Three Essays in Financial Economics:

Author: Yu Wang

Boston College Electronic Thesis or Dissertation, 2020

Boston College

Wallace E. Carroll Graduate School of Management

Department of Finance

THREE ESSAYS IN FINANCIAL ECONOMICS

a dissertation

by

YU WANG

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Finance

May 2020

THREE ESSAYS IN FINANCIAL ECONOMICS

YU WANG

ADVISORS:
Rui Albuquerque (Co-Chair), Thomas J. Chemmanur (Co-Chair)

COMMITTEE:
Alan Marcus, Hassan Tehranian

ABSTRACT

In my first essay, I develop a model of investor behavior around prescheduled macroeconomic announcements to analyze the optimal allocation of investor attention between systematic and idiosyncratic risk factors when a macroeconomic announcement is anticipated. Skilled investors, when producing information under a limited attention capacity, optimally allocate more of their attention to analyzing the idiosyncratic risk factor when they anticipate more precise public information about the systematic risk factor from the macroeconomic announcement. Consequently, my model predicts that, the more informative (precise) the macroeconomic announcement is expected to be about the underlying risk factors, *ceteris paribus*, the more uncertainty pre-announcement, the more resolution of uncertainty post-announcement, and the higher the trading volume around the announcement on the market index. My empirical analysis of trading by investors around both FOMC and CPI announcements support my model's predictions. In particular, my empirical findings are consistent with model predictions about the effect of the anticipated macroeconomic announcement precision on investor attention allocation, the effect of investor attention on the levels of pre-announcement and post-announcement trading volumes, and the effect of investor attention on the ratio of post-announcement trading volume over the pre-announcement trading volume.

In my second essay, we analyze, theoretically and empirically, how investor attention affects the stock market reaction to innovation announcements. In a dynamic model with limited investor attention, we show that the immediate reaction to innovation announcements increases, while the post-announcement stock return drift decreases, in investor attention. We empirically confirm our model predictions using a matched sample of pharmaceutical industry patent grant and subsequent FDA drug approval announcements and also a general USPTO patent sample. We show that post-announcement drift has predictive power for firm growth, profitability, and productivity, drawing implications for enhancing measures of patents' economic value and for trading strategy.

In my third essay, we analyze, theoretically and empirically, the implications of a fraction of investors in the equity market paying only delayed attention to SEO announcements. We first show theoretically that, in the above setting, the announcement effect of an SEO will be positively related to the fraction of investors paying attention to the announcement and that there will be a post-announcement stock-return drift that is negatively related to investor attention. In the second part of the paper, we test the above predictions using the media coverage of firms announcing SEOs as a proxy for investor attention, and find evidence consistent with the above predictions. In the third part of the paper, we develop and test various hypotheses relating investor attention paid to the issuing firm (between the announcement and the equity issue) to various SEO characteristics. We empirically show that SEO underpricing, institutional investor participation in SEOs, and the post-SEO equity market valuation of firms are all positively related to investor attention. The results of our identification tests show that the above results are causal.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my advisors, Prof. Rui Albuquerque and Prof. Thomas J. Chemmanur, for their continuous and warm support through my years at Boston College. Without their invaluable help, the dissertation would not have been possible. Besides, I would like to thank the members of my dissertation committee, Prof. Alan Marcus and Prof. Hassan Tehranian, for their advice in the preparation and review of my essays.

Last but not least, I would like to express my appreciation towards my family for their love and support in my life.

THREE ESSAYS IN FINANCIAL ECONOMICS

YU WANG

TABLE OF CONTENTS

Market Response to Macroeconomic Announcements under Optimal Attention Allocation: Theory and Evidence*

Yu Wang†

Abstract

I develop a model of investor behavior around prescheduled macroeconomic announcements. My model analyzes the optimal allocation of investor attention between systematic and idiosyncratic risk factors when a macroeconomic announcement is anticipated. Skilled investors, when producing information under a limited attention capacity, optimally allocate more of their attention to analyzing the idiosyncratic risk factor when they anticipate more precise public information about the systematic risk factor from the macroeconomic announcement. Consequently, my model predicts that, the more informative (precise) the macroeconomic announcement is expected to be about the underlying risk factors, *ceteris paribus*, the more uncertainty pre-announcement, the more resolution of uncertainty post-announcement, and the higher the trading volume around the announcement on the market index. My empirical analysis of trading by investors around both FOMC and CPI announcements support my model's predictions. In particular, my empirical findings are consistent with model predictions about the effect of the anticipated macroeconomic announcement precision on investor attention allocation, the effect of investor attention on the levels of pre-announcement and post-announcement trading volumes, and the effect of investor attention on the ratio of post-announcement trading volume over the pre-announcement trading volume.

*I thank my Ph.D. dissertation committee co-chairs, Rui Albuquerque and Thomas J. Chemmanur, and my dissertation committee members, Alan Marcus and Hassan Tehranian for their constant guidance and encouragement. For helpful comments and discussions, I also thank Pierluigi Balduzzi, Vincent Bogousslavsky, Philip Bond, Philip H. Dybvig, Vyacheslav (Slava) Fos, Campbell R. Harvey, David Hirshleifer, Nadya Malenko, Ngoc-Khanh Tran, and participants at the 2018 FMA Annual Meeting Doctoral Student Consortium, the Ph.D. student poster session of the 2019 American Finance Association Meeting, 2019 Midwest Finance Association Conference, 2019 Yale Whitebox Advisors Graduate Student Conference, 2019 Financial Management Association Annual Meeting, and the Finance Seminars at the University of Arkansas, the University of North Dakota, and Boston College. All remaining errors and omissions remain my own responsibility.

†Carroll School of Management, Boston College, MA 02467. Phone: (617) 552-2033. E-mail: wangakc@bc.edu.

1 Introduction

There has been considerable interest in investor behavior and asset returns around macroeconomic announcements such as Federal Open Market Committee (FOMC) announcements, Consumer Price Index (CPI) announcements, Gross Domestic Product (GDP) growth announcements, Producer Price Index (PPI) announcements, and unemployment rate announcements. Savor and Wilson (2013) document that the average return on the day of scheduled macroeconomic announcements such as CPI, PPI, unemployment, and FOMC announcements is 11.4 basis points (bp) while it is 1.1 bp for all other days. Savor and Wilson (2014) find that the expected variance of daily market returns is positively related to future aggregated quarterly announcement day returns, but not to aggregated non-announcement day returns. Lucca and Moench (2015) document an average of 49 bp increase in the return on the S&P 500 index during the 24 hours before scheduled Federal Open Market Committee (FOMC) announcements since 1994. Lucca and Moench (2015) also find that the trading volume of the E-mini S&P 500 futures is lower than usual before the announcement and spikes up right after the announcement. This paper presents a model of scheduled macroeconomic announcements that can explain the trading behavior of investors around these and other macroeconomic announcements.[1]

I develop a dynamic model to analyze the behavior of investors in optimally allocating their attention when there is a future scheduled macroeconomic announcement, producing information about the underlying risk factors, and trading on their information. There are two main ingredients in my model. First, investors trade based on both private and public signals about two different sources of risk in the economy, namely, the systematic risk factor and an idiosyncratic risk factor.[2] Second, investors optimally allocate their atten-

[1]Existing models of macroeconomic announcements include Ai and Bansal (2018) and Wachter and Zhu (2018). Neither of these two models studies the trading volume around macroeconomic announcements. Further, neither of these papers has a role for investor attention.

[2]Albuquerque, Bauer, and Schneider (2009) provide evidence consistent with the existence of private information about the macro factor and explain US investors' trading behavior ("global return chasing") accordingly.

tion within a limited attention capacity. Following the modeling approach of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), I assume an upper bound on the total precision of the private signals that can be generated by investors. Investors optimally allocate their attention between the two risk factors when producing information about these risk factors. When engaging in information production, skilled investors allocate more of their attention to the risk factor that matters more to them and receive more precise private signals about this risk factor. If more attention is paid to one risk factor, then less attention is paid to the other risk factor since each investor's total attention capacity is limited, i.e. if an investor decides to receive private signals about one risk factor with a higher precision, then she can receive private signals about the other risk factor only with a lower precision.[3]

There are three assets in my model: a stock, the market index, and the riskfree asset. The payoff of the stock is affected by both the systematic risk factor and an idiosyncratic risk factor, while the payoff of the market index is affected only by the systematic risk factor. The capital market consists of skilled investors and liquidity traders. Skilled investors are able to produce information about the future realization of both the systematic and the idiosyncratic risk factors (and therefore about the stock and the market index) under the constraint of limited attention capacity. At date 0, skilled investors optimally allocate their attention to the systematic and idiosyncratic risk factors. This attention allocation will affect the precision of the private signals (as a result of their information production) at dates 1 and 2. At date 1, each skilled investor produces information, based on which she receives private signals about the systematic and idiosyncratic risk factors (according to her *ex ante* attention allocation). She then forms her optimal portfolio. At date 2, the prescheduled macroeconomic announcement is released; each skilled investor observes the above announcement and simultaneously (but independently) produces another round of information and then rebalances her portfolio based on the public and private signals she

[3] As will be mentioned later, the riskfree rate will be normalized as a fixed constant, so the riskfree asset does not require any attention. All of investors' available attention will be allocated only between the two risk factors.

received at date 2. At date 3, all payoffs are realized. Liquidity traders, however, do not have the ability to allocate their attention optimally or to produce information; neither do they trade strategically. In other words, liquidity traders only provide a mean-zero noise in the supply of risky assets.

I now present the results of my theoretical analysis. First, for any given precision of the public signal, on the date of announcement, there is more information on the systematic risk factor observed from the macroeconomic announcement, so that both the uncertainty on the market index and the uncertainty on the stock (through the systematic risk factor) decrease, so that the equilibrium prices of both risky assets are on average higher after the announcement than before the announcement. The resolution of uncertainty (due to the macroeconomic announcement as well as information production by skilled investors) also increases investors' demands for both risky assets, so that the levels of the trading volume of both assets are higher on the date of the macroeconomic announcement than before. Because of limited attention capacity, investors' optimal attention allocation is an endogenous decision in my model, so that the precision of the private signals they receive as a result of information production is also endogenously determined rather than exogenously fixed as in classical rational expectations equilibrium (REE) models. In equilibrium, investors respond to a more precise public signal (i.e. macroeconomic announcement) by investing less of their attention in the systematic risk factor. In order to better understand the role of attention capacity in my model, it is useful to compare my results with those arising from a benchmark REE model where the precision of private signals is exogenously fixed at the average between the precision chosen by investors for the private signal for the systematic risk factor and the precision chosen for the private signal for the idiosyncratic risk factor in my optimal attention allocation model. The tilt of attention involved in producing information in my optimal attention allocation model results in more uncertainty pre-announcement, more resolution of uncertainty post-announcement, and higher trading volume around macroeconomic announcements than in the benchmark REE model with a fixed precision of private signals involved in information production by investors.

Second, as the public signal from the prescheduled macroeconomic announcement gets more precise, *ceteris paribus*, investors shift some of their attention from the systematic risk factor toward the idiosyncratic risk factor. Intuitively, the information from the prescheduled macroeconomic announcement and the information from investors' private information production about the systematic risk factor are substitutes. When investors anticipate that more information will come "for free" from the macroeconomic announcement, they reduce their attention allocated to producing information about the systematic risk factor and increase their attention allocated to the idiosyncratic risk factor. Because of this attention shift, the precision of the private signals received about the systematic risk factor is lower, and the uncertainty on the market index is higher when the macroeconomic announcement is expected to be more precise. Consequently, the price of the market index decreases before the date of the announcement and, similarly, the price of the stock increases. Thus, when the macroeconomic announcement is made, the price of the market index jumps by a greater extent at the time of this announcement if the public information is more precise.[4] Moreover, as the macroeconomic announcement gets more precise, the relative increase in the trading volume (the ratio of the post-announcement trading volume over the pre-announcement trading volume) on the market index is higher.

My model is consistent with many of the stylized facts on macroeconomic announcements that have been documented in the empirical literature. First, my model predicts a positive relation between the expected variance and the expected return on the market index upon macroeconomic announcements, which is consistent with the evidence documented by Savor and Wilson (2014). Second, my model generates the prediction of an increase in the trading volume on the market index after a macroeconomic announcement. This is consistent with the spike in the trading volume of E-mini S&P 500 futures after scheduled FOMC announce-

[4] In fact, the attention shift raises the uncertainty on the market index relative to the benchmark REE case, so that, in equilibrium, the return on the market index is higher in my model than its counterpart in the benchmark REE model.

ments as documented by Lucca and Moench (2015). Third, as the anticipated precision of the macroeconomic announcement increases, my model predicts a higher return on the market index upon the announcement. This is consistent with Brusa, Savor, and Wilson (2017) who show that, while high returns are documented in the case of FOMC announcements, similar high returns do not appear around monetary policy announcements by other central banks. Since the U.S. is the dominant financial market in the world, it is possible that the information about the upcoming macroeconomic situation in the world contained in the announcements from other central banks is not as precise as that provided by FOMC announcements so that FOMC announcements generate a uniquely high return afterwards.

Besides explaining the stylized facts documented by the existing empirical literature, my model also offers several testable implications that have not yet been tested. First, as the anticipated precision of a macroeconomic announcement increases, my model predicts a higher investor attention (e.g. as measured by the number of news articles discussing the corresponding macroeconomic variable as a proxy for investor attention to that variable) to the systematic risk factor (as proxied by a market index such as the S&P 500 index). Second, if the anticipated precision of a macroeconomic announcement is greater, my model predicts lower trading volumes both before and after the announcement. Third, if the anticipated precision of a macroeconomic announcement is greater, my model predicts a higher relative increase in the trading volume (a higher ratio between the post-announcement trading volume and the pre-announcement trading volume) on the systematic risk factor, after controlling for the information effect of the macroeconomic announcement.

I empirically test three hypotheses about trading by investors around FOMC announcements and CPI announcements. I use data from three sources. First, a sample of news articles (i.e. media coverage) on various economic variables from the RavenPack Global Macro Database from January 2000 till October 2018. Second, data on analyst forecasts on various macroeconomic variables (e.g. on the Fed funds target rate and on changes in the Consumer Price Index) and the actual announced values from Bloomberg, available from

December 1998 till December 2018. Third, transaction-level data of the trading volume on E-mini S&P 500 futures from TickData, available from July 2003 till December 2018.

To proxy for the attention paid by investors to the systematic risk factor (i.e. the market), I search for the number of news articles with *group* equal to "interest-rates" ("consumption") on RavenPack during the 72 hours before each FOMC announcement (CPI announcement) as a proxy. When a majority of investors intend to learn more about a specific variable, we expect to see a lot of discussion about it in the media, i.e. we can interpret the media coverage on interest rates as a proxy for the aggregate attention paid by investors on the systematic risk factor. To proxy for the expected precision of an upcoming macroeconomic announcement, I use the standard deviation of analyst forecasts on that macroeconomic variable before the same announcement. More precisely, I use the standard deviation of analyst forecasts on the Fed funds target rate before an FOMC announcement as an inverse proxy for the expected precision of this FOMC announcement; similarly, I use the standard deviation of analyst forecasts on the change in Consumer Price Index before a CPI announcement as an inverse proxy for the expected precision of this CPI announcement.

The results of my empirical analysis may be summarized as follows. First, the higher the anticipated precision of an upcoming FOMC announcement, the lower the attention investors pay to the Fed funds target rate before the announcement. A similar result holds for CPI announcements. Second, the higher the investor attention paid to the Fed funds target rate before an FOMC announcement, the higher the trading volumes on the market index both before and after the announcement. For CPI announcements, the result is qualitatively similar, although only the relation between investor attention and pre-announcement trading volume is statistically significant. Third, the higher the investor attention paid to the Fed funds target rate before an FOMC announcement, the lower the ratio of the post-announcement trading volume over the pre-announcement trading volume on the market index. The result is similar for CPI announcements.

The rest of the paper is organized as follows: In Section 2, I discuss how my paper is related to the existing literature. In Section 3, I describe the setup of my model. In Section 4, I characterize the equilibrium of the model, develop the analytical results, and present some results from numerical simulations. In Section 5, I discuss the testable predictions of my model. In Section 6, I present empirical tests and results on some of the predictions of my model. The proofs of all propositions and additional simulation results are provided in Appendices A and B, respectively.

2 Relation to the Existing Literature

My paper is related to several strands in the literature. The first is the theoretical literature consisting of fully rational models of macroeconomic announcements. Ai and Bansal (2018) characterize the intertemporal preferences that can generate positive announcement premia. Wachter and Zhu (2018) explain the more prominent relation between beta and expected returns on announcement days than on non-announcement days using a continuous-time rational model with possible rare disasters. They focus on the comparison between the security market line (SML) on announcement days and the SML on non-announcement days and do not study the trading volume around announcements. My model, where skilled investors allocate their attention optimally, provides not only the results on asset returns and the uncertainty-return relation but also the result on trading volume.

The second is the theoretical literature on bounded rationality and limited attention. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) develop a static model with limited attention to study the behavior of mutual funds during expansions and recessions in the economy. I extend their framework to a dynamic setting with a public (macroeconomic) announcement. Sims (2003) models limited attention by suggesting an information-processing constraint (Shannon capacity) to be added into dynamic programming problems ("rational inattention") to model the inertial reactions documented in a macroeconomic setting. With entropy as the measure of uncertainty, the "informativeness" of information channels is defined through entropy. In his rational inattention setting, agents dynamically optimize the information channel depending on the distribution of incoming information so that the transformation errors are endogenous. Maćkowiak and Wiederholt (2009) build a model of limited attention to study the attention shift from aggregate conditions to idiosyncratic conditions by price-setting firms so that the price reaction to aggregate shocks is sticky while its reaction to idiosyncratic shocks is immediate.[5] Mondria (2010) develops a model in which investors are allowed to choose the structure of the information they desire to get, and explains the comovement of prices in seemingly unrelated assets. Gabaix (2014) introduces the sparse max operator to model agents' levels of attention paid to different goods and its consequences in a setting of consumer choice.[6]

The third strand in the literature related to my paper is the empirical literature on stock returns around macroeconomic announcements. Lucca and Moench (2015) document that there is an average of 49 basis points (bp) increase in the return of S&P 500 index during the 24 hours before scheduled FOMC announcements. They also find that the trading volume of the E-mini S&P 500 futures is lower than usual before the announcement, but then spikes up immediately after the announcement. Savor and Wilson (2013) document that the average return on the day of scheduled macroeconomic announcements, such as CPI, PPI, unemployment, and FOMC announcements, is 11.4 bp while 1.1 bp for all other days. Bernanke and Kuttner (2005) document a 1% increase in various broad stock indices and industry portfolios after an unanticipated 25 bp cut in the Fed funds target rate. Boyd, Hu, and Jagannathan (2005) study the stock market reaction to announcements of the unemployment rate. Chen, Jiang, and Zhu (2018) find that, while the excess market trading volume is significantly higher on days with important macroeconomic news announcements, the excess turnover on stocks after earnings announcements on firms are significantly lower if there is a macroeconomic news announcement on the same day as the earnings announcement.

[5] Maćkowiak and Wiederholt (2015) apply the concept of rational inattention to both firms and households to match the empirical impulse responses to both monetary policy shocks and aggregate technology shocks.

[6] Follow-up work along this stream of research includes Gabaix (2016a) on basic dynamic macroeconomics and Gabaix (2016b) on macroeconomic fiscal and monetary policy.

Finally, my model is related to the broader literature on information production and trading in the capital market with fully rational investors. Starting with the seminal papers by Grossman and Stiglitz (1980) and Hellwig (1980), a number of papers have applied the noisy REE equilibrium concept to model information production and trading in the capital markets. In these models, the stock price plays a dual role: one is to clear the markets, the other is to (partially) reveal the private information generated by each investor to other investors. Admati (1985) extends the above models to a multi-asset setting, and Brennan and Cao (1997) provide an extension to a dynamic setting. Albuquerque (2012) builds a stationary model of firms with periodic but heterogeneous earnings announcement dates and dividend announcement dates, and show that the conditional variance of stock returns can increase by little or even drop at an earnings announcement if there is sufficient noise in the signals observed before the announcement. His prediction of a small post-announcement increase in the variance of stock returns is consistent with the evidence in Savor and Wilson (2013) that the realized volatility of daily stock market returns increases by only 4%.

3 Model Setup

I develop a discrete-time model to study how skilled investors optimally allocate their attention in anticipation of a prescheduled macroeconomic announcement. The model builds upon the dynamic trading model in Brennan and Cao (1997) and the static attention allocation model in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016). Different from the linear attention allocation optimization problem in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), the attention allocation optimization here becomes nonlinear because of the multiple-period dynamics and brings in mathematical complexity in solving it.

3.1 Assets and Risk Factors

There are three assets in the market: a stock, the market index, and the riskfree asset.

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

Risky assets. Asset s is a stock, and asset m is the market index. Their terminal payoffs, f_s and f_m, are represented by the following vector $\boldsymbol{f}$:

$$\boldsymbol{f} \equiv \begin{pmatrix} f_s \\ f_m \end{pmatrix} \equiv \boldsymbol{\mu} + \boldsymbol{\Gamma} \boldsymbol{z} \equiv \begin{pmatrix} \mu_s \\ \mu_m \end{pmatrix} + \begin{pmatrix} 1 & b \\ 0 & 1 \end{pmatrix} \begin{pmatrix} z_s \\ z_m \end{pmatrix} \tag{1}$$

where $\boldsymbol{z} \equiv (z_s, z_m)' \sim MVN(0, \boldsymbol{\Sigma})$ represents the vector of independent risk factors and its var-cov matrix $\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_s^2 & 0 \\ 0 & \sigma_m^2 \end{pmatrix}$ is diagonal.

Two sources of risks affect the payoff of the individual stock: the systematic (market) risk z_m (with b the corresponding market beta) and the idiosyncratic risk z_s. The market index is affected only by the systematic risk z_m.

The supply vector of risky assets is defined through the supply of risk factors, as the model will be solved on risk factors. I represent the supply vector of risk factors by $\bar{\boldsymbol{x}} + \sum_{s=1}^{t} \boldsymbol{x}_s$, where $\boldsymbol{x}_s \sim MVN(0, \sigma_x^2 \boldsymbol{I}_2)$ is the amount of additional noisy supply at time s. In particular, the supply of risk factors at $t = 1$ is given by $\bar{\boldsymbol{x}} + \boldsymbol{x}_1$, and at $t = 2$ given by $\bar{\boldsymbol{x}} + \boldsymbol{x}_1 + \boldsymbol{x}_2$. Correspondingly, the supply of risky assets is $\boldsymbol{\Gamma}'^{-1}(\bar{\boldsymbol{x}} + \sum_{s=1}^{t} \boldsymbol{x}_s)$.

For the simplicity of notations but still to distinguish the items on risk factors from the items on risky assets, I use regular letters for the terms related to risk factors, e.g. $\boldsymbol{P}_t$ for the equilibrium price vector of the synthetic assets for risk factors, and $\boldsymbol{D}_t$ for the demand vector on the synthetic assets.[7] All corresponding terms on risky assets will be emphasized by "$\tilde{\cdot}$", e.g. $\tilde{\boldsymbol{P}}_t$ and $\tilde{\boldsymbol{D}}_t$ for the equilibrium price vector of risky assets and the demand vector on risky assets, respectively.

[7]For more details on the synthetic assets, please refer to Section 4.

3.2 Timeline

There are four dates in the model (Figure 1): $t = 0, 1, 2, 3$.[8]

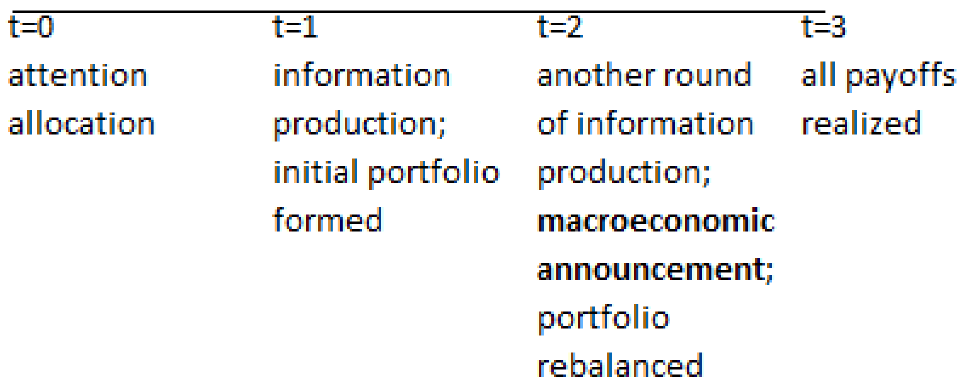

Figure 1: Timeline of Model

At $t = 0$, investors optimally allocate their attention between the systematic risk factor and the idiosyncratic risk factor.[9] This attention allocation determines the precision of the private signals each investor will receive at $t = 1$ and 2. At $t = 1$, all investors observe (independent) private signals, as a result of information production, at their chosen precision levels, and form their optimal portfolios. At $t = 2$, the prescheduled macroeconomic announcement on the market is released, and all investors observe another round of (independent) private signals at their chosen precision levels and subsequently rebalance their portfolios optimally. At $t = 3$, all payoffs are realized.

3.3 Market Participants

The capital market consists of skilled investors and liquidity traders. Skilled investors are able to produce information about the future realization of both the systematic and the

[8] As we will discuss more thoroughly in section 3.3, there are two types of investors in the market, skilled investors and liquidity traders. Only skilled investors ("investors" for short) are able to allocate attention optimally, produce information, and trade strategically. The timeline presented here is essentially for skilled investors.

