns: 525. Standard errors are obtained using 200 bootstrap replications (in parentheses). The time period is 1996 – 2004 (with citations up to 2006). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Nearest-neighbor matching		*Panel B: Kernel matching*		*Panel C: Radius matching*	
	Ln(1+CITES)	Ln(1+PATS)	Ln(1+CITES)	Ln(1+PATS)	Ln(1+CITES)	Ln(1+PATS)
	(1)	(2)	(3)	(4)	(5)	(6)
High Optvol vs. Low Optvol	0.722*** (0.104)	0.704*** (0.092)	0.468*** (0.125)	0.382*** (0.094)	1.155*** (0.072)	1.096*** (0.063)
Observations	2,130	2,130	2,130	2,130	2,130	2,130

Instrumental variable

Our second approach to correct for the potential bias due to selection is an instrumental variable strategy. Roll, Schwartz, and Subrahmanyam (2009) propose two instrumental variables that are reasonably exogenous to the relationship between options volume and innovation: (i) moneyness (i.e., the average absolute difference between the stock's market price and the option's strike price) and (ii) open interest in the stock's listed options. We focus our analysis on moneyness, while Table A12 in the Internet Appendix shows that our results are similar if we use the total open interest in the stock's listed options as an alternative.

A good instrument is a variable that is correlated with options trading (this assumption can be tested) but uncorrelated with our dependent variables except through other independent variables. That is, the instrument should be a variable that can be excluded from the original list of controls without affecting the results. As Roll, Schwartz, and Subrahmanyam (2009) argue, there are several reasons that moneyness is related to options trading. First, informed traders may be more attracted to out-of-the-money (OTM) options because they offer the greatest leverage but uninformed agents may prefer in-the-money (ITM) options to avoid overly risky positions (Pan and Poteshman, 2006). Moreover, volatility traders would avoid deep ITM or OTM options, as the vega of such options is close to zero. Specifically, Chakravarty, Gulen, and Mayhew (2004) show that the trading volume by agents speculating on volatility tends to be concentrated in at-the-money (ATM) options. In sum, these arguments suggest that moneyness is related to options trading, although they do not establish an unambiguous direction. There is no reason to believe, however, that (unsigned) moneyness is linked to innovation in any intrinsic way because exchanges periodically list new options with strike prices close to the stock's market price.

As there is no strong rationale for a mechanical link between moneyness and innovation, we use the average absolute moneyness as an instrument. This variable is measured as the yearly average of the daily absolute deviation of the exercise price of each traded option from the

closing price of the underlying asset[30]. The correlation of this variable with options volume is 0.326, which suggests that the instrument is indeed related to options trading, and is consistent with that reported in Roll, Schwartz, and Subrahmanyam (2009). We implement the instrumental variable estimator using 2SLS.

Column 1 of Table 6 presents the first stage, which regresses options volume on moneyness (and all other controls). As indicated by the simple correlation, we find that the instrument is positive and highly significant. Moreover, the first-stage *F* -stat for the "weak instrument rule of thumb" is strongly significant (and well above ten), which suggests that the hypothesis that the instrument can be excluded from the first-stage regressions is rejected and that the instrument is not weak. Columns 2 and 3 present the coefficient estimates for the second stage, where we control for endogeneity. Column 2 presents the results with cite-weighted patents as dependent variables. Consistent with the findings from the OLS specification, the coefficient estimate on *Ln(Optvol)* is positive and significant at the 1% level. In column 3, we find a very similar pattern using unweighted patents as the dependent variable. To provide additional support for the validity of our instrumental variable approach, we replicate the estimations of Table 6 using open interest as an additional instrument and rely on the Hansen *J*-statistic. Our instrument performs adequately in our tests (*p*-values = 0.93 and 0.31 in identical specifications of columns 2 and 3, respectively), indicating that we cannot reject the null hypothesis of instrument suitability.

To gauge the direction and magnitude of the bias due to the endogeneity of options trading, we can compare the OLS results from Table 2 with those obtained from the 2SLS regressions. Interestingly, the 2SLS coefficient estimates on *Ln(Optvol)* are considerably larger (i.e., more positive) than those of the OLS estimates, although the estimates from both approaches are in the same direction and statistically significant[31].

30. For traded option *k* on stock *j* for day *d*, the absolute deviation is $\text{Ln}(\text{Price}_{j,d}/\text{Strike}_k)$. This is averaged over all *k* and d within a year *t* for each stock *j*. Options without trades are not included in the calculation of the moneyness variable. We obtain very similar results if we use volume-weighted average annual moneyness for each stock *j*, where each option's moneyness is weighted by the proportion of total option volume for stock *j* contributed by that option.

31. For robustness, we also consider the instrumental variable estimator by using the control function approach (Blundell and Powell, 2004). The coefficient estimate (standard error) on *Ln(Optvol)* in the control function estimation was also above the ordinary Poisson estimate (see Internet Appendix, columns 4 and 8 of Table A1): 0.188 (0.087) for *CITES*, and 0.165 (0.065) for *PATS*.

This OLS bias toward zero could be because options trading is measured with some error or because omitted variables simultaneously make firms innovative and more attractive to informed traders. The attitudes and beliefs of CEOs could be an example of such omitted variables. For instance, overconfident CEOs could attract more informed traders, while simultaneously, they could also be more likely to pursue innovation that results in more patents and citations (Hirshleifer, Low, and Teoh, 2012).

Table 6. Moneyness as instrumental variable

This table presents estimates of 2SLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other firm-level control variables, with the average absolute moneyness, *Ln(Moneyness)*, as instrumental variable. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996-2004 (with citations up to 2006). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Method	*OLS (first stage)*	*2SLS (second stage)*	
Dependent var.	Ln(Optvol) (1)	Ln(1+CITES) (2)	Ln(1+PATS) (3)
Ln(Optvol) (instr.)		0.180***	0.162***
		(0.057)	(0.062)
InstOwn	1.051***	−0.033	−0.259*
	(0.224)	(0.179)	(0.134)
Ln(K/L)	−0.365***	0.095	0.061
	(0.080)	(0.067)	(0.050)
Ln(Sales)	0.595***	0.151**	0.103**
	(0.052)	(0.063)	(0.042)
Ln(Age)	−0.322***	−0.059	−0.014
	(0.123)	(0.101)	(0.071)
Ln(R&D stock)	0.361***	0.471***	0.194***
	(0.054)	(0.071)	(0.050)
Ln(Moneyness)	1.343***		
	(0.155)		
Observations	3,271	3,271	3,271

POSSIBLE MECHANISMS

Our evidence thus far is consistent with the implication of our leading hypothesis that options trading enhances firm innovation, even after accounting for potential endogeneity concerns. In this section, we turn to the last part of our analysis and discuss potential underlying mechanisms through which this may occur. It is of course challenging to provide definite proof, and hence our tests are only suggestive.

Broadly, we suggest two possible explanations for our results. The first is that managers prefer the "quiet" life as proposed by Hart (1983), Schmidt (1997), and Bertrand and Mullainathan (2003) and that the increased price informativeness induced by options trading serves as a monitoring mechanism that forces managers to invest in innovation if they are a priori reluctant to do so. Alternatively, the positive association between options trading and innovation could also be attributable to career concerns. Most prominently, Aghion, Van Reenen, and Zinɵ gales (2013) recently extend the Holmström (1989, 1999) career concern model in the context of institutional investors (i.e., blockholders) and innovation. Based on the observation that managers concerned with their reputations in the labor market have incentives to take actions that boost current earnings and the firm's current stock price (Narayanan, 1985), the authors' findings suggest that the presence of institutional investors "protects" managers against the reputational risk associated with long-term investments in innovation. Because of their informational advantage, they have the ability to assess managerial efforts in innovation independent of potential bad profit realizations in the short run. This, in turn, provides incentives for the manager to forgo short-term profits and to invest in innovation. To the extent that the previous literature, both theoretical and empirical, argues that options increase the amount of private information conveyed by prices (e.g., Cao, 1999; Chakravarty, Gulen, and Mayhew, 2004; Pan and Poteshman, 2006; Roll, Schwartz, and Subrahmanyam, 2009; Hu, 2014), we may expect that this rationale also applies in the context of active options markets.

To understand the extent to which the aforementioned stories might explain our findings, we implement several tests concerning the environments in which options trading activity should have differential effects on innovation. First, we examine whether the effect of options trading on innovation depends on product market competition. The quiet life story suggests that the effect of options trading on innovation is weaker in highly competitive environments because stronger competition increases the threat of bankruptcy, which induces the manager to work harder to avoid liquidation and to keep his job (Hart, 1983; Schmidt, 1997). In contrast, if informed agents serve as a "shield" that protects managers, this effect should be more pronounced when the degree of product market competition is higher. This is because competition reduces the chances of success and hence increases the reputational risk faced by managers if they do so. Second, we investigate how innovation varies with options volume and managerial entrenchment. As Ferreira, Ferreira, and Raposo (2011) show, a disciplining takeover is more likely when prices are more efficient. Thus, an implication of our preceding discussion is that if managers prefer the quiet life, the beneficial effect of options should be stronger when managers are more "entrenched." Specifically, if a firm adopts a large number of takeover defenses, it might become partially insulated from the market for corporate control. In such cases, the takeover market cannot play an effective disciplinary role, and managers have greater ability to shirk. More-over, if shareholder rights are restricted (i.e., the manager has more bargaining power against shareholders), the CEO will also be more entrenched. Third, if career concerns are the driving force behind this relationship, the effect of options trading on innovation should be stronger for younger CEOs because they are more concerned with their careers, and to boost their careers, they are likely to engage in myopic behavior. Gibbons and Murphy (1992) show that implicit incentives from career concerns are much more substantial for younger managers. Holmström (1999) notes that when managerial ability is initially unknown and managerial effort is unobservable, young managers will overwork to benefit their future careers. Thus, there should be little managerial slack for younger CEOs. As before, under the quiet life story, options trading should have less of an effect when managers are younger, while under the career concerns story, the impact of options trading on innovation should be stronger when managers are younger.

