WHAT IS THE VALUE OF AN INNOVATION? THEORY AND EVIDENCE ON THE STOCK MARKET'S REACTION TO INNOVATION ANNOUNCEMENTS*

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Abstract

We analyze, theoretically and empirically, the effect of investor attention on the stock market reaction to innovation announcements and suggest how market-based measures of the economic value of patents can be enhanced. We develop a dynamic model with limited investor attention to show that, following the immediate market reaction to innovation announcements, there will also be a stock return drift: the magnitude of the announcement effect will be increasing while that of the post-announcement drift will be decreasing in investor attention. We test our model predictions using two different datasets: a matched sample of pharmaceutical industry patent grant and subsequent FDA drug approval announcements; and a general USPTO sample of patent grant announcements. We use the media coverage of innovation announcements as a proxy for the investor attention paid to them. Consistent with model predictions, we find the following. First, in our matched patent grant and drug approval analysis, the announcement effects of patent grant announcements are smaller than those of FDA drug approval announcements; the subsequent stock return drifts, however, are larger for patent grant announcements. Second, the announcement effect of patent grant announcements is increasing in investor attention while the subsequent stock return drift is decreasing in investor attention. Third, the stock-return drift following patent grant announcements has predictive power for the economic value of patents, over and above the information contained in the announcement effect. Finally, we show that a long-short trading strategy based on investor attention is profitable over the one-month period after patent grant announcements.

Keywords: Corporate Innovation; Investor Attention; Post-Announcement Stock Return Drift; Valuation of Innovation.

JEL classification: G14; G31; G41; O31

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1 Introduction

Recently, there has been considerable interest among economists in stock market-based measures of the value of corporate innovations. For example, in a recent paper, Kogan, Papanikolaou, Seru, and Stoffman (2017) develop a new measure of the economic value of a corporate innovation making use of the stock market response to announcements of patent approvals. They show that their patent-level estimates of the economic value of patents are positively related to the scientific value of these patents (as measured by their numbers of citations) and to the subsequent growth rate of the firms holding these patents. However, one important factor that affects the stock market response to patent grant announcements is the level of attention paid by investors to such announcements. In particular, it is easy to imagine that a significant fraction of stock market investors do not pay much attention to news about patents whose future economic value is hard for anyone but a select few experts to evaluate. The objective of this paper is to analyze, theoretically and empirically, the effect of investor attention on the stock market response to innovation announcements and to incorporate the effects of the level of investor attention paid to an innovation announcement (such as a patent grant announcement) into a stock market-based measure of the economic value of a corporate innovation. To the best of our knowledge, this is the first paper in the literature to conduct such an analysis, either theoretically or empirically.

We first develop a theoretical model to analyze how differences in investor attention across different types of innovation announcements (e.g., a patent grant announcement versus an FDA drug approval announcement) affect the stock market response to these announcements, and to develop testable hypotheses. We then test these hypotheses using two different datasets: first, a matched sample of patent grants and subsequent FDA drug approvals from the biopharmaceutical industry; and second, a dataset on the universe of patent grants from the USPTO during 2000-2014, using media coverage as the proxy for the investor attention paid to various innovation announcements. We also document, for the first time in the literature, the presence of a positive stock return drift (on average) following patent grant announcements and show that this stock return drift following a patent grant announcement captures the economic value of the patent to some extent (over and above that captured by the announcement effect of the patent grant news).

For concreteness, we develop our theoretical model of the stock market's response to different kinds of innovation announcements in the context of innovations in the biopharmaceutical industry, but our results apply, with minor modifications, to innovations outside these industries as well. The two kinds of innovation announcements we have in mind in the context of the biopharmaceutical industry are: first, the announcement of a patent grant about a molecule that is potentially effective as a drug to treat an illness; and second, the approval by the U.S. Food and Drug Administration (FDA) of the molecule for use as a drug. The stock market in our model consists of two kinds of risk-averse investors who allocate their wealth between a risk-free asset and the stock of the innovating firm: those who are fully (and immediately) attentive to innovation announcements ("attentive investors") and those who temporarily neglect such announcements (but pay attention to these innovation announcements after some delay), since they are unable to immediately understand and interpret the cash flow implications of these announcements ("inattentive investors").[1] Further, we assume that the fraction of attentive investors in the equity market depends on the nature of the innovation announcement: the closer an innovation is to being monetized, the larger the fraction of investors in the stock market who are able to understand and interpret its cash flow implications immediately (attentive investors). To give an example, in the case of the biopharmaceutical industry, the fraction of investors who pay attention to the initial patent grant of a drug-related molecule may be much smaller than the fraction who pay attention to an announcement that the same molecule has undergone successful clinical trials and has been approved by the FDA.

Our model has four periods. At the beginning of the first period, a firm develops an innovation (a molecule that has the potential to be a drug for treating a certain illness) and applies for a patent on the innovation. After one period, news of the grant or denial of the patent application arrives. Only the attentive investors pay immediate attention to the patent grant announcement; inattentive investors pay only delayed attention to the patent grant announcement, taking another period to process this information and trade on it. In the subsequent (third) period, the firm conducts clinical trials and applies to the FDA for approval of the molecule for use as a drug; the FDA announces its approval or denial decision at the end of the third period.[2] In the fourth (and final) period, the firm manufactures and markets the drug (if approved by the FDA). All cash flows

[1] Our assumption here is that, while inattentive investors do not immediately incorporate the innovation announcement into their demands for the firm's equity, they correct this lack of attention over the subsequent period.

[2] An example of an announcement analogous to an FDA drug approval outside the biopharmaceutical industry is an announcement that the patent-holding firm was able to develop a workable prototype using the initial patent grant (or failed to develop such a prototype after attempting to do so).

are realized at the end of this period.

In the above setting, we show that the equilibrium stock price after an innovation announcement (patent grant or FDA approval) will reflect the weighted average of the beliefs of attentive and inattentive investors, with weights depending on the fraction of each type of investor in the equity market. We further show that, immediately after an innovation announcement, the stock of the innovating firm may be undervalued or overvalued (depending upon whether the innovation announcement reflects positive or negative news). Such under- or overvaluation will not be immediately arbitraged away, since investors who are fully attentive to the innovation announcement are risk-averse and therefore willing to bear only a limited amount of risk in order to exploit the above mispricing.[3] The above mispricing will therefore be corrected only in the subsequent period as a result of inattentive investors revising their beliefs as they better understand and interpret the cash flow consequences of the previous innovation announcement. This, in turn, implies that there will be a stock return drift subsequent to innovation announcements, the magnitude of which will depend upon the fractions of attentive and inattentive investors in the equity market (with respect to that announcement), and whose direction (positive or negative) will depend upon whether the innovation announcement carries positive or negative news.

The above model generates several testable predictions which we test in our empirical analysis. First, in a patent-drug matched sample, the abnormal stock returns upon patent grant announcements will be smaller than that upon FDA drug approval announcements (of the same molecule). Further, the stock return drift subsequent to the patent grant announcement of a given molecule will be greater than that subsequent to the FDA drug approval announcements for the same molecule. Second, our model predicts a positive relation between the extent of investor attention paid to a given patent grant announcement and the abnormal stock returns upon this announcement. Third, our model predicts a negative relation between the extent of investor attention paid to a given patent grant announcement and the post-announcement stock return drift following that announcement.

We test the above hypotheses using two different datasets: first, a matched sample of patent grant announcements and subsequent drug approvals from the biopharmaceutical industry from

[3] As will become clear when discuss the model setup, we assume, in the spirit of Grossman and Stiglitz (1976, 1980), that there is a shock to the supply of assets at each trading date. This supply shock can also be viewed as arising from trading by a separate group of "liquidity" traders, as commonly assumed in market microstructure models: see, e.g., Kyle (1985).

December 1986 to December 2016; and second, a dataset consisting of the universe of patent grant announcements from the USPTO database during January 2000-August 2014. To proxy for investor attention on the various announcements, we obtain the data on media coverage from RavenPack, which starts from January 2000 and ends in October 2018. Our results support the implications of our model. First, in the biopharmaceutical sample, drug approval news is more salient and receives more investor attention than patent grant announcements; the announcement effect, measured by CAR[-1,1], is higher, while the subsequent stock return drift, measured by CAR[2,22], is lower for drug approval announcements than for patent grant announcements. Second, in both the biopharmaceutical sample and the general USPTO sample, the announcement effect (on patent grants and/or drug approvals) increases with investor attention (proxied by the number of business-related news articles that mention the event firm around the announcement date) and the subsequent stock return drift decreases with investor attention.

Third, to analyze whether the relation between the stock market reaction (the announcement effect and the post-announcement drift) and investor attention for patent grant announcements differs across industries, we study this relation across six different technology categories: Chemicals (excluding Drugs); Computers and Communications (C&C); Drugs and Medical (D&M); Electrical and Electronics (E&E); Mechanical; and Others. Our empirical results suggest that, while attention is an important determinant of the stock market reaction across all six technology categories, it is particularly important in two categories: Drugs and Electronics. This is consistent with the fact that patents are likely to be economically more important in these two industry categories (as we discuss in more detail in Section 6.3.2).

Fourth, we establish the economic significance of post-announcement stock return drift as a measure of the economic value of an innovation over and above the abnormal stock return upon the announcement of patent grant news (i.e., the announcement effect). We accomplish this by regressing measures of the profitability, productivity, and growth of firms that are granted various patents on the announcement effect of the patent grant announcement and the subsequent stock return drifts. We show from these regressions that both the announcement effect and the stock return drift following patent grant announcements are statistically and economically significant, documenting the predictive power of these two stock market reaction variables for the future profitability, productivity, and growth generated by these patents for the firm developing them.

Finally, we analyze whether it is possible to trade profitably using the results of our empirical analysis on the relation between the stock market reaction to patent grant announcements and investor attention. To conduct this analysis, we construct a low-minus-high portfolio by holding a long (short) position in a portfolio with low (high) attention paid, on average, to the patents received by a firm (this measure, which we refer to as ATTP, is constructed at the firm-month level by averaging the attention paid to the patents granted to a firm in a given month). We show that such a portfolio is profitable on average, over the month immediately after patent grant announcements in our general USPTO sample.

The rest of the paper is organized as follows: In Section 2, we discuss how our paper is related to the existing literature. In Section 3, we present the setup of our model. In Section 4, we characterize the equilibrium of the model and analyze the effects of investor attention on innovation announcement effects and subsequent stock return drifts. In Section 5, we discuss the empirical predictions of our model and develop testable hypotheses for our empirical analysis. In Section 6, we present the results of our empirical analysis. The proofs of all propositions are presented in Appendix A, and a table with an additional empirical analysis (using an extended biopharmaceutical sample) is presented in Online Appendix B.

2 Relation to the Existing Literature

Our paper is related to several strands in the literature. The first strand is the literature on improving the measurement of the economic value of innovations. For patent-based innovation measures, Hall, Jaffe, and Trajtenberg (2005) add the number of patent citations into traditional measures of firm innovation based on R&D investment and patent counts to overcome the heterogeneity in patent qualities and find future patent citations positively related to the market values of firms. Kogan, Papanikolaou, Seru, and Stoffman (2017) construct a new measure of the economic value of innovation based on the announcement effect of patent grant news over a three-day event window. They show that this measure is positively related to the scientific value of patents and is associated with firm growth and other future performance measures of the firm to which these patents are granted. Kelly, Papanikolaou, Seru, and Taddy (2018) use textual analysis of patent documents to create new indicators of technological innovation, which is predictive of future citations and correlates strongly with measures of market value developed in Kogan, Papanikolaou, Seru, and Stoffman (2017). Similarly, Bellstam, Bhagat, and Cookson (2017) develop a measure of innovation for mature firms with and without patenting and R&D using a textual analysis of analyst reports.[4] Our paper contributes to the above literature by establishing, for the first time, that the post-announcement stock return drift following a patent grant announcement is an important measure of the economic value of patents and has predictive power for the future profitability, productivity, and growth of the patenting firm over and above that contained in the announcement effect of the patent grant.

The second strand is the broader empirical literature on the valuation of innovation. Cohen, Diether, and Malloy (2013) show that R&D ability estimated through a regression of sales on lagged R&D expenditures predicts significantly higher abnormal stock returns. They show that the stock market appears to ignore the implications of past successes by innovating firms when valuing future innovations.[5] Hirshleifer, Hsu, and Li (2013, 2018) show that investors tend to neglect signals related to innovation value, such as innovative efficiency and innovation originality, owing to limited attention. Therefore, these measures predict significantly higher abnormal stock returns in the future. Huberman and Regev (2001) document a positive stock price reaction to a tumor therapy breakthrough reported in the *New York Times*, even though *Nature* had reported the same breakthrough more than five months earlier, thus suggesting that a fraction of investors in the equity market were inattentive to the original announcement of the tumor therapy breakthrough.[6]

The third strand is the theoretical behavioral finance literature on limited attention. Hirshleifer and Teoh (2003) use a limited-attention model where only a fraction of investors pay attention to public information immediately and correctly to study the effects of firms' different presentations of financial disclosure and reporting on market prices. Hirshleifer, Lim, and Teoh (2011) use a related model to analyze the interpretation of different earnings components and investors' underreaction

[4]In addition, Cooper, Knott, and Yang (2019) measure innovation as the sales elasticity of a firm's R&D.

[5]Nicholas (2008) uses the historical patent citations to study how the stock market reaction to patentable assets changed from 1910 to 1939. Harhoff, Narin, Scherer, and Vopel (1999) use a survey of US and German patents and show that patents that are renewed to full-term are cited more highly than those that expire before their full term and that the economic value of patents is positively related to subsequent patent citations. Abrams, Akcigit, and Popadak (2013), however, show a non-monotonic and nonlinear relationship between lifetime forward patent citations and the economic value of patents using a proprietary dataset.

[6]Manela (2014) develops a model where information diffuses across investors to study the effects of the speed of information diffusion on investors' trading profits and finds empirically that the value of drug approval information is a hump-shaped function of its diffusion speed.

to earnings announcements and overreaction to accruals. Our model builds on the above two static models to develop a dynamic model to capture the stock market's reaction to announcements. Unlike in the above two static models, we introduce random supply shocks at each trading date, so that we are able to explicitly characterize the post-announcement stock return drift following innovation announcements.[7] We are also able to compare the announcement effect and the post-announcement stock return drift across multiple announcements (namely, patent grant announcement and FDA drug approval announcement) on the same patent-drug pair.[8]

The fourth and final strand in the literature our paper is related to is the empirical literature on limited attention and on media coverage as a proxy for limited attention. Peress and Schmidt (2019) study the impact of noise traders' limited attention on financial markets by exploiting episodes of sensational news that distract noise traders. Engelberg and Parsons (2011) establish the causal effect of media coverage on investor trading by studying the relationship between the trading in local markets following local paper reporting the earnings announcement of an S&P 500 firm. Fang and Peress (2009) document a negative relation between media coverage and stock return, consistent with the explanation that media coverage diminishes information asymmetry and thus decreases the expected return of stocks in equilibrium. Kempf, Manconi, and Spalt (2016) construct a firm-level shareholder distraction measures by exploiting exogenous shocks to unrelated parts of institutional shareholders' portfolios and find investor attention matters for corporate actions.[9]

3 Model Setup

We develop a discrete-time dynamic model to study how the attention of investors to announcements affects the announcement effects and post-announcement drifts. We incorporate supply shocks on risky assets to the the static limited attention model in Hirshleifer and Teoh (2003) so that we can explicitly represent the post-announcement drift.

[7]Our model is thus also distantly related to a number of empirical studies in finance and accounting that have documented under-reaction to various news events: see, e.g., Ball and Brown (1968) and Bernard and Thomas (1989), who document that prices underreact to earnings news.