[9] We may interpret the attention allocated to the systematic risk factor as the attention allocated to the market index, since the payoff of the market index is only affected by the systematic risk factor. Similarly, we may interpret the attention allocated to the idiosyncratic risk factor as the attention allocated to the stock because the additional information investors learned about the stock is equivalent to the shock from the idiosyncratic risk factor.

idiosyncratic risk factors (and therefore about the stock and the market index) under the constraint of limited attention capacity. The timeline of their behavior is presented in section 3.2. Liquidity traders, however, do not have the ability to allocate their attention optimally or to produce information; neither do they trade strategically. In other words, liquidity traders only provide a mean-zero noise in the supply of risky assets, i.e. the $\mathbf{\Gamma}'^{-1}\boldsymbol{x}_s$ terms discussed in section 3.1.

Utility of Skilled Investors. There is a continuum of *ex ante* homogeneous skilled investors ("investors" for short), indexed by $i \in [0, 1]$. Each investor is endowed with initial wealth W_0.[10,11] On each trading date ($t = 1$ and 2), each investor i forms her optimal portfolio, by choosing the demand vector $\tilde{\boldsymbol{D}}^i_t$ on risky assets, in order to maximize her expected constant absolute risk aversion (CARA) utility of terminal wealth ($t = 3$),[12]

$$\max_{\tilde{\boldsymbol{D}}^i_t} E^i_t(-\exp[-\rho W^i_3]), \text{ at } t = 1 \text{ and } t = 2, \tag{2}$$

subject to the following budget constraints:

$$\text{at } t = 1: \quad \text{initial wealth } W^i_1 \equiv W_0, \forall i \in [0, 1]; \tag{3}$$

$$\text{at } t = 2: \qquad W^i_2 = W^i_1 + (\tilde{\boldsymbol{D}}^i_1)'(\tilde{\boldsymbol{P}}_2 - \tilde{\boldsymbol{P}}_1). \tag{4}$$

Investor i's terminal wealth is expressed by

$$W^i_3 = W^i_2 + (\tilde{\boldsymbol{D}}^i_2)'(\boldsymbol{f} - \tilde{\boldsymbol{P}}_2) = W^i_1 + (\tilde{\boldsymbol{D}}^i_1)'(\tilde{\boldsymbol{P}}_2 - \tilde{\boldsymbol{P}}_1) + (\tilde{\boldsymbol{D}}^i_2)'(\boldsymbol{f} - \tilde{\boldsymbol{P}}_2). \tag{5}$$

[10]Or, equivalently, each investor is endowed with $\mathbf{\Gamma}'^{-1}(1, 1)'$ of risky assets and $W_0 - (1, 1)'\boldsymbol{P}_0$ in cash (riskfree asset), where the initial price vector, $\boldsymbol{P}_0$, of risk factors clears the market at $t = 0$. I will only need this alternative definition when comparing trading volumes across time.

[11]The assumption of homogeneous initial wealth is without loss of generality because the constant absolute risk aversion (CARA) utility used in the model has no wealth effect.

[12]Since the model will be solved *backwards*, I will explain portfolio formation (at $t = 1, 2$) first and attention allocation (at $t = 0$) next.

Attention Allocation. At $t = 0$, each investor i allocates her limited attention capacity K to the idiosyncratic and systematic risk factors so that her date-0 expected utility is maximized; i.e., for each investor i, $K_s^i + K_m^i = K$, where K_s^i is investor i's attention paid to the idiosyncratic risk factor, and K_m^i is her attention paid to the systematic risk factor. According to the allocated attention (K_s^i, K_m^i), investor i receives independent private signals for the two risk factors at $t = 1$ and 2: $\boldsymbol{\eta}_t^i = \boldsymbol{z} + \boldsymbol{\epsilon}_t^i$, where $\boldsymbol{\epsilon}_t^i \sim MVN(0, \boldsymbol{\Sigma}_\eta^i)$ and $\boldsymbol{\Sigma}_\eta^i \equiv \begin{pmatrix} [K_s^i]^{-1} & 0 \\ 0 & [K_m^i]^{-1} \end{pmatrix}$.

The utility maximization problem to be solved at $t = 0$ is therefore:

$$\max_{(K_s^i, K_m^i)} E_0(-\exp[-\rho W_3^i]), \text{ subject to } K_s^i + K_m^i = K \tag{6}$$

3.4 Macroeconomic Announcement

At $t = 2$, a public signal

$$\eta_{pub,m} = z_m + \epsilon_{pub,m}, \text{ where } \epsilon_{pub,m} \sim N(0, [prec_{pub,m}]^{-1}), \tag{7}$$

is observed by all skilled investors and reveals information on the systematic risk factor.[13]

4 Equilibrium and Results

The equilibrium concept I use is that of the symmetric noisy Rational Expectations Equilibrium (REE) of Grossman and Stiglitz (1980). All skilled investors have the same optimal attention allocation in equilibrium because of the *ex ante* homogeneity among skilled investors. However, notice that the realization of private signals is still different among investors and therefore skilled investors are *ex post* heterogeneous and allocate their portfolios differently.

[13] In later sections, I also use the formal vector $\boldsymbol{\eta}_{pub} \equiv (0, \eta_{pub,m})'$ to accommodate the matrix expression in the analytical results. See Section 4.1 for more details.

I solve for the equilibrium prices and optimal demands analytically. To take the advantage of the independence between risk factors, I solve the model on the level of risk factors and then pull back for the results on assets as linear combinations.[14] Each risk factor (together with a linear transform of the expected return $\boldsymbol{\mu}$) can be viewed as a synthetic asset created by a linear combination of risky assets, so that the payoff vector of the synthetic assets is $\boldsymbol{\Gamma}^{-1}\boldsymbol{f} \equiv \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z}$ and the supply vector of these synthetic assets is $\bar{\boldsymbol{x}} + \sum_{s=1}^{t} \boldsymbol{x}_s$ for $t = 1, 2$. Notice that, because of the fixed relation between factors and assets through a linear combination, once investors retrieve information on risky assets (from equilibrium prices or public/private signals), they also know the corresponding information on risk factors and the synthetic assets; *vice versa*.

4.1 Bayesian Updating of Beliefs

Conditional on the attention allocation, (K_s^i, K_m^i), chosen at $t = 0$, investor i observes a vector $\boldsymbol{\eta}_t^i$ of private signals on the two risk factors at $t = 1, 2$. I denote the information set of investor i at time $t \in \{1, 2\}$ by $\mathcal{F}_t^i$, i.e.,

$$\mathcal{F}_1^i = \{\boldsymbol{P}_1, \boldsymbol{\eta}_1^i\} \tag{8}$$

$$\mathcal{F}_2^i = \{\boldsymbol{P}_1, \boldsymbol{P}_2, \boldsymbol{\eta}_1^i, \boldsymbol{\eta}_2^i, \boldsymbol{\eta}_{pub}\}, \tag{9}$$

where $\boldsymbol{P}_t$ is the equilibrium price vector of the synthetic assets for risk factors, and $\boldsymbol{\eta}_{pub} = \begin{pmatrix} 0 \\ \eta_{pub,m} \end{pmatrix}$ with its precision matrix $\boldsymbol{\Sigma}_{pub}^{-1} \equiv \begin{pmatrix} 0 & 0 \\ 0 & prec_{pub,m} \end{pmatrix}$.[15,16]

As I will prove in Proposition 1, the equilibrium price vector $\boldsymbol{P}_t$ generates an unbiased

[14] This also avoids the potential concern of changing correlations among assets (including market beta) in the case of receiving signals directly on assets.

[15] Without loss of generality, I set 0 as the first component of $\boldsymbol{\eta}_{pub}$ so that the dimensions of all vectors in $\mathcal{F}_2^i$ balance. Because of the zeros in $\boldsymbol{\Sigma}_{pub}^{-1}$, the value of the first component of $\boldsymbol{\eta}_{pub}$ does not matter essentially.

[16] From the discussion at the end of the preamble of this section, it is equivalent for investors to know the prices of risky assets directly, i.e. $\mathcal{F}_1^i = \{\tilde{\boldsymbol{P}}_1, \boldsymbol{\eta}_1^i\}, \mathcal{F}_2^i = \{\tilde{\boldsymbol{P}}_1, \tilde{\boldsymbol{P}}_2, \boldsymbol{\eta}_1^i, \boldsymbol{\eta}_2^i, \boldsymbol{\eta}_{pub}\}$.

"signal" (estimator) for the final payoffs of risk factors, i.e.

$$\boldsymbol{\eta}_{\boldsymbol{p},t} \equiv \boldsymbol{z} + \boldsymbol{\epsilon}_{\boldsymbol{p},t}, \text{ where } \boldsymbol{\epsilon}_{\boldsymbol{p},t} \sim MVN(0, \boldsymbol{\Sigma}_{\boldsymbol{p},t}). \tag{10}$$

By the standard process of Bayesian updating, investor i's posterior belief about $\boldsymbol{z}$ at $t = 1$ is $\boldsymbol{z}|_{\mathcal{F}_1^i} \sim MVN(\hat{\boldsymbol{z}}_1^i, \hat{\boldsymbol{\Sigma}}_1^i)$, where

$$\begin{aligned} \hat{\boldsymbol{z}}_1^i &= \hat{\boldsymbol{\Sigma}}_1^i[(\boldsymbol{\Sigma}_{\boldsymbol{\eta}}^i)^{-1}\boldsymbol{\eta}_1^i + \boldsymbol{\Sigma}_{\boldsymbol{p},1}^{-1}\boldsymbol{\eta}_{\boldsymbol{p},1}], & (11)\\ (\hat{\boldsymbol{\Sigma}}_1^i)^{-1} &= \boldsymbol{\Sigma}^{-1} + (\boldsymbol{\Sigma}_{\boldsymbol{\eta}}^i)^{-1} + \boldsymbol{\Sigma}_{\boldsymbol{p},1}^{-1}. & (12) \end{aligned}$$

Similarly, investor i's posterior belief about $\boldsymbol{z}$ at $t = 2$ is $\boldsymbol{z}|_{\mathcal{F}_2^i} \sim MVN(\hat{\boldsymbol{z}}_2^i, \hat{\boldsymbol{\Sigma}}_2^i)$, where

$$\begin{aligned} \hat{\boldsymbol{z}}_2^i &= \hat{\boldsymbol{\Sigma}}_2^i[(\hat{\boldsymbol{\Sigma}}_1^i)^{-1}\hat{\boldsymbol{z}}_1^i + (\boldsymbol{\Sigma}_{\boldsymbol{\eta}}^i)^{-1}\boldsymbol{\eta}_2^i + \boldsymbol{\Sigma}_{\boldsymbol{p},2}^{-1}\boldsymbol{\eta}_{\boldsymbol{p},2} + \boldsymbol{\Sigma}_{pub}^{-1}\boldsymbol{\eta}_{pub}] & (13)\\ (\hat{\boldsymbol{\Sigma}}_2^i)^{-1} &= (\hat{\boldsymbol{\Sigma}}_1^i)^{-1} + (\boldsymbol{\Sigma}_{\boldsymbol{\eta}}^i)^{-1} + \boldsymbol{\Sigma}_{\boldsymbol{p},2}^{-1} + \boldsymbol{\Sigma}_{pub}^{-1} & (14) \end{aligned}$$

4.2 Equilibrium Prices and Demands

On each trading date $t = 1, 2$, given their updated beliefs about $\boldsymbol{z}$, skilled investors form their optimal portfolios $\{\boldsymbol{D}_t^i\}_{i\in[0,1]}$ to maximize their expected CARA utility of terminal wealth $E_t^i(-\exp[-\rho W_3^i])$. The equilibrium prices $\boldsymbol{P}_t$ clear markets, i.e.,

$$\int_0^1 \boldsymbol{D}_t^i di = \bar{\boldsymbol{x}} + \sum_{s=1}^{t} \boldsymbol{x}_s \tag{15}$$

Proposition 1. *At $t = 1, 2$, the vectors of equilibrium prices of the synthetic assets for risk factors are, respectively,*

$$\begin{aligned} \boldsymbol{P}_1 &= [\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \rho\overline{\hat{\boldsymbol{\Sigma}}}_1\bar{\boldsymbol{x}}] + \overline{\hat{\boldsymbol{\Sigma}}}_1[(\boldsymbol{I}_2 + \rho^{-2}\sigma_x^{-2}\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}'^{-1})\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}^{-1}(\boldsymbol{z} - \rho\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}\boldsymbol{x}_1)] & (16)\\ \boldsymbol{P}_2 &= [\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \rho\overline{\hat{\boldsymbol{\Sigma}}}_2\bar{\boldsymbol{x}}] \end{aligned}$$

$$+\hat{\overline{\boldsymbol{\Sigma}}}_2[\boldsymbol{\Sigma}_{pub}^{-1}\boldsymbol{\eta}_{pub}+\sum_{t=1}^{2}(\boldsymbol{I}_2+\rho^{-2}\sigma_x^{-2}\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}'^{-1})\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}^{-1}(\boldsymbol{z}-\rho\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}\boldsymbol{x}_t)] \tag{17}$$

where $\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}^{-1}$ *represents the average precision of private signals among all skilled investors,* $\hat{\overline{\boldsymbol{\Sigma}}}_t^{-1}$ *represents the average precision of skilled investors' posterior beliefs on* $\boldsymbol{z}$ *at* $t = 1, 2$, $\boldsymbol{\eta}_{pub} = \begin{pmatrix} 0 \\ \eta_{pub,m} \end{pmatrix}$ *is the dimension-balanced public signal with a precision matrix* $\boldsymbol{\Sigma}_{pub}^{-1} \equiv \begin{pmatrix} 0 & 0 \\ 0 & prec_{pub,m} \end{pmatrix}$, *and* I_2 *denotes the* 2×2 *identity matrix.*

Accordingly, the equilibrium price vector of risky assets at $t = 1, 2$ *is* $\tilde{\boldsymbol{P}}_t = \boldsymbol{\Gamma}\boldsymbol{P}_t$.

Conditional on the private signals and the public announcement (if applicable), the additional information investors can rationally learn from the equilibrium price $\boldsymbol{P}_t$ is

$$\boldsymbol{\eta}_{p,t} = \boldsymbol{z} - \rho\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}\boldsymbol{x}_t, \text{ where } \overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}^{-1} \equiv \int_0^1 (\boldsymbol{\Sigma}_{\boldsymbol{\eta}}^i)^{-1} di. \tag{18}$$

Thus, in (10), $\boldsymbol{\Sigma}_{\boldsymbol{p},t} = \rho^2\sigma_x^2\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}'$.

Proposition 2. *Investor* i*'s demand vector for (the synthetic asset of) risk factors at* $t = 1, 2$ *is*

$$\boldsymbol{D}_t^i = \rho^{-1}(\hat{\boldsymbol{\Sigma}}_t^i)^{-1}[\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{z}}_t^i - \boldsymbol{P}_t] \tag{19}$$

Accordingly, the demand vector for risky assets at time t *is* $\tilde{\boldsymbol{D}}_t = (\boldsymbol{\Gamma}^{-1})'\boldsymbol{D}_t^i, t = 1, 2$.

4.3 Attention Allocation

Moving backward to $t = 0$, with results from Propositions 1 and 2 substituted in, I write down the final optimization to solve:

Proposition 3. *Investor* i*'s optimal attention allocation is determined by the following utility* *maximization problem:*

$$
\begin{aligned}
& \max_{\boldsymbol{\Sigma}^i_\eta} E_0(-\exp[-\rho W^i_3]) \\
= \quad & -\det([(\hat{\boldsymbol{\Sigma}}^i_2)^{-1}\boldsymbol{V}^i_{1,\Delta\boldsymbol{P}}(\boldsymbol{y})+\boldsymbol{I}_2]^{-1}[\boldsymbol{B}'\boldsymbol{V}^i_{1,\Delta\boldsymbol{P}}(\boldsymbol{z})^{-1}\boldsymbol{B}\boldsymbol{V}^i_1(\Delta\boldsymbol{P})+\boldsymbol{I}_2]^{-1} \\
& [\boldsymbol{M}\boldsymbol{V}^i_0+\boldsymbol{I}_2]^{-1})^{-1} \qquad (20) \\
& \cdot\exp\{-\rho W_0+\frac{1}{2}(\boldsymbol{E}^i)'[(\boldsymbol{V}^i)^{-1}(\boldsymbol{M}+(\boldsymbol{V}^i)^{-1})^{-1}(\boldsymbol{V}^i)^{-1}-(\boldsymbol{V}^i)^{-1}]\boldsymbol{E}^i\}, \\
& \textit{subject to } trace([\boldsymbol{\Sigma}^i_{\boldsymbol{\eta}}]^{-1})\equiv K^i_s+K^i_m=K
\end{aligned}
$$

where $\boldsymbol{E}^i$ and $\boldsymbol{V}^i$ denote investor i's date-0 expectation and variance of $\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu}+\hat{\boldsymbol{z}}^i_1-\boldsymbol{P}_1$ (expected return at $t=1$ in investor i's opinion), respectively, and $\boldsymbol{y}\equiv\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu}+\hat{\boldsymbol{z}}^i_2-\boldsymbol{P}_2$ represents the expected return at $t=2$ in investor i's opinion, and other notations are as follows:

$$
\begin{aligned}
\boldsymbol{B} &\equiv \boldsymbol{V}^i_{1,\Delta\boldsymbol{P}}(\boldsymbol{z})[\boldsymbol{V}^{-1}(\boldsymbol{\epsilon}_{\Delta\boldsymbol{P}})(\overline{\hat{\boldsymbol{\Sigma}}_2}^{-1}-\overline{\hat{\boldsymbol{\Sigma}}_1}^{-1})\overline{\hat{\boldsymbol{\Sigma}}_1}^{-1}-(\hat{\boldsymbol{\Sigma}}^i_1)^{-1}] \\
\boldsymbol{M} &\equiv (\hat{\boldsymbol{\Sigma}}^i_1)^{-1}\boldsymbol{V}^i_{1,\Delta\boldsymbol{P}}(\boldsymbol{z})(\hat{\boldsymbol{\Sigma}}^i_1)^{-1} \\
&\quad +(\overline{\hat{\boldsymbol{\Sigma}}_2}^{-1}-\overline{\hat{\boldsymbol{\Sigma}}_1}^{-1})\overline{\hat{\boldsymbol{\Sigma}}}_2 V^i_1(\Delta\boldsymbol{P})^{-1}\overline{\hat{\boldsymbol{\Sigma}}}_2(\overline{\hat{\boldsymbol{\Sigma}}_2}^{-1}-\overline{\hat{\boldsymbol{\Sigma}}_1}^{-1}) \\
\boldsymbol{V}^i_{1,\Delta\boldsymbol{P}}(y) &\equiv \textit{cov-var matrix of } \boldsymbol{y} \textit{ conditional on } \mathcal{F}^i_1 \textit{ and } \boldsymbol{P}_2-\boldsymbol{P}_1 \\
\boldsymbol{V}^i_{1,\Delta\boldsymbol{P}}(z) &\equiv \textit{cov-var matrix of } \boldsymbol{z} \textit{ conditional on } \mathcal{F}^i_1 \textit{ and } \boldsymbol{P}_2-\boldsymbol{P}_1 \\
\boldsymbol{V}^i_1(\Delta\boldsymbol{P}) &\equiv \textit{cov-var matrix of } \boldsymbol{P}_2-\boldsymbol{P}_1 \textit{ conditional on } \mathcal{F}^i_1
\end{aligned}
$$

4.4 Simulation Results

Because of mathematical complexity, I use numerical simulations to solve for the optimal attention allocation at $t=0$ and the corresponding equilibrium prices, asset returns, and trading volumes around macroeconomic announcements. To interpret results intuitively in the stylized model, I apply a set of benchmark parameters that are symmetric between the two risk factors. Table 1 lists all the parameters used.

Parameter	Symbol	Value
Risk aversion parameter	ρ	1
Expected payoff of assets	$\boldsymbol{\mu}$	$(15, 15)'$
Market beta of stock	b	0.7
Distribution of shocks in risk factors	$\boldsymbol{z}$	$MVN(0, \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix})$
Number of skilled investors		500
Attention capacity	K	1
Expected supply of risk factors	$\bar{\boldsymbol{x}}$	$(1, 1)'$
Distribution of additional supply of risk factors	$\boldsymbol{x}_t$	$MVN(0, \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix})$

Table 1: Parameters Used in Simulation

Result 1. *Attention allocation between the systematic and idiosyncratic risk factors:*

If there is no public signal, or a very imprecise public signal, investors have to allocate their attention to both risk factors to maximize their utility. With my symmetric setup of parameters, investors devote their attention equally between the two risk factors, as shown by the y-intercept in Figure 2. As the public signal from the macroeconomic announcement gets more precise, investors shift more of their attention from the systematic risk factor to the idiosyncratic risk factor (Figure 2).

Result 2. *Equilibrium prices of the risky assets before and after the macroeconomic announcement (at $t = 1, 2$):*

From Result 1, the more precise the macroeconomic announcement, the more attention allocated to the idiosyncratic risk factor and the less attention allocated to the systematic risk factor. Thus, at $t = 1$, the private signal for the systematic risk factor from information production is less precise and thus the uncertainty on the market index is higher, so that the price of the market index decreases; similarly, the price of the stock increases. At $t = 2$, even though the new private signal on the systematic risk factor (from another round of information production) is at the same precision level as that of $t = 1$, there is more public information about the systematic risk factor because of the macroeconomic announcement, so that the overall uncertainty on the systematic risk factor is lower and hence the price of the market index increases. The price of the stock at $t = 2$ still increases as another round of

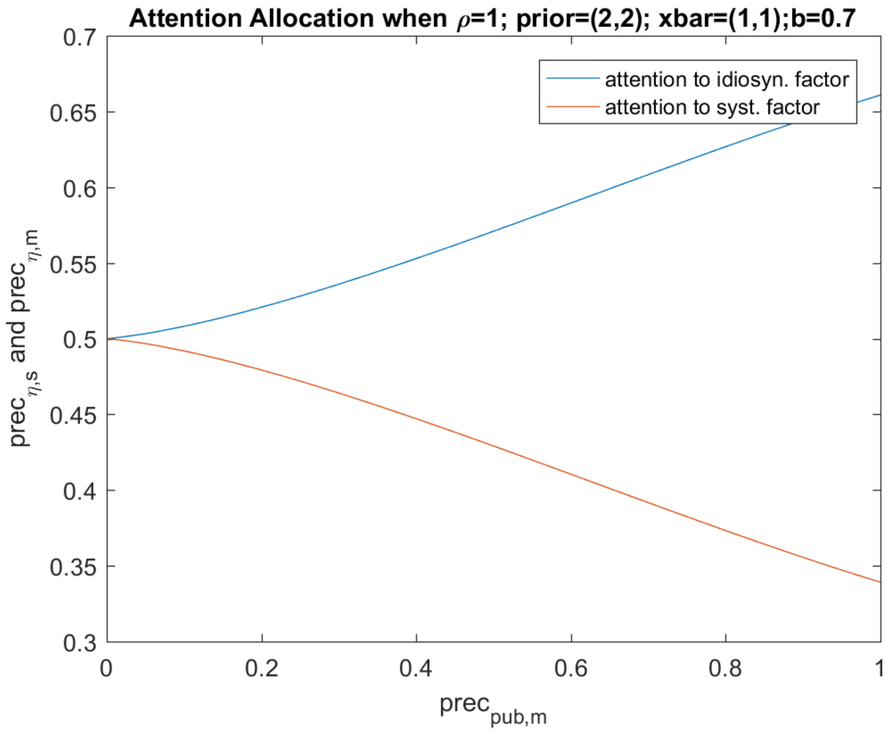

Figure 2: Attention Allocation as a Function of Public Signal Precision

more precise private signals are observed from information production, when a more precise macroeconomic announcement is anticipated. This simulation result is presented in Figure 3.