Product market competition

Table 7 presents several results related to the interaction between options volume and product market competition. To measure product market competition, we use the inverse Lerner index [as in Aghion, Bloom, Blundell, Griffith, and Howitt (2005)], defined as one minus the median gross margin across all firms in the entire Compustat database with the same three-digit industry SIC as the focal firm. Our main model allows this measure to vary over time, but we also consider its time-invariant form.

The first column reproduces our baseline results (column 4 of Table 2) and introduces the time-varying measure of product market competition. In this specification, the coefficient estimate on competition is positive and statistically significant (more competition yields more innovation), while the coefficient on *Ln(Optvol)* remains positive and significant[32]. Column 2 includes the interaction term between options trading and product market competition, which is positive and significant at the 1% level, as predicted by the career concerns hypothesis. In columns 3 and 4, we then replace the dependent variable with raw patent counts and repeat the analysis. We observe similar patterns for the interaction term. For robustness, columns 5 and 6 repeat the same specifications as above but restrict the inverse Lerner index to be constant over time. This yields similar results. Note that we are unable to estimate the main effect of competition in this model because the measure is collinear with industry effects.

Managerial entrenchment

Table 8 analyzes the interaction between options trading and managerial entrenchment. To measure the degree of managerial entrenchment, we use the "Governance Index" (G-Index) introduced by Gompers, Ishii, and Metrick (2003). It consists of 24 corporate governance provisions and is based on firm-level corporate governance provisions and firms' governing state corporate law statutes. We obtain this information from RiskMetrics. Because this covers S&P 1500 firms in 1998, 2000, 2002,

32. In line with Aghion, Bloom, Blundell, Griffith, and Howitt (2005), we find some evidence of an inverted U-shaped relationship between innovation and product market competition. If we include a term in the square of the inverse Lerner index, it is negative, whereas the linear term remains positive. This quadratic term is insignificant, however, with a coefficient estimate of –32.205 and a standard error of 28.076.

and 2004, our sample size declines in this analysis. A higher G-Index score indicates more restrictions on shareholder rights or a greater number of anti-takeover measures.

Table 7 Product market competition

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume (*Optvol*), product market competition (*Competition*), their interaction, and other firm-level control variables. Firms in columns: 548. Robust standard errors are clustered at the three-digit industry level (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 – 2004 (with citations up to 2006). Product market competition is constructed as 1 the Lerner index, where Lerner is calculated as the median gross margin from the entire Compustat database in the firm's three-digit industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Measure of competition	*Varies over time*				*Constant over time*	
Dependent var.	Ln(1+CITES)		Ln(1+PATS)		Ln(1+CITES)	Ln(1+PATS)
Method: OLS	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol) x Competition		2.467***		1.962***	3.334***	2.579***
		(0.469)		(0.249)	(0.284)	(0.319)
Ln(Optvol)	0.169**	0.169***	0.160**	0.160***	0.165***	0.156***
	(0.046)	(0.026)	(0.037)	(0.020)	(0.029)	(0.022)
Competition (1 – Lerner)	5.834***	5.054**	6.852***	6.229***		
	(1.248)	(2.024)	(0.649)	(1.213)		
InstOwn	–0.035	0.017	–0.212	–0.171	0.027	–0.165
	(0.229)	(0.183)	(0.224)	(0.181)	(0.182)	(0.181)
Ln(K/L)	0.026	0.041	0.042	0.053	0.047	0.058
	(0.100)	(0.080)	(0.088)	(0.071)	(0.081)	(0.071)
Ln(Sales)	0.132	0.147*	0.121	0.133**	0.151*	0.135**
	(0.093)	(0.085)	(0.069)	(0.063)	(0.086)	(0.063)
Ln(Age)	–0.107	–0.089	–0.032	–0.017	–0.077	–0.007
	(0.148)	(0.111)	(0.092)	(0.069)	(0.112)	(0.071)
Ln(R&D stock)	0.251***	0.243***	0.202***	0.195***	0.244***	0.197***
	(0.048)	(0.052)	(0.035)	(0.042)	(0.052)	(0.041)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

Our evidence is consistent with the findings in Table 7. In line with the career concerns hypothesis (and in contrast to the quiet life hypothesis), the positive association between options trading and innovation is stronger when managers are less entrenched. Specifically, the interaction between options volume and managerial entrenchment in column 2 of Table 8 generates a significantly negative coefficient estimate of –0.028 (significant at 5%), while the main effect of *Ln(Optvol)* remains positive and statistically significant at the 1% level. For robustness purposes, Table A13 in the Internet Appendix investigates the interaction between options trading and the "Entrenchment Index" (E-Index) (Bebchuk, Cohen, and Ferrell, 2009). The findings are similar.

CEO age

Finally, we examine how a CEO's age alters the effect of options trading on innovation. To capture CEO age, we extract information from ExecuComp. As before, this database covers firms in the S&P 1500, and hence we are left with a subsample. Under the career concerns hypothesis, we expect that the effect of options trading on innovation should be more pronounced for younger CEOs. If anything, it should increase the impact because career concerns are stronger when managers are further from retirement, as that increases the returns from influencing the market's belief about their abilities. For this reason, the investment decisions of younger CEOs should be more affected by their career concerns than those of older CEOs.

Table 9 presents evidence on the interaction between CEOs' age and options trading on innovation. The estimate in column 2 of Table 9 confirms our conjecture and shows a negative coefficient on the interaction term (–0.368) that is statistically significant at the 5% level. Consistent with our earlier findings, the coefficient on *Ln(Optvol)* continues to be positive and significant at the 1% level, while the coefficient on *CEO age* is negative (older CEOs are less innovative), although the effect is not significant.

Table 8. Managerial entrenchment

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*), managerial entrenchment (*G-Index*), their interaction, and other firm-level control variables. Firms in columns: 331. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of three-digit industry dummies, time dummies, and fixed effects by including pre- sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The G-Index is an average of 24 provisions in the firm's charter (see Gompers, Ishii, and Metrick, 2003). The measure is based on data from RiskMetrics from 1998, 2000, 2002, and 2004. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+CITES)*		*Ln(1+PATS)*	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol) x G-Index		−0.028**		−0.018
		(0.014)		(0.013)
Ln(Optvol)	0.179***	0.170***	0.159***	0.154***
	(0.032)	(0.032)	(0.029)	(0.029)
G-Index (governance index)	0.019	0.045	0.010	0.026
	(0.033)	(0.033)	(0.029)	(0.028)
InstOwn	−0.067	−0.094	−0.031	−0.048
	(0.191)	(0.191)	(0.169)	(0.168)
Ln(K/L)	0.152**	0.151**	0.109*	0.109*
	(0.077)	(0.076)	(0.063)	(0.063)
Ln(Sales)	0.111**	0.109**	0.123***	0.122***
	(0.050)	(0.049)	(0.046)	(0.046)
Ln(Age)	−0.184**	−0.169*	−0.114	−0.105
	(0.092)	(0.092)	(0.085)	(0.085)
Ln(R&D stock)	0.111***	0.115***	0.103***	0.106***
	(0.031)	(0.030)	(0.027)	(0.027)
Observations	921	921	921	921

Table 9. CEO age

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume (*Optvol*), *CEO age*, their interaction, and other firm-level control variables. Firms in columns: 337. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). CEO age is based on data from ExecuComp over the period 1996 – 2004. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+CITES)*		*Ln(1+PATS)*	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol)	–0.368**			–0.163
x Ln(CEO age)	(0.162)			(0.147)
Ln(Optvol)	0.166***	0.162***	0.161***	0.159***
	(0.044)	(0.043)	(0.035)	(0.035)
Ln(CEO age)	–0.245	–0.113	–0.309	–0.250
	(0.389)	(0.375)	(0.339)	(0.323)
InstOwn	0.005	0.036	–0.026	–0.012
	(0.227)	(0.226)	(0.202)	(0.203)
Ln(K/L)	0.050	0.045	0.097	0.095
	(0.083)	(0.082)	(0.068)	(0.068)
Ln(Sales)	0.299***	0.301***	0.241***	0.241***
	(0.068)	(0.069)	(0.060)	(0.060)
Ln(Age)	–0.155	–0.149	–0.086	–0.084
	(0.132)	(0.132)	(0.113)	(0.113)
Ln(R&D stock)	0.151***	0.155***	0.126**	0.128**
	(0.051)	(0.052)	(0.051)	(0.052)
Observations	1,996	1,996	1,996	1,996

Profitability

To strengthen our explanation, in this section, we analyze an additional economic mechanism that is supposed to directly increase the market pressure imposed by investors–a decline in profitability. Specifically, Kothari (2001) finds that financial reporting conveys substantial information to outsiders regarding firm performance that significantly influences market expectations and stock prices. Moreover, survey evidence reveals that profitability is the most important externally reported performance measure and that the majority of managers are willing to cut discretionary spending (e.g., R&D) to meet or exceed benchmarks (Graham, Harvey, and Rajgopal, 2005). Thus, the short-term pressure imposed by external agents might be substantially more pronounced for firms with earnings that reflect decreasing profitability because investors are more likely to exit based on this negative information and the stock price may decline. Managers in these firms are also at greater risk of being fired because boards aggressively fire CEOs for lower performance (Jenter and Lewellen, 2014). In sum, if it is true that options trading activity shields managers from short-term market pressures (and the risk of being fired), we expect the positive effect of options trading to be magnified for firms with a decline in profitability.