[8]In more distantly related work, Sims (2003) introduces an information-processing constraint (Shannon capacity) from information theory to the study of inertial reactions observed in macroeconomics. Peng (2005) applies the setting of limited attention to regimes such as the learning process of investors; Peng and Xiong (2006) apply such a setting to investors' category learning and consequent return comovement when investors also suffer from overconfidence.

[9]Several papers in the literature on initial public offerings (IPOs) have also used media coverage as a proxy for investor attention: see, e.g., Liu, Sherman, and Zhang (2014) and Bajo, Chemmanur, Simonyan, and Tehranian (2016).

3.1 Timeline

There are five dates in the model (Figure 1): $t = 0, 1, 2, 3, 4$.

t=0	t=1	t=2	t=3	t=4
Investment in a new drug occurs. Investors form their initial portfolios.	News on patent (associated with a drug) grants or denials arrives. Attentive investors pay attention to the news, but inattentive investors do not. Investors trade.	Inattentive investors pay attention to the news on patent grants or denials in a delayed manner and update their beliefs. Investors trade again.	News on drug approvals or denials is announced. All investors pay attention to the news. Investors trade again.	Final payoffs are realized.

Figure 1: Timeline of Model

At $t = 0$, the firm initiates a project on a drug. Investors are endowed with homogeneous wealth and trade to form their initial portfolios based on their homogeneous prior belief on the payoff of asset. At $t = 1$, the grant or denial of the patent associated to the drug is announced. Attentive investors update their beliefs conditional on the announcement immediately; inattentive investors do not pay attention to the announcement and therefore do not update their beliefs (and still hold the prior belief). All investors rebalance their portfolios. At $t = 2$, inattentive investors update their beliefs upon the patent grant/denial announcement in a delayed manner. Investors trade again to rebalance their portfolios. At $t = 3$, the FDA drug approval or denial is announced. All investors pay attention to the FDA announcement and update their beliefs immediately upon the announcement, and then rebalance their portfolios accordingly.[10] At $t = 4$, asset payoffs are realized and there is no further trading.

3.2 Assets and Announcements

There are two assets in the market: a risky asset issued by the drug firm and the riskfree asset.

Riskfree asset. The riskfree asset offers a net return of r, which is normalized to 0.[11] The riskfree asset has unlimited supply.

[10] This assumption is made only for simplicity of modeling. Our results will go through qualitatively unchanged as long as the fraction of investors who pay attention to FDA drug approvals is greater than that for patent grant announcements.

[11] The results of the model are qualitatively the same if we allow r to be a nonzero constant, so, without loss of generality, we set it as zero to keep the model simple.

Risky asset. The drug firm issues a risky asset, which can be naturally interpreted as a stock of the drug firm or, equivalently, as the terminal cash flow from the patent/drug research project. The terminal payoff of the risky asset is represented by a random variable f:

$$f = \mu + z, \text{ where } \mu = E(f) \text{ and } z \sim N(0, \sigma_0^2). \tag{1}$$

The expected supply of the risky asset is $\bar{x}$, while there is a supply shock created by liquidity traders in each period of $t = 1$ through 3. We denote the additional noisy supply at t by $x_t \sim N(0, \sigma_x^2)$. The aggregated supply of risky asset at t is $\bar{x} + \sum_{s=1}^{t} x_s$.[12] The supply shock is not observable directly.[13]

Announcements. On each date of $t = 1, 3$, a public signal $e_t = z + \epsilon_{e,t}$ is announced, where $\epsilon_{e,t} \sim N(0, \sigma_{e,t}^2)$. The error $\epsilon_{e,t}$ is independent across time.[14] In particular, $e_1 > 0$ represents the grant of patent, $e_1 < 0$ represents the denial of patent, $e_3 > 0$ represents the approval of the subsequent drug, and $e_3 < 0$ represents the denial of the subsequent drug.[15]

3.3 Market Participants

The continuum of investors consists of two types of investors: attentive investors ("type-a") and inattentive investors ("type-u"). The total mass of investors is 1; a fraction of f^a are attentive, and the rest, $f^u = 1 - f^a$, are inattentive. We use i as the generic index for "type", i.e. $i = a$ for attentive investors and $i = u$ for inattentive investors.

Attentive investors (indexed by type a). An attentive investor updates his/her belief immediately on any available announcement on each date ($t = 1, 3$). Since no investor in the market observes

[12] Here the notation $\sum \cdot$ follows the convention that $\sum_{s=m}^{n} \cdot = 0$ whenever $m > n$; e.g., $\sum_{s=1}^{0} x_s = 0$.

[13] However, since there is no private signal in the model, an investor may be able to figure out the total supply shock from the contemporaneous equilibrium price if they do know (i.e. pay attention to) all public signals available contemporaneously and historically (e.g. attentive investors at $t = 1$).

[14] Rather than using a binary random variable with realizations $\in$\{approval, denial\} paired with a high/low terminal payoff, we set the terminal payoff of asset as a normal random variable which allows continuously all possibilities (including negative values as losses) and the corresponding public signal e_t on the terminal payoff also as normal. This also allows more flexibility in the effect of the announcement on the terminal payoff of the asset, since a same approval announcement on two patents can lead to different consequences on the terminal asset payoffs — consistent with the idea in Kogan, Papanikolaou, Seru, and Stoffman (2017) that the scientific value of a patent can be very different from its economic value.

[15] We make the assumption that patent denials are publicly announced for simplicity of modeling. In practice, patents are either granted or not granted. While the former (patent grants) conveys an unambiguously positive signal, the latter (the patent application not being approved by the USPTO) conveys only an ambiguous negative signal, since firms have the ability to revise the patent application and re-apply.

any private signal, the equilibrium prices do not contain additional information about the payoff of the risky asset. Thus there is no need for attentive investors to learn from prices.

Inattentive investors (indexed by type u). Because of limited attention, inattentive investors do not pay attention to the patent grant/denial announcement e_1 immediately at $t = 1$ and delay their belief update on e_1 till $t = 2$.[16] Also because of their limited attention, they are unaware of their delay even though they may notice the change in equilibrium prices from S_0 to S_1, hence they do not learn from the equilibrium price.[17] At $t = 2$, they update their beliefs upon the patent grant/denial announcement e_1 in a delayed manner. At $t = 3$, they observe the FDA drug approval/denial announcement e_3 immediately and correctly.[18]

Utility. All investors hold the constant-absolute-risk-aversion (CARA) utility with a common risk aversion parameter ρ. On each trading date ($t = 0, 1, 2, 3$), they all optimally choose their demands $\{D_t^i\}_{i\in\{a,u\}}$ of the risky asset to maximize their personal expected utilities on terminal wealth,

$$\max_{D_t^i} E_t^i(-\exp[-\rho W_4^i]), \text{ for } i \in \{a, u\} \text{ and } t = 0, 1, 2, 3 \tag{2}$$

subject to the following budget constraints

$$\begin{aligned} W_{t+1}^i &= W_t^i + D_t^i(S_{t+1} - S_t), \text{ for } t = 0, 1, 2 & (3)\\ W_4^i &= W_3^i + D_3^i(f - S_3). & (4) \end{aligned}$$

4 Equilibrium and Results

We calculate the update of beliefs forward as more information arrives on each date. In contrast, we solve the equilibrium prices and demands backwards, since investors' demands depend on their expectation on the capital gain in each subsequent period.

[16] We can also interpret the inattention to the patent grant announcement as the inability to evaluate the announcement immediately. Since the patent may not necessarily lead to a drug eventually, it can be hard for inexperienced investors to convert it directly to an expected terminal payoff.

[17] Alternatively, the ignorance of learning from price can be interpreted as overconfidence by investors.

[18] When investors are limited in their attention capacity, it is natural that their attention is only caught by more salient news like drug approval announcements but not by less salient news like patent grant announcements.

4.1 Bayesian Updating of Beliefs

The information set for an investor of type i at time t is denoted by $\mathcal{F}_t^i$.

At $t = 0$, all investors hold the prior belief: $f = \mu + z$, where μ is the unconditional expectation of f and $z \sim N(0, \sigma_0^2)$. Since μ is a constant, the updating of beliefs occurs only on the random component z in later periods.

At $t = 1$, an attentive investor, type a, pays attention to the patent grant/denial announcement e_1, and has an information set $\mathcal{F}_1^a = \{e_1\}$. The posterior belief is

$$z|_{\mathcal{F}_1^a} \sim N(\hat{z}_1^a, (\sigma_1^a)^2), \text{ where } \hat{z}_1^a = (\sigma_1^a)^2 \sigma_{e,1}^{-2} e_1 \text{ and } (\sigma_1^a)^{-2} = \sigma_0^{-2} + \sigma_{e,1}^{-2}. \tag{5}$$

An inattentive investor, type u, does not pay attention immediately to the patent grand/denial announcement e_1, and hence still holds the prior belief

$$z|_{\mathcal{F}_1^u} \sim N(\hat{z}_1^u, (\sigma_1^u)^2), \text{ where } \hat{z}_1^u = 0 \text{ and } \sigma_1^u = \sigma_0. \tag{6}$$

At $t = 2$, there is no public signal, but inattentive investors realize that they missed the patent grant announcement at $t = 1$ and revise their beliefs in a delayed manner. Thus, all investors hold the same information set $\mathcal{F}_2 = \{e_1\}$ and all investors' posterior beliefs are the same,

$$z|_{\mathcal{F}_2} \sim N(\hat{z}_2, \sigma_2^2), \text{ where } \hat{z}_2 = \sigma_2^2 \sigma_{e,1}^{-2} e_1 \text{ and } \sigma_2^{-2} = \sigma_0^{-2} + \sigma_{e,1}^{-2}, \tag{7}$$

i.e. attentive investors still hold the same belief as they had at $t = 1$, while inattentive investors update their belief from prior to converge with attentive investors' belief.[19]

At $t = 3$, all investors pay attention to the FDA drug approval announcement e_3 and share the same information set $\mathcal{F}_3 = \{e_1, e_3\}$. Therefore, all investors' posterior beliefs are the same:

$$z|_{\mathcal{F}_3} \sim N(\hat{z}_3, \sigma_3^2), \text{ where } \hat{z}_3 = \sigma_3^2(\sigma_{e,1}^{-2} e_1 + \sigma_{e,3}^{-2} e_3) \text{ and } \sigma_3^{-2} = \sigma_0^{-2} + \sigma_{e,1}^{-2} + \sigma_{e,3}^{-2}. \tag{8}$$

[19] Notice that because of the different timing of belief updating by the two types of investors, the expectations $E_1^a[\hat{z}_2]$ and $E_1^u[\hat{z}_2]$ are different.

4.2 Equilibrium Prices and Demands

On each trading date ($t = 0, 1, 2, 3$), given their updated beliefs of z, investors decide their optimal demands $\{D_t^i\}_{i \in \{a,u\}}$ for the risky asset to maximize their expected CARA utilities of terminal wealth $E_t^i(-\exp[-\rho W_4^i])$. At each t, the equilibrium price S_t clears the market, i.e.

$$\int D_t^i di = f^a D_t^a + f^u D_t^u = \bar{x} + \sum_{s=1}^{t} x_s, \text{ for } t = 0, 1, 2, 3. \tag{9}$$

Proposition 1 (The Equilibrium Prices and Investors' Optimal Demands)

(i) For $t = 0, 1, 2, 3$, the equilibrium price S_t has the following expressions respectively:

$$\begin{aligned} S_3 &= \mu + \hat{z}_3 - \rho\sigma_3^2(\bar{x} + x_1 + x_2 + x_3), &(10)\\ S_2 &= \mu + \hat{z}_2 - \rho\sigma_2^2(\bar{x} + x_1 + x_2), &(11)\\ S_1 &= \mu + \frac{A_a}{A_a + A_u}\hat{z}_1^a - \rho(B_0\bar{x} + B_1 x_1), &(12)\\ S_0 &= \mu - \rho\frac{Q_a + Q_u + 1}{P_a + P_u}\bar{x}, &(13) \end{aligned}$$

where the constants A_a, A_u, B_0, B_1, P_a, P_u, Q_a, and Q_u are listed in Appendix A.1.

(ii) For $t = 0, 1, 2, 3$, the optimal demands of the risky asset by investors of type $i \in \{a, u\}$ are respectively

$$\begin{aligned} D_3^i &= \rho^{-1}\sigma_3^{-2}(\mu + \hat{z}_3 - S_3) \textit{ for } i \in \{a, u\}, &(14)\\ D_2^i &= \rho^{-1}\sigma_2^{-2}\frac{1 + \rho^{-2}\sigma_3^{-2}\sigma_x^{-2}}{1 + \rho^{-2}\sigma_{e,3}^{-2}\sigma_x^{-2}}(\mu + \hat{z}_2 - S_2) &\\ &\quad - \frac{\rho^{-2}\sigma_2^{-2}\sigma_x^{-2}}{1 + \rho^{-2}\sigma_{e,3}^{-2}\sigma_x^{-2}}(\bar{x} + x_1 + x_2) \textit{ for } i \in \{a, u\}, &(15)\\ D_1^a &= \rho^{-1}\frac{A_a}{f^a}(\mu + \hat{z}_1^a - S_1) - (\frac{A_a}{f^a}\sigma_2^2 - 1)(\bar{x} + x_1), &(16)\\ D_1^u &= \rho^{-1}\frac{A_u}{f^u}(\mu - S_1) - \frac{\frac{1}{2}\rho^{-2}\sigma_x^{-2}}{1 + \frac{1}{2}\rho^{-2}\sigma_x^{-2}}\frac{A_u}{f^u}\bar{x}, &(17)\\ D_0^a &= \rho^{-1}\frac{P_a}{f^a}(\mu - S_0) - \frac{Q_a}{f^a}\bar{x}, &(18)\\ D_0^u &= \rho^{-1}\frac{P_u}{f^u}(\mu - S_0) - \frac{Q_u}{f^u}\bar{x}. &(19) \end{aligned}$$

The equilibrium prices on all trading dates are in the form of "μ+(investors' belief on z)-(a term of $\bar{x}$ and supply shocks x_t)". If good news ($e_1 > 0$ and/or $e_3 > 0$) is observed from announcements, then investors modify their beliefs on z higher and thus the equilibrium prices increase; if bad news ($e_1 < 0$ and/or $e_3 < 0$) is observed from announcements, then investors modify their beliefs on z lower and thus the equilibrium prices decrease. The term of $\bar{x}$ and supply shocks x_t represents a compensation (risk premium) for holding the risky asset by investors.

Observe that investors' demands at $t = 2$ and 3 are homogeneous regardless of their attention type. This is because at $t = 2$ and 3, both attentive and inattentive investors have their beliefs updated correctly on both the patent grant announcement e_1 and the FDA drug approval announcement e_3, thus they all have homogeneous beliefs and hence homogeneous demands. In contrast, the demands at $t = 1$ and $t = 0$ depend on investor type, since only attentive investors pay attention to the patent grant announcement e_1 immediately at $t = 1$ and therefore hold different beliefs from inattentive investors.[20]

4.3 Announcement Effects and Post-Announcement Drifts

In this subsection, we are going to study the abnormal stock returns (announcement effects) at $t = 1$ and $t = 3$ and the corresponding post-announcement stock return drift at $t = 2$. This is done by looking at the differences in the equilibrium prices of the risky asset across time.

Because the supply shocks are mean zero and the analysis of announcement effects and post-announcement drifts is unrelated to risk premium, we follow Hirshleifer and Teoh (2003) to "ignore" the terms containing $\bar{x}$ and x_t and only focus on the components containing the random variables e_1 and e_3. This is technically equivalent to setting the expected supply $\bar{x}$ and all relevant supply shocks x_t to zero. For this reason, we let $\bar{x} = x_t = 0$ when necessary within this subsection for the convenience of our analysis.