Result 3. *Returns on risky assets upon the macroeconomic announcement (from $t = 1$ to $t = 2$):*

As we compare the trends of the prices of the two assets at $t = 2$ to their counterparts at $t = 1$, it is easy to see that both the return on the market index and the return on the stock should increase when the macroeconomic announcement gets more precise. This is reflected by Figure 4. This result is consistent with the strong stock market reaction to surprise Fed fund rate changes as documented in Bernanke and Kuttner (2005). It also matches the observed stylized facts on market index (Lucca and Moench, 2015) when we take potential information leakage into consideration.[17]

[17]See Bernile, Hu, and Tang (2016) and Cieslak, Morse, and Vissing-Jorgensen (2018) for discussion on information leakage during the 30-min period (news embargoes) before FOMC meetings and other informal

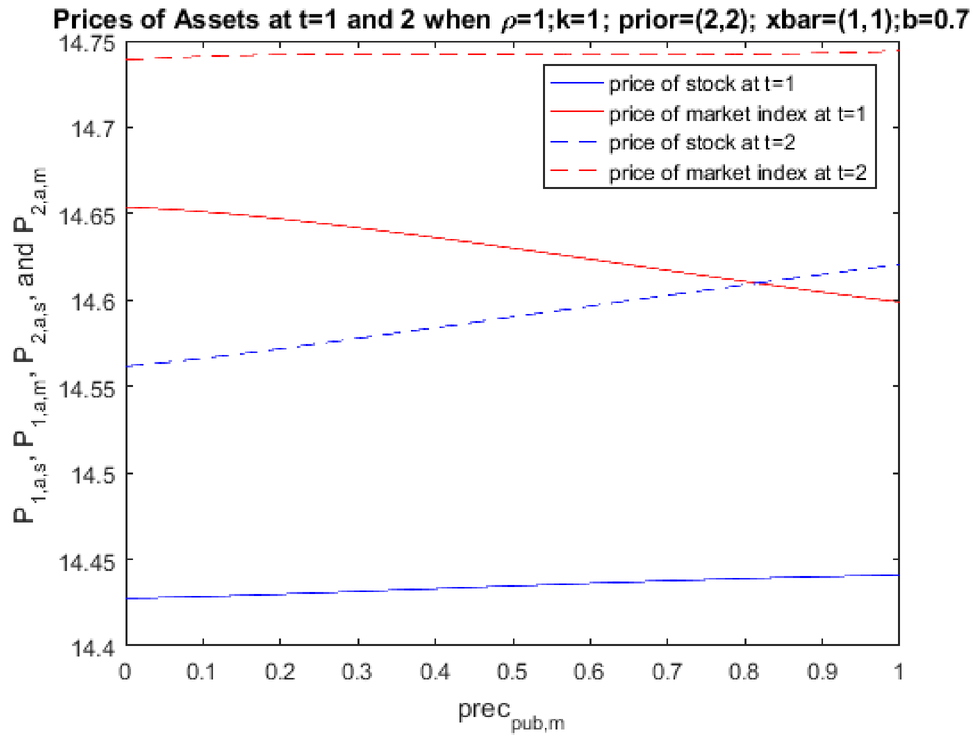

Figure 3: Equilibrium Price as a Function of Public Signal Precision

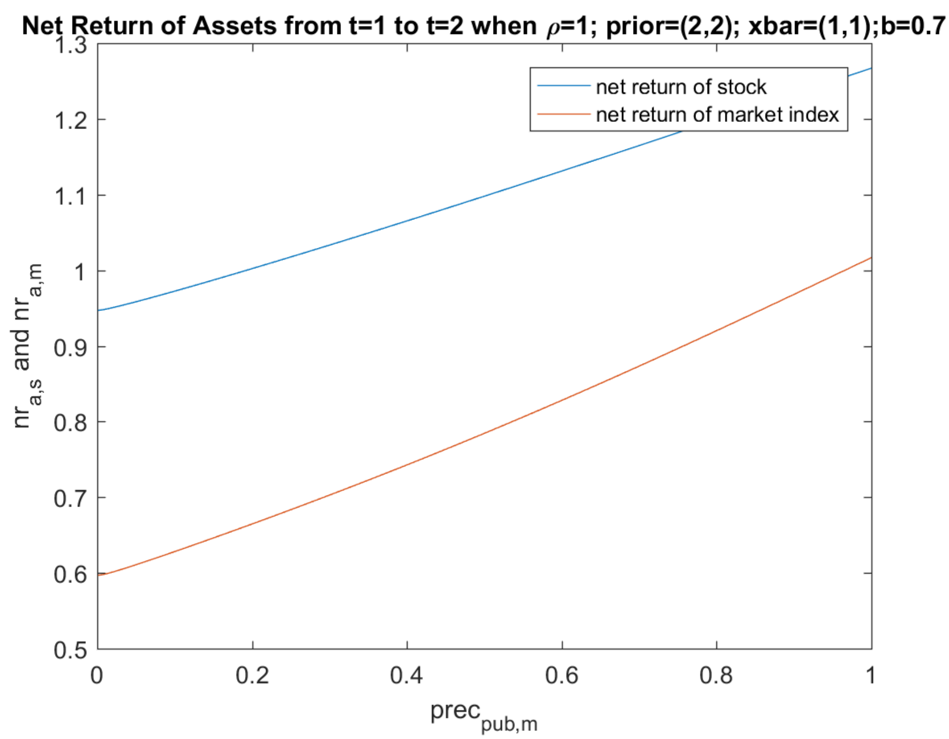

Figure 4: Return of Assets as a Function of Public Signal Precision

communication on days other than FOMC announcements, respectively.

The trend of asset returns is accompanied by a similar trend of return volatility, represented by the standard deviation of asset returns from $t = 1$ to $t = 2$ (Figure 5). This is consistent with the positive relation between the expected variance of daily market returns and the aggregated quarterly announcement day returns as documented by Savor and Wilson (2014).

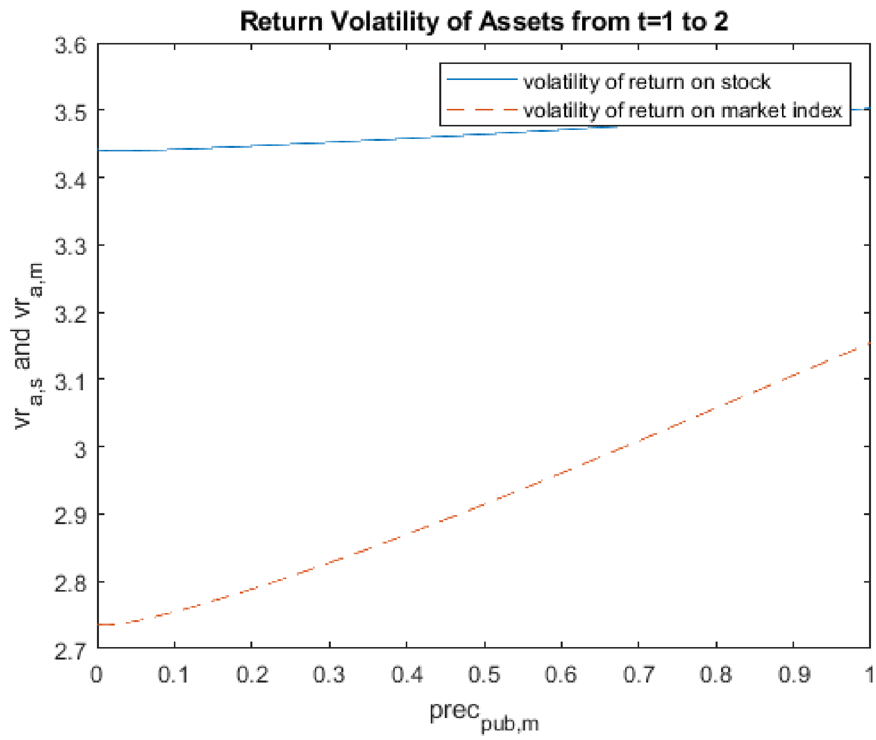

Figure 5: Return Volatility of Assets as a Function of Public Signal Precision

Result 4. Trading volumes on the market index before and after the macroeconomic announcement (at $t = 1, 2$):

As public announcement reveals more information about the market, uncertainty is lower and thus investors' demand for the index is higher. This leads to the first observation in Figure 6 that the trading volume increases on the index overall regardless of the precision of the announcement.[18] Besides, recalled from Result 1, the more precise the macroeconomic announcement, the less attention allocated to the systematic risk factor. From (13) and

[18]The trading volume on the market index at date t is define as the aggregate change in skilled investors'

(14), the posterior belief of a skilled investor i at $t = 2$ is a weighted average of her prior belief about $\boldsymbol{z}$ at $t = 2$ (i.e. her posterior belief about $\boldsymbol{z}$ at $t = 1$), her private signal received from information production at $t = 2$, the public signal observed from the macroeconomic announcement, and the additional information rationally learned from the equilibrium price vector $\boldsymbol{P}_2$, with weights determined by the precision of each component. When the precision of the macroeconomic announcement is greater, the weight of the public signal in her posterior beliefs of the market is larger. The same effect applies to all skilled investors. This will drive all skilled investors' beliefs on the systematic risk factor close to each other and therefore decrease the trading volume on the market index gradually. At $t = 1$, a similar argument holds because investors' prior beliefs at $t = 1$ take greater weights when updating their beliefs (shown in (11) and (12)), since they receive less precise private signals on the systematic risk factor when the public announcement is more precise. This leads to the downward trend shown in Figure 6.

Result 5. *Ratio of trading volumes on the market index around the macroeconomic announcement (i.e the relative change in the trading volume on the market index from* $t = 1$ *to* $t = 2$*):*

To have a better understanding of the increase in trading volume from $t = 1$ to $t = 2$, I calculate the ratio of the trading volumes across the two periods. The result is shown in Figure 7. The trading volume at $t = 2$ can be interpreted as investors' "corrections" to their initial portfolio allocation (at $t = 1$) after they observe more information at $t = 2$. First, as investors anticipate a more precise macroeconomic announcement, they allocate less attention to the systematic risk factor when producing information and thus create more "mistakes" *a priori* at $t = 1$ in their initial portfolios. Second, at $t = 2$, when investors actually observe the more precise macroeconomic announcement, they are more

holding positions on the market index, i.e.

$$TV_{m,t} = \frac{1}{N}\sum_{i=1}^{N} |D^i_{m,t} - D^i_{m,t-1}|,$$

where $D^i_{m,t}$ is the market component of the demand vector for skilled investor i at date t and N is the population of skilled investors in the market.

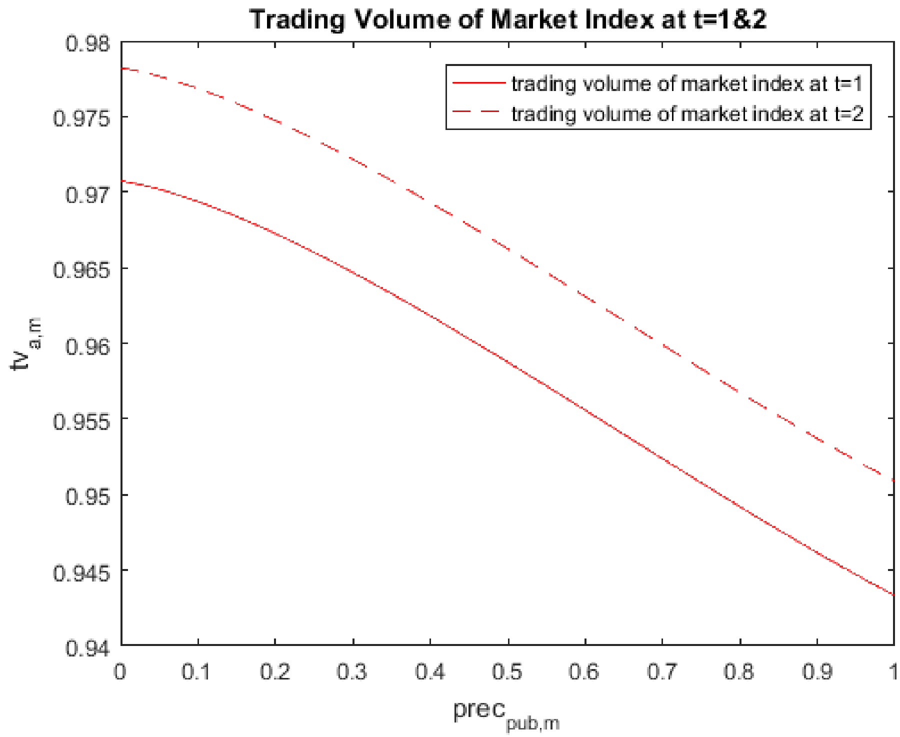

Figure 6: Level of Trading Volumes on the Market Index as a Function of Public Signal Precision

able to "correct" their "mistakes" upon announcement. Altogether, the relative increase in the trading volume on the market index increases in the precision of the macroeconomic announcement, as shown by the upward trend of the ratio with respect to the expected precision of the macroeconomic announcement.

5 Testable Predictions

The model generates several testable predictions, which I describe below. I will test some of these predictions in my empirical analysis.

Implication 1. *Attention allocation in anticipation of macroeconomic announcements with different levels of precision.*

My model predicts that when a more precise public signal about the underlying economic condition (i.e. the systematic risk factor) is expected from the upcoming macroeconomic an-

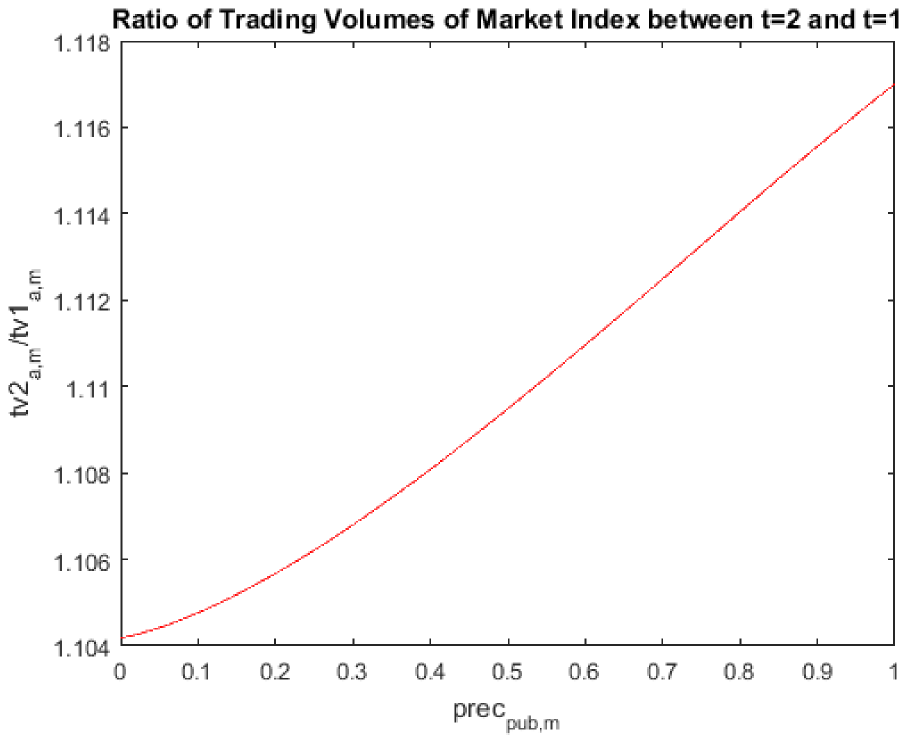

Figure 7: Ratio of Trading Volume on Market Index as a Function of Public Signal Precision

nouncement, skilled investors will allocate more of their attention to the idiosyncratic risk factors, about which investors do not expect an announcement in the near future. For each type of macroeconomic announcements (e.g. FOMC announcements, consumer price index (CPI) announcements, and unemployment rate announcements), the anticipated precision of each forthcoming announcement varies (e.g. the FOMC announcement on Dec 19, 2018 vs. the FOMC announcement on Nov 8, 2018). Thus an empirical implication of my model is that, among a fixed type of macroeconomic announcements (e.g. all FOMC announcements) investors pay more attention to information production about idiosyncratic risk factors when a more precise FOMC announcement is expected. Potential proxies for attention/inattention include trading volume on assets (Hou, Xiong, and Peng, 2009), whether an announcement occurs on Friday (DellaVigna and Pollet, 2009), whether the number of competing announcements is high on the same day (Hirshleifer, Lim, and Teoh, 2009), and media coverage (Engelberg and Parsons, 2011; Fang and Peress, 2009).

Implication 2. *Return on the market index around different macroeconomic announcements.*

My model predicts that the market return will be higher around a more precise macroeconomic announcement than around a less precise announcement. This is consistent with the observation documented by Brusa, Savor, and Wilson (2017) that, while high returns are documented in the case of FOMC announcements, similar high returns do not appear around monetary policy announcements by other (non-U.S.) central banks. This is consistent with my model's predictions, since the U.S. is the dominant financial market in the world. This is also consistent with the evidence of Lucca and Moench (2015) who study the pre-FOMC return on the S&P 500 index. While the pre-FOMC market return in Lucca and Moench (2015) is specific to the 24 hours before the scheduled FOMC announcements, it does not exclude the possibility of information leakage during that period. Bernile, Hu, and Tang (2016) use high-frequency data to find that during news embargoes before scheduled FOMC announcements, there are significant E-mini S&P 500 futures abnormal order imbalances in the same direction as the policy surprises to be revealed in the following announcements about 30 mins later.[19] The result predicted by my model here is consistent with their observation if I take information leakage into consideration.

Implication 3. *The level of trading volume around macroeconomic announcements.*

My model predicts that the level of trading volume on the market index will increase after a macroeconomic announcement. This is consistent with the stylized fact that trading volumes are higher after announcements. For example, Lucca and Moench (2015) document that the trading volume of E-mini S&P 500 futures spikes up right after scheduled FOMC announcements.

Implication 4. *Trading volumes around different macroeconomic announcements.*

My model predicts that the relative increase in the trading volume of the market index will be higher when the macroeconomic announcement is more precise. In the context of

[19] Cieslak, Morse, and Vissing-Jorgensen (2018) also mention that there is informal communication about the Fed policies before the official FOMC announcement.

various macroeconomic announcements, I expect to observe a higher increase in the trading volume of the market index (e.g. E-mini S&P 500 futures) around FOMC announcements than other macroeconomic announcements, since the former announcements are expected to be more precise about the forward-looking economic economic conditions.

Implication 5. *Market return and trading volume around scheduled vs. unscheduled announcements.*

If an announcement pops up as a surprise, investors will not allocate their attention in the same way as in the case where the announcement is anticipated *a priori*. In that case, we should only observe the information effect related to the announcement, but not those related to attention shifting. Thus, conditional on the same magnitude of the information surprise contained in the announcement, both the market return and the trading volume on the market index should be lower around an unscheduled macroeconomic announcement than around a scheduled macroeconomic announcement. This has not been tested so far in the literature and can therefore serve as a unique test of my model.

6 Empirical Analysis

In this section I present empirical tests of some of the empirical implications discussed in the previous section.

6.1 Proxies Used in the Empirical Analysis

The key element of my model is the attention paid by investors to information production on the systematic and idiosyncratic risk factors, which in turn drives the changes in the trading volumes before and after the macroeconomic announcement when investors expect varying precisions of the upcoming macroeconomic announcement. However, neither the precision of the private signals received by investors nor the precision of the public signal from the macroeconomic announcement is directly observable. In order to proxy for the precisions of these two signals (private and public, respectively), I use the following two proxies. First, I use the media coverage received by a certain risk factor (e.g. the systematic risk factor) as a proxy for the attention paid by investors to that factor. When a majority of investors intend to learn more about a certain risk factor (e.g. the systematic risk factor), we expect to see a lot of discussion about it in the media, i.e. we can interpret the media coverage on the risk factor as a proxy for the aggregate attention level paid by investors. I therefore use the count of news articles on the macroeconomic variable (e.g. interest rate or consumption) as a proxy for investor attention on the systematic risk factor before a macroeconomic announcement (e.g. FOMC announcement or CPI announcement) in my empirical analysis.

Second, I use the standard deviation of analyst forecasts regarding a particular macroeconomic variable (e.g. the Fed funds target rate or the change in Consumer Price Index) as an inverse proxy for the expected precision of the upcoming macroeconomic announcement regarding that variable. Intuitively, if most of the analyst forecasts on a macroeconomic variable (e.g. the Fed funds target rate or the change in Consumer Price Index) before the actual announcement (e.g. FOMC announcement or CPI announcement) agree with each other, investors expect the actual announced value to be close to (or even the same as) the forecast value; the public signal from the upcoming announcement is therefore expected to reflect the economic condition very precisely. In contrast, if there is a large dispersion in the analyst forecasts before the announcement, the public signal from the upcoming announcement is expected to reflect the economic condition less precisely.

6.2 Hypothesis Tested

Here I test the following three hypotheses:

1. *Relation between the expected precision of the upcoming macroeconomic announcement and the attention allocation of investors:* As predicted by my model, the more precise the upcoming macroeconomic announcement, the less attention paid by skilled investors to produce information about the systematic risk factor. Hence, I expect that, when the standard

deviation of analyst forecasts before a macroeconomic announcement is greater (i.e. a less precise upcoming announcement), there will be more news articles discussing the corresponding macroeconomic variable. In particular, I expect more news articles on “interest-rates” when the standard deviation of analyst forecasts about the Fed funds rate is greater before an FOMC announcement. Similarly, I expect more news articles on “consumption” when the standard deviation of analyst forecasts about the change in Consumer Price Index is greater before a CPI announcement. This is the first hypothesis that I test here ($\mathbf{H_1}$).

2. *Relation between the attention paid to the systematic risk factor and the level of trading volume on the market index:* When more news articles discuss the corresponding macroeconomic variable (i.e. more aggregate attention is paid by investors to the systematic risk factor) before a macroeconomic announcement, the uncertainty about the market index is lower (both before and after the announcement), and thus investors would like to hold more of the market index in their portfolios. This will create higher trading volumes on the market index both before and after the macroeconomic announcement. More precisely, we expect higher trading volumes on the market index both before and after an FOMC announcement when more news articles discuss about “interest-rates” before the announcement. Similarly, we expect higher trading volumes on the market index both before and after a CPI announcement when more news articles discuss about “consumption” before the announcement. This is the second hypothesis that I test here ($\mathbf{H_2}$).

3. *Relation between the attention paid to the systematic risk factor and the ratio of the pre-announcement trading volume over the post-announcement trading volume:* When more news articles discuss the corresponding macroeconomic variable (i.e. more aggregate attention is paid by investors to the systematic risk factor) before a macroeconomic announcement, investors make less “mistakes” when they decide the weight of the market index in their portfolio before the macroeconomic announcement and thus there is less need to modify their position on the market index after the announcement. This will create a smaller relative

increase in the trading volume on the market index from before the announcement to after the announcement. More precisely, we expect a lower ratio of the post-FOMC trading volume on the market index over the pre-FOMC trading volume on the market index when more news articles discuss about "interest-rates" before the announcement. Similarly, we expect a lower ratio of the post-CPI trading volume on the market index over the pre-CPI trading volume on the market index when more news articles discuss about "consumption" before the announcement. This is the third hypothesis that I test here ($\mathbf{H_3}$).

6.3 Data

The data of analyst forecasts on macroeconomic variables (before macroeconomic announcements) is obtained from Bloomberg, available from December 1998 till December 2018. The data contains the forecast value reported by each analyst firm and the actual announced value(s) of the macroeconomic variable for each macroeconomic announcement. I define the variables $SD(-\infty, 0]$, $SD(-\infty, -3days)$, and $SD[-30days, -3days)$ as the standard deviation of all analyst forecasts before each given macroeconomic announcement, the standard deviation of all analyst forecasts more than three days before each given macroeconomic announcement (i.e. the $(-\infty, -3$ days$)$ window), and the standard deviation of analyst forecasts more than three days but no more than 30 days before each given macroeconomic announcement (i.e. the $[-30$ days$, -3$ days$)$ window), respectively.[20] To control for the information effect in post-announcement trading, I define $AnnSurp$ (short for "announcement surprise") as the difference between the actual announced value of the macroeconomic variable and the forecast mean, $AbsAnnSurp$ as the absolute difference between the actual announced value and the forecast mean (i.e. the absolute value of $AnnSurp$, $|AnnSurp|$), and $NormAnnSurp$ as the normalized absolute difference between the actual announced

[20] The second and the third definitions of the standard deviation guarantee that the window of measurement for analyst forecast dispersion is strictly before the windows of measurement for the number of news counts and for the trading volumes (to be defined later).

value and the forecast mean (i.e. $AbsAnnSurp/SD(-\infty,0])$.[21]

The transaction-level data of the trading volume on E-mini S&P 500 futures is downloaded from TickData, available from July 2003 till December 2018. The transaction shares of E-mini S&P 500 futures are then aggregated within various windows before or after each macroeconomic announcement. The trading volume during the 72-hour window before an announcement is denoted by $TV[-72hrs,0]$, the trading volume during the 24-hour window after an announcement is denoted by $TV[0,24hrs]$, and similarly, the trading volume during the 72-hour window after an announcement is denoted by $TV[0,72hrs]$. I also study two ratios of trading volumes, one is $Ratio\_24to72$, defined as the ratio of the trading volume on E-mini S&P 500 futures during the 24-hour window after an announcement over the trading volume on E-mini S&P 500 futures during the 72-hour window before the same announcement (i.e. $TV[0,24hrs]/TV[-72hrs,0]$), the other is $Ratio\_72to72$, defined as the ratio of the trading volume on E-mini S&P 500 futures during the 72-hour window after an announcement over the trading volume on E-mini S&P 500 futures during the 72-hour window before the same announcement (i.e. $TV[0,72hrs]/TV[-72hrs,0]$).

The data on news articles is downloaded from the RavenPack Global Macro database, available from January 2000 till October 2018. Each news article has a specific *rp_story_id* and the corresponding classification information such as *group*. I count the distinct number of *rp_story_id* with *group* equal to "interest-rates" ("consumption") during the 72-hour window before each FOMC announcement (CPI announcement), denoted by $News[-72hrs,0]$.

The final sample of my empirical analysis has 124 FOMC announcements from Aug 2003 till Dec 2018, among which 122 of them have available analyst forecasts information, and 184 CPI announcements within the same period with available analyst forecasts data. Table 2 shows the summary statistics of all variables, Panel A for FOMC announcements and Panel B for CPI announcements.

[21]The number of observations for $NormAnnSurp$ is much smaller than those of the other two variables on announcement surprise in the case of FOMC announcements, however, because of the zero standard deviations among analyst forecasts for many of the FOMC announcements.

6.4 Empirical Tests and Results

The first test is on the effect of announcement precision on the attention allocation by investors ($\mathbf{H_1}$). I run the OLS regression of the news counts during the 72 hours before each announcement, $News[-72hrs, 0]$, on the three measures of the standard deviation of analyst forecasts before the same upcoming announcement (defined in the previous subsection): $SD(-\infty, 0]$, $SD(-\infty, -3days)$, $SD[-30days, -3days)$, respectively. My model predicts that, the less precise the upcoming announcement is anticipated by investors (i.e. the higher the standard deviation of the analyst forecasts), the more attention is paid to the information production of the systematic risk factor (i.e. the more news there are discussing about interest rates). Thus, we expect a positive relation between the standard deviation of analyst forecasts, regardless of which measure of standard deviation is used, and the counts of news articles on interest rates before announcement. The results presented in Table 3 is consistent with $\mathbf{H_1}$ for both FOMC and CPI announcements.