Table 10 reports the results. In column 1, we regress the citation-weighted patent count on the lagged change in profitability (adjusted by assets) and options trading (and all other controls). We find that higher profitability growth has a negative association with innovation, but the effect is not significant, while the coefficient estimate on *Ln(Optvol)* remains positive and significant. Column 2 interacts the profitability variable with options volume. The coefficient on this interaction is negative and significant at the 1% level, suggesting that innovation is more sensitive to options trading when firms' profitability growth is lower. As before, columns 3 and 4 of Table 10 present the robustness test by replacing the dependent variable with simple patent counts. Although we observe a similar pattern, the coefficient on the interaction term is insignificant. This is interesting, however, because at face value, this result combined with the insignificant interactions in Tables 8 and 9 when the dependent variable is replaced with *Ln(1+PATS)* indicate that the effect of our mechanism stems from its impact on R&D quality rather than on higher patent propensities.

Table IO. Profitability

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume (*Optvol*), lagged change in profitability ($\Delta ROAt-1$), their interaction, and other firm-level control variables. Firms in columns: 526. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+CITES)*		*Ln(1+PATS)*	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol) x Δ ROA_{t-1}		-0.308*** (0.116)		–0.127 (0.082)
Ln(Optvol)	0.176*** (0.033)	0.173*** (0.033)	0.165*** (0.028)	0.163*** (0.028)
Δ ROA_{t-1}	–0.256 (0.229)	0.517 (0.386)	–0.062 (0.151)	0.258 (0.265)
InstOwn	–0.124 (0.175)	–0.124 (0.175)	–0.245 (0.158)	–0.245 (0.158)
Ln(K/L)	0.052 (0.058)	0.053 (0.058)	0.066 (0.051)	0.066 (0.051)
Ln(Sales)	0.121*** (0.047)	0.119** (0.047)	0.128*** (0.039)	0.127*** (0.039)
Ln(Age)	–0.088 (0.094)	–0.088 (0.095)	–0.032 (0.081)	–0.032 (0.081)
Ln(R&D stock)	0.259*** (0.052)	0.260*** (0.052)	0.205*** (0.049)	0.206*** (0.049)
Observations	2,658	2,658	2,658	2,658

CEO compensation

Thus far, we have not considered how managerial compensation can help to motivate innovation. Under the optimal contracting view (Holmström and Tirole, 1993), it is efficient for firms in active option markets to grant their managers more stock- and less cash-based pay, as prices are more informative. Moreover, managerial compensation packages that are closely tied to stock prices may decrease risk aversion and motivate the manager to expend effort in long-term intangible assets. In particular, it is commonly argued that incentives in the form of stock options prevent managers from making myopic decisions and provide them with increased incentives to take on risky projects. Consistent with this, Coles, Daniel, and Naveen (2006) find that compensation structures with higher vega incentives (controlling for delta) are associated with riskier investment policy as captured by increased R&D, increased focus, and reduced PP&E. Similarly, Francis, Hasan, and Sharma (2011) show that incentives in the form of vested and unvested options have a positive and significant effect on patents and citations. Hence, it is possible that part of the positive effect of options trading activity on innovation might be attributable to contractual incentives. We explore this explicitly by conditioning on executive compensation schemes.

The data on compensation come from ExecuComp. Following prior literature (e.g., Coles, Daniel, and Naveen, 2006), the primary characteristics of compensation that we consider are CEO delta and CEO option holdings vega. Delta is defined as the dollar change in a CEO's stock and option portfolio for a 1% change in stock price and measures the CEO's incentives to increase the stock price. Vega is the dollar change in a CEO's option holdings for a 1% change in stock return volatility; it measures the risk-taking incentives generated by the CEO's option holdings. These values are calculated using the one-year approximation method of Core and Guay (2002). We also control for CEO cash compensation (salary plus bonus) and CEO tenure, as the number of years in office may be associated with different compensation schemes.

In column 1 of Table 11, we re-estimate Eq. (1) on the subsample of firms with non-missing compensation variables. The coefficient on *Ln(Optvol)* is 0.157 and significant at the 1% level. In column 2, we

add the compensation variables. The coefficients on *Ln(1+CEO vega)* and *Ln(1+CEO delta)* are positive but insignificant, while the key coefficient on options volume continues to be positive but becomes smaller in magnitude (i.e., declines to 0.142), which represents a decrease of approximately 10% from the estimate in column 1[33]. In columns 3 and 4, we repeat the specifications of the first two columns but use patent counts as the dependent variable. We observe a similar pattern for the coefficient on *Ln(Optvol)*, i.e., it continues to be positive and significant but declines by approximately 13% once the compensation variables are included. Interestingly, the coefficient on *Ln(1+CEO vega)* becomes significant, which means that higher vega implies more innovative outputs (as one might expect). Overall, these findings suggest that managerial compensation schemes capture part of the size effect of options trading on innovation and are thus part of the story, although the specific channel underlying this mechanism is rather ambiguous.

However, taking Table 11 as a whole, we note that options volume has a robust positive effect on innovation across all specifications, indicating that the relationship between options trading activity and innovation goes substantially beyond compensation structures. This is what one would expect under the career concerns explanation. Specifically, although the design of the compensation contract can overcome some of the disincentives to innovate, it does not shield managers from the reputational effects of failed innovation. As Gillan, Hartzell, and Parrino (2009) show, in 2000, 54% of the firms in the S&P 500 had no explicit employment agreement with their CEOs (i.e., the CEOs were employed "at will"). The median time horizon of the remaining 45% was three years. Hence, because CEOs enter the labor market repeatedly, their payoffs are ultimately not determined by explicit contracts but by the effect their respective reputation has on their ability to contract in the future[34].

33. The insignificant coefficient on CEO delta is consistent with the result in Fang, Tian, and Tice (2014), indicating that greater pay-performance sensitivity is not associated with more innovation. This finding remains unaltered if we replace CEO delta with the scaled wealth-performance sensitivity measure of Edmans, Gabaix, and Landier (2009). In an identical specification to column 2, the coefficient (standard error) on this variable is 0.037 (0.048) whereas the coefficient (standard error) on options volume is 0.137 (0.045).

34. Incorporating the choice of compensation contracts as a consequence of options trading into our analysis clearly goes beyond the scope of this paper, but endogenizing this decision represents an interesting avenue for future research.

Table II. Controlling for CEO compensation

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume *(Optvol)*, CEO compensation variables, and other firm-level control variables. Compensation variables are based on data from ExecuComp over the period 1996 -2004. *CEO vega* is the dollar change in the CEO's wealth for a 0.01 change in the standard deviation of returns; *CEO delta* is the dollar change in the CEO's wealth for a 0.01 change in the stock price; and vega and delta values are calculated using the one-year approximation method of Core and Guay (2002). *CEO cash compensation* is the sum of CEO salary and bonus, and *CEO tenure* is the number of years the CEO has held the position. Firms in columns: 323. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+CITES)*		*Ln(1+PATS)*	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol)	0.157***	0.142***	0.157***	0.137***
	(0.043)	(0.045)	(0.035)	(0.037)
Ln(1+CEO vega)		0.070		0.106***
		(0.044)		(0.033)
Ln(1+CEO delta)		0.021		0.015
		(0.058)		(0.048)
Ln(1+CEO tenure)		−0.037		−0.032
		(0.050)		(0.042)
Ln(1+CEO cash compensation)		−0.066		−0.094**
		(0.047)		(0.040)
InstOwn	−0.107	−0.125	−0.135	−0.168
	(0.204)	(0.210)	(0.188)	(0.193)
Ln(K/L)	0.013	0.022	0.048	0.058
	(0.085)	(0.086)	(0.070)	(0.069)
Ln(Sales)	0.301***	0.292***	0.254***	0.247***
	(0.072)	(0.073)	(0.063)	(0.062)
Ln(Age)	−0.164	−0.168	−0.075	−0.084
	(0.127)	(0.128)	(0.116)	(0.117)
Ln(R&D stock)	0.148***	0.145***	0.113**	0.106**
	(0.055)	(0.055)	(0.052)	(0.051)
Observations	1,845	1,845	1,845	1,845

DISCUSSION AND CONCLUSION

How do financial derivatives affect managerial investment decisions in the real economy? Specifically, do they hinder or promote innovation? This paper attempts to answer these questions by studying the relationship between innovation and options markets.

Our findings contrast with the view that developed financial markets exacerbate myopic behavior by managers and suggest instead that the presence of informed traders in the options market boosts innovation, even after accounting for R&D investments and the potential endogeneity of options volume. In particular, firms with more options trading activity obtain more patents and patent citations per dollar of R&D invested. We interpret these findings as evidence that the enhanced information efficiency induced by options reduces information asymmetries related to R&D, which provides managers with incentives to invest in innovation. This positive impact could derive from a change in the direction of innovative activities or an increase in R&D spending and productivity. Our findings support the former: firms with greater options trading activity pursue a more creative, diverse, and risky innovation strategy.