By taking the difference between (11) and (10), we rewrite the price change of the risky asset

[20] This is the case, since investors' demand for the firm's equity at $t = 0$ is a function of their belief of the expected return at $t = 1$, which depends on investor type since attentive investors pay attention to the patent grant news at $t = 1$ and take this into consideration when they form their expectation of the firm's stock price at $t = 0$, while inattentive investors do not have this component in their expectation. i.e. $E_0^a(S1) \neq E_0^u(S1)$.

from $t = 2$ to $t = 3$ as follows

$$S_3 - S_2 \;=\; \underbrace{\sigma_3^2\sigma_{e,3}^{-2}e_3 + (\sigma_3^2 - \sigma_2^2)\sigma_{e,1}^{-2}e_1}_{\hat{z}_3 - \hat{z}_2} - \rho[(\sigma_3^2 - \sigma_2^2)(\bar{x} + x_1 + x_2) + \sigma_3^2 x_3]. \tag{20}$$

The price change consists of two components: the first component (consisting of the first and second terms) is the belief updating on z because of the information from the FDA drug approval announcement e_3; the second component is the change in risk premium because of both uncertainty resolution and supply shocks. Silencing the terms on $\bar{x}$ and x_t, we establish the following proposition:

Proposition 2 (The Announcement Effect of FDA Approval Announcements)

(i) The abnormal stock return upon an FDA drug approval announcement is increasing in the realization $e_3 > 0$ of the announcement. This is given by:

$$AE_3 \equiv \sigma_3^2\sigma_{e,3}^{-2}e_3 + (\sigma_3^2 - \sigma_2^2)\sigma_{e,1}^{-2}e_1. \tag{21}$$

(ii) For any given realizations of e_3 and e_1, the abnormal stock return upon an FDA drug approval announcement, AE_3, is independent of the fraction of attentive investors f^a.

Similarly, by taking the difference between (12) and (13), we rewrite the price change of the risky asset from $t = 0$ to $t = 1$ as follows

$$S_1 - S_0 = \frac{A_a}{A_a + A_u}\underbrace{(\sigma_1^a)^2\sigma_{e,1}^{-2}e_1}_{\hat{z}_1^a} - \rho[(B_0 - \frac{Q_a + Q_u + 1}{P_a + P_u})\bar{x} + B_1 x_1]. \tag{22}$$

The first part represents the average change in investors' beliefs (from 0 to $\hat{z}_1^a$ by attentive investors, diluted by the zero change in inattentive investors' beliefs) and the second part represents the change in risk premium because of both uncertainty resolution and supply shock. Silencing both $\bar{x}$ and x_1, we derive the following proposition:

Proposition 3 (The Announcement Effect of Patent Grant Announcements)

(i) The abnormal stock return upon a patent grant announcement is increasing in the realization

$e_1 > 0$ of the announcement, given by:

$$AE_1 \equiv \frac{A_a}{A_a + A_u}(\sigma_1^a)^2\sigma_{e,1}^{-2}e_1, \tag{23}$$

where the constants A_a and A_u are both positive and increasing functions of f^a and f^u respectively (defined in Appendix A.1).

(ii) *For any given realization of $e_1 > 0$, the abnormal stock return upon a patent grant announcement will be increasing in the proportion of investors who are attentive to the announcement, i.e. AE_1 is an increasing function of f^a for any $e_1 > 0$.*

Intuitively, if few investors are attentive at $t = 1$, then few investors will update their beliefs using the patent grant announcement e_1, and thus the equilibrium price will not reflect e_1 as much in the announcement effect. Moreover, we can rewrite AE_1 as follows,

$$AE_1 = \frac{A_a}{A_a + A_u}\frac{\sigma_{e,1}^{-2}}{\sigma_0^{-2} + \sigma_{e,1}^{-2}}e_1 \tag{24}$$

which increases in the precision $\sigma_{e,1}^{-2}$ of the patent grant announcement. This is consistent with the intuition that, the more precise a signal is, the greater effect it has on the asset's price.

Taking the difference between (12) and (11) and noticing that $\hat{z}_1^a = \hat{z}_2$, we write the price change from $t = 1$ to $t = 2$ as

$$S_2 - S_1 = \frac{A_u}{A_a + A_u}\underbrace{\sigma_2^2\sigma_{e,1}^{-2}e_1}_{\hat{z}_1^a} - \rho[(\sigma_2^2 - B_0)\bar{x} + (\sigma_2^2 - B_1)x_1 + \sigma_2^2 x_2]. \tag{25}$$

The first term is the portion of the price change as a result of the belief correction by inattentive investors and the second term is the change in risk premium because of both uncertainty resolution and supply shocks. Silencing the terms on $\bar{x}$ and x_t, we derive the following proposition:

Proposition 4 (Post-Announcement Drift around Patent Grant Announcements)

(i) *If the patent grant announcement is positive, the stock of the innovating firm will be undervalued upon announcement and there will be a positive post-announcement stock return drift* *in this case, given by:*

$$\frac{A_u}{A_a + A_u}\sigma_2^2\sigma_{e,1}^{-2}e_1, \tag{26}$$

where the constants A_a and A_u are both positive and increasing functions of f^a and f^u respectively (defined in Appendix A.1).

(ii) *If the patent grant announcement is negative, the stock of the innovating firm will be overvalued upon announcement and there will be a negative post-announcement stock return drift in this case, given by:*

$$\frac{A_u}{A_a + A_u}\sigma_2^2\sigma_{e,1}^{-2}e_1, \tag{27}$$

where the constants A_a and A_u are both positive and increasing functions of f^a and f^u respectively (defined in Appendix A.1).

(iii) *The extent of the post-announcement stock return drift (positive or negative) decreases as the fraction of attentive investors f^a increases: i.e.,*

$$Drift_2 \equiv \frac{A_u}{A_a + A_u}\sigma_2^2\sigma_{e,1}^{-2}e_1 \tag{28}$$

decreases with f^a when $e_1 > 0$ and increases with f^a when $e_1 < 0$.

Because of the presence of inattentive investors, the equilibrium price does not fully reflect the information contained in the patent grant announcement e_1 at $t = 1$, and the price reaction is lower than its counterpart in the full-attention case. The more attentive investors on site, the larger the immediate price reaction (announcement effect) and hence the lower post-announcement drift.

Proposition 5 (Comparison of Announcement Effects)

When the proportion of inattentive investors is large enough so that

$$\frac{f^u}{f^a} > \frac{1-R}{R}(1+\rho^{-2}\sigma_2^{-2}\sigma_x^{-2})[\sigma_{e,1}^{-2}\sigma_0^2 + (1+\frac{1}{2}\rho^{-2}\sigma_2^{-2}\sigma_x^{-2})^{-1}], \tag{29}$$

where the positive constant R is defined in Appendix A.1, the abnormal stock returns following patent grant announcements will, on average, be smaller than those following FDA drug approval *announcements. More precisely, when (29) holds,*

$$E[AE_1|e_1 > 0] < E[AE_3|e_1 > 0, e_3 > 0]. \tag{30}$$

5 Implications and Testable Hypotheses

Our model generates several testable implications. In this section, we develop testable hypotheses based on these implications for our empirical analysis.

1. *The relation between the nature of innovation announcements, abnormal stock returns upon these announcements, and the post-announcement stock return drift:* Our model predicts that the larger the fraction of investors who pay attention to a particular innovation announcement, the larger the abnormal stock return upon this announcement (i.e., the announcement effect) and the smaller the subsequent stock return drift. Thus, our Proposition 5 implies that, in a patent-drug matched sample, the abnormal stock return upon patent grant announcements will be smaller than that upon FDA drug approval announcements. Further, the stock return drift following patent grant announcements will be greater than that following FDA drug approval announcements. This is the first hypothesis that we test here ($\mathbf{H_1}$).

2. *The relation between a proxy for investor attention and the abnormal stock return following patent grant announcements and FDA drug approvals:* Proposition 3 of our model predicts a positive relation between the extent of investor attention paid to patent grant announcements and the abnormal stock returns upon such announcements. Our model makes a similar prediction about the relation between the extent of investor attention paid to FDA drug approvals and the abnormal stock returns upon the announcement of such approvals. This is the second hypothesis that we test here ($\mathbf{H_2}$). We use a proxy for investor attention (namely, media coverage) to test the above hypothesis in two different samples. First, in a paired sample of patent grant announcements and FDA drug approvals in the biopharmaceutical industry. Second, in the entire sample of patent grant announcements across all industries from the USPTO database ("general sample" of patent grant announcements).

3. *The relation between a proxy for investor attention and the post-announcement drift following patent grant announcements:* Proposition 4 of our model predicts a negative relation between the extent of investor attention paid to a given patent grant announcement and the post-announcement stock return drift following that announcement. This is the third hypothesis that we test here ($\mathbf{H_3}$). We use a proxy for investor attention (namely, media coverage) to test the above hypothesis in two different samples. First, in a paired sample of patent grant announcements and FDA drug approvals in the biopharmaceutical industry. Second, in the entire sample of patent grant announcements across all industries from the USPTO database.

4. *The stock return drift following patent grant announcements as a measure of the economic value of patents:* Our model suggests that the stock return drift following patent grant announcements is a predictor of the economic value created by the patent for the firm to which the patent is granted, over and above the abnormal stock return (announcement effect) upon the patent grant announcement. This is the fourth hypothesis that we test here ($\mathbf{H_4}$). We test this hypothesis using the entire sample of patent grant announcements from the USPTO database.

5. *Trading strategy based on investor attention paid to patent grant announcements:* Our model suggests that a long-short trading strategy that is long in the stock of firms which receive low investor attention to their patent grant announcements (on average) and that is short in the stock of firms which receive high investor attention to such announcements (on average) will be able to generate positive abnormal profits over the subsequent period (e.g., a month). This is the final hypothesis that we test here ($\mathbf{H_5}$).

6 Empirical Analysis

We now test the testable hypotheses developed above empirically. We first focus on the biopharmaceutical industry since we can pin down the event dates accurately for different types of innovation news, which exhibit sharp contrast in the technical uncertainty involved and hence the investor attention received. Specifically, we examine the market reaction to drug-related patent grant news and the corresponding FDA drug approval news, which may occur, in some cases, years later after the patent grant date. When the USPTO issues a drug-related patent to a firm, there is still a significant amount of technical uncertainty that needs to be resolved before the firm can obtain drug approval from the FDA. The probability of eventual success (i.e., FDA approval) is also very low. However, when the FDA approves a drug, the technical uncertainty has been fully resolved, and the firm stands ready to bring in the cash flow stream from selling the drug. Therefore, drug approval news is usually more salient and easier to evaluate for investors than patent grant news. This, in turn, means that a larger fraction of investors are likely to pay immediate attention to drug approval announcements than to patent grant announcements. Based on our theoretical model predictions, we therefore expect a stronger announcement effect and a weaker post-announcement drift for drug approval news than those for drug-related patent grant news ($\mathbf{H_1}$). Examining the two types of innovation announcements helps us understand the role of investor attention in evaluating intangible assets. To test the other hypotheses that require explicit measures of investor attention ($\mathbf{H_2}$, $\mathbf{H_3}$, and $\mathbf{H_5}$), we use media coverage as a proxy for investor attention and examine how attention affects the market reaction to these two types of news.

6.1 Data, measures of innovation and attention, and summary statistics

We conduct our empirical analysis of biopharmaceutical patents and drugs using two different samples. First, we use a paired sample where we pair each FDA-approved drug with the corresponding key patent protecting that drug. This allows us to eliminate fundamental differences between the patent grant and drug approval news in terms of the nature of the underlying molecule to a considerable extent. Second, since the pairing of patent grants and drug approvals reduces the sample size significantly, we also conduct the empirical analysis in the biopharmaceutical industry using a (larger) sample of extended patent grant news and FDA drug approvals without requiring the matching between drug and patent (presented in Online Appendix B).

To construct our drug approval sample for the biopharmaceutical industry, we first obtain drug approval news from FDA.gov. The sample ranges from 1960 to 2016. The data contain the drug name, application number, approval date, submission classification, the name of the company that submits the drug approval application, and other drug-related information. The dataset contains many different types of applications.[21] To ensure that the news is related to new drug approvals,

[21] There are 10 types of submission classifications. However, only Type 1 refers to new drug approval (New

we only keep those new drug applications (NDA) classified as New Molecular Entity (Type 1) and biologics license applications (BLA). Since the company that submits the application may differ from the company that owns the drug at the time of FDA approval, we search in business news for any potential changes in ownership between the application and drug approval dates to ensure that the drug approval news is matched with the company that owns the drug at the time of FDA approval. We then match this cleaned dataset with CRSP to find drug approval news for public firms so that we can study the stock market reaction to this type of news. In the end, the filtered drug sample consists of 573 drug approval events from July 1966 to December 2016.

To construct our patent grant sample in the biopharmaceutical industry, we obtain the drug-related patents from the Medtrack database, which starts in 1980. A drug can be protected by multiple patents. However, only the patent listed as "product," "product (generic)," "product (specific)," or "composition" is the key patent that provides exclusivity to the drug on the market. The patent type obtained from Medtrack allows us to pin down the key patent associated with each drug. For example, Lipitor (a blockbuster drug that treats high cholesterol and triglyceride levels) is associated with multiple patents. However, only one patent (patent number 4181893) is the key patent that we keep to pair with Lipitor since the other patents do not provide protection for market exclusivity. To study the stock market reaction to patent grant news, we also require the company that owns the patent to be public at the time of patent grant. We identify public firms by merging the key product patent dataset from Medtrack with the patent dataset provided by Kogan, Papanikolaou, Seru, and Stoffman (2017), which contains an identifier for public firms for all industries from 1926 to 2010. We obtain the patent data in 2011–2014 from Gao, Hsu, Li, and Zhang (2018). In the end, the filtered drug-related key product patent sample consists of 733 patent grant events from December 1986 to July 2014.

We then construct a paired drug-patent sample that links each drug with its associated key product patent by merging these two datasets (drug approval news and drug-related key product patent grant news for public firms). As discussed earlier, when a patent is granted, there is still a significant amount of technical uncertainty, which will not be fully resolved till the FDA approval. The two types of news differ also in terms of success probability and the time it takes to obtain

Molecular Entity). The others refer to new combination, new dosage form, new indication, etc. The details are listed here: https://www.fda.gov/drugs/informationondrugs/ucm075234.htm#chemtype_reviewclass.

the eventual cash flow. Pairing allows us to contrast these two types of news more cleanly, since the eventual cash flow stream is the same for a patent and for its paired drug. Therefore, in the paired sample, the difference in market reactions to these two types of news are likely to be driven mainly by differences in technical uncertainty and investor attention (which, in turn, may also be affected by differences in technical uncertainty). However, pairing also limits the sample size significantly (due to data availability). The paired sample consists of 117 patent grant events from December 1986 to June 2014 and 117 matching drug approval events from May 1991 to December 2016. Therefore, we also test our hypotheses in the extended (or unpaired) drug approval sample, the extended drug-related key product patent grant sample, and the general patent sample for all industries from the USPTO.

To construct the general patent sample for all industries, we utilize the patent datasets from Kogan, Papanikolaou, Seru, and Stoffman (2017) and Gao, Hsu, Li, and Zhang (2018). We keep all the patents granted to public firms from January 2000 to August 2014. We start the sample from 2000 since our investor attention measure, media coverage, starts from 2000 (see more details below).