The second test is on the effects of the attention allocation by investors on the levels of trading volumes before and after announcements ($\mathbf{H_2}$). I run the OLS regression of the trading volumes on the E-mini S&P 500 futures 72 hours before and 24 hours after the macroeconomic announcements, respectively, on the number of news articles in the corresponding news group ("interest-rates" for FOMC and "consumption" for CPI) during the 72 hours before the same announcement. As predicted by the model, when more attention is paid to the systematic risk factor (i.e. the market), the higher the precision of the private signals received by investors, the lower the uncertainty on the market index, and the higher are the levels of the trading volume both before and after the announcement. Thus we expect both a positive relationship between the news counts and the pre-announcement trading volume and a positive relationship between the news counts and the post-announcement trading volume. To distinguish this attention effect from the classical information effect, I control for the announcement surprises by including $AbsAnnSurp$, the absolute difference between the actual announced value of the macroeconomic variable and its forecast mean, in the multivariate regression. Alternatively, I also control for the announcement surprises by $NormAnnSurp$, the normalized absolute difference between the actual announced value of the macroeconomic variable and the forecast mean. In all the OLS regressions, with or without controlling for announcement surprises, I find a positive relation between $News[-72hrs, 0]$ and the pre-announcement trading volume (measured by $TV[-72hrs, 0]$) and a positive relation between $News[-72hrs, 0]$ and the post-announcement trading volume (measured by $TV[0, 24hrs]$), as shown in Table 4. This is consistent with $\mathbf{H_2}$ for both FOMC and CPI announcements.

The third test is on the effect of investor attention on the ratio of the post-announcement trading volume over the pre-announcement trading volume on the E-mini S&P 500 futures ($\mathbf{H_3}$). I run the OLS regression of the ratio of trading volumes (as measured by $Ratio\_24to72$ and $Ratio\_72to72$) on the number of news articles on interest rates during the 72 hours before announcements (as measured by $News[-72hrs, 0]$). My model predicts that, when more attention is paid to the systematic risk factor (i.e. the market) before announcement, investors make less "mistakes" when forming their initial portfolios and thus there is less need for them to modify their portfolios after announcement, resulting in a lower ratio of trading volumes. Therefore, we expect a negative relationship between the number of news articles and the ratio of trading volumes around announcement. The results presented in Tables 5 and 6 are consistent with $\mathbf{H_3}$, both for the FOMC announcement and the CPI announcement.

7 Conclusion

I develop a model of investor behavior around prescheduled macroeconomic announcements. My model analyzes the optimal allocation of investor attention between systematic and idiosyncratic risk factors when a macroeconomic announcement is anticipated. Skilled investors, when producing information under a limited attention capacity, optimally allocate more of their attention to analyzing the idiosyncratic risk factor when they anticipate more precise public information about the systematic risk factor from the macroeconomic announcement. Consequently, my model predicts that, the more informative (precise) the macroeconomic announcement is expected to be about the underlying risk factors, *ceteris paribus*, the more uncertainty pre-announcement, the more resolution of uncertainty post-announcement, and the higher the trading volume around the announcement on the market index. My empirical analysis of trading by investors around both FOMC and CPI announcements support my model's predictions. In particular, my empirical findings are consistent with model predictions about the effect of the anticipated macroeconomic announcement precision on investor attention allocation, the effect of investor attention on the levels of pre-announcement and post-announcement trading volumes, and the effect of investor attention on the ratio of post-announcement trading volume over the pre-announcement trading volume.

References

Admati, Anat R, 1985, A noisy rational expectations equilibrium for multi-asset securities markets, *Econometrica: Journal of the Econometric Society* 629–657.

Ai, Hengjie, and Ravi Bansal, 2018, Risk preferences and the macroeconomic announcement premium, *Econometrica* 86, 1383–1430.

Albuquerque, Rui, 2012, Skewness in stock returns: reconciling the evidence on firm versus aggregate returns, *The Review of Financial Studies* 25, 1630–1673.

Albuquerque, Rui, Gregory H. Bauer, and Martin Schneider, 2009, Global private information in international equity markets, *Journal of Financial Economics* 94, 18 – 46.

Bernanke, Ben S, and Kenneth N Kuttner, 2005, What explains the stock market's reaction to federal reserve policy?, *The Journal of finance* 60, 1221–1257.

Bernile, Gennaro, Jianfeng Hu, and Yuehua Tang, 2016, Can information be locked up? informed trading ahead of macro-news announcements, *Journal of Financial Economics* 121, 496–520.

Boyd, John H, Jian Hu, and Ravi Jagannathan, 2005, The stock market's reaction to unemployment news: Why bad news is usually good for stocks, *The Journal of Finance* 60, 649–672.

Brennan, Michael J, and H Henry Cao, 1997, International portfolio investment flows, *The Journal of Finance* 52, 1851–1880.

Brusa, Francesca, Pavel G Savor, and Mungo Ivor Wilson, 2017, One central bank to rule them all .

Chen, Linda H., George J. Jiang, and Kevin X. Zhu, 2018, Total attention: The effect of macroeconomic news on market reaction to earnings news, *Journal of Banking & Finance* 97, 142 – 156.

Cieslak, Anna, Adair Morse, and Annette Vissing-Jorgensen, 2018, Stock returns over the FOMC cycle .

DellaVigna, Stefano, and Joshua M Pollet, 2009, Investor inattention and friday earnings announcements, *The Journal of Finance* 64, 709–749.

Engelberg, Joseph E., and Christopher A. Parsons, 2011, The causal impact of media in financial markets, *The Journal of Finance* 66, 67–97.

Fang, Lily, and Joel Peress, 2009, Media coverage and the cross-section of stock returns, *The Journal of Finance* 64, 2023–2052.

Gabaix, Xavier, 2014, A sparsity-based model of bounded rationality, *The Quarterly Journal of Economics* 129, 1661–1710.

Gabaix, Xavier, 2016a, Behavioral macroeconomics via sparse dynamic programming, Technical report, National Bureau of Economic Research.

Gabaix, Xavier, 2016b, A behavioral new keynesian model, Technical report, National Bureau of Economic Research.

Grossman, Sanford J, and Joseph E Stiglitz, 1980, On the impossibility of informationally efficient markets, *The American economic review* 70, 393–408.

Hellwig, Martin F, 1980, On the aggregation of information in competitive markets, *Journal of economic theory* 22, 477–498.

Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, *The Journal of Finance* 64, 2289–2325.

Hou, Kewei, Wei Xiong, and Lin Peng, 2009, A tale of two anomalies: The implications of investor attention for price and earnings momentum .

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2016, A rational theory of mutual funds' attention allocation, *Econometrica* 84, 571–626.

Lucca, David O, and Emanuel Moench, 2015, The pre-FOMC announcement drift, *The Journal of Finance* 70, 329–371.

Maćkowiak, Bartosz, and Mirko Wiederholt, 2009, Optimal sticky prices under rational inattention, *American Economic Review* 99, 769–803.

Maćkowiak, Bartosz, and Mirko Wiederholt, 2015, Business cycle dynamics under rational inattention, *The Review of Economic Studies* 82, 1502–1532.

Mondria, Jordi, 2010, Portfolio choice, attention allocation, and price comovement, *Journal of Economic Theory* 145, 1837–1864.

Savor, Pavel, and Mungo Wilson, 2013, How much do investors care about macroeconomic risk? evidence from scheduled economic announcements, *Journal of Financial and Quantitative Analysis* 48, 343–375.

Savor, Pavel, and Mungo Wilson, 2014, Asset pricing: A tale of two days, *Journal of Financial Economics* 113, 171–201.

Sims, Christopher A, 2003, Implications of rational inattention, *Journal of monetary Economics* 50, 665–690.

Wachter, Jessica A, and Yicheng Zhu, 2018, The macroeconomic announcement premium, Technical report, National Bureau of Economic Research.

Appendices

A Proof of Propositions

A.1 Proof of Proposition 1

Following Brennan and Cao (1997), I conjecture a linear structure for the equilibrium price which in general reads as

$$\begin{aligned} \boldsymbol{P}_t &= [\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \rho\overline{\hat{\boldsymbol{\Sigma}}_t}\bar{\boldsymbol{x}}] \\ &\quad + \overline{\hat{\boldsymbol{\Sigma}}_t}\sum_{j=1}^{t}[\boldsymbol{\Sigma}_{pub,j}^{-1}\boldsymbol{\eta}_{pub,j} + (\boldsymbol{I}_2 + \rho^{-2}\sigma_x^{-2}\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}'^{-1})\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}^{-1}(\boldsymbol{z} - \rho\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}\boldsymbol{x}_j)] \end{aligned} \tag{A.1}$$

where $\boldsymbol{\Sigma}_{pub,j}^{-1} = \boldsymbol{0}$ (a 2×2 zero matrix) if there is no public announcement at time j. This linear form generates an unbiased estimator for $\boldsymbol{z}$,

$$\boldsymbol{\eta}_{\boldsymbol{p},t} \equiv \boldsymbol{z} - \rho\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}\boldsymbol{x}_j. \tag{A.2}$$

Following the Bayesian updating in Section 4.1 and applying the demand vectors in Proposition 2, it is straightforward to confirm that (A.1) clears the market at both $t = 1$ and $t = 2$. Written specifically for each trading period, I have expressions (16) and (17).

This completes the proof of Proposition 1.

A.2 Proof of Proposition 2

Notice from Proposition 1 that the conditional distribution of $\boldsymbol{z}$ in the belief of any given investor i at $t = 2$ is normal, so that the utility maximization problem $\max_{\boldsymbol{D}_2^i} E_2^i(-\exp[-\rho W_3^i])$ is equivalent to the classical maximization for a mean-variance utility,

$$\max_{\boldsymbol{D}_2^i}(\boldsymbol{D}_2^i)'(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{z}}_2^i - \boldsymbol{P}_2) - \frac{\rho}{2}(\boldsymbol{D}_2^i)'\hat{\boldsymbol{\Sigma}}_2^i\boldsymbol{D}_2^i \tag{A.3}$$

A standard procedure confirms (19) for $t=2$. The case of $t=1$ is more complex since when investors form their beliefs about their terminal wealth W_3^i at $t=1$, not only their beliefs on $\boldsymbol{z}$ matter, but also their beliefs on the capital gain $\boldsymbol{P}_2-\boldsymbol{P}_1$ do. I will confirm the optimal demand at $t=1$ through the calculation of expected utilities.[22]

To calculate the expected utility at $t=1$, I decompose the belief updating process from $t=1$ to $t=2$ into two steps, with $\Delta\boldsymbol{P}$ as an intermediate additional information.

Step 1. Investors update their beliefs $\boldsymbol{z}|_{\mathcal{F}_1^i} \sim MVN(\hat{\boldsymbol{z}}_1^i, \hat{\boldsymbol{\Sigma}}_1^i)$ conditional on the change in price $\Delta\boldsymbol{P} \equiv \boldsymbol{P}_2-\boldsymbol{P}_1$. In order to do so, I compare (16) and (17) to establish an unbiased estimator for $\boldsymbol{z}$ based on the additional information revealed by $\Delta\boldsymbol{P}$ as follows:[23]

$$
\begin{aligned}
& (\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})^{-1}\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1}(\boldsymbol{P}_2-\boldsymbol{P}_1) + (\boldsymbol{P}_1 - \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu}) \\
= \;& \boldsymbol{z} + (\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})^{-1}[\boldsymbol{\Sigma}_{pub}^{-1}\boldsymbol{\epsilon}_{pub} - \rho(\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}^{-1} + \boldsymbol{\Sigma}_{\boldsymbol{p},2}^{-1})\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}\boldsymbol{x}_2] \\
\equiv \;& \boldsymbol{z} + \boldsymbol{\epsilon}_{\Delta\boldsymbol{p}}
\end{aligned}
\tag{A.4}
$$

The expectation and variance of the noise $\boldsymbol{\epsilon}_{\Delta\boldsymbol{p}}$ are

$$
E(\boldsymbol{\epsilon}_{\Delta\boldsymbol{p}}) = 0 \tag{A.5}
$$

$$
V(\boldsymbol{\epsilon}_{\Delta\boldsymbol{p}}) = (\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})^{-1} + (\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})^{-1}(\overline{\boldsymbol{\Sigma}}_{\boldsymbol{\eta}}^{-1} + \rho^2\sigma_x^2 I_2)(\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})'^{-1} \tag{A.6}
$$

We denote the mean and variance of $\boldsymbol{z}$ conditional on both $\mathcal{F}_1^i$ and $\Delta\boldsymbol{P}$ by $E_{1,\Delta\boldsymbol{P}}^i(\boldsymbol{z})$ and $V_{1,\Delta\boldsymbol{P}}^i(\boldsymbol{z})$ respectively, and by Bayes Law,

$$
V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{z})^{-1} \equiv V[z|\mathcal{F}_1^i, \boldsymbol{P}_2-\boldsymbol{P}_1]^{-1} = (\hat{\boldsymbol{\Sigma}}_1^i)^{-1} + V(\boldsymbol{\epsilon}_{\Delta\boldsymbol{p}})^{-1} \tag{A.7}
$$

$$
E_{1,\Delta\boldsymbol{P}}^i(\boldsymbol{z}) = V_{1,\Delta\boldsymbol{p}}^i(z)[(\hat{\boldsymbol{\Sigma}}_1^i)^{-1}\hat{\boldsymbol{z}}_1^i + V(\boldsymbol{\epsilon}_{\Delta p})^{-1}(\boldsymbol{z}+\boldsymbol{\epsilon}_{\Delta p})] \tag{A.8}
$$

[22]To prove Proposition 3, I also need to trace the expected utility back to $t=0$.
[23]Notice that the signal $\boldsymbol{\epsilon}_{\Delta p}$ is orthogonal to the information set $\mathcal{F}_1^i$.

Incidentally, I will later need the following expectation and variance in calculation:

$$E_1^i(\Delta\boldsymbol{P}) = \overline{\hat{\boldsymbol{\Sigma}}}_2(\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})[\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + E_1^i(\boldsymbol{z}) - \boldsymbol{P}_1] \tag{A.9}$$

$$V_1^i(\Delta\boldsymbol{P}) = \overline{\hat{\boldsymbol{\Sigma}}}_2(\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})[\hat{\boldsymbol{\Sigma}}_1^i + V(\epsilon_{\Delta\boldsymbol{P}})](\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})'\overline{\hat{\boldsymbol{\Sigma}}}_2' \tag{A.10}$$

Step 2. Investors further update their beliefs by their expected excess returns, denoted by

$$\boldsymbol{y}_t \equiv \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{z}}_t^i - \boldsymbol{P}_t, \text{ for } t = 1, 2 \tag{A.11}$$

The intermediate conditional expectation is

$$\begin{aligned} E_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2) &\equiv E(\boldsymbol{y}_2|\mathcal{F}_1^i, \Delta p) \\ &= E_{1,\Delta\boldsymbol{P}}^i(\boldsymbol{z}) - \Delta\boldsymbol{P} - (\boldsymbol{P}_1 - \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu}) \\ &= \boldsymbol{A} + \boldsymbol{B}\Delta\boldsymbol{P}, \end{aligned} \tag{A.12}$$

where

$$\boldsymbol{A} = V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{z})(\hat{\boldsymbol{\Sigma}}_1^i)^{-1}(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{z}}_1^i - \boldsymbol{P}_1), \tag{A.13}$$

$$\boldsymbol{B} = V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{z})V(\boldsymbol{\epsilon}_{\Delta\boldsymbol{p}})^{-1}(\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})^{-1}\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \boldsymbol{I}_2, \tag{A.14}$$

and the intermediate conditional variance is

$$\begin{aligned} V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2) &\equiv V(\boldsymbol{y}_2|\mathcal{F}_1^i, \Delta p) \\ &= V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{z}) - E[\hat{\boldsymbol{\Sigma}}_2^i|\mathcal{F}_1^i, \Delta\boldsymbol{P}] \\ &= [(\hat{\boldsymbol{\Sigma}}_1^i)^{-1} + V(\boldsymbol{\epsilon}_{\Delta\boldsymbol{p}})^{-1}]^{-1} - \hat{\boldsymbol{\Sigma}}_2^i. \end{aligned} \tag{A.15}$$

The last equality applies the fact that all expected variances under the assumption of normality are independent of the actual realizations of signals.

Notice that $\mathcal{F}_2^i = \{\boldsymbol{P}_1, \boldsymbol{P}_2, \boldsymbol{\eta}_1^i, \boldsymbol{\eta}_2^i, \boldsymbol{\eta}_{pub}\} = span\{\mathcal{F}_1^i, \Delta\boldsymbol{P}, \boldsymbol{y}_2\}$, so the conditional expectation $E_1^i(\cdot)$ can be calculated from $E_2^i(\cdot)$ through the calculation of $E_{1,\Delta\boldsymbol{p}}^i(\cdot)$.

Calculation of expected utilities:

Now I evaluate the sequence of expected utilities in the order of $E_2^i(\cdot) \to E_{1,\Delta\boldsymbol{p}}^i(\cdot) \to E_1^i(\cdot)$. The expected utility at $t = 2$ is simply

$$E_2^i(-\exp[-\rho W_3^i]) = -\exp\{-\rho W_2^i - \frac{1}{2}\boldsymbol{y}_2'(\hat{\boldsymbol{\Sigma}}_2^i)^{-1}\boldsymbol{y}_2\}. \tag{A.16}$$

Applying (A.12) and (A.15), the expected utility conditional on $\mathcal{F}_1^i$ and $\Delta\boldsymbol{P}$ is

$$\begin{aligned}
& E_{1,\Delta\boldsymbol{p}}^i(-\exp[-\rho W_3^i]) \\
= \; & E_{1,\Delta\boldsymbol{p}}^i(E_2^i(-\exp[-\rho W_3^i])) \\
= \; & \int -\exp\{-\rho W_2^i - \frac{1}{2}\boldsymbol{y}_2'(\hat{\boldsymbol{\Sigma}}_2^i)^{-1}\boldsymbol{y}_2\} \det(2\pi V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2))^{-\frac{1}{2}} \\
& \exp\{-\frac{1}{2}(\boldsymbol{y}_2 - E_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2))'V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2)^{-1}(\boldsymbol{y}_2 - E_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2))\}d\boldsymbol{y}_2 \\
= \; & -\det(2\pi V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2))^{-\frac{1}{2}} \exp(-\rho W_2^i) \\
& \int \exp\{-\frac{1}{2}[\boldsymbol{y}_2'(\hat{\boldsymbol{\Sigma}}_2^i)^{-1}\boldsymbol{y}_2 + (\boldsymbol{y}_2 - E_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2))'V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2)^{-1}(\boldsymbol{y}_2 - E_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2))]\}d\boldsymbol{y}_2 \\
= \; & -\det(V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2)^{-1}[(\hat{\boldsymbol{\Sigma}}_2^i)^{-1} + V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2)^{-1}]^{-1})^{\frac{1}{2}} \\
& \exp(-\rho W_2^i - \frac{1}{2}E_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2)'V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2)^{-1}[\boldsymbol{I}_2 - \hat{\boldsymbol{\Sigma}}_2^i V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{z})^{-1}]E_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2))
\end{aligned}$$

To arrive at the last step in the above, I complete the squares with respect to $\boldsymbol{y}_2$ in the second to the last step.

With (A.9) and (A.10), investor i's conditional expectation at $t = 1$ can be calculated as follows

$$\begin{aligned}
& E_1^i(-\exp[-\rho W_3^i]) \\
= \; & E_1^i(E_{1,\Delta\boldsymbol{p}}^i(-\exp[-\rho W_3^i])) \\
= \; & -\det(V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2)^{-1}[(\hat{\boldsymbol{\Sigma}}_2^i)^{-1} + V_{1,\Delta\boldsymbol{p}}^i(\boldsymbol{y}_2)^{-1}]^{-1})^{\frac{1}{2}}
\end{aligned}$$

$$
\begin{aligned}
& \int \exp(-\rho[W_0 + (\boldsymbol{D}_1^i)'\Delta \boldsymbol{P}] - \frac{1}{2} E^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{y}_2)' V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{y}_2)^{-1} [\boldsymbol{I}_2 - \hat{\boldsymbol{\Sigma}}^i_2 V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})^{-1}] E^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{y}_2)) \\
& \det(2\pi V_1^i(\Delta \boldsymbol{P}))^{-\frac{1}{2}} \exp\{-\frac{1}{2}[\Delta \boldsymbol{P} - E_1^i(\Delta \boldsymbol{P})]' V_1^i[\Delta \boldsymbol{P})^{-1}(\Delta \boldsymbol{P} - E_1^i(\Delta \boldsymbol{P})]\} d(\Delta \boldsymbol{P}) \\
= \; & -\det([(\hat{\boldsymbol{\Sigma}}^i_2)^{-1} V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{y}_2) + \boldsymbol{I}_2]^{-1} V_1^i(\Delta \boldsymbol{P})^{-1} [\boldsymbol{B}' V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})^{-1} \boldsymbol{B} + V_1^i(\Delta \boldsymbol{P})^{-1}]^{-1})^{\frac{1}{2}} \\
& \exp\{-\rho W_0 + \frac{1}{2}[\boldsymbol{B}' V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})^{-1} \boldsymbol{A} - V_1^i(\Delta \boldsymbol{P})^{-1} E_1^i(\Delta \boldsymbol{P})^{-1} + \rho \boldsymbol{D}_1^i]' \\
& \;[\boldsymbol{B}' V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})^{-1} \boldsymbol{B} + V_1^i(\Delta \boldsymbol{P})^{-1}]^{-1} [\boldsymbol{B}' V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})^{-1} \boldsymbol{A} - V_1^i(\Delta \boldsymbol{P})^{-1} E_1^i(\Delta \boldsymbol{P}) + \rho \boldsymbol{D}_1^i] \\
& \;-\frac{1}{2}[\boldsymbol{A}' V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})^{-1} \boldsymbol{A} + E_1^i(\Delta \boldsymbol{P})' V_1^i(\Delta \boldsymbol{P})^{-1} E_1^i(\Delta \boldsymbol{P})]\}
\end{aligned}
$$

Differentiating the result from the last step with respect to $\boldsymbol{D}_1^i$, I confirm that (19) also holds for $t = 1$. With the optimal portfolio allocation at $t = 1$, the conditional expected utility above is further simplified into

$$
\begin{aligned}
& E_1^i(-\exp[-\rho W_3^i]) \\
= \; & -\det([(\hat{\boldsymbol{\Sigma}}^i_2)^{-1} V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{y}_2) + \boldsymbol{I}_2]^{-1} V_1^i(\Delta \boldsymbol{P})^{-1} [\boldsymbol{B}' V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})^{-1} \boldsymbol{B} + V_1^i(\Delta \boldsymbol{P})^{-1}]^{-1})^{\frac{1}{2}} \\
& \exp\{-\rho W_0 - \frac{1}{2}[\boldsymbol{A}' V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})^{-1} \boldsymbol{A} + E_1^i(\Delta \boldsymbol{P})' V_1^i(\Delta \boldsymbol{P})^{-1} E_1^i(\Delta \boldsymbol{P})]\} \qquad \text{(A.17)}
\end{aligned}
$$

This completes the proof of Proposition 2.