Our results complement those of Roll, Schwartz, and Subrahmanyam (2009), who find that option markets increase firm valuations by allowing agents to cover more contingencies and by stimulating trading on private information. Specifically, we strengthen their claims by establishing a direct link between options trading activity and managerial investment decisions and show that higher levels of options volume are associated with a more efficient allocation of R&D resources, which then translates into higher firm value. To show this, we rely on two findings. First, Hall, Jaffe, and Trajtenberg (2005) provide evidence that an extra citation per patent boosts a firm's market value by 3%. Second, we repeat the tests in Hall, Jaffe, and Trajtenberg (2005) with a slightly augmented set of control variables. We find that the raw number of patent counts and cite-weighted patent counts have a positive and significant association with a firm's market value[35]. In summary, these pieces of evidence suggest that informed traders in the options market reward successful innovation outcomes with a higher

35. These results are tabulated in Table A14 in the Internet Appendix.

valuation. Together with the core finding of our paper that the main effect of options trading is to alter the quality of innovation outputs, the above evidence seems to reveal one possible "bright" side of financial derivatives: their positive impact on firms' market value by motivating firms to invest in innovative activities. We discuss several possible mechanisms that could contribute to these findings. First, in line with Aghion, Van Reenen, and Zingales (2013) and contrary to the view that informed traders have a disciplinary effect on managers by "forcing" them to innovate, we find that the presence of informed traders improves the incentives to innovate by reducing career concerns. The beneficial effect of options trading is more pronounced when product market competition is intense, when managers are less entrenched, and for younger CEOs. We complement their findings by showing that informed agents play a crucial role in motivating innovation, even if these agents cannot intervene directly in firms' operations (i.e., compared to blockholders). Second, given the pressure from investors to meet profitability targets, decreasing investments in innovation is one of the major real earnings management tools that managers often use to report positive or increasing income. Our analysis indicates that informed traders do recognize the consequences of cutting R&D activities and therefore mitigate myopic investment problems. Finally, we show that the role of informed trading in motivating innovation exists beyond the structure of managerial compensation and corresponding incentives. Although compensation is a mechanism that links options trading activity and innovation, this effect appears to be substantially dominated by reputation-based incentives, at least in our setting.

While our findings on these mechanisms are consistent with our theory, an unanswered question remains, namely, what is the bottom-line impact of options trading on innovation after accounting for the proposed economic mechanisms. To that end, we directly control for all five mechanism variables and re-estimate an augmented version of Eq. (1). The results are tabulated in the Internet Appendix, Table A15. Overall, we find that options trading continues to be positively and significantly (at the 1% level) related to innovation even after controlling for its dependence on these mechanisms but becomes smaller in magnitude (i.e., declines from 0.216 to 0.154), which reflects a 29% decrease from the baseline model[36]. This suggests that while our mechanisms are able

36. To avoid excessive missing values in this test, we fill in years missing the G-Index with the preceding year's G-Index. Further, note that the magnitude of the baseline estimate differs from that reported in Table 2,

to explain a significant proportion of the positive effect of options trading on innovation, the remaining effect remains strikingly large. Specifically, a coefficient of 0.154 suggests that an increase of 200% in the dollar volume of options traded is associated with a 31% increase in cite-weighted patents. For the median firm in this subsample, this implies that an increase in the trading volume from $15 million to $45 million leads to approximately seven additional cite-weighted patents (i.e., from 21 to 28). This result is both economically and statistically significant.

Clearly, we made some simplifying assumptions throughout the paper. Specifically, we assume that managers can influence corporate innovation. However, even in the absence of a specific link, there are several reasons to believe that managers can indeed influence patent- based measures of innovation. As Lerner and Wulf (2007) emphasize, managers can change the compensation schemes of R&D executives toward more long-term incentives, which can significantly improve the quality of innovative outputs. Managers could also initiate reorganizations with new strategic priorities. For instance, Daniel Vasella, the CEO of Novartis from 1996 to 2010, generated a large increase in R&D productivity with two major strategic moves. First, Vasella expanded Novartis's research from a narrow focus on internal discovery and development capabilities to exploration in new areas through extensive collaborations and the establishment of science-based research institutes. Second, he assigned budget and performance responsibilities over R&D to the business units by setting precise goals, cutting waste, and rewarding successful innovators (Datar and Reavis, 2003).

Moreover, while our study draws on one particular "bright" side of financial derivatives, we are agnostic about how these instruments may affect other stakeholder groups in other ways. Although innovation is important for the growth and wealth of nations, we do not conclude that the greater research productivity shown in our study enhances social welfare. With estimates of the current size of the market for derivatives at approximately $700 trillion, this should, however, be a concern for academics, government regulators, managers, and investors. We leave a proper evaluation of the net effects of financial derivatives for future research.

column 4, because we have only a subsample of firms (i.e., firms included in the S&P 1500 index) with non-missing mechanism variables. This allows us to compare the change in coefficients on the same observations.

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INTERNET APPENDIX FOR "THE BRIGHT SIDE OF FINANCIAL DERIVATIVES: OPTIONS TRADING AND FIRM INNOVATION"

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This Internet Appendix provides additional material to the results presented in "*The Bright Side of Financial Derivatives: Options Trading and Firm Innovation*." In Section A.1, we describe the construction of the main data set. In Section A.2, we discuss and report robustness checks for the baseline results reported in Section 4 of the paper. In Section A.3, we report additional tests that supplement other parts of the main article. Descriptive statistics are in Table A16.

Main data set

The main firm-level data sample is generated through the combination of several data sets. Because we are using patents (weighted by total future citations) as our key measure of innovation, we rely on the matching of the United States Patent and Trademark Office (USPTO) to the North American Compustat data hosted at the National Bureau of Economic Research (NBER) (see Hall, Jaffe, and Trajtenberg, 2001; Jaffe and Trajtenberg, 2002, for details). The main matching was performed based on the concordance file provided by Bessen (2009) that connects the assignee identification number of the NBER patent data set to the Compustat GVKEY identification number. These connections reflected the firms and subsidiaries identified in the Who Owns Whom? database (published annually by Dun & Bradstreet International). Ownership may change through mergers, acquisitions, or spin-offs, and when an organization is acquired/merged/spun-off, its patents likely transfer to the new owner. These changes have been tracked using data on the mergers and acquisitions of public companies reported in the SDC database. We

use the updated version of the NBER match containing citations through 2006 (downloaded from the NBER Patent Data Project website, https://sites.google.com/site/patentdataproject/). All patents granted between 1976 and 2004 are included (just under three million patents), and citation information is available from 1976 to 2006 (over 23 million citations). The need to have some patent data is the main reason that our sample is considerably smaller than the full Compustat sample.

The second data set we draw on comes from OptionMetrics LLC, a financial research firm specializing in the analysis of option markets. The IvyDB U.S. data set from OptionMetrics contains daily closing option prices (bid and ask) for all U.S. exchange-listed and Nasdaq equities and market indexes, as well as all U.S.-listed index and equity options, starting from January 1996 (which is why this is the first year in our sample). In addition to option prices, it also contains daily time-series of the underlying spot prices, dividend payments and projections, stock splits, historical daily interest rate curves and, most important, option volumes. Implied volatilities and sensitivities (delta, gamma, vega, and theta) for each option are also calculated. The comprehensive nature of the database makes it most suitable for empirical work on option markets. The primary key (Security ID) for all data contained in IvyDB is linked to the security's CUSIP number and ticker symbol, and hence merging the two data sets is straightforward.

Third, we obtain data on institutional ownership from Thomson Reuters' CDA/Spectrum Institutional Holdings data set. Starting in 1978, all institutions with more than $100 million in securities under discretionary management have been required to report their holdings to the Securities and Exchange Commission (SEC) using Form 13F. Each quarter, these institutions must disclose any common stock positions greater than 10,000 shares or greater than $200,000 in value. The data include the number of institutional owners, the number of share issues and the percentage of outstanding shares held by each institution. For each fiscal year, we take the average of the four quarterly institutional holdings given by Form 13F and treat that as our measure of institutional ownership (*InstOwn*). As the ownership data do not cover all the firms in the data set, we lose 304 firms when we match the Compustat accounting data and ownership data.

We began with the NBER USPTO/Compustat match and kept all domestic firms trading on NYSE (stock exchange code 11), Amex (12) and Nasdaq (14) with non-missing accounting data on fixed assets (PPENT), employees (EMP), and sales (SALE) that are listed on Compustat for at least three years. As our preferred regressions use fixed effects, we condition our sample on firms that had received at least one citation and had at least two years of non-missing data on all variables. This leaves us with a merged data set of 1,329 firms and 9,265 observations between 1996 (the first year of the options data) and 2004 (the last year of the patent data). For reasons explained in the main article, our final sample consists of firms with positive options volume that are active in five broadly defined R&D-intensive industries: (i) pharmaceuticals (SIC code 283), (ii) industrial and commercial machinery and computer equipment (35), (iii) electronics and communications (36), (iv) transportation equipment (37), and (v) instruments and related products (38). This leaves us with 3,271 observations on 548 firms, which is our baseline sample.