To proxy for investor attention, we use media coverage data obtained from RavenPack. Specifically, we use the number of business-related news articles that mention the event firm around the event date to measure the level of media coverage for that event. Presumably, investor attention increases with media coverage. Many studies have used media coverage as a direct measure of investor attention. Compared to other attention measures based on firm characteristics (such as firm size and analyst coverage), this measure is more directly linked to specific news and reflects investor attention in a timelier fashion since it is much less persistent than firm characteristics. We use two windows to compute media coverage in our empirical analysis. Media[-7, 0] is the number of news articles that mention the event firm over the week before the event. Media[-1, 1] is the number of news articles that mention the event firm over the three-day window around the event. If a firm has multiple events on a given day, we scale the media coverage measures by the number of events. The media coverage data in RavenPack start from the year 2000. Due to this limitation, our sample starts in 2000 when we test the effect of investor attention on the market reaction to various innovation announcements.

To examine the stock market reaction to innovation announcements, we use cumulative abnormal stock returns (CAR) during the three-day event window around the event date (CAR[-1, 1]) to measure the announcement effect and the CAR over the 21 trading days following the event date (CAR[2, 22]) to measure the post-announcement drift. For each event, we first compute the abnormal stock return relative to the Fama and French (1993) three-factor model using a twelve-month estimation window (with a minimum of 100 valid daily returns) that ends 30 trading days before the event date. If a firm has multiple events in the same day, we treat them as one event and scale the CARs by the number of events occurring in that day.

Table 1 reports summary statistics for the 117 paired drug-related patent grant announcements (Panel A), the 117 paired drug approval announcements (Panel B), the 773 extended drug-related patent announcements (Panel C), the 573 drug approval announcements (Panel D), and the 879,251 patent grant events in the general sample (Panel E). The general patent grant sample is from January 2000 to August 2014 due to the availability of RavenPack data (as mentioned above). In addition to CARs, we also report firm characteristics for the event firms in each sample and patent originality as we control for these variables in multivariate regressions (detailed later). For each event occurring in year t, BM is the book value of equity in the fiscal year ending in calendar year $t-1$ divided by the market value of equity at the end of year $t-1$. ME is the market value of equity at the end of year $t-1$. ROA is the income before extraordinary items (Compustat item IB) divided by the book value of total assets (Compustat item AT) in the fiscal year ending in calendar year $t-1$. Following Hall, Jaffee, and Trajtenberg (2001), we measure patent originality with the Herfindahl index of the patents cited by the focal patent across the three-digit technology classes assigned by the USPTO.

To reduce the impact of outliers, we compute summary statistics after winsorizing these variables at the 1% and 99% levels within each sample. For each variable, we report the number of observations (Obs.), mean, standard deviation (SD), minimum (Min), and maximum (Max).

Panel B of Table 1 shows that, for the 117 drug approval events, the average announcement effect, CAR[-1, 1], is substantial and economically significant, 1.69%. The average drift, CAR[2, 22], is very small, 0.32%. The event firms are typically large and are typically "value" firms since their average book-to-market equity is high, 0.91. The average market capitalization of the event firms is $54,684 million. They are, on average, profitable with an average ROA of 0.07. The average number of news articles mentioning the event firms over the week before ([-7, 0]) and the three-day window around the drug approval date ([-1, 1]) is 10.27 and 6.49, respectively.[22]

In contrast, Panel A shows that the market reacts quite differently to the matched 117 key patent grant announcements. The average announcement effect, CAR[-1, 1], is much smaller, 0.97%. The average drift, CAR[2, 22], is very large, 2.10%. Furthermore, the patent owner at the time of patent grant can differ from the drug owner at the time of drug approval due to merger and acquisition and patent sale etc. Indeed, the patent event firms differ from the drug event firms in many aspects. The average market capitalization of the event firms is $\$31,128$ million. Their average BM is 1.24. They are, on average, not profitable with an average ROA of -0.03. The average patent originality score is 0.45. The average number of news articles mentioning the event firms over the week before and the three-day window around the patent grant date is 7.3 and 2.91, respectively.[23] This is consistent with our model assumption that drug approval announcements are more salient and, therefore, receives much greater investor attention. We found a similar pattern in Panel C and Panel D, which present results from the extended (unmatched) biopharmaceutical sample, for patent grants and FDA drug approvals, respectively.

Panel E reports the same set of statistics for the general patent grant sample across all industries. The announcement effect is small, 0.01%, but the stock return drift is much larger, 0.07%. The average size of these firms is $\$52,782$ million. The median BM is 0.42. They are, on average, profitable. The media coverage over [-7, 0] and [-1,1] is 1.29 and 0.65, respectively.

6.2 Market reaction to innovation announcements in the biopharmaceutical industry

In this section, we formally test Hypothesis 1 ($\mathbf{H_1}$) by contrasting market reactions to two major types of announcements in the biopharmaceutical industry: patent grant announcements and FDA drug approval announcements. As shown in Table 1, drug approval announcements are more salient and receive more investor attention. Therefore, compared to patent grant announcements, we expect a stronger announcement effect and a weaker post-announcement drift for drug approval announcements, as predicted by our hypothesis $\mathbf{H_1}$. We first examine this hypothesis using uni-

[22]The number of observations for media coverage is 88 instead of 117 since the media coverage data start in 2000, while the paired drug approval sample starts in 1991.

[23]The number of observations for media coverage is 47 instead of 117 since the media coverage data start in 2000, while the paired patent grant sample starts in 1986.

variate tests in the paired drug-patent sample and the extended sample (i.e., without requiring a matching between the drug and the patent). The paired sample allows us to control for the fundamental value of the innovation (in the event of success) to ensure a cleaner contrast. We then test $\mathbf{H_1}$ using multivariate tests, which allow us to control for differences in firm characteristics as well to ensure an even cleaner contrast. As discussed before, the firm that owns the drug at the time of drug approval may differ from the firm that owns the patent at the time of patent grant. Therefore, controlling for firm characteristics that may affect the market reaction to various announcements provides a cleaner test. As in Table 1, we winsorize both dependent and independent variables at the 1% and 99% levels to reduce the impact of outliers. We compute t-statistics based on standard errors clustered at the firm and event day levels.

Table 2 provides significant support for $\mathbf{H_1}$ in general. The univariate tests in Panel A show a sharp contrast in both the announcement effect (CAR[-1, 1]) and the post-announcement drift (CAR[2, 22]) between these two types of announcements. For example, CAR[-1, 1] for the paired drug approval announcements and patent grant announcements is 1.69% (t = 2.81) and 0.97% (t = 1.91), respectively. This contrast is even larger for the extended sample: 3.32% (t = 2.54) versus 0.22 (t = 1.17). The difference is substantial, although statistically insignificant for the paired sample. But it is statistically significant at the 5% level for the extended sample, perhaps owing to the stronger statistical power associated with the much larger sample size. Furthermore, the stock return drift over the 21 trading days is substantial and significant for the patent grant announcements (2.10% with a t-statistic of 1.91 in the paired sample and 1.56% with a t-statistic of 2.93 in the extended sample), but it is small and insignificant for the drug approval announcements in both samples.[24] The difference in the stock return drift across these two types of announcements is large, although statistically insignificant in the paired sample (1.78% with a t-statistic of 1.47). However, this difference is large and statistically significant at the 5% level in the extended sample (1.47% with a t-statistic of 2.22).

The results of our multivariate analysis, presented in Panel B of Table 2, show a similar contrast, especially in the extended sample. Specifically, we report the slopes (in percentage) and t-statistics (in parentheses) from our pooled regression of the CARs of the two types of announcements on a

[24]Note that this is broadly consistent with our model predictions, since our assumption is that all investors pay attention to FDA drug approvals. Under this assumption, our model predicts that there will not be any post-announcement stock return drift following FDA drug approvals.

dummy variable, *drug approval*, that equals 1 (0) for drug approval announcements (patent grant announcements), controlling for firm characteristics and patent originality. The control variables, such as BM, ME, ROA, and patent originality, are defined as in Table 1. We use the natural log of BM and ME to reduce the skewness of these characteristics. In addition, we use Log(1+BM) since many firms in these samples have negative BM. We also control for the three-digit technology class fixed effect (Tech Class FE) in various regressions. After controlling for major characteristics that are known to be associated with stock returns, the difference in the announcement effect and in the stock return drift across the two types of announcements is 2.80% ($t = 1.80$) and 1.31% ($t = 1.91$), respectively, in the extended sample.

The above results imply that the equity market is more efficient in evaluating drug approval announcements than it is in evaluating patent grant announcements. While this may be due to the high technical uncertainty associated with the former (patent grant announcements) as well as the low attention paid to it, the low attention to patent grant announcements may be partly due to the high uncertainty associated with patent grant announcements. In other words, misvaluation of innovation due to limited attention may be more severe when technical uncertainty is higher. The two go hand-in-hand. If there is no technical uncertainty, the valuation job is much easier and the rewards for paying attention are likely to be higher. Therefore, the market is more likely to pay attention and hence is more efficient at incorporating new information associated with low uncertainty. On the other hand, when there is a significant amount of technical uncertainty, the valuation job is much more difficult and the reward for paying attention is likely to be lower. Therefore, investors are likely to shy away and pay less attention, which may lead to severe mispricing and market inefficiency for announcements associated with more uncertainty.[25]

We next test the effect of investor attention on the market reaction to these two different types of announcements directly, as predicted by our hypotheses $\mathbf{H_2}$ and $\mathbf{H_3}$.

6.3 Investor attention and the market reaction to innovation announcements

Our theoretical model predicts that investor attention plays an important role in the announcement effect and post-announcement stock return drift for innovation announcements. We test $\mathbf{H_2}$ and $\mathbf{H_3}$

[25] Studies have shown that cognitive biases tend to be stronger among harder-to-value firms (see, e.g., Zhang (2006), Kumar (2009)). Our study further confirms this by contrasting the market reaction to different types of announcements with drastic differences in valuation uncertainty and in investor attention.

in the biopharmaceutical industry first and then in the general patent sample across all industries. Since RavenPack provides media coverage only from the year 2000 onward, our sample periods start in the year 2000 for all these tests.

6.3.1 Empirical analysis of the biopharmaceutical industry sample

To test the role of investor attention on the announcement effect and the post-announcement drift, we conduct both univariate and multivariate regressions. Our inferences mainly rely on results from multivariate regressions since it is important to control for other aspects that may affect the market reaction to various innovation announcements. As discussed earlier, we measure attention using media coverage computed over two different windows for robustness: the week before the event date, and the three days around the event date. The attention dummy variable equals 1 if media coverage is above the corresponding sample median and 0 otherwise. All the control variables are defined as in Tables 1 and 2.

Table 3 reports the results for our paired drug-patent sample. Panel A reports the effect of attention on patent grant announcements, while Panel B reports the effect of attention on drug approval announcements.[26] Panel A shows that, for patent grant announcements, the coefficient of attention in multivariate regressions with the announcement effect (CAR[-1, 1]) as the dependent variable is significantly positive, regardless of whether attention is measured by Media[-7, 0] or Media[-1, 1]. This is consistent with our hypothesis $\mathbf{H_2}$. Similarly, for both attention measures, the coefficient of attention in multivariate regressions with the post-announcement drift (CAR[2, 22]) as the dependent variable is significantly negative, which is consistent with our hypothesis $\mathbf{H_3}$. In sum, the results in Panel A show that the announcement effect increases with attention, and the post-announcement drift decreases with attention using both media coverage measures for patent grant announcements.

We now discuss the results related to the effect of investor attention on the stock market reaction to drug approval announcements, presented in Panel B of Table 3. We find that, even in the case of FDA drug approval announcements, the announcement effect increases in investor attention while the post-announcement drift decreases in attention. For example, regardless of whether attention is measured by Media[-7, 0] or Media[-1, 1], the coefficient of attention in our

[26] The corresponding results for the extended sample are presented in the Online Appendix B.

multivariate analysis with the announcement effect of drug approvals as the dependent variable is positive and statistically significant, consistent with our hypothesis $\mathbf{H_2}$. Similarly, the coefficient of attention in our multivariate regression with the post-announcement drift as the dependent variable is significantly negative when we measure attention by Media[-7, 0], although it is negative but insignificant when we measure attention by Media[-1, 1]. These latter results are broadly consistent with our hypothesis $\mathbf{H_3}$ (albeit weaker than the corresponding results in the case of patent grant announcements).

6.3.2 Empirical analysis of patent grant announcements across all industries using the general patent sample

Although our model on investor attention is motivated by the innovation process in the biopharmaceutical industry, the implications of our model apply to all innovation-related events. Therefore, we now examine the stock market reaction to patent grant announcements in the general sample, which includes all public firms' patents granted from 2000 to August 2014. Similar to our previous analyses, we present univariate regressions first with attention alone as the independent variable and then present multivariate regressions with controls. To test the role of investor attention, we use the same methodology that we used above for the biopharmaceutical industry. In order to control for the heterogeneity in the stock market reaction to patent grant events, we control for the technology class of patents, year, and industry fixed effects in our multivariate regressions in addition to other controls such as patent originality.

The results are presented in Table 4. Columns (1) to (5) present the results of our analysis on the announcement effects of patent grant announcements, and Columns (6) to (10) present the results of our analysis of the post-announcement stock return drift following such announcements. Similar to the results from the biopharmaceutical industry, the results from the general sample using multivariate regression analyses show that, while the announcement effect of patent grant announcements is positively related to attention, the post-announcement stock return drift is negatively related to attention. For example, the coefficient of attention in our multivariate regressions with the announcement effect as the dependent variable is significantly positive when attention is measured by Media[-1,1], though it is insignificant if it is measured by Media[-7,0]. This is consistent with our hypothesis $\mathbf{H_2}$. On the other hand, we can see that, regardless of whether attention is measured by Media[-7,0] or Media[-1,1], the coefficient of attention in our multivariate regressions with post-announcement drift as the dependent variable is negative and significant. These results are consistent with our hypothesis $\mathbf{H_3}$.

Since the importance of patents varies significantly across different technological categories, we expect a stronger role of attention in those categories where patents matter more. To test this hypothesis, we classify patents into six technology categories following Hall, Jaffe, and Trajtenberg (2001). Specifically, we first aggregate the 400 three-digit technology classes (assigned by the USPTO) into 36 two-digit technological sub-categories. We then further aggregate these into 6 main technology categories: Chemicals (excluding Drugs); Computers and Communications (C&C); Drugs and Medical (D&M); Electrical and Electronics (E&E); Mechanical; and Others.

The results presented in Table 5 support the hypothesis above. Our multivariate regressions with the announcement effect as the dependent variable (Panel A) show that the coefficient of attention is positive across all technological categories, although the coefficient is statistically significant only for four categories: Computers, Drugs, Electronics, and Others. This is again consistent with our hypothesis $\mathbf{H_2}$. Turning now to the post-announcement drift (Panel B), our multivariate regressions show that the coefficient of attention is negative and significant across all technology categories, though it is statistically significant only for Computers and Electronics. This is again consistent with our hypothesis $\mathbf{H_3}$. Overall, our empirical analysis within major technology categories suggests that, while attention is an important determinant of the stock market reaction to innovation announcements across all technology categories, it is particularly important in two categories: Computers and Electronics.

6.4 The predictive power of the stock return drift following patent grant announcements for firm profitability, productivity, and growth

Economists have linked innovation activities to productivity and economic growth as early as Schumpeter (1942), both theoretically and empirically. For example, Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992) model innovation as a crucial factor that increase future productivity and growth. In addition, corporate finance theory also models innovation as a growth option that can improve firms' future profitability. Empirical studies link innovation activities to the stock market (e.g., Pakes (1985), Austin (1993), Hall, Jaffe, and Trajtenberg (2005), and Kogan, Papanikolaou, Seru, and Stoffman (2017)). In particular, Kogan et al. (2017) develop a new measure of the economic value of corporate innovation based on the three-day stock market response to patent grant announcements. To validate this measure of patent value, they show that this measure is positively and significantly related to firms' future profitability, productivity, growth, and future citations received by firms' patents.