A.3 Proof of Proposition 3

Continuing from the calculation of expected utility in the proof of Proposition 2, I now move backwards to $t = 0$ and calculate investors' unconditional expected utility at $t = 0$. Skilled investors allocate their attention before observing any information. Recall that $\boldsymbol{y}_1 \equiv \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{z}}_1^i - \boldsymbol{P}_1$, and I take a closer look at the exponent of the second component in (A.17):

$$
\begin{aligned}
& \boldsymbol{A}' V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})^{-1} \boldsymbol{A} + E_1^i(\Delta \boldsymbol{P})' V_1^i(\Delta \boldsymbol{P})^{-1} E_1^i(\Delta \boldsymbol{P}) \\
= \; & [\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{z}}_1^i - \boldsymbol{P}_1]' \{(\hat{\boldsymbol{\Sigma}}^i_1)'^{-1} V^i_{1,\Delta \boldsymbol{p}}(\boldsymbol{z})' (\hat{\boldsymbol{\Sigma}}^i_1)^{-1} \\
& + (\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})' \overline{\hat{\boldsymbol{\Sigma}}}_2' V_1^i(\Delta \boldsymbol{P})^{-1} \overline{\hat{\boldsymbol{\Sigma}}}_2 (\overline{\hat{\boldsymbol{\Sigma}}}_2^{-1} - \overline{\hat{\boldsymbol{\Sigma}}}_1^{-1})\} [\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{z}}_1^i - \boldsymbol{P}_1] \qquad \text{(A.18)}
\end{aligned}
$$

$$\equiv \quad \boldsymbol{y}_1' \boldsymbol{M} \boldsymbol{y}_1,$$

where I denote the middle component (all terms inside the curly brackets in (A.18)) above by $\boldsymbol{M}$ for convenience. The calculation of the unconditional expectation and variance of $\boldsymbol{y}_1$ is standard and straightforward. i.e.,

$$\boldsymbol{E}^i \equiv E_0(\boldsymbol{y}_1) = \rho \overline{\hat{\boldsymbol{\Sigma}}}_1 \bar{x} \tag{A.19}$$

$$\boldsymbol{V}^i \equiv V_0(\boldsymbol{y}_1) = \overline{\hat{\boldsymbol{\Sigma}}}_1 \boldsymbol{\Sigma}^{-1} \overline{\hat{\boldsymbol{\Sigma}}}_1' - (\hat{\boldsymbol{\Sigma}}_1^i)' + (\overline{\hat{\boldsymbol{\Sigma}}}_1 \boldsymbol{\Sigma}^{-1} - \boldsymbol{I}_2) \boldsymbol{\Sigma}_{\boldsymbol{p},1} (\overline{\hat{\boldsymbol{\Sigma}}}_1 \boldsymbol{\Sigma}^{-1} - \boldsymbol{I}_2)' \tag{A.20}$$

Finally, the expected utility at $t = 0$ of investor i is

$$\begin{aligned}
& E_0(-\exp[-\rho W_3^i]) \\
= \; & E_0(E_1^i(-\exp[-\rho W_3^i])) \\
= \; & -\det([(\hat{\boldsymbol{\Sigma}}_2^i)^{-1} V_{1,\Delta \boldsymbol{p}}^i(\boldsymbol{y}_2) + \boldsymbol{I}_2]^{-1} V_1^i(\Delta \boldsymbol{P})^{-1} [\boldsymbol{B}' V_{1,\Delta \boldsymbol{p}}^i(\boldsymbol{z})^{-1} \boldsymbol{B} + V_1^i(\Delta \boldsymbol{P})^{-1}]^{-1})^{\frac{1}{2}} \\
& \int \exp[-\rho W_0 - \frac{1}{2} \boldsymbol{y}_1' \boldsymbol{M} \boldsymbol{y}_1] \det(2\pi \boldsymbol{V}^i)^{-\frac{1}{2}} \exp\{-\frac{1}{2}(\boldsymbol{y}_1 - \boldsymbol{E}^i)'(\boldsymbol{V}^i)^{-1}(\boldsymbol{y}_1 - \boldsymbol{E}^i)\} d\boldsymbol{y}_1 \\
= \; & -\det([(\hat{\boldsymbol{\Sigma}}_2^i)^{-1} V_{1,\Delta \boldsymbol{p}}^i(\boldsymbol{y}_2) + \boldsymbol{I}_2]^{-1} [\boldsymbol{B}' V_{1,\Delta \boldsymbol{p}}^i(\boldsymbol{z})^{-1} \boldsymbol{B} V_1^i(\Delta \boldsymbol{P}) + \boldsymbol{I}_2]^{-1} [\boldsymbol{M} \boldsymbol{V}^i + \boldsymbol{I}_2]^{-1})^{\frac{1}{2}} \\
& \exp\{-\rho W_0 + \frac{1}{2}(\boldsymbol{E}^i)'[(\boldsymbol{V}^i)'^{-1}(\boldsymbol{M} + (\boldsymbol{V}^i)^{-1})'^{-1}(\boldsymbol{V}^i)^{-1} - (\boldsymbol{V}^i)^{-1}]\boldsymbol{E}^i\}
\end{aligned} \tag{A.21}$$

This completes the proof of Proposition 3.

B Additional Simulation Results

Because my model is solved on the level of risk factors, here I supply the simulation results on the level of risk factors as references to help interpret the results on assets in the main text. All parameters are same as exhibited in Table 1.

Result B.1. Equilibrium Prices of the Synthetic Assets on Risk Factors:

From Result 1 in Section 4.4, as the precision of the announcement increases, more attention is allocated toward the idiosyncratic risk factor. Thus , at $t = 1$, the private signals for the idiosyncratic risk factor are more precise and lowers the uncertainty, so that the price of the synthetic asset on the idiosyncratic risk factor is higher. At $t = 2$, there is no public signal revealed for the idiosyncratic risk factor, but the private signals received by the skilled investors are of the same precision as at $t = 1$, so by a same argument as above the price of the synthetic asset also increases at $t = 2$ (Figure B.1).

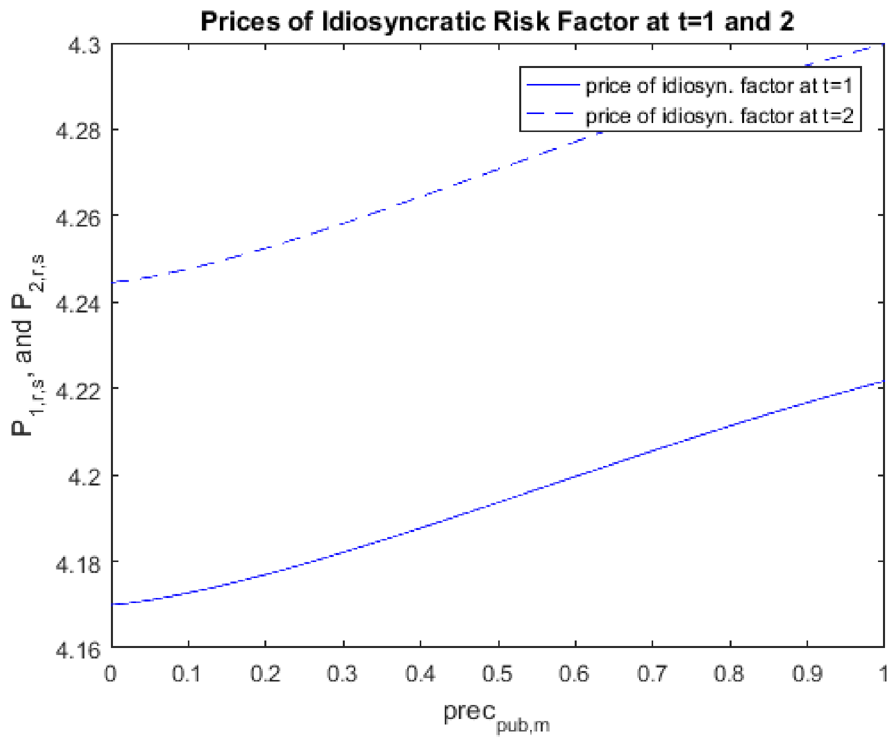

Figure B.1: Equilibrium Price of Synthetic Asset for Idiosyncratic Risk Factor

By an analogy of the discussion above, the price of the synthetic asset on the systematic risk factor at $t = 1$ decreases in the precision of the anticipating macroeconomic announcement. At $t = 2$, however, since more information about the market is released through the announcement, the uncertainty on the systematic risk factor is significantly lowered and thus cancels out the uncertainty from the less precise private signals and further increases the price of the synthetic asset on the systematic risk factor (Figure B.2).

Result B.2. Returns on Synthetic Assets for Risk Factors:

As more precise an announcement is expected, more attention is allocated to the id-

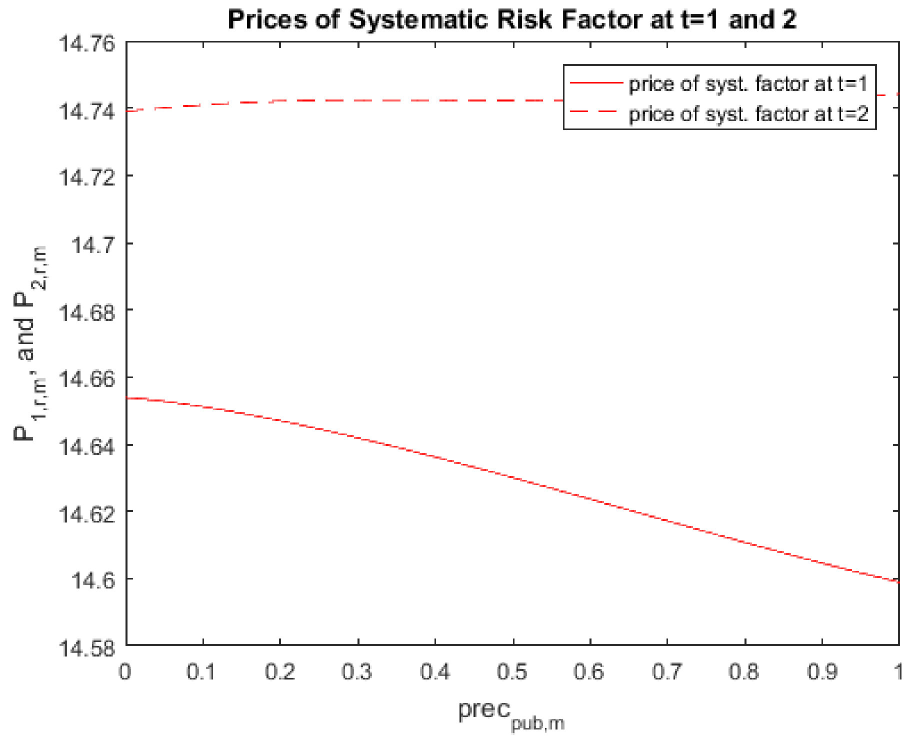

Figure B.2: Equilibrium Price of Synthetic Asset for Systematic Risk Factor

iosyncratic risk factor so that the incremental information received in the period before the announcement increases and the return on the synthetic asset for the idiosyncratic risk factor increases. For the systematic risk factor, even though the private signals on it are less precise because of attention shifting, the public signal from the announcement compensates for the information loss and further increases the precision of the incremental information within the period from $t = 1$ to $t = 2$. Thus, the return of the synthetic asset for the systematic risk factor increases (Figure B.3). The trend of returns on the synthetic assets is accompanied by a similar trend in the standard deviation of returns on these synthetic assets, as shown in Figure B.4, confirming the increase in uncertainty on the systematic risk factor and the decrease of uncertainty on the idiosyncratic risk factor as the public signal gets more precise.

Result B.3. Trading volume of the risk factors:

The overall levels of the trading volumes on both the synthetic asset for the systematic risk factor and the synthetic asset for the idiosyncratic risk factor are higher at $t = 2$ than at $t = 1$ because the uncertainty on both synthetic assets are lower after another round of

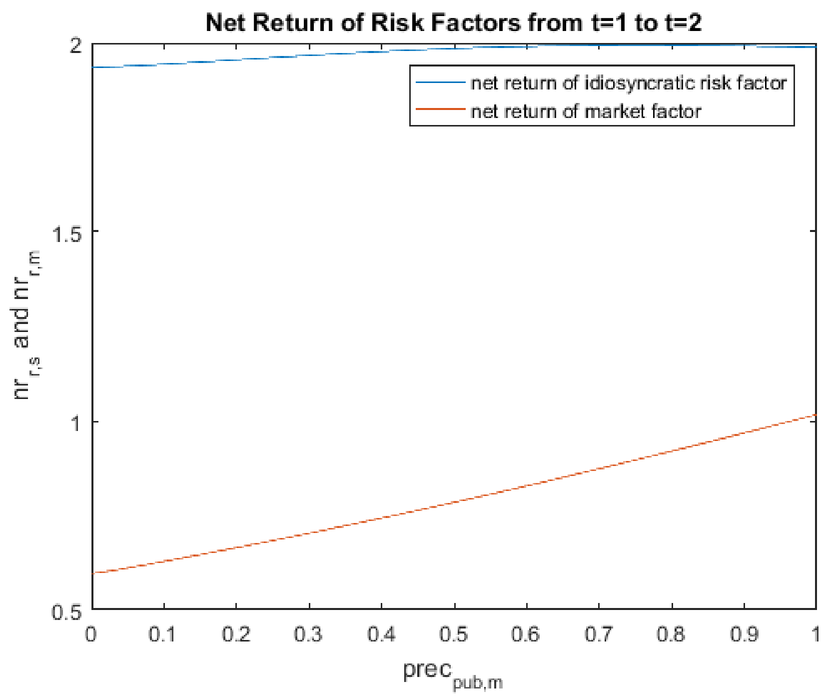

Figure B.3: Return on Synthetic Assets for Risk Factors

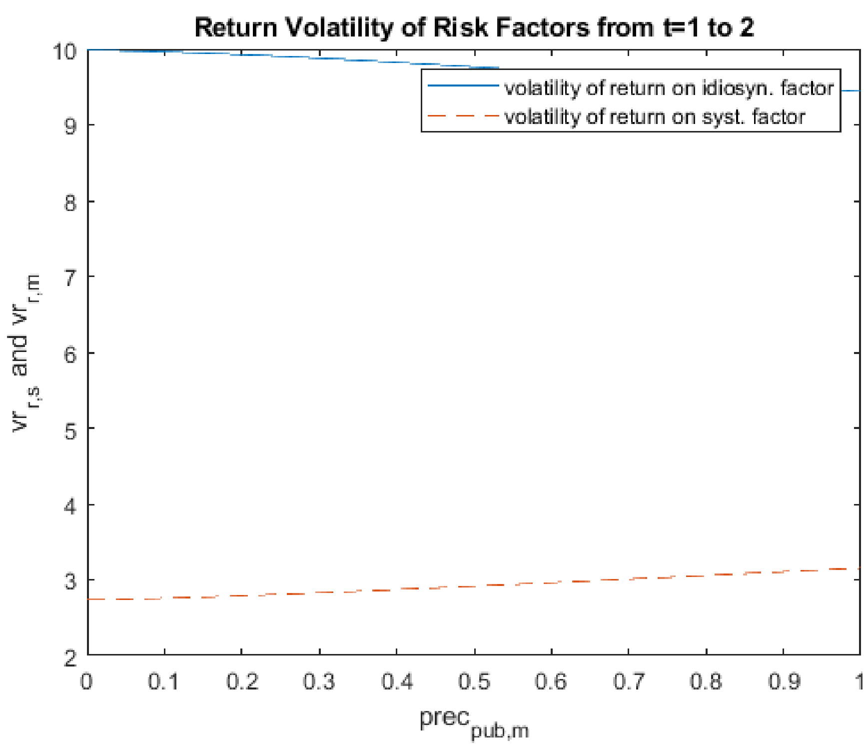

Figure B.4: Return Volatility of Synthetic Assets for Risk Factors information production and the announcement at $t = 2$. As the announcement gets more precise, since more attention is shifted away from the systematic risk factor, investors' beliefs on the systematic risk factor get more similar to each other and create the downward trend in trading volume (Figure B.5).

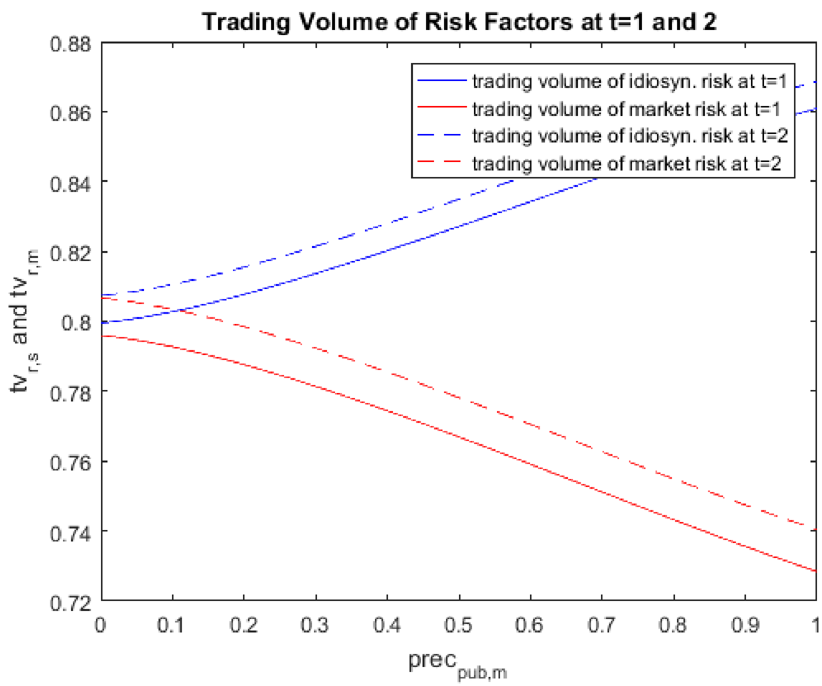

Figure B.5: Level of Trading Volumes on Synthetic Assets for Risk Factors

Table 2: **Summary Statistics for Macroeconomic Announcements**

This table reports summary statistics for the variables used in regressions. The sample contains analyst forecasts on the macroeconomic variable (i.e. Fed funds target rate for FOMC, and change in Consumer Price Index for CPI), the trading volume data on the E-mini S&P 500 futures, and the number of news articles on the macroeconomic variable from July 2003 to Oct 2018. There are 124 FOMC announcements within the period and 122 among them have available analyst forecasts data; there are 184 CPI announcements within the period with available analyst forecasts data. $News[-72hrs, 0]$ is defined as the number of the news articles in RavenPack within groups "interest-rates" and "consumption" for FOMC and CPI, respectively. $TV[-72hrs, 0]$ is defined as the trading volume on E-mini S&P 500 futures during the 72-hour window before announcement. $TV[0, 24hrs]$ is defined as the trading volume on E-mini S&P 500 futures during the 24-hour window after announcement. $TV[0, 72hrs]$ is defined as the trading volume on E-mini S&P 500 futures during the 72-hour window after announcement. $Ratio\_24to72$ is defined as the ratio of the trading volume on E-mini S&P 500 futures during the 24-hour window after announcement over the trading volume on E-mini S&P 500 futures during the 72-hour window before announcement. $Ratio\_72to72$ is defined as the ratio of the trading volume on E-mini S&P 500 futures during the 72-hour window after announcement over the trading volume on E-mini S&P 500 futures during the 72-hour window before announcement. $SD(-\infty, 0]$ is the standard deviation of all analyst forecasts for each given announcement. $SD(-\infty, -3days)$ is the standard deviation of analyst forecasts from the first available forecast until three days before the announcement (i.e. the $(-\infty, -3$ days) window). $SD[-30days, -3days)$ is the standard deviation of analyst forecasts from one month before till three days before the announcement (i.e. the $[-30$ days, -3 days) window). $AnnSurp$ is defined as the difference between the actual announced interest rate and the forecast mean. $AbsAnnSurp$ is the absolute difference between the actual announced value and the forecast mean, i.e. $|AnnSurp|$. $NormAnnSurp$ is the normalized absolute difference between the actual announced value and the forecast mean, i.e. $|AnnSurp|/SD(-\infty, 0]$.

Panel A: FOMC announcements						
	Mean	Median	SD	Min	Max	Obs
$News[-72hrs, 0]$	29.71	26	19.91	4	127	122
$TV[-72hrs, 0]$	3.383e+06	3.338e+06	1.788e+06	667,649	1.024e+07	122
$TV[0, 24hrs]$	2.039e+06	1.901e+06	893,249	625,552	5.848e+06	122
$TV[0, 72hrs]$	4.434e+06	4.089e+06	2.146e+06	1.140e+06	1.457e+07	122
$Ratio\_24to72$	0.701	0.621	0.304	0.289	1.913	122
$Ratio\_72to72$	1.556	1.246	0.781	0.479	3.702	122
$SD(-\infty, 0]$	0.0224	0	0.0422	0	0.211	122
$SD(-\infty, -3days)$	0.0207	0	0.0384	0	0.203	122
$SD[-30days, -3days)$	0.0198	0	0.0384	0	0.203	122
$AnnSurp$	-0.00470	0	0.0361	-0.229	0.0712	122
$AbsAnnSurp$	0.0107	0	0.0348	0	0.229	122
$NormAnnSurp$	0.325	0.180	0.400	0	1.798	43

Panel B: CPI announcements						
	Mean	Median	SD	Min	Max	Obs
$News[-72hrs, 0]$	90.79	88	40.32	12	221	184
$TV[-72hrs, 0]$	3.557e+06	3.210e+06	2.079e+06	523,380	1.125e+07	184
$TV[0, 24hrs]$	1.619e+06	1.489e+06	799,936	251,428	5.007e+06	183
$TV[0, 72hrs]$	3.586e+06	3.096e+06	2.353e+06	83,626	1.479e+07	184
$Ratio\_24to72$	0.563	0.470	0.305	0.160	1.611	183
$Ratio\_72to72$	1.413	1.123	1.121	0.0175	4.493	184
$SD(-\infty, 0]$	0.0935	0.0876	0.0322	0.0337	0.279	184
$SD(-\infty, -3days)$	0.0921	0.0851	0.0336	0.0308	0.284	184
$SD[-30days, -3days)$	0.0920	0.0851	0.0336	0.0308	0.284	184
$AnnSurp$	-0.00733	-0.00548	0.125	-0.458	0.397	184
$AbsAnnSurp$	0.0935	0.0735	0.0825	1.19e-08	0.458	184
$NormAnnSurp$	1.017	0.821	0.872	2.36e-07	4.925	184

Table 3: **Effect of Expected Announcement Precision on Investor Attention**
This table reports the results from regressions of the number of news articles on the macroeconomic variable (i.e. Fed funds target rate for FOMC, and change in Consumer Price Index for CPI) during the 72-hour window before the macroeconomic announcement (i.e. FOMC or CPI announcement) on the standard deviation of analyst forecasts on the the macroeconomic variable for the corresponding announcement. The sample contains analyst forecasts on the macroeconomic variable (i.e. Fed funds target rate for FOMC, and change in Consumer Price Index for CPI), the trading volume data on the E-mini S&P 500 futures, and the number of news articles on the macroeconomic variable (i.e. the news articles in RavenPack within groups "interest-rates" and "consumption" for FOMC and CPI, respectively) from July 2003 to Oct 2018. There are 124 FOMC announcements within the period and 122 among them have available analyst forecasts data; there are 184 CPI announcements within the period with available analyst forecasts data. ***Significant at 1%, **significant at 5%, *significant at 10%. Standard errors are show in brackets.

Panel A: FOMC announcements			
	$News[-72hrs, 0]$	$News[-72hrs, 0]$	$News[-72hrs, 0]$
$SD(-\infty, 0]$	89.86**		
	(42.34)		
$SD(-\infty, -3days)$		119.2**	
		(46.09)	
$SD[-30days, -3days)$			98.34**
			(46.47)
Constant	27.70***	27.25***	27.76***
	(2.014)	(2.003)	(2.002)
Observations	122	122	122
R-squared	0.036	0.053	0.036

Panel B: CPI announcements			
	$News[-72hrs, 0]$	$News[-72hrs, 0]$	$News[-72hrs, 0]$
$SD(-\infty, 0]$	246.1***		
	(90.89)		
$SD(-\infty, -3days)$		219.6**	
		(87.36)	
$SD[-30days, -3days)$			223.7**
			(87.25)
Constant	67.77***	70.56***	70.20***
	(8.991)	(8.564)	(8.548)
Observations	184	184	184
R-squared	0.039	0.034	0.035

Table 4: **Effect of Investor Attention on the Levels of Trading Volume Before and After Macroeconomic Announcements**

This table reports the results from regressions of the trading volume around the FOMC and CPI announcements on the number of corresponding news articles (i.e. the news articles in RavenPack within groups "interest-rates" and "consumption" for FOMC and CPI, respectively) during the 72-hour window before announcement. The pre-announcement trading volume is measured during the 72 hours before announcement and the post-announcement trading volume is measured during the 24 hours after announcement. The sample contains analyst forecasts on the Fed funds target rate, the trading volume data on the E-mini S&P 500 futures, and the number of news articles on interest rates from July 2003 to Oct 2018. There are 124 FOMC announcements within the period and 122 among them have available analyst forecasts data; there are 184 CPI announcements within the period with available analyst forecasts data. ***Significant at 1%, **significant at 5%, *significant at 10%. Standard errors are shown in brackets.

Panel A: FOMC Announcements

	Previous 3 days	Post 1 day				
	$TV[-72hrs, 0]$	$TV[0, 24hrs]$	$TV[0, 24hrs]$	$TV[0, 24hrs]$	$TV[0, 24hrs]$	$TV[0, 24hrs]$
$News[-72hrs, 0]$	30,776***	12,446***			10,340***	7,627
	(8,019)	(4,163)			(3,878)	(6,183)
$AbsAnnSurp$			6.738e+06***		6.095e+06***	
			(2.263e+06)		(2.221e+06)	
$NormAnnSurp$				812,523**		814,096**
				(399,111)		(396,597)
Constant	2.492e+06***	1.709e+06***	1.967e+06***	1.895e+06***	1.667e+06***	1.634e+06***
	(286,969)	(148,974)	(82,028)	(204,478)	(138,165)	(293,592)
Observations	124	124	122	43	122	43
R-squared	0.108	0.068	0.069	0.092	0.121	0.125

Panel B: CPI Announcements

	Previous 3 days	Post 1 day				
	$TV[-72hrs, 0]$	$TV[0, 24hrs]$	$TV[0, 24hrs]$	$TV[0, 24hrs]$	$TV[0, 24hrs]$	$TV[0, 24hrs]$
$News[-72hrs, 0]$	17,214***	1,815			1,555	1,802
	(3,604)	(1,469)			(1,479)	(1,473)
$AbsAnnSurp$			1.059e+06		955,760	
			(725,620)		(732,086)	
$NormAnnSurp$				22,127		19,565
				(69,060)		(68,997)
Constant	1.994e+06***	1.454e+06***	1.521e+06***	1.597e+06***	1.389e+06***	1.435e+06***
	(357,805)	(146,111)	(89,287)	(91,321)	(154,006)	(160,394)
Observations	184	183	183	183	183	183
R-squared	0.111	0.008	0.012	0.001	0.018	0.009

Table 5: **Effect of Investor Attention on the Ratio of Trading Volumes Around FOMC Announcements**

This table reports the results from regressions of the ratio of the trading volumes around the FOMC announcement on the number of news articles on interest rates during the 72-hour window before FOMC announcement. In Panel A, the ratio is defined as the trading volume during the 24 hours after announcement over the trading volume during the 72 hours before announcement. In Panel B, the ratio is defined as the trading volume during the 72 hours after announcement over the trading volume during the 72 hours before announcement. The sample contains analyst forecasts on the Fed funds target rate, the trading volume data on the E-mini S&P 500 futures, and the number of news articles on interest rates from July 2003 to Oct 2018. There are 124 FOMC announcements within the period and 122 among them have available analyst forecasts data. ***Significant at 1%, **significant at 5%, *significant at 10%. Standard errors are shown in brackets.