Robustness tests for the baseline results

We conduct a rich set of robustness checks of our baseline results and report them in Tables A1 - A11. First, we check whether our results are robust to alternative econometric models. We begin with a Poisson model where the dependent variable is the number of cite-weighted patents and the number of (unweighed) patents and report the results in Table A1. The coefficients on *Ln(Optvol)* remain positive and significant across all columns, consistent with our baseline findings. For example, the coefficient estimate on *Ln(Optvol)* is 0.143 (p-value < 0.01) if we reproduce our baseline fixed effects model of cite-weighted patents (column 4 of Table 2 in the main article) and is 0.106 (p-value < 0.05) when we use simple patent counts as the dependent variable. Next, because our dependent variables are right-skewed (e.g., 24% of our sample firms have zero citations), we use three modeling strategies that take this into account. We report the results in Table A2. In columns 1 and 2, we adopt a quantile regression approach at the 75th percentile. The baseline results continue to hold, and we obtain similar findings if we run the quantile regressions at the 70th, 80th, 85th, and the 95th percentiles. We then use zero-inflated negative binomial (columns 3 and 4) and zero-inflated Poisson models (columns 5 and 6). We also find consistent results.

Second, because our main analysis uses contemporaneous independent variables, we run alternative specifications where we lag the variables. As a first step, our approach was to empirically explore the effects of time lags between options trading and the dependent variables. Estimating models with various time lags (i.e., from $t - 1$ to $t - 5$) for the options trading variable, we found broadly consistent results for all models, but with coefficients on *Ln(Optvol)* that were consistently larger than those obtained from the contemporaneous models. We present the results of models with one- and three-year lagged explanatory variables, as adding further lags reduces the number of observations for firms in the data set, without providing any appreciable gain in the precision of the estimates. The coefficients on *Ln(Optvol)* are shown in Panels A (one-year lag) and B (three-year lag) of Table A3, and are positive in all regressions. For example, the coefficients in column 1 suggest that increasing options trading activity from the sample median ($8.5 million) to the 75th percentile ($53.5 million) is associated with a 98% increase in future cite-weighted patents in the following year and a 67% increase in three years, all significant at the 1% level.

Third, we examine whether the effect of options volume on innovation is monotonic (i.e., after conditioning on covariates). In Table A4, we begin with the inclusion of *Ln(Optvol)* and its squared term. We find that the impact of *Ln(Optvol)* on cite-weighted patents remains positive and significant (coefficient = 0.105 and p-value < 0.1 in column 1 of Table A4), but the coefficient estimate on the squared term, *Ln(Optvol) x Ln(Optvol)*, is not significant. Next, we create a dummy variable, *High Optvol*, that equals one if the options volume for a given firm is above the median in that year and zero otherwise and interact this dummy with *Ln(Optvol)*. We then re-estimate Eq. (1) in the main article by adding the *High Optvol* dummy and the interaction term, *Ln(Optvol) x High Optvol*. However, as shown in columns 2, 4, and 6, the coefficient estimates on the interaction terms are not statistically significant, while the coefficients on *Ln(Optvol)* remain positive and highly significant. In untabulated analyses, we obtain similar results if we replace the dependent variable with unweighted patent counts. Overall, and consistent with the bivariate relationship in Fig. 1 in the main article, it appears that the effect of options trading activity on innovation is monotonic.

Fourth, our preferred control for R&D inputs is a continuous measure of the depreciated sum of past R&D expenditures. Although widely used in

prior studies, it may partly conceal some of the effects of R&D. To mitigate such concerns, we include only the contemporaneous R&D flow and establish dummy variables based on deciles of the distribution of *R&D stock*. We report the results in Tables A5 and A6, respectively. In both cases, the coefficients on options volume continue to be positive and significant. For example, according to columns 1 and 2 of Table A5, an increase in options volume from the sample median ($8.5 million) to the 75th percentile ($53.5 million) is associated with a 74% increase in citations and a 74% increase in the number of patents filed.

Fifth, as our sample period (1996 - 2004) includes the "dot-com bubble," which is conventionally dated between 1996 and 2000, we rerun our regressions for the two subperiods 1996-2000 and 2001 - 2004. As Table A7 shows, the coefficients on *Ln(Optvol)* are positive and significant (at the 1% level) in both subperiods, which provides reassurance that our results are not driven by high coefficient magnitudes in the earlier or later periods.

Finally, in Table A8, we report the regression results after the inclusion of additional (financial) control variables. In Table A9, we report the regression results after controlling for firms' external knowledge acquisition activities. In Table A10, we report the regression results on the differential effect of options trading on innovation in R&D- and non-R&D-intensive industries based on a matched sample. In Table A11, we report the within-firm regression results that compare changes in innovation before and after firms' inclusion in options markets. These findings are discussed in Section 4.2 of the main article.

Other tests

In this section, we present additional regression results that supplement other parts of the paper. We discuss these results in the main text.

In Table A12, we report the results from the two-stage least-squares regression (2SLS) using the average open interest across all options on a stock throughout the calendar year as an alternative instrument.

In Table A13, we present the regression results on the interaction between options volume and managerial entrenchment using the "Entrenchment Index" (E-Index) (see Bebchuk, Cohen, and Ferrell, 2009, for details).

In Table A14, we report the regression results from examining the effect of firm innovation (and options volume) on a firm's market valuation (*Tobin's Q*).

In Table A15, we present the regression results from examining the effect of options volume on innovation after controlling for all five economic mechanisms.

Table AI. Poisson model

This table presents estimates of Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies and time dummies. The time period is 1996-2004 (with citations up to 2006); fixed effects are based on including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*CITES*				*PATS*			
Method: Poisson	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Optvol)	0.230***	0.139***	0.238***	0.143***	0.132***	0.117***	0.122**	0.106**
	(0.062)	(0.034)	(0.067)	(0.035)	(0.051)	(0.042)	(0.053)	(0.044)
InstOwn	-0.040	-0.088	-0.055	-0.102	-0.189	-0.083	-0.090	-0.054
	(0.240)	(0.221)	(0.219)	(0.215)	(0.237)	(0.235)	(0.223)	(0.222)
Ln(K/L)	0.634***	0.519***	0.676***	0.555***	0.477**	0.371**	0.530***	0.427***
	(0.232)	(0.164)	(0.252)	(0.170)	(0.186)	(0.165)	(0.195)	(0.165)
Ln(Sales)	0.531***	0.250***	0.219*	0.128*	0.610***	0.330***	0.214**	0.148**
	(0.091)	(0.067)	(0.117)	(0.076)	(0.070)	(0.065)	(0.095)	(0.069)
Ln(Age)	-0.042	-0.261**	-0.175*	-0.330***	-0.014	-0.255**	-0.191**	-0.352***
	(0.110)	(0.112)	(0.102)	(0.099)	(0.086)	(0.109)	(0.086)	(0.093)
Ln(R&D stock)			0.349**	0.165*			0.469***	0.275***
			(0.138)	(0.090)			(0.109)	(0.091)
Firm fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3,271	3,271	3,271	3,271	3,271	3,271	3,271	3,271

Table A2 Other (alternative) specifications

This table presents estimates of quantile (at the 75th percentile), zero-inflated NB, and zero-inflated Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other firm-level control variables. Firms in all columns: 548. Robust standard errors in columns 1 and 2 are obtained from 200 bootstrap replications. All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre- sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 - 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Method	*Quantile regression*		*Zero-inflated NB*		*Zero-inflated Poisson*	
Dependent var.	Ln(1+CITES)	Ln(1+PATS)	CITES	PATS	CITES	PATS
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.105***	0.106***	0.164***	0.142***	0.155***	0.115**
	(0.016)	(0.013)	(0.028)	(0.024)	(0.040)	(0.049)
InstOwn	-0.034	-0.153*	0.046	0.102	-0.088	0.004
	(0.128)	(0.088)	(0.164)	(0.175)	(0.211)	(0.218)
Ln(K/L)	0.021	0.032	0.167**	0.182***	0.564***	0.449***
	(0.052)	(0.036)	(0.070)	(0.060)	(0.168)	(0.163)
Ln(Sales)	0.123***	0.118***	0.108***	0.138***	0.114	0.137**
	(0.025)	(0.021)	(0.038)	(0.043)	(0.074)	(0.068)
Ln(Age)	-0.167***	-0.082*	-0.215**	-0.235***	-0.318***	-0.356***
	(0.060)	(0.044)	(0.087)	(0.076)	(0.097)	(0.092)
Ln(R&D stock)	0.315***	0.262***	0.285***	0.266***	0.163*	0.276***
	(0.030)	(0.025)	(0.039)	(0.044)	(0.088)	(0.089)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