Our analyses above show that the announcement effect during the three-day event window may not fully capture the economic value of patents since some investors may not pay attention to patent grant announcements within the three-day event window due to limited attention. As we show above, there is a significant stock return drift over the one month after the patent grant date. This evidence suggests that it takes more than three days for the market to fully react to patent grant announcements.

Therefore, we conjecture that both the announcement effect and the post-announcement drift convey useful information about the economic value of a patent, and we expect both to predict significantly higher productivity, productivity, and growth ($\mathbf{H_4}$). To test this hypothesis, we first create a measure of the announcement effect and the stock return drift for a firm in year t by summing all the CAR[-1, 1] and CAR[2, 22], respectively, for patents granted to the firm from the beginning of December of year $t-1$ to the end of November of year t. We end the observation in November to make sure that the drift period does not overlap with the next calendar year. We then conduct panel regressions of next year's profitability, productivity, and firm growth on the announcement effect, stock return drift, and other control variables. All dependent variables are measured in year $t+1$, and independent variables are measured in year t. All variables are winsorized at 1% and 99% level to reduce the effect of outliers.

Specifically, we measure profitability by ROA or OIBDA, where ROA is the sum of income (ib) and depreciation (dp) divided by lagged assets and OIBDA is the sum of operating income before depreciation (oibdp) and interest income (tii) divided by lagged assets. We measure productivity by total factor productivity (TFP) or assets turnover (sales/assets). TFP is constructed as in Olley and Pakes (1996) and İmrohoroğlu and Tüzel (2014). We measure firm growth by the growth rate in four aspects: gross profit computed as sales (sale) minus cost of goods sold (cogs); output computed as sales plus change in inventory (invt); firm capital stock computed as the total (gross) property, plant, and equipment (ppegt); and labor as employees (emp). We also control for other firm characteristics, such as Tobin's Q defined as market-to-book assets, year-end market capitalization (ME), capital expenditure (capx) scaled by lagged assets, R&D expenditure (xrd) scaled by lagged assets, and advertisement expenditure (xad) scaled by lagged assets.[27]

We report the results in Table 6. Consistent with Kogan et al. (2017), the economic value of patents measured by the three-day announcement effect generally predicts significantly higher profitability, productivity, and growth. More importantly, we find an even more robust pattern with respect to the post-announcement stock return drift, as we conjecture in our hypothesis $\mathbf{H_4}$. The coefficient of the drift is statistically significant for all the eight outcome variables. Moreover, the economic magnitude of the coefficients on the drift are comparable with that of the coefficients on the announcement effect. This illustrates the importance of taking into account the effect of stock return drift in creating measures of patent value based on the stock market reaction to patent grant announcements.

Overall, the evidence we present in this section is consistent with our hypothesis $\mathbf{H_4}$, suggesting that the post-announcement stock return drift following patent grant announcements provides a measure of the economic value of the patent, over and above the economic value reflected in the announcement effect of patent grant announcements.

6.5 A profitable trading strategy based on investor attention to patent grant announcements

The evidence above collectively suggests that the stock market tends to underreact to innovation announcements, especially when there is still significant technical uncertainty to be resolved (such as in the case of patent grant announcements) so that investor attention is low. Therefore, we next examine whether there exists a profitable trading strategy based on our empirical analyses presented above.

Following the literature on anomalies, we present a trading strategy based on investor attention to patent grant announcements using our general patent sample. The analysis is conducted at the firm level. Specifically, we form portfolios based on a variable that captures the average investor attention to the announcements of patents granted to a firm in a given month, named as attention

[27] In Tobin's Q, the market value of assets is computed as total assets plus market capitalization (prcc_f multiplied by csho) minus common equity (ceq) minus deferred taxes (txdb).

per patent (ATTP). At the end of each month, we first compute ATTP for each firm as the ratio of the aggregate number of news articles mentioning a firm during a three-day window around various patent grant dates divided by the number of patents granted to this firm in a month. We then form three portfolios based on the 30th and 70th percentiles of ATTP among firms with non-zero ATTP. Firms with ATTP below (above) the 30th percentile are included in the Low (High) ATTP portfolio. We also construct a low-minus-high (Low-High) portfolio by holding a long (short) position in the low (high) ATTP portfolio. We then hold these portfolios over the next month and rebalance them each month.[28] Panels A and B of Table 7 report the average and median ATTP and firm size (in millions) for these three portfolios. Panel C reports their average monthly returns in excess of one-month Treasury bill rate (Exret) as well as their average monthly industry-adjusted returns. The portfolio industry-adjusted returns (Ind-adjret) are based on the difference between individual firms returns and the returns of firms in the same industry (based on the Fama-French 48 industry classifications). In Panels D and E, we report the alphas and R^2 from the regression of the time-series of portfolio excess returns on various factor models: the Fama and French (2015) five-factor model (the market factor, the size factor, the value factor, the robust-minus-weak factor, and the conservative-minus-aggressive factor) and the investment-based factor model (q-factor model) of Hou, Xue, and Zhang (2015). All returns and alphas are value-weighted. The t-statistics are reported in parentheses. The sample is from 2000 to 2014.

On average, there are 186 firms in the "Low" ATTP group, 131 firms in the "Middle" ATTP group, and 124 firms in the "High" ATTP group. The mean (median) ATTP ranges from 0.111 (0.134) to 6.554 (4.876) for the three ATTP portfolios. The mean (median) size of the low, middle, and high ATTP portfolios are $2,627 million ($682 million), $8,167 million ($2,628 million), and $39,198 million ($12,386 million), respectively. The excess returns, industry-adjusted returns, and alphas from different factor models decrease monotonically with ATTP. Furthermore, this effect is economically and statistically significant. The monthly value-weighted return of the hedge portfolio is 0.49% ($t = 2.50$). The industry-adjusted return and alphas are also economically and statistically significant, ranging from 0.24% to 0.40% per month. Furthermore, these results are mainly driven by the low ATTP portfolio. Overall, these results suggest that exploiting investor's inattention to innovation events can be profitable, thus providing evidence consistent with our hypothesis $\mathbf{H_5}$.

[28] We neglect the trading cost associated with these monthly rebalanced portfolios in our analysis.

7 Conclusion

We analyze, theoretically and empirically, the effect of investor attention on the stock market reaction to innovation announcements and suggest how market-based measures of the economic value of patents can be improved. We first develop a dynamic model with limited investor attention to analyze how differences in investor attention across different types of innovation announcements affect the stock market response to these announcements. We establish that, in addition to an announcement effect (abnormal stock return upon announcement), innovation announcements will be followed by a stock return drift. Further, while the announcement effect of an innovation announcement will be increasing in investor attention, the post-announcement drift will be decreasing in investor attention. We then empirically test these hypotheses using two different datasets: first, a matched sample of patent grant announcements from the biopharmaceutical industry and subsequent FDA drug approval announcements; and second, a dataset containing the universe of patent grant announcements from the USPTO. We use the media coverage received by the innovating firm around various innovation announcements as proxies for the investor attention paid to them.

Our findings may be summarized as follows. First, using our matched patent-drug sample from the biopharmaceutical industry, we find that the abnormal stock returns upon patent grant announcements are smaller than those upon FDA drug approval announcements; the subsequent stock return drifts, however, are larger for patent grant announcements compared to the corresponding FDA drug approval announcements. Second, regardless of whether we use the matched patent grant and drug approval sample from the biopharmaceutical industry or the general sample of all patent grants from the USPTO, we show that the announcement effect of patent grant announcements is increasing in the investor attention paid to these announcements while the subsequent stock return drift is decreasing in this investor attention. We establish that the stock-return drift following patent grant announcements has predictive power for the economic value of patents for the patenting firm, over and above any information contained in their announcement effect. Finally, we show that a long-short portfolio using investor attention is profitable over the month after patent grant announcements in our general patent sample. Overall, we show, theoretically and empirically, that incorporating the effects of investor attention to patent grant announcements into a stock market-based measure of the economic value of patents granted to firms would considerably enhance the predictive power of such a measure for the future performance of the firms to which these patents are granted.

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Appendices

A Proof of Propositions

A.1 List of Constants in Propositions and Proofs

$$
\begin{aligned}
A_a &= f^a \sigma_2^{-2}(1+\rho^{-2}\sigma_2^{-2}\sigma_x^{-2}) > 0 && \text{(A.1)}\\
A_u &= f^u \sigma_2^{-2}[\sigma_{e,1}^{-2}\sigma_0^2 + (1+\frac{1}{2}\rho^{-2}\sigma_2^{-2}\sigma_x^{-2})^{-1}]^{-1} > 0 && \text{(A.2)}\\
B_0 &= (A_a+A_u)^{-1}[A_a\sigma_2^2 + f^u + \frac{1}{2}A_u\rho^{-2}\sigma_x^{-2}(1+\frac{1}{2}\rho^{-2}\sigma_2^{-2}\sigma_x^{-2})^{-1}] > 0 && \text{(A.3)}\\
B_1 &= (A_a+A_u)^{-1}(A_a\sigma_2^2 + f^u) > 0 && \text{(A.4)}\\
E &= \frac{A_a}{f^a}(\frac{A_u}{A_a+A_u})^2 + \sigma_0^{-2}(\sigma_1^a)^{-2}\sigma_{e,1}^2 > 0 && \text{(A.5)}\\
F &= \frac{A_a}{f^a}(B_1-\sigma_2^2)^2 + \rho^{-2}\sigma_x^{-2} + (2B_1-\sigma_2^2) - \frac{1}{E}(\frac{A_u}{A_a+A_u})^2[\frac{A_a}{f^a}(B_1-\sigma_2^2)+1]^2 && \text{(A.6)}\\
G &= (f^a)^{-1}\frac{A_a}{A_a+A_u}\frac{A_u}{A_a+A_u} + B_1\sigma_0^{-2}(\sigma_1^a)^{-2}\sigma_{e,1}^2 > 0 && \text{(A.7)}\\
H &= \sigma_0^{-2}(\sigma_1^a)^{-2}\sigma_{e,1}^2[(\sigma_2^2 - B_0 - B_1) - \frac{A_a}{f^a}(B_0-\sigma_2^2)(B_1-\sigma_2^2)] \\
&\quad +(\frac{A_u}{A_a+A_u})^2(1-\frac{A_a}{f^a}\sigma_2^2) && \text{(A.8)}\\
I &= \frac{1}{2}\frac{A_u}{f^u}\rho^{-2}\sigma_x^{-2}(1+\frac{1}{2}\rho^{-2}\sigma_2^{-2}\sigma_x^{-2})^{-1} > 0 && \text{(A.9)}\\
J &= B_0 - \sigma_2^2[1-(1+\frac{1}{2}\rho^{-2}\sigma_2^{-2}\sigma_x^{-2})^{-1}] && \text{(A.10)}\\
K &= \frac{A_u}{f^u}(\frac{A_a}{A_a+A_u})^2 + \sigma_0^{-2}(\sigma_1^a)^{-2}\sigma_{e,1}^2 > 0 && \text{(A.11)}\\
L &= \frac{A_u}{f^u}B_1^2\sigma_0^{-2}(\sigma_1^a)^{-2}\sigma_{e,1}^2 + K\rho^{-2}\sigma_x^{-2} > 0 && \text{(A.12)}\\
M &= (\frac{A_a}{A_a+A_u})^2\rho^{-2}\sigma_x^{-2} + B_1^2\sigma_0^{-2}(\sigma_1^a)^{-2}\sigma_{e,1}^2 > 0 && \text{(A.13)}\\
P_a &= f^a[\frac{G^2}{EF} + (\frac{A_a}{A_a+A_u})^2]^{-1}E && \text{(A.14)}\\
P_u &= f^u\frac{L}{M} > 0 && \text{(A.15)}\\
Q_a &= f^a[\frac{G^2}{EF} + (\frac{A_a}{A_a+A_u})^2]^{-1}\{EB_0 + \frac{GH}{EF} + \frac{A_aA_u}{(A_a+A_u)^2}[\frac{A_a}{f^a}(B_0-\sigma_2^2)+1]\} && \text{(A.16)}\\
Q_u &= f^u(\frac{L}{M}B_0 - \frac{A_u}{f^u}J) && \text{(A.17)}
\end{aligned}
$$

$$R = \frac{\sigma_{e,1}^2}{\sigma_{e,3}^2}\frac{\sigma_3^2}{\sigma_2^2}\frac{\sqrt{\sigma_0^2+\sigma_{e,3}^2}}{\sqrt{\sigma_0^2+\sigma_{e,1}^2}} - \frac{\sigma_3^2}{\sigma_{e,3}^2} \quad (A.18)$$

A.2 Proof of Propositions

Proof of Proposition 1. For each investor j of type $i \in \{a, u\}$, his/her utility maximization problem (UMP) is solved backwards from $t = 3$ to $t = 0$, although his/her belief on the random component z of the terminal payoff f is updated forward as explained in Section 4.1.

At $t = 3$, an investor of type i solves the utility maximization problem

$$\max_{D_3^i} E_3^i[-\exp(-\rho W_4^i)], \text{ where } W_4^i = W_3^i + D_3^i(f - S_3) = W_3^i + D_3^i(\mu + z - S_3) \quad (A.19)$$

The only random component here is z, which follows normal distribution as shown in (8), hence the above expected utility is

$$E_3^i[-\exp(-\rho W_4^i)] = -\exp\{-\rho[W_3^i + D_3^i(\mu + \hat{z}_3 - S_3)] + \frac{\rho^2}{2}(D_3^i)^2\sigma_3^2\}, \quad (A.20)$$

Differentiate with respect to D_3^i, and solve for D_3^i, we get the optimal demand of a type-i investor as

$$D_3^i = \rho^{-1}\sigma_3^{-2}(\mu + \hat{z}_3 - S_3). \quad (A.21)$$

To clear the markets, $\sum_{i=a,u} D_3^i = \bar{x} + x_1 + x_2 + x_3$, since the total mass of investors is 1, we have the market clearing condition as

$$\bar{x} + x_1 + x_2 + x_3 = \rho^{-1}\sigma_3^{-2}(\mu + \hat{z}_3 - S_3), \quad (A.22)$$

and consequently the equilibrium asset price at $t = 3$ is

$$S_3 = \mu + \hat{z}_3 - \rho\sigma_3^2(\bar{x} + x_1 + x_2 + x_3) \quad (A.23)$$

The value function (optimized utility function) at $t = 3$ is therefore:

$$E_3^i[-\exp(-\rho W_4^i)] = -\exp\{-\rho[W_2^i + D_2^i(\mu + \hat{z}_3 - \rho\sigma_3^2(\bar{x} + x_1 + x_2 + x_3) - S_2)]$$

$$-\frac{\rho^2}{2}\sigma_3^2(\bar{x}+x_1+x_2+x_3)^2\} \tag{A.24}$$

At $t=2$, an investor of type i solves the utility maximization problem $\max_{D_2^i} E_2^i[-\exp(-\rho W_4^i)]$, which, continuing from (A.24), is equivalent to

$$\max_{D_2^i} E_2^i[-\exp\{-\rho[W_2^i+D_2^i(\mu+\hat{z}_3-\rho\sigma_3^2(\bar{x}+x_1+x_2+x_3)-S_2)]-\frac{\rho^2}{2}\sigma_3^2(\bar{x}+x_1+x_2+x_3)^2\}] \tag{A.25}$$