Panel A: Ratio of Trading Volumes, One Day Post-FOMC over Three Days Pre-FOMC

	Post 1 day/Previous 3 days				
	Ratio_24to72	*Ratio_24to72*	*Ratio_24to72*	*Ratio_24to72*	*Ratio_24to72*
$News[-72hrs, 0]$	-0.00427***			-0.00480***	-0.00352*
	(0.00134)			(0.00128)	(0.00203)
$AbsAnnSurp$		2.477***		2.775***	
		(0.766)		(0.731)	
$NormAnnSurp$			0.291**		0.290**
			(0.133)		(0.130)
Constant	0.828***	0.674***	0.668***	0.814***	0.789***
	(0.0478)	(0.0277)	(0.0684)	(0.0455)	(0.0965)
Observations	122	122	43	122	43
R-squared	0.078	0.080	0.104	0.178	0.166

Panel B: Ratio of Trading Volumes, Three Days Post-FOMC over Three Days Pre-FOMC

	Post 3 day/Previous 3 days				
	Ratio_72to72	*Ratio_72to72*	*Ratio_72to72*	*Ratio_72to72*	*Ratio_72to72*
$News[-72hrs, 0]$	-0.0149***			-0.0160***	-0.0123**
	(0.00331)			(0.00321)	(0.00490)
$AbsAnnSurp$		4.907**		5.904***	
		(2.000)		(1.837)	
$NormAnnSurp$			0.629*		0.626*
			(0.334)		(0.314)
Constant	2.000***	1.504***	1.442***	1.970***	1.865***
	(0.118)	(0.0725)	(0.171)	(0.114)	(0.233)
Observations	122	122	43	122	43
R-squared	0.145	0.048	0.079	0.213	0.205

Table 6: **Effect of Investor Attention on the Ratio of Trading Volumes Around CPI Announcements**

This table reports the results from regressions of the ratio of the trading volumes around the CPI announcement on the number of news articles on interest rates during the 72-hour window before CPI announcement. In Panel A, the ratio is defined as the trading volume during the 24 hours after announcement over the trading volume during the 72 hours before announcement. In Panel B, the ratio is defined as the trading volume during the 72 hours after announcement over the trading volume during the 72 hours before announcement. The sample contains analyst forecasts on the change in Consumer Price Index, the trading volume data on the E-mini S&P 500 futures, and the number of news articles on consumption from July 2003 to Oct 2018. There are 184 CPI announcements within the period with available analyst forecasts data. ***Significant at 1%, **significant at 5%, *significant at 10%. Standard errors are shown in brackets.

Panel A: Ratio of Trading Volumes, One Day Post-CPI over Three Days Pre-CPI

	Post 1 day/Previous 3 days				
	Ratio_24to72	*Ratio_24to72*	*Ratio_24to72*	*Ratio_24to72*	*Ratio_24to72*
$News[-72hrs, 0]$	-0.00279***			-0.00292***	-0.00280***
	(0.000524)			(0.000525)	(0.000524)
AbsAnnSurp		0.300		0.494*	
		(0.278)		(0.260)	
NormAnnSurp			0.0173		0.0213
			(0.0263)		(0.0246)
Constant	0.816***	0.535***	0.545***	0.783***	0.796***
	(0.0521)	(0.0342)	(0.0348)	(0.0546)	(0.0571)
Observations	183	183	183	183	183
R-squared	0.135	0.006	0.002	0.152	0.139

Panel B: Ratio of the Trading Volumes, Three Days Post-CPI over Three Days Pre-CPI

	Post 3 days/Previous 3 days				
	Ratio_72to72	*Ratio_72to72*	*Ratio_72to72*	*Ratio_72to72*	*Ratio_72to72*
$News[-72hrs, 0]$	-0.0113***			-0.0116***	-0.0113***
	(0.00188)			(0.00189)	(0.00189)
AbsAnnSurp		0.501		1.176	
		(1.006)		(0.925)	
NormAnnSurp			0.0167		0.0254
			(0.0952)		(0.0873)
Constant	2.436***	1.366***	1.396***	2.353***	2.411***
	(0.187)	(0.125)	(0.127)	(0.198)	(0.206)
Observations	184	184	184	184	184
R-squared	0.164	0.001	0.000	0.172	0.165

What is the Value of an Innovation? Theory and Evidence on the Stock Market's Reaction to Innovation Announcements*

Thomas J. Chemmanur† Dongmei Li‡ Kevin Tseng§ Yu Wang¶

Abstract

We analyze, theoretically and empirically, how investor attention affects the stock market reaction to innovation announcements. In a dynamic model with limited investor attention, we show that the immediate reaction to innovation announcements increases, while the post-announcement stock return drift decreases, in investor attention. We empirically confirm our model predictions using a matched sample of pharmaceutical industry patent grant and subsequent FDA drug approval announcements and also a general USPTO patent sample. We show that post-announcement drift has predictive power for firm growth, profitability, and productivity, drawing implications for enhancing measures of patents' economic value and for trading strategy.

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

JEL classification: G14; G31; G41; O31

---

*For helpful comments and discussions, we thank Anup Agrawal, Onur Bayar, Karan Bhanot, James R. Brown, Natasha Burns, Carl Chen, Kristine Hankins, Po-Hsuan Hsu, Ravi Jagannathan, Palani-Rajan Kadapakkam, Paul Koch, Lei Kong, Karthik Krishnan, Xuan Tian, Tony Via, John Wald, Xinyan Yan, Qianqian Yu, participants in the 2019 Summer Finance Workshop at the University of Dayton and the Ph.D. student poster session of the 2020 American Finance Association Annual Meeting, and seminar participants at Brock University, the University of Kansas, the University of Texas at San Antonio, Southern Illinois University Carbondale, and Boston College. We thank Jin Cai, Destan Kirimhan, and Yafei Zhang for their excellent research assistance. The views expressed here are the authors' and not necessarily those of the Federal Reserve Bank of Richmond or the Federal Reserve System. Any remaining errors are the authors' responsibility.

†Carroll School of Management, Boston College, MA 02467. Phone: (617) 552-3980. Fax: (617) 552-0431. E-mail: chemmanu@bc.edu.

‡Darla Moore School of Business, University of South Carolina, SC 29208. Phone: (803) 777-6747. E-mail: dongmei.li@moore.sc.edu.

§Federal Reserve Bank of Richmond, NC 28202. Phone: (704) 358-2110. E-mail: kevin.tseng@rich.frb.org.

¶Carroll School of Management, Boston College, MA 02467. Phone: (617) 552-2033. E-mail: wangakc@bc.edu.

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

[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

markets the drug (if approved by the FDA). All cash flows 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

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).

[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).

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 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: Computers 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

[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.

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 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]

[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 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.

3.1 Timeline

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

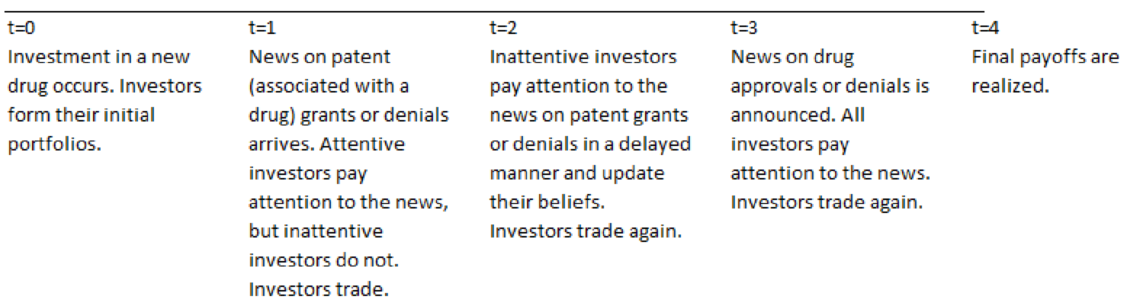

Figure 1: Timeline of Model

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.

[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.

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.

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]

[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.

[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.

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 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

$$W_{t+1}^i \;=\; W_t^i + D_t^i(S_{t+1} - S_t), \text{ for } t = 0, 1, 2 \tag{3}$$

[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.

$$W_4^i \;=\; W_3^i + D_3^i(f - S_3). \tag{4}$$

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.

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/denial 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/denial announcement e_3 and share the same information set $\mathcal{F}_3 = \{e_1, e_3\}$. Therefore, all investors' posterior beliefs are the same:

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

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:

$$S_3 = \mu + \hat{z}_3 - \rho\sigma_3^2(\bar{x} + x_1 + x_2 + x_3), \tag{10}$$

$$S_2 = \mu + \hat{z}_2 - \rho\sigma_2^2(\bar{x} + x_1 + x_2), \tag{11}$$

$$S_1 = \mu + \frac{A_a}{A_a + A_u}\hat{z}_1^a - \rho(B_0\bar{x} + B_1 x_1), \tag{12}$$

$$S_0 = \mu - \rho\frac{Q_a + Q_u + 1}{P_a + P_u}\bar{x}, \tag{13}$$

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 $i \in \{a, u\}$

[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.

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/denial announcement e_1 and the FDA drug approval/denial 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]

[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. $E_0^a(S_1) \neq E_0^u(S_1)$.

4.3 Announcement Effects and Post-Announcement Drifts

In this subsection, we 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 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/denial 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/denial 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 the 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 drifts:* 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 returns 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 (see Proposition 2). 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, 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

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

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 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

[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

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 univariate 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

in 2000, while the paired patent grant sample starts in 1986.

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 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

[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.

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 $\mathbf{H_3}$ 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

[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.

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 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).

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

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]

[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).

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 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 $\mathbf{H_5}$.

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

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

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.

References

Abrams, David S, Ufuk Akcigit, and Jillian Popadak, 2013, Patent value and citations: Creative destruction or strategic disruption?, Working Paper 19647, National Bureau of Economic Research.

Aghion, Philippe, and Peter Howitt, 1992, A model of growth through creative destruction, *Econometrica* 60, 323–351.

Austin, David H, 1993, An event-study approach to measuring innovative output: The case of biotechnology, *The American Economic Review* 83, 253–258.

Bajo, Emanuele, Thomas J. Chemmanur, Karen Simonyan, and Hassan Tehranian, 2016, Underwriter networks, investor attention, and initial public offerings, *Journal of Financial Economics* 122, 376 – 408.

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159–178.

Bellstam, Gustaf, Sanjai Bhagat, and J Anthony Cookson, 2017, A text-based analysis of corporate innovation, *Colorado Working Paper* .

Bernard, Victor L., and Jacob K. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium?, *Journal of Accounting Research* 27, 1–36.

Cohen, Lauren, Karl Diether, and Christopher Malloy, 2013, Misvaluing innovation, *The Review of Financial Studies* 26, 635–666.

Cooper, Michael J., Anne Marie Knott, and Wenhao Yang, 2019, RQ innovative efficiency and firm value, *Utah Working Paper* .

Engelberg, Joseph E., and Christopher A. Parsons, 2011, The causal impact of media in financial markets, *The Journal of Finance* 66, 67–97.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3 – 56.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1 – 22.

Fang, Lily, and Joel Peress, 2009, Media coverage and the cross-section of stock returns, *The Journal of Finance* 64, 2023–2052.

Gao, Huasheng, Po-Hsuan Hsu, Kai Li, and Jin Zhang, 2018, The real effect of smoking bans: evidence from corporate innovation, *Journal of Financial and Quantitative Analysis* 1–88.

Grossman, Gene M, and Elhanan Helpman, 1991, Trade, knowledge spillovers, and growth, *European Economic Review* 35, 517–526.

Grossman, Sanford J., and Joseph E. Stiglitz, 1976, Information and competitive price systems, *The American Economic Review* 66, 246–253.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *The American Economic Review* 70, 393–408.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, Working Paper 8498, National Bureau of Economic Research.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg, 2005, Market value and patent citations, *The RAND Journal of Economics* 36, 16–38.

Harhoff, Dietmar, Francis Narin, Frederic M Scherer, and Katrin Vopel, 1999, Citation frequency and the value of patented inventions, *The Review of Economics and Statistics* 81, 511–515.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative efficiency and stock returns, *Journal of Financial Economics* 107, 632 – 654.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2018, Innovative originality, profitability, and stock returns, *The Review of Financial Studies* 31, 2553–2605.

Hirshleifer, David, Sonya S. Lim, and Siew Hong Teoh, 2011, Limited investor attention and stock market misreactions to accounting information, *The Review of Asset Pricing Studies* 1, 35–73.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337 – 386.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *The Review of Financial Studies* 28, 650–705.

Huberman, Gur, and Tomer Regev, 2001, Contagious speculation and a cure for cancer: A nonevent that made stock prices soar, *The Journal of Finance* 56, 387–396.

İmrohoroğlu, Ayşe, and Şelale Tüzel, 2014, Firm-level productivity, risk, and return, *Management Science* 60, 2073–2090.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy, 2018, Measuring technological innovation over the long run, Technical report, National Bureau of Economic Research.

Kempf, Elisabeth, Alberto Manconi, and Oliver Spalt, 2016, Distracted shareholders and corporate actions, *The Review of Financial Studies* 30, 1660–1695.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological innovation, resource allocation, and growth, *The Quarterly Journal of Economics* 132, 665–712.

Kumar, Alok, 2009, Hard-to-value stocks, behavioral biases, and informed trading, *Journal of Financial and Quantitative Analysis* 44, 13751401.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1335.

Liu, Laura Xiaolei, Ann E. Sherman, and Yong Zhang, 2014, The long-run role of the media: Evidence from initial public offerings, *Management Science* 60, 1945–1964.

Manela, Asaf, 2014, The value of diffusing information, *Journal of Financial Economics* 111, 181–199.

Nicholas, Tom, 2008, Does innovation cause stock market runups? evidence from the great crash, *American Economic Review* 98, 1370–96.

Olley, G. Steven, and Ariel Pakes, 1996, The dynamics of productivity in the telecommunications equipment industry, *Econometrica* 64, 1263–1297.

Pakes, Ariel, 1985, On patents, R&D, and the stock market rate of return, *Journal of Political Economy* 93, 390–409.

Peng, Lin, 2005, Learning with information capacity constraints, *Journal of Financial and Quantitative Analysis* 40, 307–329.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Peress, Joel, and Daniel Schmidt, 2019, Glued to the TV: Distracted noise traders and stock market liquidity, *Journal of Finance* forthcoming.

Romer, Paul M, 1990, Endogenous technological change, *Journal of Political Economy* 98, S71–S102.

Schumpeter, Joseph, 1942, Creative destruction, *Capitalism, Socialism and Democracy* 825, 82–85.

Sims, Christopher A, 2003, Implications of rational inattention, *Journal of Monetary Economics* 50, 665–690.

Zhang, X. Frank, 2006, Information uncertainty and stock returns, *The Journal of Finance* 61, 105–137.

Appendices

A Proof of Propositions

A.1 List of Constants in Propositions and Proofs

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

$$Q_a = f^a[\frac{G^2}{EF} + (\frac{A_a}{A_a + A_u})^2]^{-1}\{EB_0 + \frac{GH}{EF} + \frac{A_a A_u}{(A_a + A_u)^2}[\frac{A_a}{f^a}(B_0 - \sigma_2^2) + 1]\} \quad (A.16)$$

$$Q_u = f^u(\frac{L}{M}B_0 - \frac{A_u}{f^u}J) \quad (A.17)$$

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

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:

$$\begin{aligned} E_3^i[-\exp(-\rho W_4^i)] &= -\exp\{-\rho[W_2^i + D_2^i(\mu + \hat{z}_3 - \rho\sigma_3^2(\bar{x} + x_1 + x_2 + x_3) - S_2)] \\ &\quad -\frac{\rho^2}{2}\sigma_3^2(\bar{x} + x_1 + x_2 + x_3)^2\} \end{aligned} \tag{A.24}$$

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:

$$E_2^i[-\exp(-\rho W_4^i)]$$

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

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

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

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:

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

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

$$\begin{aligned}
&E_1^a[-\exp(-\rho W_4^a)] \\
&\propto \int_{\mathcal{R}} -\exp\{-\rho[W_1^a + D_1^a(\mu + \hat{z}_1^a - \rho\sigma_2^2(\bar{x} + x_1 + x_2) - S_1)] - \frac{\rho^2}{2}\sigma_2^2(\bar{x} + x_1 + x_2)^2\} \\
&\quad \cdot \exp(-\frac{1}{2}\sigma_x^{-2}x_2^2)dx_2 \\
&\propto -\exp\{-\rho[W_1^a + D_1^a(\mu + \hat{z}_1^a - \rho\sigma_2^2(\bar{x} + x_1) - S_1)] - \frac{\rho^2}{2}\sigma_2^2(\bar{x} + x_1)^2 \\
&\qquad + \frac{1}{2}\rho^2\sigma_2^2(1 + \rho^{-2}\sigma_2^{-2}\sigma_x^{-2})^{-1}[D_1^a - (\bar{x} + x_1)]^2\}
\end{aligned} \tag{A.33}$$

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

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

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

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

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

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

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, $\sum\limits_{i=a,u} D_0^i = f^a D_0^a + f^u D_0^u = \bar{x}$. 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]

$$E[e_t|e_t > 0] \quad = \quad \frac{1}{P(e_t > 0)}\int_{\mathbb{R}+} x p_{e_t}(x)dx$$

[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.

$$= 2\int_{\mathbb{R}^+} \frac{x}{\sqrt{2\pi(\sigma_0^2+\sigma_{e,t}^2)}} \exp[-\frac{x^2}{2(\sigma_0^2+\sigma_{e,t}^2)}]dx$$

$$= \sqrt{\frac{2}{\pi}}\sqrt{\sigma_0^2+\sigma_{e,t}^2} \tag{A.46}$$

Thus, (30) is equivalent to

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

which is further equivalent to

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

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

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

is equivalent to

$$1 + \sigma_{e,3}^2\sigma_0^{-2} + \sigma_{e,3}^2\sigma_{e,1}^{-2} > 0, \tag{A.50}$$

which trivially holds.

This completes the proof of Proposition 5.

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

Technology categories	(1) Chemical CAR[-1,1]	(2) Computers CAR[-1,1]	(3) Drugs CAR[-1,1]	(4) Electronics CAR[-1,1]	(5) Mechanical CAR[-1,1]	(6) Others 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

The Role of Investor Attention in Seasoned Equity Offerings: Theory and Evidence*

Thomas J. Chemmanur† Karen Simonyan‡ Yu Wang§ Xiang Zheng¶

Abstract

Models of seasoned equity offerings (SEOs) such as Myers and Majluf (1984) assume that all investors in the economy pay immediate attention to SEO announcements and the pricing of SEOs. In this paper, we analyze, theoretically and empirically, the implications of only a fraction of investors in the equity market paying immediate attention to SEO announcements. We first show theoretically that, in the above setting, the announcement effect of an SEO will be positively related to the fraction of investors paying attention to the announcement and that there will be a post-announcement stock-return drift that is negatively related to investor attention. In the second part of the paper, we test the above predictions using the media coverage of firms announcing SEOs as a proxy for investor attention, and find evidence consistent with the above predictions. In the third part of the paper, we develop and test various hypotheses relating investor attention paid to an issuing firm to various SEO characteristics. We empirically show that institutional investor participation in SEOs, the post-SEO equity market valuation of firms, SEO underpricing, and SEO valuation are all positively related to investor attention. The results of our identification tests show that the above results are causal.

Keywords: Seasoned Equity Offerings; Limited Attention; Announcement Effect; Post-announcement Drift.

JEL classification: G23; G24; G32

*For helpful comments or discussions, we thank Jie He, Shan He, Gang Hu, Harshit Rajaiya, Jiajie Xu, conference participants at the Ph.D. student poster session of the 2020 American Finance Association Annual Meeting, and seminar participants at Boston College and Suffolk University. Any errors remain our own responsibility.

†Professor of Finance and Hillenbrand Distinguished Fellow, Finance Department, Fulton Hall 336, Carroll School of Management, Boston College, Chestnut Hill, MA 02467, Tel: (617) 552-3980, Fax: (617) 552-0431, Email: chemmanu@bc.edu.

‡Associate Professor of Finance, Sawyer Business School, Suffolk University, 8 Ashburton Place, Boston, MA 02108, Email: ksimonya@suffolk.edu.

§Ph.D. Candidate, Finance Department, Fulton 333, Carroll School of Management, Boston College, Chestnut Hill, MA 02467, Tel: (617) 552-2033, Email: wangakc@bc.edu.

¶Ph.D. Candidate, Finance Department, Fulton 341, Carroll School of Management, Boston College, Chestnut Hill, MA 02467, Tel: (617) 552-2062, Email: zhengxr@bc.edu.

1 Introduction

Equity issues are an important source of external financing for corporations. Corresponding to their importance, there is a large theoretical and empirical literature in corporate finance that has studied various phenomena around seasoned equity offerings (SEOs). In particular, there is an important theoretical literature (see, e.g. Myers and Majluf (1984) or Giammarino and Lewis (1988)) that has attempted to explain the negative announcement effect that has been widely documented upon the announcement of an SEO (see, e.g. Asquith and Mullins (1986) or Masulis and Korwar (1986)). The theoretical literature has focused on the asymmetric information facing the firm in the equity market as the main driving force to explain the negative announcement effect of an equity issue. Further, in models such as Myers and Majluf (1984), a crucial assumption is that all investors pay immediate attention to the equity issue announcement. The objective of this paper is to relax the above assumption, assuming instead that only a fraction of investors in the equity market pay attention to the SEO announcement, while the remaining fraction update their beliefs in a delayed manner after the announcement. We then analyze the consequences of such partial investor attention paid to SEOs theoretically and empirically in this paper.

In the first part of the paper, our focus is on theoretically analyzing a setting where an SEO conveys a negative signal to the equity market, but where, unlike in Myers and Majluf (1984), a fraction of investors do not pay immediate attention to the equity issue and update their beliefs about the firm announcing the equity issue only in a delayed manner. We show that, in the above setting with limited investor attention, the equity market underreacts to the SEO announcement (compared to the full attention setting). Further, we show that the announcement effect of an equity issue is increasing in investor attention (the fraction of investors paying attention to the SEO announcement). We then show that there will be a post-announcement stock return drift (driven by inattentive investors engaging in delayed updating of their beliefs after the SEO announcement). Further, this post-announcement stock return drift will be negatively related to the extent of investor attention paid to the SEO announcement. Finally, our model implies that both the abnormal stock return upon an SEO announcement and the post-announcement stock return drift will have predictive power for the subsequent operating performance of the firm.[1]

[1] We would like to emphasize here that the goal of our model is not to argue for the negativity of the SEO issuance as a signal for the firm value (i.e. the negativity of the announcement effect upon SEO *per se*, as implied already by

In the second part of the paper, we empirically test the implications of the above theory for the announcement effect of an SEO and the post-announcement drift associated with the SEO announcement. We conduct the above empirical analyses making use of the media coverage of an SEO firm in the days before its SEO announcement as a proxy for investor attention and using data on SEOs from 2000 to 2018. In using media coverage as a proxy for investor attention, we follow several papers in the IPO literature that have used media coverage as a proxy for investor attention: see, e.g. Liu, Sherman, and Zhang (2014) or Bajo, Chemmanur, Simonyan, and Tehranian (2016). Our baseline results from the above empirical analyses are as follows. First, the announcement effect of an equity issue is positively related to the investor attention paid to the SEO announcement: i.e., while the announcement effect is negative, it is larger in magnitude for SEOs with greater investor attention paid to the announcement. Second, the post-announcement stock return drift is decreasing in the investor attention paid to the SEO announcement: i.e., the post-announcement drift, while it is also negative, will be decreasing in magnitude with greater investor attention. Third, both the above variables (i.e., the announcement effect of the SEO on firm equity and the post-announcement stock return drift) have predictive power for the future operating performance of a firm (as confirmed by running a multivariate regression of post-SEO operating performance on the SEO announcement effect and on the post-SEO stock return drift).

We conduct two different identification tests to establish the causality of our baseline results. First, it may be argued that SEO firms with certain firm characteristics (omitted in our baseline regressions) may be more likely to attract investor attention, so that the baseline results we document above may be driven by such omitted variables rather than the investor attention received by the firm's SEO announcement. To rule out the above omitted variable problem, our first identification test analyzes the relationship between the "abnormal" media coverage received by the SEO firm prior to its SEO announcement (where abnormal media coverage is defined as the media coverage immediately prior to the SEO announcement minus the media coverage one year previously) and the relevant SEO characteristics (namely, the SEO announcement effect and the post-announcement stock return drift). Second, it may be argued that there may be some informational or other confounding event occurring before the SEO announcement that affects both the

the model of Myers and Majluf (1984)), but rather, to study the split of the overall stock market reaction to SEO issuance between the immediate announcement effect and the subsequent post-SEO announcement stock return drift depending on the level of investor attention.

media coverage received by the firm prior to its SEO announcement and the relevant SEO characteristics (namely, the SEO announcement effect and the post-announcement stock return drift). To control for this type of endogeneity, we instrument for the investor attention received by the SEO firm immediately before the SEO announcement using the media coverage received by the firm one year before the SEO announcement. Using the above instrument, we conduct an instrumental variable (IV) analysis of the relation between investor attention and the SEO announcement effect and also the relation between investor attention and the post-SEO stock return drift.[2] The results of the above two identification tests are also consistent with the predictions of our theory, thus confirming that the relationships we documented earlier in our baseline analyses are causal.