Table A3. Lagged explanatory variables

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on (lagged) options volume (*Optvol*) and other (lagged) firm-level control variables. Firms in all columns: 526 in Panel A and 399 in Panel B. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 - 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Method	*OLS*		*NB*		*Poisson*	
Dependent var.	Ln(1+CITES)	Ln(1+PATS)	CITES	PATS	CITES	PATS
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: One-year lag			
Ln(Optvol)	0.185***	0.179***	0.181***	0.152***	0.146***	0.123**
	(0.033)	(0.028)	(0.033)	(0.027)	(0.047)	(0.056)
InstOwn	-0.108	-0.215	0.002	0.025	-0.103	-0.024
	(0.182)	(0.162)	(0.202)	(0.172)	(0.215)	(0.204)
Ln(K/L)	0.023	0.042	0.078	0.151**	0.610***	0.463***
	(0.060)	(0.050)	(0.079)	(0.067)	(0.191)	(0.170)
Ln(Sales)	0.123***	0.126***	0.132***	0.152***	0.147	0.170**
	(0.044)	(0.036)	(0.043)	(0.040)	(0.090)	(0.072)
Ln(Age)	-0.116	-0.059	-0.215**	-0.258***	-0.353***	-0.385***
	(0.090)	(0.077)	(0.100)	(0.082)	(0.104)	(0.091)
Ln(R&D stock)	0.255***	0.200***	0.311***	0.265***	0.146	0.242**
	(0.050)	(0.046)	(0.047)	(0.045)	(0.105)	(0.101)
Observations	2,658	2,658	2,658	2,658	2,658	2,658
			Panel B: Three-year lag			
Ln(Optvol)	0.130***	0.179***	0.138***	0.164***	0.157***	0.132**
	(0.042)	(0.039)	(0.044)	(0.033)	(0.049)	(0.061)
InstOwn	-0.058	-0.194	0.142	0.027	-0.064	0.099
	(0.222)	(0.201)	(0.243)	(0.192)	(0.265)	(0.213)
Ln(K/L)	0.005	0.048	0.179**	0.143**	0.733***	0.578***
	(0.068)	(0.062)	(0.084)	(0.070)	(0.222)	(0.174)
Ln(Sales)	0.159***	0.158***	0.186***	0.167***	0.153	0.205***
	(0.047)	(0.042)	(0.054)	(0.042)	(0.115)	(0.076)
Ln(Age)	-0.099	-0.105	-0.211*	-0.294***	-0.409***	-0.452***
	(0.099)	(0.091)	(0.112)	(0.083)	(0.120)	(0.092)
Ln(R&D stock)	0.215***	0.170***	0.259***	0.236***	0.118	0.182*
	(0.051)	(0.051)	(0.053)	(0.048)	(0.122)	(0.105)
Observations	1,687	1,687	1,687	1,687	1,687	1,687

Table A4. Monotonic relationship?

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) on options volume (*Optvol*), its squared term, a dummy variable for high options volume (*High Optvol*), its interaction with options volume and other firm-level control variables. *High Optvol* equals one if the options volume for a given firm is above the median in year *t* and zero otherwise. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996-2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Method	*OLS*		*NB*		*Poisson*	
Dependent var.	Ln(1+CITES) (1)	Ln(1+CITES) (2)	CITES (3)	CITES (4)	CITES (5)	CITES (6)
Ln(Optvol)		0.065		-0.012		-0.045
x High Optvol		(0.069)		(0.067)		(0.072)
High Optvol		-0.159		0.042		0.166
		(0.269)		(0.251)		(0.259)
Ln(Optvol)	0.009		-0.003		-0.011	
x Ln(Optvol)	(0.008)		(0.008)		(0.008)	
Ln(Optvol)	0.105*	0.127***	0.176***	0.162***	0.254***	0.184***
	(0.059)	(0.044)	(0.060)	(0.046)	(0.074)	(0.059)
InstOwn	-0.017	-0.024	0.066	0.068	-0.126	-0.103
	(0.159)	(0.159)	(0.178)	(0.178)	(0.222)	(0.222)
Ln(K/L)	0.025	0.024	0.107	0.106	0.540***	0.553***
	(0.052)	(0.052)	(0.067)	(0.067)	(0.172)	(0.172)
Ln(Sales)	0.127***	0.127***	0.135***	0.135***	0.140*	0.128*
	(0.041)	(0.041)	(0.040)	(0.040)	(0.072)	(0.075)
Ln(Age)	-0.107	-0.106	-0.213**	-0.213**	-0.326***	-0.328***
	(0.084)	(0.084)	(0.095)	(0.095)	(0.102)	(0.102)
Ln(R&D stock)	0.253***	0.253***	0.301***	0.300***	0.159*	0.164*
	(0.046)	(0.046)	(0.042)	(0.042)	(0.085)	(0.086)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

Table A5. Contemporaneous R&D spending

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and firms' unweighted patent counts (*PATS*) on options volume (*Optvol*), contemporaneous R&D spending (*XRD*) and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996-2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Method	*OLS*		*NB*		*Poisson*	
Dependent var.	Ln(1+CITES) (1)	Ln(1+PATS (2)	CITES (3)	PATS (4)	CITES (5)	PATS (6)
Ln(Optvol)	0.140***	0.136***	0.133***	0.122***	0.141***	0.091*
	(0.030)	(0.025)	(0.029)	(0.025)	(0.043)	(0.052)
InstOwn	-0.041	-0.218	0.021	-0.032	-0.084	-0.039
	(0.156)	(0.137)	(0.177)	(0.147)	(0.207)	(0.214)
Ln(K/L)	0.026	0.042	0.099	0.141**	0.562***	0.430***
	(0.052)	(0.044)	(0.065)	(0.058)	(0.171)	(0.164)
Ln(Sales)	0.100**	0.095***	0.131***	0.132***	0.078	0.094
	(0.042)	(0.034)	(0.042)	(0.039)	(0.070)	(0.064)
Ln(Age)	-0.040	0.024	-0.144	-0.151**	-0.298***	-0.291***
	(0.082)	(0.067)	(0.093)	(0.075)	(0.109)	(0.103)
Ln(1+XRD)	0.316***	0.256***	0.331***	0.290***	0.224**	0.349***
	(0.052)	(0.046)	(0.048)	(0.047)	(0.093)	(0.084)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

Table A6. R&D stock dummy variables

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*), *R&D stock* dummy variables based on deciles of its distribution, and other firm-level control variables. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996-2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Method	*OLS*		*NB*		*Poisson*	
Dependent var.	Ln(1+CITES) (1)	Ln(1+PATS) (2)	CITES (3)	PATS (4)	CITES (5)	PATS (6)
Ln(Optvol)	0.163***	0.145***	0.149***	0.132***	0.147***	0.115***
	(0.029)	(0.024)	(0.028)	(0.024)	(0.032)	(0.043)
InstOwn	-0.088	-0.188	0.073	-0.039	-0.271	-0.187
	(0.166)	(0.140)	(0.176)	(0.146)	(0.217)	(0.220)
Ln(K/L)	0.024	0.035	0.100	0.144**	0.473***	0.381**
	(0.053)	(0.043)	(0.067)	(0.058)	(0.152)	(0.156)
Ln(Sales)	0.105***	0.081**	0.095**	0.093**	0.144**	0.177***
	(0.040)	(0.033)	(0.039)	(0.037)	(0.067)	(0.062)
Ln(Age)	-0.131	-0.067	-0.255***	-0.244***	-0.258***	-0.296***
	(0.083)	(0.067)	(0.095)	(0.075)	(0.094)	(0.096)
R&D stock, 10%	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark
R&D stock, 20%	0.162	-0.096	0.119	-0.125	0.028	-0.259
	(0.145)	(0.090)	(0.161)	(0.132)	(0.187)	(0.220)
R&D stock, 30%	0.533***	0.174*	0.648***	0.332**	0.265	0.172
	(0.145)	(0.099)	(0.160)	(0.132)	(0.191)	(0.229)
R&D stock, 40%	0.648***	0.257**	0.578***	0.423***	0.207	0.323
	(0.154)	(0.113)	(0.168)	(0.137)	(0.199)	(0.237)
R&D stock, 50%	0.793***	0.347***	0.668***	0.621***	0.425**	0.567**
	(0.180)	(0.134)	(0.177)	(0.160)	(0.206)	(0.255)
R&D stock, 60%	0.784***	0.480***	0.887***	0.829***	0.436*	0.638**
	(0.182)	(0.140)	(0.184)	(0.160)	(0.229)	(0.260)
R&D stock, 70%	0.959***	0.635***	1.106***	0.998***	0.625***	0.805***
	(0.192)	(0.155)	(0.201)	(0.170)	(0.231)	(0.265)
R&D stock, 80%	1.259***	0.804***	1.379***	1.135***	0.941***	1.065***
	(0.206)	(0.175)	(0.210)	(0.185)	(0.234)	(0.275)
R&D stock, 90%	1.611***	1.285***	1.881***	1.610***	1.156***	1.438***
	(0.251)	(0.225)	(0.244)	(0.219)	(0.305)	(0.312)
R&D stock, 100%	1.858***	1.613***	2.260***	1.975***	0.966**	1.523***
	(0.316)	(0.302)	(0.296)	(0.284)	(0.383)	(0.376)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

Table A7. Internet bubble

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) on options volume (*Optvol*) and other firm-level control variables for the two subperiods 1996 - 2000 (during the "dot-com bubble") and 2001 - 2004 (after the "dot-com bubble"). Firms in columns: 501 in columns 1 - 3 and 398 in columns 4 - 6. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996-2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Period	*"1996 - 2000"*			*"2001 - 2004"*		
Method	OLS	NB	Poisson	OLS	NB	Poisson
	Ln(1+CITES)	CITES	CITES	Ln(1+CITES)	CITES	CITES
Dependent var.	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.176***	0.134***	0.149***	0.161***	0.164***	0.179**
	(0.035)	(0.031)	(0.039)	(0.037)	(0.045)	(0.070)
InstOwn	0.002	0.089	-0.131	-0.303	-0.018	0.179
	(0.188)	(0.170)	(0.209)	(0.185)	(0.280)	(0.443)
Ln(K/L)	0.026	0.086	0.533***	0.048	0.125	0.769***
	(0.066)	(0.072)	(0.170)	(0.060)	(0.098)	(0.224)
Ln(Sales)	0.173***	0.144***	0.127	0.061	0.095	0.049
	(0.049)	(0.042)	(0.078)	(0.042)	(0.065)	(0.088)
Ln(Age)	-0.256***	-0.284***	-0.334***	0.121	-0.026	-0.291*
	(0.096)	(0.091)	(0.097)	(0.098)	(0.137)	(0.176)
Ln(R&D stock)	0.260***	0.291***	0.167*	0.243***	0.372***	0.205**
	(0.054)	(0.040)	(0.094)	(0.049)	(0.075)	(0.101)
Observations	1,906	1,906	1,906	1,365	1,365	1,365