In the above UMP, there are two independent random variables, one is $\hat{z}_3$, the other is x_3, conditional on the information set $\mathcal{F}_2=\{e_1\}$ for all investors. We calculate the expectations w.r.t. these two random variables one after another. The expectation with respect to $\hat{z}_3|_{\mathcal{F}_2} \sim N(\hat{z}_2,\sigma_2^2-\sigma_3^2)$ follows the standard procedure of calculating the expectation of a log-normal random variable, i.e. conditional on both the information set $\mathcal{F}_2$ and the supply shock x_3, the expected utility is[29]

$$E_{2,x_3}^i[-\exp(-\rho W_4^i)] \tag{A.26}$$

$$=E_{2,x_3}^i[-\exp\{-\rho[W_2^i+D_2^i(\mu+\hat{z}_2-\rho\sigma_3^2(\bar{x}+x_1+x_2+x_3)-S_2)] \tag{A.27}$$

$$-\frac{\rho^2}{2}\sigma_3^2(\bar{x}+x_1+x_2+x_3)^2+\frac{\rho^2}{2}(D_2^i)^2(\sigma_2^2-\sigma_3^2)\}] \tag{A.28}$$

Moving further from $E_{2,x_3}^i[\cdot]$ to $E_2^i[\cdot]$, we follow the more general procedure to calculate an expectation w.r.t. a random variable, i.e. multiply the function by the density function of the random variable and then integrate w.r.t. the random variable:

$$\begin{aligned}
&E_2^i[-\exp(-\rho W_4^i)]\\
\propto &\int_{\mathcal{R}} -\exp\{-\rho[W_2^i+D_2^i(\mu+\hat{z}_2-\rho\sigma_3^2(\bar{x}+x_1+x_2+x_3)-S_2)]\\
&\quad -\frac{\rho^2}{2}\sigma_3^2(\bar{x}+x_1+x_2+x_3)^2+\frac{\rho^2}{2}(D_2^i)^2(\sigma_2^2-\sigma_3^2)-\frac{1}{2}\sigma_x^{-2}x_3^2\}dx_3\\
\propto &-\exp\{-\rho[W_2^i+D_2^i(\mu+\hat{z}_2-\rho\sigma_3^2(\bar{x}+x_1+x_2)-S_2)]
\end{aligned}$$

[29]The conditional distribution of $\hat{z}_3$ is normal, with conditional expectation and conditional variation calculated as:

$$\begin{aligned}
E_2^i[\hat{z}_3] &= E_2^i[E_3^i(z)]=E_2^i[z]=\hat{z}_2\\
V_2^i[\hat{z}_3] &= V_2^i[E_3^i(z)]=V_2^i(z)-E_2^i[V_3^i(z)]=\sigma_2^2-\sigma_3^2
\end{aligned}$$

$$- \frac{\rho^2}{2}\sigma_3^2(\bar{x} + x_1 + x_2)^2 + \frac{\rho^2}{2}(D_2^i)^2(\sigma_2^2 - \sigma_3^2)$$
$$+ \frac{1}{2}\rho^2\sigma_3^2(1 + \rho^{-2}\sigma_3^{-2}\sigma_x^{-2})^{-1}[D_2^i - (\bar{x} + x_1 + x_2)]^2\}$$

Differentiate w.r.t. D_2^i and solve for D_2^i, then we get the optimal demand of a type-i investor as

$$D_2^i = \rho^{-1}\sigma_2^{-2}\frac{1 + \rho^{-2}\sigma_3^{-2}\sigma_x^{-2}}{1 + \rho^{-2}\sigma_{e,3}^{-2}\sigma_x^{-2}}(\mu + \hat{z}_2 - S_2) - \frac{\rho^{-2}\sigma_2^{-2}\sigma_x^{-2}}{1 + \rho^{-2}\sigma_{e,3}^{-2}\sigma_x^{-2}}(\bar{x} + x_1 + x_2) \tag{A.29}$$

To clear the markets, $\sum_{i=a,u} D_2^i = \bar{x} + x_1 + x_2$, since the total mass of investors is 1, we have the market clearing condition as

$$\bar{x} + x_1 + x_2 = \rho^{-1}\sigma_2^{-2}\frac{1 + \rho^{-2}\sigma_3^{-2}\sigma_x^{-2}}{1 + \rho^{-2}\sigma_{e,3}^{-2}\sigma_x^{-2}}(\mu + \hat{z}_2 - S_2) - \frac{\rho^{-2}\sigma_2^{-2}\sigma_x^{-2}}{1 + \rho^{-2}\sigma_{e,3}^{-2}\sigma_x^{-2}}(\bar{x} + x_1 + x_2), \tag{A.30}$$

and consequently the equilibrium asset price at $t = 2$ is

$$S_2 = \mu + \hat{z}_2 - \rho\sigma_2^2(\bar{x} + x_1 + x_2) \tag{A.31}$$

The value function (optimized utility function) at $t = 2$ is therefore:

$$E_2^i[-\exp(-\rho W_4^i)]$$
$$\propto -\exp\{-\rho[W_1^i + D_1^i(\mu + \hat{z}_2 - \rho\sigma_2^2(\bar{x} + x_1 + x_2) - S_1)] - \frac{\rho^2}{2}\sigma_2^2(\bar{x} + x_1 + x_2)^2\} \tag{A.32}$$

At $t = 1$, the two groups of investors behave differently: attentive investors pay attention to the announcement e_1 but inattentive investors do not.

Type-a investors. Attentive investors update their beliefs to $\hat{z}_1^a = \hat{z}_2$ upon announcement e_1 immediately. Since they rationally expect the structure of the equilibrium price S_1, they are able to back out the supply shock x_1 once they observe S_1. Continuing from (A.32), the expected CARA utility on terminal wealth for an attentive investor is

$$E_1^a[-\exp(-\rho W_4^a)]$$
$$\propto \int_{\mathcal{R}} -\exp\{-\rho[W_1^a + D_1^a(\mu + \hat{z}_1^a - \rho\sigma_2^2(\bar{x} + x_1 + x_2) - S_1)] - \frac{\rho^2}{2}\sigma_2^2(\bar{x} + x_1 + x_2)^2\}$$

$$
\begin{aligned}
&\cdot \exp(-\frac{1}{2}\sigma_x^{-2}x_2^2)dx_2 \\
&\propto -\exp\{-\rho[W_1^a + D_1^a(\mu + \hat{z}_1^a - \rho\sigma_2^2(\bar{x} + x_1) - S_1)] - \frac{\rho^2}{2}\sigma_2^2(\bar{x} + x_1)^2 \\
&\quad + \frac{1}{2}\rho^2\sigma_2^2(1 + \rho^{-2}\sigma_2^{-2}\sigma_x^{-2})^{-1}[D_1^a - (\bar{x} + x_1)]^2\}
\end{aligned} \tag{A.33}
$$

Differentiate with respect to D_1^a, set the derivative to zero, and we obtain the optimal demand by an attentive investor as

$$
D_1^a = \rho^{-1}\frac{A_a}{f^a}(\mu + \hat{z}_1^a - S_1) - (\frac{A_a}{f^a}\sigma_2^2 - 1)(\bar{x} + x_1) \tag{A.34}
$$

Type-u investors. Inattentive investors do not update their beliefs immediately upon announcement e_1 and remain with their prior belief on $z \sim N(0, \sigma_0^2)$. Since they do not hold the correct posterior belief $\hat{z}_1^a$ as attentive investors do, they are not able to back out the contemporaneous supply shock x_1 even though they know the linear structure of the equilibrium price. Continuing from (A.32), the expected CARA utility on terminal wealth for an attentive investor is

$$
\begin{aligned}
&E_1^u[-\exp(-\rho W_4^u)] \\
&\propto -\exp\{-\rho[W_1^u + D_1^u(\mu - \rho\sigma_2^2\bar{x} - S_1)] + \frac{\rho^2}{2}\sigma_2^2\sigma_{e,1}^{-2}\sigma_0^2(D_1^u)^2 \\
&\quad + \frac{\rho^2}{2}\sigma_2^2(1 + \frac{1}{2}\rho^{-2}\sigma_2^{-2}\sigma_x^{-2})^{-1}(D_1^u - \bar{x})^2\}
\end{aligned} \tag{A.35}
$$

Differentiate with respect to D_1^u, set the derivative to zero, and we obtain the optimal demand by an attentive investor as

$$
D_1^u = \rho^{-1}\frac{A_u}{f^u}(\mu - S_1) - \frac{\frac{1}{2}\rho^{-2}\sigma_x^{-2}}{1 + \frac{1}{2}\rho^{-2}\sigma_x^{-2}}\frac{A_u}{f^u}\bar{x} \tag{A.36}
$$

To clear the markets, $\sum_{i=a,u} D_1^i = f^a D_1^a + f^u D_1^u = \bar{x} + x_1$. Applying (A.34) and (A.36) to the previous equation, we have

$$
S_1 = \mu + \frac{A_a}{A_a + A_u}\hat{z}_1^a - \rho(B_0\bar{x} + B_1 x_1) \tag{A.37}
$$

At $t = 0$, both groups of investors hold the same prior belief on $z \sim N(0, \sigma_0^2)$. However, because attentive investors and inattentive investors will not have the same posterior belief at $t = 1$, their expectation on the expected return of the stock and the equilibrium price at $t = 1$ and hence their optimal demands of the stock at $t = 0$ are different.

Type-a investors. The calculation of expected utility at $t = 0$ is similar in essence to that at $t = 1$, i.e. plug (A.34) and (A.37) into (A.33) to obtain the value function for a representative type-a investor and then integrate the product of the value function with the density functions of $\hat{z}_1^a$ and x_1 with respect to both $\hat{z}_1^a$ and x_1, and we finally get

$$
\begin{aligned}
&E_0^a[-\exp(-\rho W_4^a)] \\
&\propto -\exp\{-\rho W_0 - \rho D_0^a(\mu - \rho B_0\bar{x} - S_0) + \frac{\rho^2}{2E^2F}(GD_0^a + H\bar{x})^2 \\
&\quad + \frac{\rho^2}{2E}[\frac{A_a}{A_a + A_u}D_0^a + \frac{A_u}{A_a + A_u}(\frac{A_a}{f^a}(B_0 - \sigma_2^2) + 1)\bar{x}]^2\}
\end{aligned}
$$

Differentiate with respect to D_0^a, set the derivative to zero, and we obtain the optimal demand by an attentive investor as

$$D_0^a = \rho^{-1}\frac{P_a}{f^a}(\mu - S_0) - \frac{Q_a}{f^a}\bar{x} \tag{A.38}$$

Type-u investors. The calculation of expected utility at $t = 0$ is similar in essence to that at $t = 1$, i.e. plug (A.36) and (A.37) into (A.35) to obtain the value function for a representative type-u investor and then integrate the product of the value function with the density functions of $\hat{z}_1^a$ and x_1 with respect to both $\hat{z}_1^a$ and x_1, and we finally get

$$
\begin{aligned}
&E_0^u[-\exp(-\rho W_4^u)] \\
&\propto -\exp\{-\rho W_0 - \rho D_0^u(\mu - \rho B_0\bar{x} - S_0) + \frac{\rho^2}{2K}(\frac{A_a}{A_a + A_u})^2(D_0^u - \frac{A_u}{f^u}J\bar{x})^2 \\
&\quad + \frac{\rho^2}{2KL}[(\sigma_1^a)^{-2}\sigma_0^{-2}\sigma_{e,1}^2 B_1]^2(D_0^u - \frac{A_u}{f^u}J\bar{x})^2\}
\end{aligned}
$$

Differentiate with respect to D_0^u, set the derivative to zero, and we obtain the optimal demand by an attentive investor as

$$D_0^u = \rho^{-1}\frac{P_u}{f^u}(\mu - S_0) - \frac{Q_u}{f^u}\bar{x} \tag{A.39}$$

To clear the markets, $\sum_{i=a,u} D_0^i = f^a D_0^a + f^u D_0^u = \bar{x}$. Applying (A.38) and (A.39) to the previous equation, we have

$$S_0 = \mu - \rho \frac{Q_a + Q_u + 1}{P_a + P_u} \bar{x} \tag{A.40}$$

This completes the proof for Proposition 1.

Proof of Proposition 2. The calculation of (20) is straightforward by taking the difference between (10) and (11) and then setting all the $\bar{x}$ and x_t terms to zero, i.e.,

$$(S_3 - S_2)|_{\bar{x}=x_1=x_2=x_3=0} = \sigma_3^2 \sigma_{e,3}^{-2} e_3 + (\sigma_3^2 - \sigma_2^2)\sigma_{e,1}^{-2} e_1. \tag{A.41}$$

AE_3 denotes the right hand side of the above equation and is independent of f^a and f^u. Notice that the coefficient of e_3, $\sigma_3^2 \sigma_{e,3}^{-2}$, is a quotient of variances and hence it is positive. Therefore, AE_3 increases with e_3 when $e_3 > 0$.

Proof of Proposition 3.

(i) The calculation of (22) is straightforward by taking the difference between (12) and (13) and then setting both $\bar{x}$ and x_1 to zero, i.e.,

$$(S_1 - S_0)|_{\bar{x}=x_1=0} = \frac{A_a}{A_a + A_u} (\sigma_1^a)^2 \sigma_{e,1}^{-2} e_1. \tag{A.42}$$

AE_1 denotes the right hand side of the above equation. Because both A_a and A_u are positive, the coefficient of e_1 is then positive, and therefore AE_1 increases with e_1 when $e_1 > 0$.

(ii) We calculate the partial derivative of AE_1 with respect to f^a, applying the relation that $f^u = 1 - f^a$,

$$\frac{\partial AE_1}{\partial f^a} = \frac{A_a A_u}{f^a f^u (A_a + A_u)^2} (\sigma_1^a)^2 \sigma_{e,1}^{-2} e_1. \tag{A.43}$$

Since all components of the coefficient of e_1 are positive, the above partial derivative is positive for any $e_1 > 0$.

This completes the proof of Proposition 3.

Proof of Proposition 4.

(i) The calculation of (26) is by taking the difference between (11) and (12), noticing that $\hat{z}_1^a = \hat{z}_2$, and then setting all the $\bar{x}$ and x_t terms to zero, i.e.,

$$(S_2 - S_1)|_{\bar{x}=x_1=x_2=0} = \frac{A_u}{A_a + A_u}\sigma_2^2\sigma_{e,1}^{-2}e_1. \tag{A.44}$$

$Drift_2$ denotes the right hand side of the above equation. The coefficient of e_1 above is positive since both A_a and A_u are positive, hence $Drift_2$ has the same sign as e_1 (i.e. proportional to e_1).

(ii) We take the partial derivative of $Drift_2$ with respect to f^a, applying the relation that $f^u = 1 - f^a$,

$$\frac{\partial Drift_2}{\partial f^a} = -\frac{A_a A_u}{f^a f^u (A_a + A_u)^2}\sigma_2^2\sigma_{e,1}^{-2}e_1. \tag{A.45}$$

Since all of A_a, A_u, f^a, and f^u are positive, the partial derivative above has an opposite sign as e_1.

This completes the proof of Proposition 4.