In the third part of the paper, we extend our analysis to study the relationship between investor attention and the pricing and characteristics of the SEO itself (in the U.S., the actual SEO occurs four to six weeks after the SEO announcement). We first develop testable hypotheses regarding the relation between the investor attention received by a firm immediately before the actual SEO and the pricing of the SEO and other SEO characteristics. In order to develop these testable hypotheses, we start by assuming that, for institutional investors to participate in a firm's SEO, they not only need to receive information about various aspects of the firm from the SEO underwriter, but also to pay attention to or "recognize" this information. This last assumption is in the spirit of Merton's (1987) investor recognition or attention model, which assumes that an investor will incorporate a security into his portfolio only if he pays attention to (or acquires information about) that security by incurring a cost. While Merton (1987) posits several possible sources of this "attention" or "recognition" cost, he views this cost mainly as arising from the cost of investors becoming aware of (or familiar with) a firm: in his setting, investors consider investing only in the stock of firms with which they have a certain level of familiarity. In a similar vein, we can think of institutional and other investors considering for investment only the stock of firms making SEO that they have become familiar with by incurring an "attention cost". Then, if a larger number of institutions have paid attention to a firm's SEO, we would expect to find, *ceteris paribus*, a larger number of institutional investors investing in the equity of the SEO firm. Further, if the demand for the SEO

[2]It should be noted that our IV analysis using the media coverage received by the firm one year before the SEO announcement as the instrument rules out the possibility that our results are driven by asymmetric information rather than investor attention, since it is unlikely that any private information held by firm insiders is so long-lived (i.e., having a one year horizon).

firm's equity from institutional investors is greater for SEOs receiving greater investor attention, we expect the market clearing price of the equity of such firms to be higher (for a given supply of shares offered in the SEO). We therefore expect to find a positive relationship between investor attention and post-SEO market valuations. As we discuss in more detail in Subsection 7.1, if SEO underpricing is unrelated to investor attention (e.g., driven only by considerations of information extraction as argued by Benveniste and Spindt (1989)), then we expect to find a positive relation between investor attention and firm valuation at the SEO offer price as well. If, however, SEO underpricing is itself positively related to investor attention (as implied by the theoretical SEO model of Chemmanur and Jiao (2011) or by the IPO model of Liu, Lu, Sherman, and Zhang (2019)), then the relation between investor attention and firm valuation at the SEO offer price will turn ambiguous.

We test the above hypotheses using the media coverage received by the firm prior to the actual equity issue (i.e., after the SEO announcement but before the pricing of the SEO) as a proxy for investor attention. First, we find that the institutional investor participation in an SEO is increasing in the investor attention received by the SEO firm. This result also holds after we control for SEO underpricing. Second, we find that the post-SEO secondary market valuation of the SEO firm is increasing in investor attention. This result holds regardless of whether the market valuation is calculated using the closing stock price of the firm on the first trading day post-SEO, or using the stock price one quarter after the completion of the SEO. Third, we find that the underpricing of an SEO (as measured by the stock return from the SEO offer price to the closing price on the first trading day) is positively related to the investor attention received by the SEO firm. Fourth, we find that firm valuation at the SEO offer price is also positively related to the investor attention received by the SEO firm. We conduct two identification tests: the first, analyzing the relation between the "abnormal" media coverage received by the SEO firm and various SEO characteristics; and the second, an IV analysis using the media coverage received by the SEO firm one year prior to the SEO announcement as an instrument for the media coverage received by the firm immediately before the SEO. The above two identification tests establish that the baseline results we discussed earlier are causal.

The rest of this paper is organized as follows. Section 2 discusses how our paper is related to the existing literature and describes its contribution relative to this literature. Section 3 presents the set-up of our theoretical analysis of the relationship between investor attention, the announcement effect of an SEO, and the post-SEO stock return drift; Section 4 develops results and describes the testable implications of our theoretical model. Section 5 describes our data and discusses our proxies for investor attention. Section 6 describes our empirical tests and results on the relation between the investor attention received by a firm prior to an SEO and the SEO announcement and the post-SEO stock return drift and our empirical analysis of the predictive power of the SEO announcement effect and post-SEO stock return drift for post-SEO operating performance. Section 7 develops testable hypotheses on the relationship between the investor attention received by an SEO firm and various SEO characteristics and presents our empirical tests (and results) of the above hypotheses. Section 8 concludes. Online Appendix A.1 gives a list of constants used in various propositions and proofs. The proofs of all propositions are confined to Online Appendix A.2. Online Appendix A.3 presents some additional empirical tests not included in the main text due to space limitations.

2 Relationship to the Existing Literature and Contribution

Our paper is related to several strands in the literature. The first strand is the theoretical and empirical literature on the stock market reaction to SEO announcements: see, e.g., Myers and Majluf (1984) or Giammarino and Lewis (1988). The theoretical model of Myers and Majluf (1984) suggests that equity issues will have a negative announcement effect in a setting of asymmetric information, since they convey that insiders of a firm announcing an equity issue have less favorable private information about their firm's future prospects. Since, in Myers and Majluf (1984), all investors pay immediate attention to the equity issue announcement, there will be no post-announcement drift in their setting. Thus, our model can be viewed as building on the Myers and Majluf (1984) setting where the announcement of an equity issue conveys a negative signal to the equity market, but where, unlike in Myers and Majluf (1984), a fraction of investors do not pay immediate attention to the equity issue and update their beliefs about the firm announcing an equity issue only in a delayed manner, thereby giving rise to a significant post-announcement stock return drift.[3]

[3]There is also a large empirical literature documenting the negative stock market reaction to the announcement of equity issues: see, e.g., Asquith and Mullins (1986) or Masulis and Korwar (1986). Asquith and Mullins (1986)

The second strand is the theoretical and empirical literature on the pricing of SEOs as well as the discounting and underpricing of SEOs. Two theoretical models of the pricing of SEOs are those of Chemmanur and Jiao (2011) and Gerard and Nanda (1993). These papers develop theoretical rationales for the pricing of SEOs, and, in particular, for SEO discounts and underpricing based on asymmetric information (albeit driven by different motivations). Unlike the above papers, our focus in the third part of this paper is on empirically analyzing the implications of investor attention on SEO underpricing, post-SEO firm valuation, and institutional investor participation in SEOs.

There is also a large empirical literature on the underpricing of SEOs. Since Smith (1977), who first empirically documented a significant SEO underpricing, the academic literature has offered various explanations for this phenomenon. Loderer, Sheehan, and Kadlec (1991) document a more significant SEO underpricing for stocks listed on the Nasdaq than stocks listed on other exchanges such as NYSE and Amex. Corwin (2003) studies the determinants of SEO underpricing such as offer size, uncertainty of firm value, the magnitude of preoffer returns, price rounding, and the pricing relative to the bid quote. Altınkılıç and Hansen (2003) decompose SEO discounting into a predictable component and a surprise component, and argue that the surprise component is used by underwriters as a channel to release additional information to investors. Gao and Ritter (2010) study the effect of various choices of offer method on consequent SEO characteristics such as discount and underpricing. Gibson, Safieddine, and Sonti (2004) show that SEO firms with the greatest increase in institutional investment around the issue date significantly outperform those with the greatest decrease in institutional investment. Chemmanur, He, and Hu (2009) analyze the relation between institutional trading around SEOs and various SEO characteristics, and conclude that their findings are consistent with institutions being able to produce information about the firm making the SEO. Huang and Zhang (2011) document a negative relation between the number of managing underwriters and SEO discount. Gustafson (2018) documents a higher offer price and less post-issue return for over-night SEO offerings than non-overnight offerings. Unlike the above empirical papers, our focus in the second part of this paper is on the relation between investor attention paid to a firm making an SEO and SEO underpricing, immediate post-SEO firm valuation, and the participation of institutional investors in the SEO which has not been analyzed

documents a significant negative SEO announcement effect and find that the extent of price reduction is negatively related to the size for the equity issue.

before in the literature.[4]

The third strand is the theoretical literature on limited attention. Hirshleifer and Teoh (2003) use a static 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 to earnings announcements and overreaction to accruals. Our model builds on the above two static models by introducing random supply shocks on trading dates, so that we are able to explicitly characterize the post-announcement drift following SEO announcements.[5] The broader "investor recognition" or "investor attention" literature that builds on Merton (1987)'s model is also related to our paper: we build on this literature to develop testable hypotheses for own empirical analysis of the relation between investor attention and various SEO characteristics such as SEO underpricing and post-SEO equity valuation. One paper from this literature that is related to ours is Liu, Lu, Sherman, and Zhang (2019) who develop a model, in the context of IPO, in which underwriters attract potential investors to an IPO by offering underpriced shares. In their setting, IPO underpricing is a way of compensating investors for their cost of paying attention to the firm going public.

The fourth and final strand in the literature our paper is related to is the empirical literature on investor attention in the context of IPOs. In the context of IPOs, Bajo, Chemmanur, Simonyan, and Tehranian (2016) study two functions of underwriters, information dissemination and information extraction, within underwriter networks in IPOs and find that higher investor attention leads to more favorable IPO characteristics, using pre-IPO media coverage as a proxy for investor attention. Chemmanur, Krishnan, and Yu (2018) analyze the role of backing by venture capitalists (VCs) in enhancing the investor attention paid to an IPO firm and the role of this enhanced investor attention in offering favorable IPO characteristics. Da, Engelberg, and Gao (2011) use Google Search Volume Index data to proxy for retail investor attention and document a positive relation between the retail investor attention and the initial return of IPOs and a negative relation between

[4] Pinto-Gutiérrez (2018) empirically analyzes the relation between the media coverage received by an SEO firm prior to its offering and the SEO discount, and also the relation between the above media coverage and the abnormal stock return during the three-day window around the day of the equity issue (not the SEO announcement day). However, the above paper does not analyze any of the relationships that we study in this paper.

[5] Peng (2005) applies the setting of limited attention to regimes such as the learning process of investors; Peng and Xiong (2006) applies such a setting to investors' category learning and consequent return comovement when investors also suffer from overconfidence.

the retail investor attention and the long-run stock return performance after IPO. Liu, Sherman, and Zhang (2014) use media coverage as a proxy for investor attention to document a positive relation between investor attention and long-run stock return performance. Cook, Kieschnick, and Van Ness (2006), document the positive effects of underwriters' promotional efforts in IPOs on IPO offer price revision, and IPO initial return.[6] Unlike the above literature, that has focused on the effect of investor attention in IPOs, the focus of our paper is the role of investor attention in SEOs. In particular, we are the first to analyze the effect of pre-SEO investor attention on the stock market reaction to SEO announcements, and also the first to analyze the effect of investor attention on various SEO characteristics.

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. The model builds upon the SEO model of Myers and Majluf (1984) and the static limited attention model in Hirshleifer and Teoh (2003). By introducing a supply shock into the model, we are able to explicitly represent the drift and study the corresponding comparative statics on both the announcement effect and the post-announcement drift.

3.1 Timeline

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

At $t = 0$, investors are endowed with homogeneous wealth (or equal shares of the asset). There is no trading on this day. All investors hold homogeneous prior belief on the payoff of asset. At $t = 1$, an upcoming seasoned equity offering (SEO) is announced. Attentive investors update their beliefs conditional on the announcement; inattentive investors do not update their beliefs (still hold the prior belief). Investors trade to rebalance their portfolios. At $t = 2$, inattentive investors realize that they missed the SEO announcement (at $t = 1$) and correct their beliefs in a delayed manner.

[6] The broader literature on the role of media coverage in the financial market is also distantly related. 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 a 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.

t=0	t=1	t=2	t=3
Investors form their initial portfolios based on their prior beliefs of the firm.	An upcoming SEO is announced. Attentive investors pay attention to the announcement, but inattentive investors do not. Investors trade.	Inattentive investors notice that they missed the SEO announcement at t=1 and correct their beliefs in a delayed manner at t=2. Investors trade again.	All payoffs are realized.

Figure 1: **Timeline of Model**

There is no change in attentive investors' beliefs at $t = 2$. Investors then trade again. At $t = 3$, asset payoff is realized and there is no further trading.

3.2 Assets and the SEO Announcement

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

Riskfree asset. The riskfree asset offers a net return of r, which is normalized to 0.[7] The riskfree asset has unlimited supply.

Risky asset. The SEO firm issues a risky asset, which can be naturally interpreted as a stock of the firm or, equivalently, as the liquidation value of the firm in the end. 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 unconditional expected supply of the risky asset is $\bar{x}$ and there is an independent supply shock $x_t \sim N(0, \sigma_x^2)$ at each period of $t = 1$ and $t = 2$, i.e. the aggregate supply of the risky asset at t is $\bar{x} + \sum_{s=1}^{t} x_s$ where $x_s \sim N(0, \sigma_x^2)$, for $t = 1, 2$.[8]

The SEO announcement. On date $t = 1$, a public signal $e_1 = z + \epsilon_1$ is revealed by the SEO announcement, where $\epsilon_1 \sim N(0, \sigma_e^2)$.[9] The error term ϵ_1 is independent of all other shocks in the

[7] 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 in exhibition.

[8] The supply shock is not observable directly. However, since there is no private signal in the model, an investor may be able to figure out the total supply shock from the equilibrium price if they do know (pay attention to) all public signals available contemporaneously (e.g. attentive investors at $t = 1$). More will be mentioned in the next subsection.

[9] Our objective in this paper is not to endogenously show that the expected announcement effect of an SEO is negative, which has already been shown in the theoretical literature by models such as Myers and Majluf (1984) or Giammarino and Lewis (1988). Given this, we wish to take the signal conveyed by an SEO announcement, e_1,

model. We can interpret the public signal e_1 as an exogenous signal conveyed by the SEO (equity issue) announcement to the stock market about the firm's future cash flow.[10]

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 the SEO announcement at date $t = 1$. Since no investor in the market observes any private signal, the equilibrium prices do not contain additional information about the terminal payoff of the risky asset. However, the equilibrium price does reflect information about the current supply shock. Therefore, attentive investors always keep track of contemporaneous supply shocks as they pay attention to all public signals immediately.

Inattentive investors (indexed by type u). Because of limited attention, inattentive investors do not pay immediate attention to the public signal e_1 made available to them by the SEO announcement at $t = 1$ and delay their belief updating on e_1 till $t = 2$. 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 are not able to figure out the supply shock x_1 right away.Instead, on a later date, $t = 2$, they notice that they missed the SEO announcement (or, equivalently, they are finally able to evaluate the effect of SEO on the firm value) and update their beliefs based on e_1 in a delayed manner and rebalance their portfolios. This assumption is similar in spirit to the assumptions made by Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2011).[11,12]

as exogenous, and theoretically analyze, for the first time in the literature, how the equity market reaction to this signal is modified in an announcement where a fraction of the investors do not pay immediate attention to the signal conveyed by the SEO announcement.

[10]We focus primarily on the case where $e_1 < 0$ in our analysis of the SEO announcement effect and post-SEO announcement drift. As documented extensively by empirical literature, the average announcement effect of an equity issue is negative: see, e.g. Asquith and Mullins (1986), and theoretically, models of equity issues such as Myers and Majluf (1984) predict a negative announcement effect for an equity issue.

[11]We can also interpret the inattention to the SEO announcement as the inability to evaluate the effect of announcement immediately. Since the SEO announcement may occur significantly ahead of the actual offering, investors may wait for more updates about the firm performance (and thus to evaluate the firm stock) before the actual offering to make their trading decisions.

[12]Once inattentive investors pay attention to e_1 and understand the components in the equilibrium price S_1, they are able to figure out the supply shock x_1 retroactively at $t = 2$ and thus they learn about x_2 by observing the

Utility. All investors hold the constant-absolute-risk-aversion (CARA) utility with a common risk aversion parameter ρ. On each trading date ($t = 0,1,2$), 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,

$$\max_{D_t^i} E_t^i(-\exp[-\rho W_3^i]), \text{ for } i \in \{a,u\} \text{ and } t = 0,1,2, \tag{2}$$

subject to the following budget constraints

$$W_{t+1}^i = W_t^i + D_t^i(S_{t+1} - S_t), \text{ for } t = 0,1, \tag{3}$$

$$W_3^i = W_2^i + D_2^i(f - S_2). \tag{4}$$

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.

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 SEO announcement e_1, and has an information set $\mathcal{F}_1^a = \{e_1\}$. The posterior belief is

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

An inattentive investor, type u, does not pay attention immediately to the SEO announcement e_1,

equilibrium price S_2.

and hence still holds the prior belief, i.e.

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

At $t = 2$, an attentive investor, type a, has no change in his/her information set, $\mathcal{F}_2^a = \mathcal{F}_1^a = \{e_1\}$ and therefore has no change in belief, i.e.

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

An inattentive investor, type u, now notices the upcoming SEO, i.e. the public signal e_1, (or is finally able to interpret the effect of the SEO announcement on the firm's fundamental value f), so the information set is now $\mathcal{F}_2^u = \{e_1\}$. The posterior belief of a type-u investor is

$$z|_{\mathcal{F}_2^u} \sim N(\hat{z}_2^u, (\sigma_2^u)^2), \text{ where } \hat{z}_2^u = (\sigma_2^u)^2\sigma_e^{-2}e_1 \text{ and } (\sigma_2^u)^{-2} = \sigma_0^{-2} + \sigma_e^{-2}. \tag{8}$$

Therefore, investors of both types have same posterior beliefs, i.e. $\hat{z}_2^i$ and σ_2^i are both independent of $i = a$ or u, and hence can be denoted by $\hat{z}_2$ and σ_2 respectively for conciseness and without ambiguity.[13]

4.2 Equilibrium Prices and Demands

On each trading date ($t = 0, 1, 2$), 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 $E_t^i(-\exp[-\rho W_3^i])$. At each t, the equilibrium price S_t clears the market, i.e.[14]

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

[13]Notice that although all investors have the same posterior belief at $t = 2$, their conditional expectations of $\hat{z}_2$ at $t = 1$, i.e. $E_1^i[\hat{z}_2]$ for $i \in \{a, u\}$, are different, because the SEO announcement e_1 is in $\mathcal{F}_1^a$ and hence deterministic for attentive investors at $t = 1$ but not in $\mathcal{F}_1^u$ and hence still random for inattentive investors at $t = 1$.

[14]Here we apply the convention that $\sum_{s=M}^{N} x_s = 0$ for any integers $N < M$.

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

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

$$S_2 = \mu + \hat{z}_2 - \rho\sigma_2^2(\bar{x} + x_1 + x_2), \tag{10}$$

$$S_1 = \mu + \frac{A_a}{A_a + A_u}\hat{z}_1^a - \rho(B_0\bar{x} + B_1 x_1), \tag{11}$$

$$S_0 = \mu - \rho\frac{Q_a + Q_u + 1}{P_a + P_u}\bar{x}, \tag{12}$$

where the definitions of all 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 $t = 0, 1, 2$, the optimal demands of the risky asset by investors of type $i \in \{a, u\}$ are respectively

$$D_2^i = \rho^{-1}\sigma_2^{-2}(\mu + \hat{z}_2 - S_2) \text{ for } i \in \{a, u\}, \tag{13}$$

$$D_1^a = \rho^{-1}\frac{A_a}{f^a}(\mu + \hat{z}_1^a - S_1) - [\frac{A_a}{f^a}(\sigma_1^a)^2 - 1](\bar{x} + x_1), \tag{14}$$

$$D_1^u = \rho^{-1}\frac{A_u}{f^u}(\mu - S_1) - [\frac{A_u}{f^u}\sigma_0^2 - 1]\bar{x}, \tag{15}$$

$$D_0^a = \rho^{-1}\frac{P_a}{f^a}(\mu - S_0) - \frac{Q_a}{f^a}\bar{x}, \tag{16}$$

$$D_0^u = \rho^{-1}\frac{P_u}{f^u}(\mu - S_0) - \frac{Q_u}{f^u}\bar{x}, \tag{17}$$

where the definitions of all constants are listed in Appendix A.1.

The equilibrium prices on all trading dates are in the form of "μ+(investors' belief on z)-(a term of $\bar{x}$ and x_s for $x \leq t$)". Generally speaking, if investors interpret the public signal from the announcement at $t = 1$ as good news on the terminal firm value, i.e. $e_1 > 0$, then investors modify their beliefs on z upward and thus the equilibrium prices increase; if, however, the announcement is interpreted as bad news on the terminal firm value, i.e. $e_1 < 0$, then investors modify their beliefs on z downward and thus the equilibrium prices decrease. The term containing $\bar{x}$ and $x_s(x \leq t)$ represents a compensation (risk premium) for holding the risky asset by investors.

On each date, the optimal demand of risky asset by an investor increases with the investor's conditional expectation of z. Observe that investors' demands at $t = 2$ are homogeneous regardless of their attention type. This is because at $t = 2$ both attentive and inattentive investors have their beliefs updated correctly on the SEO announcement e_1, thus they all have homogeneous beliefs and hence homogeneous demands. In contrast, the demands at $t = 1$ and $t = 0$ depend on the attention type since only attentive investors pay attention to the SEO announcement e_1 immediately at $t = 1$ and therefore hold different beliefs from inattentive investors.

4.3 SEO Announcement Effect and Post-SEO Announcement Drift

In this subsection, we study the abnormal stock returns (announcement effects) at $t = 1$ and the corresponding post-announcement stock return drifts from $t = 1$ to $t = 2$. 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, without loss of generality, we follow Hirshleifer and Teoh (2003) to set $\bar{x} = x_t = 0$ (for $t = 1, 2$) within this subsection for our analysis on the announcement effect and post-announcement drift around SEOs.

By taking the difference between (11) and (12), we rewrite the price change of the risky asset from $t = 0$ to $t = 1$ as follows

$$S_1 - S_0 = \frac{A_a}{A_a + A_u} \frac{\sigma_0^{-2} + \sigma_e^{-2}}{\sigma_e^{-2}} e_1 - \rho[(B_0 - \frac{Q_a + Q_u + 1}{P_a + P_u})\bar{x} - B_1 x_1] \tag{18}$$

The first term 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 term represents the change in risk premium because of both uncertainty resolution and supply shock. Since the supply shock x_1 is on average zero and the change in risk premium is not the focus of our study, we silence the terms containing $\bar{x}$ and x_1 by setting both $\bar{x}$ and x_1 to zero, and focus on the first component to analyze the effect of investor attention on the announcement effect of SEOs.

Proposition 2 (The Announcement Effect of an SEO)

(i) Let the public signal $e_1 < 0$. Then, the abnormal stock return upon the announcement of an SEO will be negative with its magnitude increasing in the realization e_1 of the announcement, given by:

$$\frac{A_a}{A_a + A_u} \frac{\sigma_0^{-2} + \sigma_e^{-2}}{\sigma_e^{-2}} e_1 < 0, \tag{19}$$

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 public signal e_1 from the SEO announcement, the magnitude of the abnormal stock return upon announcement will be increasing in the proportion of investors who are attentive to the announcement.*

Intuitively, as more investors pay immediate attention to the public signal revealed by the SEO announcement, i.e., the higher the fraction f^a of attentive investors in the equity market, the greater the immediate updating of beliefs reflecting the information contained in the signal e_1. This means that the equilibrium price S_1 reflects a larger proportion of the information contained in e_1, thus creating an announcement effect of a larger magnitude.

We now turn to calculating the post-SEO announcement stock return drift as a function of investor attention. When fewer investors delay their belief updating till $t = 2$ (i.e. the larger the fraction f^a of attentive investors in the market), the smaller the proportion of information reflected in the post-SEO announcement drift. We can calculate the price change given by $S_2 - S_1$, by taking the difference between (10) and (11):

$$S_2 - S_1 \quad = \quad \frac{A_u}{A_a + A_u} \frac{\sigma_0^{-2} + \sigma_e^{-2}}{\sigma_e^{-2}} e_1 - \rho[(\sigma_2^2 - B_0)\bar{x} + (\sigma_2^2 - B_1)x_1 + \sigma_2^2 x_2]. \tag{20}$$

The price change $S_2 - S_1$ consists of two parts: the first part is the delayed belief update by inattentive investors with respect to the public signal e_1 at SEO; the second part is the change in risk premium as a combination of uncertainty resolution over time and the additional supply shock realized contemporaneously. Since the supply shocks x_1 and x_2 are on average zero and the change in risk premium is not the focus of our study, we follow Hirshleifer and Teoh (2003) to silence the terms on $\bar{x}$ and x_t by setting $\bar{x} = x_t = 0$ (for $t = 1, 2$), and focus on the first component of the price change $S_2 - S_1$ to analyze the effect of investor attention on the post-SEO announcement stock return drift.

Proposition 3 (Post-SEO Announcement Stock Return Drift)

(i) *Let the public signal $e_1 < 0$. Then, there will be a negative post-SEO announcement stock return drift given by*

$$\frac{A_u}{A_a + A_u} \frac{\sigma_0^{-2} + \sigma_e^{-2}}{\sigma_e^{-2}} e_1 < 0, \tag{21}$$

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 public signal e_1 at the SEO announcement, the magnitude of the post-SEO announcement stock return drift decreases as the proportion of attentive investors f^a increases.

4.4 Implications and Testable Hypotheses

Our model generates several testable implications and we develop corresponding testable hypotheses for our empirical analysis.

1. *Relationship between a proxy for investor attention and the abnormal stock return following SEO announcements:* Proposition 2 of our model predicts a positive relation between the extent of investor attention paid to a given SEO announcement and the magnitude of the abnormal stock return upon that announcement. Since the abnormal stock return is on average negative after SEO announcements, in the spirit of Myers and Majluf (1984) and also as shown in the next section of this paper, our model predicts a more negative abnormal stock return when more investor attention is paid to the SEO announcement. This is the first hypothesis that we test here (**H1**). We use a proxy for investor attention (namely, media coverage) to test the above hypothesis.