Table A8. Additional (financial) controls

This table presents estimates of OLS, NB, and Poisson panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other (additional) firm-level control variables. *Illiquidity* is the natural logarithm of the relative effective spread measured over firm *i*'s fiscal year *t*, where the relative effective spread is defined as the absolute value of the difference between the execution price and the midpoint of the prevailing bid-ask quote divided by the midpoint of the prevailing bid-ask quote; *Leverage* is the book value of debt (DLTT+DLC) divided by the book value of assets (AT); *Tobin's Q* is calculated as (market value of equity (PRCC F CSHO) plus the book value of assets (AT) minus the book value of equity (CEQ) minus balance sheet deferred taxes (TXDB)) divided by the book value of assets (AT); *ROA* is operating income before depreciation (OIDBP) divided by the book value of assets (AT); *Capex* is defined as capital expenditures (CAPX) scaled by the book value of assets (AT); and *Analyst coverage* is the arithmetic mean of the 12 monthly numbers of earnings forecasts for firm *i* extracted from the I/B/E/S summary file. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996-2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Method	*OLS*		*NB*		*Poisson*	
Dependent var.	Ln(1+CITES)	Ln(1+PATS)	CITES	PATS	CITES	PATS
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.110***	0.097***	0.118***	0.099***	0.152***	0.104**
	(0.022)	(0.019)	(0.023)	(0.020)	(0.044)	(0.051)
InstOwn	0.005	-0.290	-0.184	-0.212	-0.340	-0.226
	(0.242)	(0.183)	(0.299)	(0.210)	(0.298)	(0.292)
Ln(K/L)	-0.077	0.018	0.041	0.089	0.373***	0.255***
	(0.070)	(0.054)	(0.096)	(0.073)	(0.128)	(0.084)
Ln(Sales)	0.064	0.048	0.069	0.047	-0.177	0.045
	(0.060)	(0.045)	(0.059)	(0.053)	(0.117)	(0.088)
Ln(Age)	-0.041	0.048	-0.097	-0.064	-0.285**	-0.281**
	(0.113)	(0.086)	(0.122)	(0.091)	(0.131)	(0.124)
Ln(R&D stock)	0.274***	0.254***	0.269***	0.304***	0.492***	0.473***
	(0.069)	(0.054)	(0.061)	(0.059)	(0.118)	(0.085)
Illiquidity	-0.109*	-0.136**	-0.173**	-0.162***	-0.088	-0.032
	(0.062)	(0.052)	(0.068)	(0.055)	(0.086)	(0.067)
Leverage	0.548*	0.280	0.500	0.254	0.315	0.003
	(0.296)	(0.229)	(0.338)	(0.236)	(0.402)	(0.451)

Method	*OLS*		*NB*		*Poisson*	
Dependent var.	Ln(1+CITES)	Ln(1+PATS)	CITES	PATS	CITES	PATS
	(1)	(2)	(3)	(4)	(5)	(6)
Tobin's *Q*	-0.073	-0.047	-0.135	-0.085	-0.038	0.105
	(0.082)	(0.059)	(0.085)	(0.063)	(0.111)	(0.118)
ROA	-0.553	-0.531**	-0.871**	-0.758***	0.716	-0.205
	(0.373)	(0.251)	(0.361)	(0.286)	(0.449)	(0.448)
Capex	1.613	0.087	-0.344	-0.402	0.564	1.196
	(1.041)	(0.758)	(0.995)	(0.801)	(0.952)	(1.188)
Ln(1+Analyst coverage)	-0.003	0.044	0.029	0.050	0.070	0.039
	(0.080)	(0.064)	(0.083)	(0.064)	(0.073)	(0.058)
Observations	3,271	3,271	3,271	3,271	3,271	3,271

Table A9. External knowledge acquisition

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*), *collaboration frequency*, *collaboration intensity*, *acquisitions*, and other firm-level control variables. *Collaboration frequency* is the natural logarithm of (one plus) the number of R&D alliances formed over the previous five years (i.e., from *t* 5 to *t* 1); *Collaboration intensity* is the number of a firm's jointly owned patents filed over the previous five years scaled by its total number of patents filed over the same period; and *Acquisitions* is the acquisition expenditure (ACQ) divided by the book value of assets (AT). Firms in columns: 236 in columns 1 and 2; 548 in columns 3 - 6. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 - 2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Control variable	*Collaboration frequency*		*Collaboration intensity*		*Acquisitions*	
Dependent var.	Ln(1+CITES)	Ln(1+PATS)	Ln(1+CITES)	Ln(1+PATS)	Ln(1+CITES)	Ln(1+PATS)
Method: OLS	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Optvol)	0.107***	0.090***	0.116***	0.158***	0.114***	0.156***
	(0.020)	(0.017)	(0.019)	(0.024)	(0.019)	(0.024)
InstOwn	-0.186	-0.252*	-0.164	-0.224	-0.153	-0.211
	(0.152)	(0.139)	(0.153)	(0.141)	(0.152)	(0.139)
Ln(K/L)	-0.012	0.040	-0.011	0.042	-0.014	0.040
	(0.048)	(0.043)	(0.049)	(0.044)	(0.048)	(0.044)
Ln(Sales)	0.129***	0.122***	0.121***	0.111***	0.130***	0.122***
	(0.036)	(0.033)	(0.037)	(0.034)	(0.036)	(0.033)
Ln(Age)	-0.062	-0.032	-0.059	-0.032	-0.057	-0.027
	(0.077)	(0.069)	(0.078)	(0.069)	(0.077)	(0.069)
Ln(R&D stock)	0.250***	0.193***	0.263***	0.210***	0.259***	0.204***
	(0.041)	(0.043)	(0.042)	(0.044)	(0.042)	(0.043)
Collaboration freq.	0.106***	0.129***				
	(0.035)	(0.032)				
Collaboration int.			-0.731*	-0.923***		
			(0.393)	(0.303)		
Acquisitions					-0.570**	-0.539**
					(0.290)	(0.257)
Observations	1,446	1,446	3,271	3,271	3,271	3,271

Table AIO. High-versus low-tech industries

This table presents estimates of OLS panel regressions on a matched sample of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume *(Optvol)*, a dummy variable that equals one if a firm is operating in a high-tech industry (*Dummy for high-tech*), their interaction, and other firm-level control variables. Firms in the matched sample: 547. Firms in columns 3 and 7: 311. Firms in columns 4 and 8: 236. Robust standard errors are clustered by firm (in parentheses). The matched sample is constructed using nearest-neighbor matching with scores given by a probit model in which the dependent variable is *Dummy for high-tech*. The propensity score is estimated using the following firm characteristics: *Ln(Optvol)*, *InstOwn*, *Ln(K/L)*, *Ln(Sales)*, *Ln(Age)*, *Ln(R&D stock)*, *Illiquidity*, *Leverage*, *Tobin's Q*, *ROA*, *Capex*, *Ln(Analyst coverage)* and fixed effects. All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996-2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+CITES)*				*Ln(1+PATS)*			
Matched sample	All	All	High-tech	Low-tech	All	All	High-tech	Low-tech
Method: OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Optvol) x Dummy for high-tech		0.186***				0.193***		
		(0.059)				(0.056)		
Ln(Optvol)	0.120***	0.004	0.144***	0.070	0.113***	-0.007	0.147***	0.046
	(0.039)	(0.052)	(0.049)	(0.058)	(0.034)	(0.049)	(0.040)	(0.051)
Dummy for high-tech	1.219**	0.932*			0.543	0.243		
	(0.485)	(0.510)			(0.578)	(0.605)		
InstOwn	-0.092	-0.053	-0.148	0.199	-0.164	-0.123	-0.287	0.208
	(0.189)	(0.188)	(0.248)	(0.252)	(0.170)	(0.170)	(0.231)	(0.216)
Ln(K/L)	-0.068	-0.071	0.085	-0.252*	-0.023	-0.025	0.090	-0.166
	(0.098)	(0.097)	(0.134)	(0.143)	(0.079)	(0.079)	(0.111)	(0.109)
Ln(Sales)	0.104*	0.091	0.180**	-0.076	0.100*	0.086*	0.163**	-0.031
	(0.062)	(0.062)	(0.087)	(0.081)	(0.053)	(0.052)	(0.075)	(0.065)
Ln(Age)	-0.138	-0.150*	-0.155	-0.156	-0.099	-0.111	-0.114	-0.119
	(0.085)	(0.084)	(0.113)	(0.118)	(0.073)	(0.072)	(0.097)	(0.102)
Ln(R&D stock)	0.167***	0.167***	0.212***	0.099**	0.143***	0.143***	0.158***	0.114***
	(0.034)	(0.034)	(0.050)	(0.043)	(0.028)	(0.027)	(0.041)	(0.035)
Observations	2,906	2,906	1,453	1,453	2,906	2,906	1,453	1,453