Proof of Proposition 5. For any $t \in \{1, 3\}$, the conditional expectation of $e_t \sim N(0, \sigma_0^2 + \sigma_{e,t}^2)$ is calculated as follows:[30]

$$\begin{aligned} E[e_t|e_t > 0] &= \frac{1}{P(e_t > 0)}\int_{\mathbb{R}^+} x p_{e_t}(x)dx \\ &= 2\int_{\mathbb{R}^+} \frac{x}{\sqrt{2\pi(\sigma_0^2 + \sigma_{e,t}^2)}}\exp[-\frac{x^2}{2(\sigma_0^2 + \sigma_{e,t}^2)}]dx \\ &= \sqrt{\frac{2}{\pi}}\sqrt{\sigma_0^2 + \sigma_{e,t}^2} \end{aligned} \tag{A.46}$$

[30]Rigorously, for any given firm, $e_1 = z + \epsilon_{e,1}$ and $e_3 = z + \epsilon_{e,3}$ are connected by the fundamental value z (which is also a random variable) of the firm and thus not independent of each other. However, notice that the inequality we are showing consists of a linear combination of e_1 and e_3, and by the law of total expectation (also called "the law of iterated expectations"),

$$E[e_t|e_t > 0] = E[E[e_t|e_t > 0, z = z_0]|e_t > 0], \text{ for } t = 1, 3,$$

it is equivalent to treat e_1 and e_3 as mutually independent in our calculation here.

Thus, (30) is equivalent to

$$\frac{A_a}{A_a + A_u}(\sigma_1^a)^2\sigma_{e,1}^{-2}\sqrt{\frac{2}{\pi}}\sqrt{\sigma_0^2 + \sigma_{e,1}^2} < \sigma_3^2\sigma_{e,3}^{-2}\sqrt{\frac{2}{\pi}}\sqrt{\sigma_0^2 + \sigma_{e,3}^2} + (\sigma_3^2 - \sigma_2^2)\sigma_{e,1}^{-2}\sqrt{\frac{2}{\pi}}\sqrt{\sigma_0^2 + \sigma_{e,1}^2}, \quad \text{(A.47)}$$

which is further equivalent to

$$\frac{f^u}{f^a} > \frac{1-R}{R}(1 + \rho^{-2}\sigma_2^{-2}\sigma_x^{-2})[\sigma_{e,1}^{-2}\sigma_0^2 + (1 + \frac{1}{2}\rho^{-2}\sigma_2^{-2}\sigma_x^{-2})^{-1}] \quad \text{(A.48)}$$

assuming $R > 0$, where the constant R is as defined in Appendix A.1 and we will show next that $R > 0$. In fact, the condition

$$R = \frac{\sigma_{e,1}^2}{\sigma_{e,3}^2}\frac{\sigma_3^2}{\sigma_2^2}\frac{\sqrt{\sigma_0^2 + \sigma_{e,3}^2}}{\sqrt{\sigma_0^2 + \sigma_{e,1}^2}} - \frac{\sigma_3^2}{\sigma_{e,3}^2} > 0 \quad \text{(A.49)}$$

is equivalent to

$$1 + \sigma_{e,3}^2\sigma_0^{-2} + \sigma_{e,3}^2\sigma_{e,1}^{-2} > 0, \quad \text{(A.50)}$$

which trivially holds.

This completes the proof of Proposition 5.

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Table 1

Summary statistics

This table reports summary statistics for the paired drug-related patent grant sample (Panel A), the paired drug approval sample (Panel B), the extended drug-related patent grant sample (Panel C), the extended drug approval sample (Panel D), and the general patent grant sample (Panel E). The paired drug approval (patent grant) sample only includes those drug approval announcements (patent grant announcements) for which we can match an approved drug with its key product patent from Medtrack. In addition, we also require the event firms to be public on the event day. The paired drug approval sample consists of 117 drug approval events from May 1991 to December 2016, and the paired patent grant sample consists of 117 patent grant events from December 1986 to June 2014. The extended patent grant (drug approval) sample relaxes the requirement of identifying matched drug approval (patent grant) announcements. The extended patent grant sample consists of 733 patents granted from December 1986 to July 2014. The extended drug approval sample consists of 573 drugs approved from July 1966 to December 2016. The general patent grant sample also requires the event firms to be public on the grant date and is from January 2000 to August 2014. The abnormal return (AR) is estimated relative to the Fama-French (1992) three-factor model using a twelve-month estimation window that ends 30 trading days before the event day and has a minimum of 100 valid daily returns. CAR[-1, 1] is the cumulative abnormal return (in percentage) over the three trading days around the event date (0). CAR[2, 22] is the cumulative abnormal return (in percentage) over the 21 trading days following the event. If a firm has multiple events in the same day, we scale the CARs by the number of events during the same day. For each event occurring in year *t*, BM is the book value of equity in fiscal year ending in calendar year *t*-1 divided by the market value of equity at the end of year *t*-1. ME is the market value of equity at the end of year *t*-1. ROA is income before extraordinary items (Compustat item IB) divided by the book value of total assets (Compustat item AT) in fiscal year ending in calendar year *t*-1. Patent originality is measured as the Herfindahl index of the patents cited by the focal patent across three-digit technology classes assigned by the USPTO following Hall, Jaffee, Trajtenberg (2001). Media [-7, 0] is the number of news articles that mention the event firm over the week before the event. Media [-1, 1] is the number of news articles that mention the event firm over the three-day window around the event. The media coverage data start from year 2000. For each variable, we report the number of observations (Obs.), mean, standard deviation (SD), minimum (Min), and maximum (Max). All statistics are computed after winsorization at the 1% and 99% levels for each sample.

Panel A. Paired drug-related patent grant sample	Obs.	Mean	Std. Dev	Min	Max
CAR[-1,1]	117	0.97	5.42	-11.71	25.88
CAR[2,22]	117	2.10	12.20	-31.19	47.84
Log(1+BM)	113	0.44	0.68	-0.12	3.13
Log(ME)	114	8.74	2.24	2.85	12.41
ROA	113	-0.03	0.38	-1.71	0.32
Patent originality	117	0.45	0.32	0.00	1.00
Media [-7,0]	47	7.30	9.39	0.00	49.00
Media [-1,1]	47	2.91	3.41	0.00	12.00
Pane B. Paired drug approval sample	Obs.	Mean	Std. Dev	Min	Max
CAR[-1,1]	117	1.69	5.92	-13.53	26.74
CAR[2,22]	117	0.32	7.82	-16.88	23.48
Log(1+BM)	109	0.41	0.58	-0.04	2.27
Log(ME)	110	9.76	1.99	4.65	12.48
ROA	113	0.07	0.30	-1.26	0.58
Media [-7,0]	88	10.27	9.67	0.00	52.00
Media [-1,1]	88	6.49	6.38	0.00	41.00
Panel C. Extended drug-related patent grant sample	Obs.	Mean	Std. Dev	Min	Max
CAR[-1,1]	733	0.22	5.11	-35.07	52.38
CAR[2,22]	733	1.56	12.90	-46.77	92.92
Log(1+BM)	699	0.48	0.65	-0.15	2.85
Log(ME)	701	8.64	2.47	2.62	12.44
ROA	710	-0.02	0.32	-1.26	0.39
Patent originality	733	0.46	0.32	0.00	1.00
Media [-7,0]	522	7.39	9.00	0.00	77.00
Media [-1,1]	522	3.24	4.41	0.00	42.00
Pane D. Extended drug approval sample	Obs.	Mean	Std. Dev	Min	Max
CAR[-1,1]	573	3.32	29.80	-31.31	625.25
CAR[2,22]	573	0.09	10.11	-67.62	59.42
Log(1+BM)	520	0.41	0.56	-0.15	2.85
Log(ME)	530	8.85	2.26	2.62	12.44
ROA	542	0.05	0.29	-1.26	0.39
Media [-7,0]	276	9.79	9.67	0.00	58.00
Media [-1,1]	276	6.11	6.20	0.00	42.00
Panel E. General patent grant sample	Obs.	Mean	Std. Dev	Min	Max
CAR[-1,1]	879204	0.01	2.01	-84.97	198.57
CAR[2,22]	879251	0.07	5.36	-171.96	518.81
Log(1+BM)	849580	0.94	1.12	-0.01	4.43
Log(ME)	854445	9.23	2.13	4.03	12.86
ROA	868062	0.10	0.11	-0.39	0.38
Patent originality	879251	0.48	0.29	0.00	1.00
Media [-7,0]	879251	1.29	3.15	0.00	408.00
Media [-1,1]	879251	0.65	1.83	0.00	189.00

Table 2

Market reaction to innovation announcements in the biopharmaceutical industry

This table reports announcement effect and post-announcement effect of patent grant announcements and drug approval announcements. Panel A reports cumulative abnormal returns (CAR) of these two types of announcements for both the paired samples and the extended samples. The paired samples and CARs (in percentage) are described as in Table 1. The extended patent grant (drug approval) sample relaxes the requirement of identifying matched drug approval (patent grant) announcements. All samples require event firms to be public on the event date. The extended patent grant sample consists of 733 patents granted from December 1986 to July 2014. The extended drug approval sample consists of 573 drugs approved from July 1966 to December 2016. Panel B reports the slopes (in percentage) and *t*-statistics (in parentheses) from pooled regression of CARs of the two types of announcements on a dummy variable, *drug approval*, that equals 1 (0) for drug approval announcements (patent grant announcements), controlling for firm characteristics and patent originality. BM, ME, ROA, and patent originality are defined as in Table 1. We also include dummies to control for three-digit technology class fixed effect (Tech Class FE) in the regressions. *T-statistics* are based on standard errors that are clustered at the firm and event day levels. All variables are winsorized t the 1% and 99% levels for each sample. *, **, *** denote the significance level at the 10%, 5%, and 1%, respectively.

Panel A. Univariate results

Panel A1: Paired sample

	(1)	(2)	(3)	(4)
	Patent grant		Drug approval	
	CAR[-1,1]	CAR[2,22]	CAR[-1,1]	CAR[2,22]
Mean	0.97*	2.10*	1.69***	0.32
t-statistics	(1.91)	(1.91)	(2.81)	(0.48)
Observations	117	117	117	117

Panel A2: Extended sample

	(1)	(2)	(3)	(4)
	Patent grant		Drug approval	
	CAR[-1,1]	CAR[2,22]	CAR[-1,1]	CAR[2,22]
Mean	0.22	1.56***	3.32**	0.09
t-statistics	(1.17)	(2.93)	(2.54)	(0.22)
Observations	733	733	573	573

Panel B. Multivariate results from pooled sample (patent grant announcements plus drug approval announcements)

Panel B1. Paired sample				
	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-1,1]	CAR[2,22]	CAR[2,22]
Drug approval dummy	0.71	0.58	-1.78	-2.37*
	(1.00)	(0.92)	(-1.47)	(-1.85)
Log(1+BM)		-0.70		-1.04
		(-1.24)		(-0.95)
Log(ME)		-0.00		-0.39
		(-0.02)		(-0.70)
ROA		-3.27		-2.11
		(-1.52)		(-0.51)
Patent originality		0.81		-1.18
		(0.81)		(-0.59)
Constant	0.97*	-5.48	2.10*	9.70
	(1.91)	(-1.62)	(1.91)	(1.17)
Tech Class FE		Y		Y
Observations	234	215	234	215
R-squared	0.00	0.15	0.01	0.09

Panel B2. Extended sample				
	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-1,1]	CAR[2,22]	CAR[2,22]
Drug approval dummy	3.10**	2.80*	-1.47**	-1.31*
	(2.35)	(1.80)	(-2.22)	(-1.91)
Log(1+BM)		-0.15		-0.81
		(-0.48)		(-1.42)
Log(ME)		-0.09		0.04
		(-0.47)		(0.19)
ROA		-4.90*		0.69
		(-1.75)		(0.32)
Constant	0.22	0.98	1.56***	1.25
	(1.17)	(0.55)	(2.93)	(0.55)
Observations	1,306	1,180	1,306	1,180
R-squared	0.01	0.01	0.00	0.00

Table 3

Investor attention and market reaction to innovation announcements in the biopharmaceutical industry

This table reports slopes (in percentage) and *t*-statistics (in parentheses) from regressions of cumulative abnormal returns (CAR) on investor attention, with or without other control variables, for the paired patent grant announcements sample (Panel A) and the paired drug approval announcements sample (Panel B), respectively. The CARs and the paired samples as defined as in Table 1, except that the samples start in year 2000 due to availability of media coverage data. Attention dummy equals 1 if media coverage is above the corresponding sample median and 0 otherwise. We measure media coverage as the number of announcements articles that mention the event firm in the three-day window around the event (media[-1, 1]) or in the week before the event (media[-7, 0]). BM, ME, ROA, and patent originality are defined as in Table 1. We also include dummies to control for three-digit technology class fixed effect (Tech Class FE) in the regressions. *T-statistics* (in parentheses) are estimated based on standard errors that are clustered at the firm and event day level. *, **, *** denote the significance level at the 10%, 5%, and 1%, respectively.

Panel A: Investor attention and market reaction to patent grant announcements (2000-2014)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attention measure	Media[-7,0]		Media[-1,1]		Media[-7,0]		Media[-1,1]	
	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[2,22]	CAR[2,22]	CAR[2,22]	CAR[2,22]
Attention dummy	0.85	3.07**	1.67	4.37**	-11.24***	-13.38***	-9.27***	-8.65***
	(0.62)	(2.32)	(1.16)	(2.59)	(-3.17)	(-3.36)	(-3.26)	(-3.41)
Log(1+BM)		-1.03		-0.85		-0.46		-1.04
		(-0.68)		(-0.58)		(-0.17)		(-0.35)
Log(ME)		-1.06		-1.20*		1.99		1.40
		(-1.54)		(-1.70)		(1.63)		(1.01)
ROA		-0.39		-0.59		-16.36		-16.06
		(-0.24)		(-0.33)		(-1.66)		(-1.30)
Patent originality		1.07		-0.24		-13.15**		-7.68
		(0.49)		(-0.13)		(-2.69)		(-1.57)
Constant	0.72	10.34	0.59	11.28	6.75**	-32.48*	5.01*	-27.33
	(0.70)	(1.51)	(0.64)	(1.61)	(2.15)	(-1.76)	(1.84)	(-1.19)
Tech Class FE		Y		Y		Y		Y
Observations	47	45	47	45	47	45	47	45
R-squared	0.01	0.37	0.02	0.42	0.15	0.72	0.09	0.62

Panel B: Investor attention and market reaction to drug approval announcements (2000-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attention measure	Media[-7,0]		Media[-1,1]		Media[-7,0]		Media[-1,1]	
	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[2,22]	CAR[2,22]	CAR[2,22]	CAR[2,22]
Attention dummy	0.47	2.29**	0.87	2.68**	-3.75**	-2.14	-2.75	-0.86
	(0.38)	(2.45)	(0.65)	(2.27)	(-2.21)	(-1.24)	(-1.61)	(-0.40)
Log(1+BM)		-0.71		-0.48		2.77*		2.92*
		(-0.80)		(-0.64)		(1.81)		(1.68)
Log(ME)		-0.65		-0.61		0.82		0.75
		(-1.46)		(-1.35)		(1.17)		(1.01)
ROA		-1.00		-1.42		0.14		0.07
		(-0.30)		(-0.41)		(0.03)		(0.01)
Patent originality		1.31		1.17		1.24		1.35
		(0.86)		(0.72)		(0.44)		(0.48)
Constant	1.59	-2.90	1.35	3.56	2.85**	9.24*	2.37	-18.16*
	(1.27)	(-0.94)	(1.20)	(0.73)	(2.05)	(1.89)	(1.54)	(-1.83)
Tech Class FE		Y		Y		Y		Y
Observations	88	77	88	77	88	77	88	77
R-squared	0.00	0.25	0.01	0.26	0.06	0.21	0.03	0.20

Table 4

Investor attention and market reaction to patent grant announcements in the general patent (USPTO) sample