Table AII. Within-firm relationship

This table presents estimates of OLS panel regressions of within-firm changes in patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) before and after the option listing event. *Post* is a dummy variable equal to unity to indicate the post-listing period; *Inclusion year #* are dummy variables indicating the relative year around the listing event (the omitted category is the year of the event). Firms in columns: 93. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996-2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+CITES)*		*Ln(1+CITES)*	
Method: OLS	(1)	(2)	(3)	(4)
Post	0.370**		0.277*	
	(0.146)		(0.118)	
Inclusion year –3		0.240		0.008
		(0.154)		(0.080)
Inclusion year –2		0.207		0.084
		(0.144)		(0.075)
Inclusion year –1		0.313**		0.135
		(0.142)		(0.098)
Inclusion year 1		0.243*		0.116
		(0.131)		(0.078)
Inclusion year 2		0.568***		0.271***
		(0.148)		(0.103)
Inclusion year 3		0.636***		0.335***
		(0.145)		(0.114)
Inclusion year 4		0.558***		0.526***
		(0.162)		(0.124)
InstOwn	-0.088	0.010	-0.159	-0.111
	(0.257)	(0.256)	(0.245)	(0.241)
Ln(K/L)	-0.058	-0.061	-0.011	-0.014
	(0.073)	(0.074)	(0.061)	(0.062)
Ln(Sales)	0.196***	0.198***	0.133***	0.134***
	(0.052)	(0.053)	(0.044)	(0.045)
Ln(Age)	-0.225**	-0.225**	-0.072	-0.070
	(0.112)	(0.112)	(0.087)	(0.087)
Ln(R&D stock)	0.211***	0.218***	0.252***	0.255***
	(0.043)	(0.044)	(0.048)	(0.048)
Observations	744	614	744	614

Table AI2. Open interest as instrumental variable

This table presents estimates of 2SLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on options volume (*Optvol*) and other firm-level control variables, with the total open interest *Ln(Open int.)* as an instrumental variable. Firms in all columns: 548. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The time period is 1996 - 2004 (with citations up to 2006). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Method	*OLS* *(first stage)*	*2SLS* *(second stage)*	
Dependent var.	Ln(Optvol)	Ln(1+CITES)	Ln(1+PATS)
	(1)	(2)	(3)
Ln(Optvol) *(instr.)*		0.087***	0.102***
		(0.029)	(0.024)
InstOwn	1.185***	-0.028	-0.218
	(0.140)	(0.156)	(0.137)
Ln(K/L)	-0.205***	0.015	0.039
	(0.053)	(0.053)	(0.045)
Ln(Sales)	0.242***	0.156***	0.133***
	(0.028)	(0.041)	(0.033)
Ln(Age)	-0.412***	-0.121	-0.036
	(0.065)	(0.083)	(0.068)
Ln(R&D stock)	0.056**	0.273***	0.217***
	(0.028)	(0.046)	(0.044)
Ln(Open int.)	1.207***		
	(0.028)		
Observations	3,271	3,271	3,271

Table A13. Managerial entrenchment (E-Index)

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and un-weighted patent counts (*PATS*), managerial entrenchment (*E-Index*), their interaction, and other firm-level control variables. Firms in columns: 331. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of three-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). The E-Index is an average of six provisions in the firm's charter (see Bebchuk, Cohen, and Ferrell, 2009). The measure is based on data from RiskMetrics from 1998, 2000, 2002, and 2004. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+CITES)*		*Ln(1+PATS)*	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol) x E-Index		0.032**		-0.031**
		(0.015)		(0.013)
Ln(Optvol)	0.168***	0.160***	0.151***	0.144***
	(0.031)	(0.031)	(0.028)	(0.028)
E-Index (entrenchment index)	-0.014	0.012	-0.016	0.009
	(0.034)	(0.034)	(0.029)	(0.029)
InstOwn	-0.020	-0.048	-0.015	-0.041
	(0.192)	(0.193)	(0.170)	(0.170)
Ln(K/L)	0.106	0.107	0.075	0.076
	(0.070)	(0.069)	(0.059)	(0.058)
Ln(Sales)	0.108**	0.103**	0.126***	0.120***
	(0.047)	(0.047)	(0.044)	(0.044)
Ln(Age)	-0.183**	-0.173*	-0.106	-0.098
	(0.090)	(0.090)	(0.084)	(0.084)
Ln(R&D stock)	0.126***	0.124***	0.116***	0.114***
	(0.028)	(0.028)	(0.024)	(0.024)
Observations	921	921	921	921

Table AI4. Tobin's Q

This table presents estimates of OLS regressions of firms' market value (*Tobin's Q*) on firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*), *one-year lagged Tobin's Q*, options volume (*Optvol*), and other firm-level control variables. Firms in all columns: 526. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies and time dummies. The time period is 1996-2004 (with citations up to 2006); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.: Tobin's Q		
Method: OLS	(1)	(2)
Ln(1+CITES)	0.050*	
	(0.026)	
Ln(1+PATS)		0.059*
		(0.033)
One-year lagged Tobin's *Q*	0.383***	0.383***
	(0.049)	(0.049)
Ln(Optvol)	0.236***	0.236***
	(0.037)	(0.037)
InstOwn	-0.052	-0.041
	(0.202)	(0.202)
Ln(K/L)	0.057	0.054
	(0.106)	(0.106)
Ln(Sales)	-0.221***	-0.225***
	(0.069)	(0.071)
Ln(Age)	-0.173	-0.175
	(0.112)	(0.111)
Ln(R&D stock)	0.030	0.028
	(0.039)	(0.039)
Leverage	-1.625***	-1.610***
	(0.297)	(0.295)
ROA	1.823***	1.830***
	(0.641)	(0.638)
Capex	0.598	0.634
	(2.470)	(2.476)
Observations	2,658	2,658

Table AI5. Controlling for possible mechanisms.

This table presents estimates of OLS panel regressions of firms' patents weighted by the number of forward citations (*CITES*) and unweighted patent counts (*PATS*) on product market competition (*Competition*), managerial entrenchment (*G-Index*), *CEO age*, lagged change in profitability (Δ ROA_{t-1}), stock-based compensation (*CEO vega* and *CEO delta*), and other firm-level control variables. Firms in columns: 285. Robust standard errors are clustered by firm (in parentheses). All regressions control for a full set of four-digit industry dummies, time dummies, and fixed effects by including pre-sample means of the dependent variable as proposed by Blundell, Griffith, and Van Reenen (1999). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent var.	*Ln(1+CITES)*		*Ln(1+PATS)*	
Method: OLS	(1)	(2)	(3)	(4)
Ln(Optvol)	0.216***	0.154***	0.192***	0.155***
	(0.050)	(0.050)	(0.042)	(0.043)
Competition (1 – Lerner)		8.454***		5.384***
		(2.619)		(1.764)
G-Index (governance index)		-0.033		-0.032
		(0.028)		(0.025)
Ln(CEO age)		-0.807**		-0.605*
		(0.396)		(0.325)
Δ ROA*t*–1		-0.162		-0.123
		(0.406)		(0.307)
Ln(CEO vega)		0.038		0.113***
		(0.054)		(0.041)
Ln(CEO delta)		0.072		0.044
		(0.055)		(0.046)
InstOwn	-0.072	-0.092	-0.139	-0.145
	(0.293)	(0.296)	(0.259)	(0.266)
Ln(K/L)	0.023	0.055	0.079	0.099
	(0.102)	(0.101)	(0.084)	(0.080)
Ln(Sales)	0.231***	0.248***	0.227***	0.240***
	(0.082)	(0.080)	(0.072)	(0.071)
Ln(Age)	-0.147	-0.122	-0.102	-0.068
	(0.154)	(0.154)	(0.142)	(0.140)
Ln(R&D stock)	0.140**	0.142**	0.080	0.082
	(0.062)	(0.061)	(0.059)	(0.058)
Observations	1,530	1,530	1,530	1,530

Table AI6. Descriptive statistics (robustness tests)

This table reports summary statistics for variables used in robustness tests.

	Mean	*StdDev*	*Min*	*Median*	*Max*	*Observations*	*Source*
Co-patents/	0.03	0.09	0	0	1	2,391	USPTO
Patents[$t-5,t-1$]	0.16	0.16	0	0.13	0.91	3,271	Compustat
Leverage Tobin's	3.0	2.8	0.40	2.1	39.1	3,271	Compustat
Q Capex/ Assets	0.05	0.05	0.00	0.04	0.53	3,271	Compustat
Acquisition exp.	85.1	458	-3,557	0	8,800	3,271	Compustat
(in $m) Average open interest	396	1,056	0.03	92.4	13,267	3,271	OptionMetrics
Stock illiquidity	-5.5	2.1	-11.6	-5.5	2.9	3,271	TAQ
Analyst coverage	8.4	7.9	0	6.1	45.6	3,271	I/B/E/S SDC
R&D alliances	3.7	15.2	0	0	270	1,446	Platinum
[$t-5,t-1$]	2.1	1.1	0	2	5	921	RiskMetrics and
Entrenchment index	.3	.9			3	,845	Bebchuk et al.
EO tenure							(2009) ExecuComp
CEO cash comp. (in $000s)	1,340	1,492	0	962	43,512	1,845	ExecuComp

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Probabilidad de incumplimiento e indicadores de riesgo en la banca europea: un enfoque regulatorio

Do financial derivatives enhance or impede innovation? We aim to answer this question by examining the relationship between equity options markets and standard measures of firm innovation. Our baseline results show that firms with more options trading activity generate more patents and patent citations per dollar of R&D invested. We then investigate how more active options markets affect firms' innovation strategy. Our results suggest that firms with greater trading activity pursue a more creative, diverse and risky innovation strategy. We discuss potential underlying mechanisms and show that options appear to mitigate managerial career concerns that would induce managers to take actions that boost short-term performance measures. Finally, using several econometric specifications that try to account for the potential endogeneity of options trading, we argue that the positive effect of options trading on firm innovation is causal.

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