This table reports slopes (in percentage) and *t*-statistics (in parentheses) from regressions of cumulative abnormal returns (CAR) of patent grant announcements with identifiable permno from CRSP on investor attention, with or without other control variables. The sample is from January 2000 to August 2014. The CARs and media coverage are measured as in Table 1. Attention dummy equals 1 if media coverage is above the corresponding sample median and 0 otherwise. We measure media coverage as the number of news articles that mention the event firm in the three-day window around the event (media[-1, 1]) or in the week before the event (media[-7, 0]). BM, ME, ROA, and patent originality are defined as in Table 1. We also include dummies to control for three-digit technology class fixed effect (Tech Class FE) in the regressions. Industry fixed effect is based on Fama-French (1997) 48 industry classifications. We also control for year fixed effects. *T-statistics* are estimated based on standard errors that are clustered at the firm and event day level. *, **, *** denote the significance level at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Attention measure		Media[-7,0]		Media[-1,1]			Media[-7,0]		Media[-1,1]	
	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[2,22]	CAR[2,22]	CAR[2,22]	CAR[2,22]	CAR[2,22]
Attention dummy		0.01*	-0.00	0.03***	0.02***		-0.02	-0.11***	-0.06**	-0.12***
		(1.72)	(-0.17)	(4.00)	(2.88)		(-0.70)	(-3.83)	(-2.19)	(-4.68)
Log(1+BM)			-0.01		-0.01			-0.13***		-0.12***
			(-1.38)		(-1.08)			(-4.12)		(-3.99)
Log(ME)			0.00		0.00			-0.01		-0.01
			(0.49)		(0.29)			(-0.55)		(-0.29)
ROA			0.03		0.04			-0.47*		-0.49*
			(0.46)		(0.51)			(-1.86)		(-1.91)
Patent originality			0.01		0.01			0.00		0.00
			(0.92)		(0.91)			(0.12)		(0.13)
Constant	0.01	0.00		-0.01		0.07***	0.08***		0.10***	
	(1.11)	(0.14)		(-1.02)		(3.51)	(3.20)		(3.47)	
Tech Class FE			Y		Y			Y		Y
Industry FE			Y		Y			Y		Y
Year FE			Y		Y			Y		Y
Observations	879,204	879,204	836,544	879,204	836,544	879,251	879,251	836,544	879,251	836,544
R-squared	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 5

Investor attention and market reaction to patent grant announcements in the general sample by technology categories

This table reports slopes (in percentage) and *t*-statistics (in parentheses) from regressions of cumulative abnormal returns (CAR) of patent grant announcements of public firms on investor attention dummy and other control variables within six major (one-digit) technology categories as defined in Hall, Jaffe, and Trajtenberg (2001). The sample is from January 2000 to August 2014. Panel A reports the results from using CARs (-1, 1) as the dependent variable, while Panel B reports the results from using CARs (2, 22) as the dependent variable. CARs are defined as in Table 1. The attention dummy equals 1 if media coverage is above the corresponding sample median and 0 otherwise. We measure media coverage as the number of news articles that mention the event firm in the three-day window around the event (i.e., media[-1, 1] as in Table 4). BM, ME, ROA, and patent originality are defined as in Table 1. We also control for three-digit technology class fixed effect (Tech Class FE) in the regressions. *T-statistics* are estimated based on standard errors that are clustered at the firm and event day level. *, **, *** denote the significance level at the 10%, 5%, and 1%, respectively.

Panel A: Investor attention and abnormal stock returns upon the announcement of patent grant announcements

	(1)	(2)	(3)	(4)	(5)	(6)
Technology categories	Chemical	Computers	Drugs	Electronics	Mechanical	Others
	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]
Attention dummy	0.02	0.01*	0.12**	0.03**	0.02	0.03*
	(0.85)	(1.70)	(2.33)	(2.04)	(1.51)	(1.70)
Log(1+BM)	-0.03	0.00	-0.05	-0.01	-0.01	-0.02
	(-1.63)	(0.21)	(-1.38)	(-0.54)	(-0.44)	(-0.98)
Log(ME)	-0.02	0.01	-0.01	0.00	0.01	-0.01
	(-1.28)	(1.39)	(-0.42)	(0.15)	(0.50)	(-0.58)
ROA	0.30	0.02	-0.19	0.07	0.27	0.04
	(1.51)	(0.24)	(-0.93)	(0.58)	(1.49)	(0.16)
Patent originality	0.01	0.01	-0.02	-0.00	0.00	-0.02
	(0.49)	(1.42)	(-0.37)	(-0.23)	(0.25)	(-0.70)
Tech Class FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	79,230	322,649	51,328	195,974	88,328	56,323
R-squared	0.00	0.00	0.00	0.00	0.00	0.01

Panel B: Investor attention and stock return drift after the announcement of patent grant announcements

Technology categories	(1) Chemical CAR[2,22]	(2) Computers CAR[2,22]	(3) Drugs CAR[2,22]	(4) Electronics CAR[2,22]	(5) Mechanical CAR[2,22]	(6) Others CAR[2,22]
Attention dummy	-0.07	-0.14***	-0.17	-0.09**	-0.07	-0.06
	(-1.13)	(-3.91)	(-1.47)	(-2.43)	(-1.38)	(-1.02)
Log(1+BM)	-0.02	-0.13***	-0.45***	-0.10**	-0.09*	-0.14**
	(-0.43)	(-3.30)	(-2.82)	(-2.18)	(-1.84)	(-2.01)
Log(ME)	0.05	-0.01	0.00	0.01	0.01	-0.01
	(1.27)	(-0.41)	(0.08)	(0.25)	(0.18)	(-0.29)
ROA	-1.18*	-0.30	-2.56***	0.31	0.86	-0.22
	(-1.84)	(-1.01)	(-3.68)	(0.93)	(1.39)	(-0.26)
Patent originality	0.09	0.02	0.08	-0.04	-0.08	-0.03
	(1.17)	(0.79)	(0.62)	(-1.03)	(-1.52)	(-0.34)
Tech Class FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	79,230	322,649	51,328	195,974	88,328	56,323
R-squared	0.01	0.00	0.01	0.00	0.01	0.01

Table 6

Profitability, productivity, and firm growth

This table reports slopes (in percentage) and *t*-statistics (in parentheses) from panel regressions of future profitability, productivity, and firm growth on the announcement effect, drift, and other control variables. All dependent variables are measured in year *t+1*, and independent variables are measured in year *t*. The sample period is from 1976 to 2014. Profitability is measured by ROA or OIBDA. ROA is the sum of income (ib) and depreciation (dp) divided by lagged assets. OIBDA is the sum of Operating Income Before Depreciation (oibdp) and Interest Income (tii) divided by lagged assets. Productivity is measured by TFP or assets turnover (sales/assets). TFP is constructed as in Olley and Pakes (1996) and Imrohoroglu and Tuzel (2013). Firm growth is measured by the growth rate in four variables--gross profit defined as sales (sale) minus cost of goods sold (cogs); output defined as sales plus change in inventory (invt); firm capital stock computed as the total (gross) property, plant and equipment (ppegt); and labor as employees (emp). Announcement effect in year *t* is measured as the sum of CAR[-1, 1] for patents granted from December of year *t-1* to November of year *t*. Drift in year *t* is measured as the sum of CAR[2, 22] for patents granted from December of year *t-1* to November of year *t*. CARs are defined as in Table 1. Q is defined as market to book assets in year t. ME is market capitalization at the end of year t. Capex/lagged assets is capital expenditure in year t scaled by assets in year t-2. *T-statistics* are estimated based on standard errors that are clustered at the firm and year levels. *, **, *** denote the significance level at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Profitability		Productivity			Growth in		
	ROA	OIBDA	Sale/Assets	TFP	Gross Profit	Output	Capital	Labor
Announcement effect (CAR[-1,1])	2.75***	2.42***	4.18**	2.95	3.99	1.98	0.83	2.14**
	(5.05)	(3.62)	(2.43)	(1.29)	(1.58)	(0.74)	(0.87)	(2.10)
Drift (CAR[2,22])	1.23***	1.21***	3.97***	2.78***	4.26***	4.49***	0.69**	2.31***
	(6.95)	(6.42)	(6.71)	(5.20)	(7.25)	(7.36)	(2.14)	(6.30)
Log(Q)	2.70***	3.38***	31.76***	22.57***	15.25***	22.36***	14.84***	13.56***
	(4.59)	(5.08)	(20.73)	(16.88)	(9.68)	(15.42)	(16.43)	(19.41)
Log(ME)	1.52***	1.71***	-10.25***	8.21***	-2.71***	-3.59***	1.31***	-0.59**
	(4.97)	(5.91)	(-11.12)	(8.60)	(-3.80)	(-5.24)	(3.46)	(-2.28)
CAPEX/ Lagged Assets	19.18***	24.52***	24.87***	-19.51**	-10.63	-18.50**	40.55***	1.08
	(6.06)	(7.05)	(2.79)	(-2.50)	(-0.84)	(-2.11)	(8.15)	(0.21)
R&D/ Lagged Assets	-29.20***	-31.31***	6.26	-21.28*	-23.47**	3.99	-4.34	-3.43
	(-7.12)	(-8.13)	(0.92)	(-2.03)	(-2.66)	(0.48)	(-1.00)	(-0.92)
Advertisement/ Lagged Assets	-0.00	-0.00	-0.01***	0.01*	-0.00	-0.00***	-0.00	-0.00
	(-0.53)	(-0.93)	(-2.86)	(2.00)	(-1.44)	(-2.76)	(-0.50)	(-0.84)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	32,500	32,392	32,503	24,430	32,320	32,298	32,244	31,835
R-squared	0.71	0.78	0.79	0.66	0.19	0.23	0.34	0.27

Table 7

Trading strategy based on investor attention and patent grant announcement using the general patent sample

This table presents the results from a trading strategy based on media coverage and patent grant announcements. At the end of each month, we compute the attention per patent (ATTP) measure for each firm with patent grant announcements as the ratio of total number of news articles mentioning a firm during a three-day window around each patent grant announcements to the total number of patents granted in this month. We then form three portfolios based on the 30th and 70th percentiles of ATTP. We also construct a low-minus-high (Low–High) portfolio by holding a long (short) position in the low (high) ATTP portfolio. We then hold these portfolios over the next month. Panel A and B report the average and median ATTP and firm size (in millions) for these three portfolios. Panel C reports their average monthly returns in excess of one-month Treasury bill rate (Exret) as well as their average monthly industry-adjusted returns. The portfolio industry-adjusted returns (Ind-adjret) are based on the difference between individual firms' returns and the returns of firms in the same industry (based on the Fama-French 48 industry classifications). In Panels D and E, we report the alphas and R^2 from the regression of the time-series of portfolio excess returns on various factor models: the Fama-French (2015) five factors (the market factor, the size factor, the value factor, the robust-minus-weak factor, and the conservative-minus-aggressive factor), and the investment-based factor model (q-factor model) of Hou, Xue, and Zhang (HXZ 2015). All returns and alphas are value-weighted. The *t*-statistics are reported in parentheses. R-square is adjusted. ***, **, and * denote the significance levels at the 1%, 5%, and 10%, respectively, for the Low-High portfolio. The sample is from 2000 to 2014.

		A. Mean		B. Median		C. Returns		D. Alphas		E. R^2	
Rank of ATTP	Firm No.	ATTP	Size ($mn)	ATTP	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	FF 5f	HXZ (q-factor)
L	186	0.111	2627	0.134	682	0.73%	0.36%	0.34%	0.31%	0.89	0.88
						(1.73)	(2.70)	(2.25)	(2.05)		
M	131	1.327	8167	1.193	2628	0.59%	0.08%	0.13%	0.16%	0.80	0.80
						(1.50)	(0.75)	(0.68)	(0.89)		
H	124	6.554	39198	4.876	12836	0.24%	-0.04%	0.04%	0.04%	0.95	0.93
						(0.69)	(-1.43)	(0.43)	(0.41)		
L-H						0.49%**	0.40%**	0.30%*	0.27%*	0.36	0.38
						(2.50)	(2.60)	(1.80)	(1.69)		

Online Appendix B

Investor attention and market reaction to innovation announcements in the drug industry in extended sample

This table reports slopes (in percentage) and *t*-statistics (in parentheses) from regressions of cumulative abnormal returns (CAR) on investor attention, with or without other control variables, for the extended patent grant announcements sample (Panel A) and the extended drug approval announcements sample (Panel B), respectively. The CARs and the extended samples as defined as in Table 1, except that the samples start in year 2000 due to availability of media coverage data. Attention dummy equals 1 if media coverage is above the corresponding sample median and 0 otherwise. We measure media coverage as the number of news articles that mention the event firm in the three-day window around the event (media[-1, 1]) or in the week before the event (media[-7, 0]). BM, ME, ROA, and patent originality are defined as in Table 1. We also include dummies to control for three-digit technology class fixed effect (Tech Class FE) in the regressions. *T-statistics* (in parentheses) are estimated based on standard errors that are clustered at the firm and event day level. *, **, *** denote the significance level at the 10%, 5%, and 1%, respectively.

Panel A: Investor attention and market reaction to patent grant announcements (2000-2014)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attention measure	Media[-7,0]		Media[-1,1]		Media[-7,0]		Media[-1,1]	
	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[2,22]	CAR[2,22]	CAR[2,22]	CAR[2,22]
Attention dummy	0.43	0.07	0.70**	0.48	-3.20***	-2.76***	-1.61	-0.72
	(1.20)	(0.22)	(1.97)	(0.95)	(-3.05)	(-2.62)	(-1.41)	(-0.54)
Log(1+BM)		0.33		0.30		-0.97		-1.20
		(0.87)		(0.79)		(-0.93)		(-1.12)
Log(ME)		0.18		0.14		0.48		0.23
		(1.02)		(0.75)		(0.99)		(0.47)
ROA		-0.27		-0.27		-3.72		-3.47
		(-0.22)		(-0.22)		(-0.89)		(-0.83)
Patent originality		1.32**		1.34**		-1.80		-1.74
		(2.00)		(2.02)		(-0.97)		(-0.93)
Constant	-0.13	1.49	-0.20	1.89	3.04***	-6.77	2.32**	-4.10
	(-0.41)	(0.79)	(-0.73)	(0.92)	(2.91)	(-1.34)	(2.40)	(-0.78)
Tech Class FE		Y		Y		Y		Y
Observations	522	486	522	486	522	486	522	486
R-squared	0.00	0.05	0.00	0.05	0.01	0.05	0.00	0.05

Panel B: Investor attention and market reaction to drug approval announcements (2000-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attention measure	Media[-7,0]		Media[-1,1]		Media[-7,0]		Media[-1,1]	
	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[-1,1]	CAR[2,22]	CAR[2,22]	CAR[2,22]	CAR[2,22]
Attention dummy	1.51	12.21	-7.16	-3.80	-0.41	-1.03	-0.52	-1.63
	(0.30)	(1.14)	(-1.14)	(-0.63)	(-0.29)	(-0.63)	(-0.35)	(-1.11)
Log(1+BM)		-4.69		-3.17		0.55		0.45
		(-1.36)		(-1.50)		(0.58)		(0.51)
Log(ME)		-3.96		-2.48		0.16		0.09
		(-1.27)		(-1.39)		(0.25)		(0.16)
ROA		-4.84		-7.15		3.89		4.01
		(-0.73)		(-0.86)		(0.88)		(0.90)
Constant	5.15*	37.33	10.32	32.34	0.65	-0.84	0.74	0.27
	(1.92)	(1.35)	(1.64)	(1.34)	(0.50)	(-0.13)	(0.58)	0.04
Tech Class FE		Y		Y		Y		Y
Observations	276	237	276	237	276	237	276	237
R-squared	0.00	0.05	0.01	0.03	0.00	0.02	0.00	0.02