2. *Relationship between a proxy for investor attention and the post-announcement drift following SEO announcements:* Proposition 3 of our model predicts a negative relation between the extent of investor attention paid to a given SEO announcement and the magnitude of the post-announcement stock return drift following that announcement. Since our model predicts that the post-announcement drift overall will be negative, we expect a less negative drift when more investor attention is paid to the SEO announcement. This is the second hypothesis that we test here (**H2**). We use a proxy for investor attention (namely, media coverage) to test the above hypothesis.

3. *The predictability of the abnormal stock return and the post-announcement drift following SEO announcements on long-term firm performance:* as shown in Propositions 2 and 3, both the abnormal stock return upon the SEO announcement and the subsequent post-announcement drift are positively correlated with the information released at the SEO announcement, about the firm's future cash flows. Therefore, we expect both the abnormal stock return upon the SEO announcement and the subsequent post-announcement drift to be positively correlated with the

long-term firm cash flow and, more broadly, with the post-SEO operating performance of the firm. This is the third hypothesis that we test here (**H3**). We use multiple proxies for the firm operating performance (e.g. ROA, and cash flow) to test this hypothesis.

5 Data and Sample Selection

We collect data on SEOs from the Securities Data Company (SDC)/Platinum Global New Issues database. We first obtain the list of all SEOs conducted in the U.S. from 2000 to 2018 and then select only offerings of common shares (thus excluding all other types of offerings such as real estate investment trusts, units, rights, spin-offs, American Depository Receipts, etc.) from this list. We collect data on SEO firms' media coverage from RavenPack News Analytics (Dow Jones Edition). RavenPack covers news items from Dow Jones Newswires, regional editions of Wall Street Journal, Barron's, and MarketWatch starting from January 1, 2000 (thus the starting date of our sample period is determined by the availability of media coverage data collected from RavenPack). We obtain accounting data from Compustat; stock return data from the Center for Research in Security Prices (CRSP); analyst forecast data from the Institutional Brokers' Estimation System (IBES) database; and institutional holdings data from Thomson Reuters' institutional holdings (13F) database.

5.1 Measures of Investor Attention and Summary Statistics

We use the pre-SEO media coverage of firms conducting SEOs as our proxy for the amount of attention paid by market investors to SEO firms. We construct our measures of investor attention for each SEO firm by counting the number of news items mentioning the firm over a certain period of time (namely, 1 week, 2 weeks, 1 month, and 2 months) prior to the SEO announcement date (*NumNewsFile*) or prior to the SEO issue date (*NumNewsIss*). For example, *NumNewsFile [-60:-1]* and *NumNewsIss [-60:-1]* are the numbers of news items covering an SEO firm over a two-month period (60-day period from day -60 to day -1) prior to the SEO announcement date and prior to the SEO issue date, respectively. We also construct abnormal investor attention measures (*AbnNumNewsFile* and *AbnNumNewsIss*) as the difference between the media coverage of an SEO firm immediately prior to its SEO as described above and the media coverage of the same firm exactly one year before its SEO announcement date. In other words, e.g., *AbnNumNewsFile [-60:-1]* is equal to *NumNewsFile [-60:-1]* minus *PriorYrNumNewsFile [-60:-1]*, where *PriorYrNumNewsFile [-60:-1]* is the number of news items covering an SEO firm over a two-month period ending one year prior to its SEO announcement date.

5.2 Summary Statistics of SEO Characteristics, Investor Attention, and Other Control Variables

Panel A of Table 1 reports the summary statistics of our investor attention measures for SEO firms in our sample. The average numbers of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to their SEO announcement dates are 2.15, 4.04, 8.32, and 15.62, respectively; while the average numbers of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to their SEO issue dates are 3.02, 5.10, 10.13, and 19.60, respectively. Further, the mean abnormal media coverage proxies measuring abnormal investor attention both prior to the SEO announcement date and prior to the SEO issue date are positive, suggesting that SEO firms receive somewhat more investor attention prior to their SEOs. For example, the mean abnormal numbers of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to the SEO announcement date are 0.49, 0.87, 1.82, and 3.21, respectively; while the mean abnormal numbers of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to the SEO issue date are 1.62, 2.28, 3.50, and 5.62, respectively.

Panel B of Table 1 reports the summary statistics of various SEO firm characteristics as well as certain SEO characteristics.[15] For example, the average book value of SEO firms' assets at the end of the fiscal year prior to the SEO announcement is $505 million, the mean return on assets (ROA measured at the end of the first post-announcement fiscal quarter) is -3.74%, the mean industry-adjusted Q ratio (measured using the issue day closing price) is -0.041, the mean SEO underpricing (the percentage difference between the issue day closing price and the SEO offer price) is 3.6%, the mean midpoint of initial filing price range is $24.1, and the mean number of institutional investors holding SEO firm shares at the end of the first post-issue fiscal quarter is 132.

[15] We winsorize all firm and SEO characteristics variables at the 0.5% and 99.5% levels to reduce potential biases in our analysis caused by outliers. Our results without winsorization are qualitatively similar to those reported in this paper.

6 Investor Attention and the Market Reaction to SEO Announcements

In this section, we present our empirical findings on how the extent of investor attention paid to firms prior to the firms' SEOs affects the market reaction to the announcements of these SEOs. We first present the summary statistics of SEO announcement effect and the results from the baseline regression on the relationship between investor attention and SEO announcement effect in Section 6.1. Next, we present the summary statistics of SEO post-announcement drift and the empirical results on the relationship between investor attention and SEO post-announcement drift in Subsection 6.2. Further, in Subsection 6.3 we examine the relationship between the market reaction to SEO announcement (namely, the announcement effect and the post-announcement drift) and the post-announcement operating performance of the SEO firm. Finally, we address potential endogeneity concerns by presenting a set of robustness tests and instrumental variable analyses in Subsection 6.4.

6.1 Investor Attention and SEO Announcement Effects

In this subsection, we first present the summary statistics of SEO announcement effect. We estimate SEO announcement effect as the cumulative abnormal return (CAR) over a certain window around the SEO announcement date. We estimate abnormal returns using the market model with CRSP value-weighted index return as the market return; market model variables (alphas and betas) are estimated over a 150-day period ending 50 days prior to the SEO announcement date.[16] Panel A of Table 2 reports the summary statistics of SEO announcement effects measured in various event windows and their statistical significance. The mean abnormal return on the SEO announcement day, *CAR [0:0]*, is -0.76%, which is statistically significantly different from zero at the 1% level. We will use *CAR [0:0]* as our main measure of SEO announcement effect in our subsequent tests. Further, the mean cumulative abnormal returns upon SEO announcements over the 3-day (*CAR [-1:1]*), 5-day (*CAR [-2:2]*), and 7-day (*CAR [-3:3]*) windows are -2.30%, -2.13%, and -2.07%, respectively. These announcement effects are statistically significantly different from zero at the 1%

[16] We also estimate abnormal returns using alternative models such as Fama-French three-factor model, and Carhart four-factor model(see, e.g., Fama and French (1993), and Carhart (1997)). Our results remain qualitatively similar using these alternative estimation models.

level as well. Our findings in Panel A of Table 2 are consistent with the existing literature which has documented negative announcement effects for SEOs.

Next, we test our first hypothesis **H1** which predicts that the more investors pay attention to the SEO firm the more negative the announcement effect of the SEO will be. We test this hypothesis in a multivariate regression setting by regressing the announcement-day abnormal return (*CAR [0:0]*) on our investor attention proxies and other controls. The announcement-day abnormal return is estimated using the market model as described above in this subsection. The independent variables of interest in our regressions are our four investor attention measures (*NumNewsFile [-7:-1]*, *NumNewsFile [-14:-1]*, *NumNewsFile [-30:-1]*, *NumNewsFile [-60:-1]*) as described in Subsection 5.1. We also add several control variables to rule out potentially confounding effects. First, we control for lead SEO underwriter reputation. Following Bajo, Chemmanur, Simonyan, and Tehranian (2016), we construct a measure of lead SEO underwriter reputation, *UndwrtReputation*, as the lead SEO underwriter's share of total proceeds raised in the SEO market over previous five years. In our regressions we also control for SEO firm size (*FirmSize*), which is the natural logarithm of the book value of the SEO firm's total assets at the end of the fiscal quarter prior to the SEO announcement date; the midpoint of initial filing range (*MidFilePrice*); the level of information asymmetry about the SEO firm using the earnings surprise for the fiscal quarter prior to the SEO announcement date (*PriorQtrEarnSurpFile*), where earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price; and the return on the CRSP value-weighted index over a one-month (21-trading-day) period prior to the SEO announcement date (*PriorMktRetFile*). Finally, we also include announcement year $\times$ two-digit SIC industry code fixed effects to control for time-varying unobservables across different industries.

Table 3 presents the results of our regressions of the SEO announcement effect on various investor attention proxies. The coefficient estimates of all four investor attention measures in our regressions are negative and statistically significant at the 1% level. Given that the mean abnormal returns upon SEO announcements are negative as shown in Table 2, this finding suggests that the announcements of SEOs conducted by firms which receive more attention from market investors are associated with more negative announcement-period abnormal returns. The results in Table 3 are also economically significant. For example, a one-standard-deviation increase in the number of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to the SEO announcement date (which correspond to an increase in the number of news items by approximately 5, 9, 18, and 32, respectively) decreases the announcement-day abnormal return (*CAR [0:0]*) by 0.27, 0.32, 0.33, and 0.29 percentage points, respectively (i.e., augments the negative SEO announcement effect by 35.2%, 41.4%, 43.9%, and 38.0%, respectively). These findings suggest that, indeed, the greater the extent of investor attention paid to the SEO firm the more negative the SEO announcement effect, and provide support for our hypothesis **H1**.

6.2 Investor Attention and SEO Post-Announcement Stock Return Drift

In this subsection, we first present the summary statistics of SEO post-announcement drift. We estimate the post-announcement drift as the cumulative abnormal return (CAR) over a certain window after the SEO announcement date. Abnormal returns are estimated using the market model as described in Subsection 6.1. Panel B of Table 2 reports the summary statistics of two measures for the SEO post-announcement drift and their statistical significance. The mean SEO post-announcement cumulative abnormal return over the one-month (21-trading day) period (*CAR [1:21]*) and the two-month (42-trading day) period (*CAR [1:42]*) post the SEO announcement date are −3.53% and −5.63%, respectively. These SEO post-announcement drift measures are statistically significantly different from zero at the 1% level. Overall, the summary statistics in Table 2 indicate that not all information about SEOs (or the firms conducting SEOs) is incorporated in SEO firms' stock prices upon the announcements of SEOs, but that information continues to be incorporated in the stock price over a longer period of time in the form of SEO post-announcement drift.

Next, we test our second hypothesis **H2** which predicts that the more investors pay attention to the SEO firm the less negative the SEO post-announcement drift will be. We test this hypothesis in a multivariate regression setting by regressing the SEO post-announcement cumulative abnormal return over a one-month (21-trading-day) period (*CAR [1:21]*) on our investor attention proxies and the same set of control variables and fixed effects as described in Subsection 6.1. The results of our regressions are reported in Table 4. The coefficient estimates of all four investor attention measures in our regressions are positive and statistically significant at the 1% level. This suggests that the SEO post-announcement drift is less negative for those firms which receive more investor attention upon their SEO announcements. These findings are also economically significant. For example, a one-standard-deviation increase in the number of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to the SEO announcement date (which corresponds to an increase in the number of news items by approximately 5, 9, 18, and 32, respectively) increases the post-announcement one-month cumulative abnormal return (*CAR [1:21]*) by 1.24, 1.35, 1.05, and 0.74 percentage points, respectively (i.e., shrinks the negative post-announcement drift by 35.1%, 38.3%, 29.9%, and 20.9%, respectively). These results suggest that, indeed, the greater the extent of investor attention paid to SEO firms the less negative the SEO post-announcement drift, and provide support for our hypothesis **H2**.

6.3 The Relationship between SEO Announcement Effect, Post-announcement Stock Return Drift, and Subsequent Operating Performance

In this subsection, we test our hypothesis **H3**, which predicts that both SEO announcement effect and SEO post-announcement drift will be positively correlated with the SEO firm's post-SEO operating performance. In other words, we examine whether better market reaction upon SEO announcement (less negative announcement effect and less negative post-announcement drift) leads to better post-SEO operating performance. We measure the post-announcement operating performance of the firm conducting SEO using two proxies measured in four windows: return on assets (*ROA*) and cash flow (*Cash Flow*), each measured over the one, two, three, and four fiscal quarters after the SEO announcement. *ROA* is defined as the ratio of net income to the book value of total assets, and *Cash Flow* is defined as the ratio of income before extraordinary items plus depreciation to the book value of total assets. We regress these measures of post-SEO operating performance on the proxy for announcement effect (*CAR [0:0]*) and the proxy for SEO post-announcement drift (*CAR [1:21]*) while controlling for the same set of control variables and fixed effects as described in Subsection 6.1.

The results of our regressions are presented in Table 5: Panel A presents the results of our regressions using ROA as the dependent variable and Panel B presents the results of our regressions using Cash Flow as the dependent variable. Table 5 shows that the coefficient estimates of both *CAR [0:0]* and *CAR [1:21]* are positive in all four regressions in both Panels A and B and they are statistically significant for both operating performance proxies measured over the two, three, and four fiscal quarters after the SEO announcement. These findings suggest that firms with better market reaction upon their SEO announcements realize better post-SEO operating performance starting two fiscal quarters after their SEO announcements. Further, our finding of *CAR [0:0]* and *CAR [1:21]* both having significantly positive coefficient estimates also suggests that the information released at the SEO announcement regarding the firm's future expected (operating) performance is incorporated into the firm's stock price not only upon the announcement of the SEO (announcement effect) but also over a longer period of time after the announcement (post-announcement drift).

The results in Table 5 are also economically significant. For example, a one-standard-deviation increase in announcement-day abnormal return and a one-standard-deviation increase in one-month post-announcement cumulative abnormal return lead to an increase in *ROA* computed over three fiscal quarters after SEO by 0.79 and 0.86 percentage points, respectively. Similarly, a one-standard-deviation increase in the announcement-day abnormal return and a one-standard-deviation increase in the one-month post-announcement cumulative abnormal return lead to increases of 0.72 and 0.89 percentage points, respectively, in *Cash Flow* measured over the three fiscal quarters after SEO. These findings provide support for our hypothesis **H3**.

6.4 Identification

While our baseline results are consistent with our hypotheses ($\mathbf{H_1}$ through $\mathbf{H_3}$) derived from our theoretical model, our baseline empirical design may suffer from potential endogeneity problems. The first problem is due to potential omitted variables. One could argue that certain (long-term) firm characteristics omitted from our baseline analysis may affect both the extent of attention paid by investors to a firm conducting an SEO as well as the market reaction upon its SEO announcement, so that the baseline results we reported above can potentially be driven by such omitted variables rather than investor attention. In order to address this potential omitted variable problem, we regress the measures of SEO announcement effect and SEO post-announcement drift on measures of abnormal media coverage as described in Subsection 5.1, where abnormal media coverage for a given firm is computed as the media coverage received by that firm immediately prior to its SEO announcement minus the media coverage of the same firm one year before the SEO announcement.

The results of our regressions are presented in Panels A (for SEO announcement effect) and B (for SEO post-announcement drift) of Table 6. In Panel A of Table 6, all four measures of abnormal investor attention have significantly negative coefficient estimates, consistent with our baseline results in Table 3. This finding indicates that the negative relation between investor attention and SEO announcement effect we documented in our baseline regressions was not driven by omitted variables. In Panel B of Table 6, three out of four measures for abnormal investor attention have positive coefficient estimates and one of them (*AbnNumNewsFile [-14:-1]*) is statistically significant. These results are also broadly consistent with our baseline findings in Table 4 and provide a weak indication that our baseline findings on the positive relation between investor attention and SEO post-announcement drift is unlikely to be caused by omitted variables.

The second potential problem that our baseline analysis may suffer from is that there could be some informational or other confounding events happening prior to a firm's SEO announcement which could potentially affect both the extent of attention paid by investors to the firm as well as the market reaction upon its SEO announcement that we study here. We address this potential endogeneity concern by making use of an instrumental variable analysis. We instrument for the extent of investor attention received by the firm immediately before its SEO announcement using the media coverage received by the firm one year before the SEO announcement.[17] For example, we use *PriorYrNumNewsFile [-60:-1]*, which is the number of news items covering an SEO firm over the two-month period ending one year prior to its SEO announcement date, as our instrumental variable for *NumNewsFile [-60:-1]*. We expect the media coverage received by an SEO firm one year before its SEO announcement to be positively correlated with the media coverage received by the firm immediately before it SEO announcement; however, we do not expect the SEO characteristics we study here (SEO announcement effect and SEO-post announcement drift) to be correlated with the media coverage received by the SEO firm one year before its SEO announcement.

The results of our instrumental variable analysis are presented in Panels A (for SEO announcement effect) and B (for SEO post-announcement drift) of Table 7. In our first-stage regressions we regress the SEO firm's media coverage prior to its SEO announcement on the media coverage on the same firm one year before the SEO announcement (i.e. our instrumental variable) and the same set of control variables and industry × year fixed effects as described in Subsection 6.1. Both Panels A and B of Table 7 show, consistent with our expectation discussed above, that in first-

[17] Liu and McConnell (2013) use a similar instrument in their instrumental variable analysis to study the role of media coverage in corporate governance.

stage regressions our instrumental variables are significantly positively correlated with our investor attention measures. We also report the F-statistics of the weak instruments test (or the test of excluded instruments) for each first-stage regression in Table 7. This test is used to determine whether instrumental variables used in first-stage regressions are strong. In their survey of the literature on weak instruments, Stock, Wright, and Yogo (2002) develop benchmarks for the necessary magnitude of the F-statistic. They point out that if the number of instruments is equal to one, then the critical value of the F-statistic is 8.96. Given that the F-statistics reported for our first-stage regressions in Table 7 are all well above the critical value of 8.96, the null hypothesis that our instruments are weak is strongly rejected.

Our second-stage regressions in both Panels A and B of Table 7 show that the coefficient estimates of predicted values of investor attention measures from all first-stage regressions have the same signs as reported in baseline regressions in Tables 3 and 4, and three out of four coefficient estimates in Panel A and all four coefficient estimates in Panel B are statistically significant. These results suggest that, even after controlling for the potential endogeneity of investor attention paid to SEO firms immediately prior to their SEO announcements, firms which receive a higher level of investor attention prior to their SEO announcement dates are associated with larger (more negative) SEO announcement effects and smaller (less negative) SEO post-announcement drifts. Overall, our analysis in this subsection, which deals with the potential endogeneity of investor attention, demonstrates the robustness of our baseline findings in previous subsections on the relationship between investor attention and the market reaction upon SEO announcements.

7 The Relationship between Investor Attention and SEO Characteristics

In this section, we study the relationship between the extent of investor attention paid to firms conducting SEOs and certain SEO-related offering and firm characteristics such as SEO initial returns (underpricing), SEO equity valuation of the firms conducting SEOs, and the extent of post-SEO institutional investor interest on the shares of the SEO firms. We first develop testable hypotheses regarding these relations in Subsection 7.1. In subsequent subsections (7.2 to 7.5), we present our empirical findings on the relation between investor attention and institutional investor holdings of SEO firms' equity, SEO equity market valuation, SEO underpricing, and SEO valuation. Finally, we discuss the results of our two identification tests that establish causality in Subsection 7.6.

7.1 Theory and Hypothesis Development

We first develop testable hypotheses regarding the relation between the investor attention received by a firm immediately before its actual SEO and the pricing of the SEO and other SEO characteristics. In order to develop these testable hypotheses, we start by assuming that, for institutional investors to participate in a firm's SEO, they not only need to receive information about various aspects of the firm from the SEO underwriter, but also need to pay attention to or "recognize" this information. This assumption is in the spirit of Merton's (1987) investor recognition or attention model, which assumes that an investor will incorporate a security into his portfolio only if he pays attention to (or acquires information about) that security by incurring a cost. While Merton (1987) posits several possible sources of this "attention" or "recognition" cost, he views this cost mainly as arising from the cost of investors becoming aware of (or familiar with) a firm. In his setting, investors consider investing only in the stock of firms with which they have a certain level of familiarity. Similarly, in our setting, we can think of institutional and other investors considering for investing only in the stock of firms making SEOs that they have become familiar with by incurring an attention cost. Then we would expect the extent of institutional investor participation in the SEOs of firms that received greater investor attention to be greater. This is the first hypothesis that we test here (**H4**).

This has implications for the valuation of equity both in the immediate aftermarket (pricing in the equity market after the SEO) and for firm valuation at the SEO offer price as well. We first discuss the relation between investor attention and post-SEO secondary market valuation. Since the demand from investors for the equity of firms whose SEOs receive greater investor attention will be greater (for a given supply of shares offered in the SEO), the market clearing price for the equity of these firms will be higher as well. Assuming that the immediate aftermarket share price of the SEO firm is the market clearing price, this implies that there will be a positive relation between investor attention and the immediate post-SEO market valuation of firms (**H5**).

We now turn to the relation between investor attention and SEO initial returns and as well as the relation between investor attention and SEO firm valuation at the offer price. These relations depend on the process of price setting in SEOs. While there is no consensus in the theoretical or empirical literature in SEOs on how the SEO offer price is set, there is some agreement that the office price is set at a discount to the expected market clearing price (which can be viewed as the same as the expected aftermarket price) giving rise to positive SEO initial returns (SEO underpricing). There are a number of alternative theories about the drivers of SEO underpricing. One theory, obtained by analogy to IPOs, is the one advanced by Benveniste and Spindt (1989). Benveniste and Spindt (1989) argue that the equity of the firm making IPO is priced at a discount to the market clearing (immediate secondary market) price in order to ensure that institutions have an incentive to reveal their true demand for the firm's equity (i.e., it ensures that their incentive compatibility or truth-telling conditions hold). If the discount applied to the market clearing price to arrive at the SEO offer price is driven by considerations similar to those advanced by Benveniste and Spindt (1989) in the context of IPOs (i.e., unrelated to investor attention), then we would expect pre-SEO investor attention to be unrelated to SEO initial returns (**H6A**).

However, there have also been some theories suggesting that there may be a positive relation between investor attention and SEO initial returns. For example, Chemmanur and Jiao (2011) show in their theoretical analysis that SEO initial returns (underpricing) may be positively related to pre-SEO institutional demand for SEO firm equity.[18] Given that SEOs characterized by greater investor attention are likely to have greater pre-SEO institutional investor demand as well, this implies a positive relationship between investor attention and SEO initial returns (**H6B**).[19]

Consider now the relation between investor attention and firm valuation at the SEO offer price. If SEO underpricing is unrelated to investor attention (e.g., driven only by considerations of information extraction, as posited by Benveniste and Spindt (1989)), then we would expect an unambiguously positive relation between investor attention and firm relation at the SEO offer price (**H7A**). On the other hand, if SEO underpricing is positively related to investor attention

[18]See Proposition 8 of Chemmanur and Jiao (2011).

[19]An alternative theory that suggests a positive relation between investor attention and SEO underpricing is provided by Liu, Sherman, and Zhang (2014) and Liu, Lu, Sherman, and Zhang (2019). They argue in the context of IPOs that IPO underpricing is a way of compensating investors for their cost of paying attention to the IPO firm. In a similar vein, it may be argued that SEO underpricing (initial returns) is a way of enhancing the investor attention paid to an SEO by implicitly compensating investors for their cost of paying attention to the firm making SEO. Given the alternative theory, we will show some specifications in our empirical analysis of SEO valuation, post-SEO valuation, and institutional investor participation in SEOs where we control for the extent of SEO initial returns (underpricing).

(e.g., following the argument made by Chemmanur and Jiao (2011) discussed above), then the predicted relation between investor attention and firm valuation at the SEO offer price becomes ambiguous (**H7B**). This is because the greater secondary market price associated with greater investor attention may potentially be overcome by the even greater SEO underpricing associated with greater investor attention, so that the relation between investor attention and firm valuation at the SEO offer price may turn negative.

7.2 Investor Attention and Post-SEO Participation of Institutional Investors

In this subsection, we test our hypothesis **H4** which predicts that a greater extent of investor attention received by a firm prior to its SEO will be associated with greater institutional investor ownership of the firm's equity after the SEO. We measure the extent of institutional investors' ownership of issuing firm's equity after its SEO by the number of institutional investors holding firm's shares at the end of the first quarter after the SEO (*InstN*). We regress *InstN* on our four investor attention measures (*NumNewsIss*) as described in Subsection 5.1 and other control variables including underwriter reputation, firm size, the midpoint of initial filing range, the level of information asymmetry about the SEO firm earnings surprise one quarter prior to the SEO issue date, one-month stock market return prior to the SEO issue date, and issue year $\times$ two-digit SIC industry code fixed effects. In our regressions we include only those SEOs for which the number of days between the SEO announcement date and the SEO issue date is greater than the number of days that we use to measure investor attention. For example, if in a regression we use the investor attention measured over the 7-day window prior to the SEO issue date, then this regression is applied only to a sub-sample of SEOs with at least a 7-day gap between the SEO announcement date and the SEO issue date.

We report the results of our regressions in Table 8. In regression specifications (2), (4), (6), and (8) we include SEO underpricing as an additional control variable in order to control for the potential effect of SEO underpricing on the post-SEO institutional investor ownership of the issuing firm's equity. Table 8 demonstrates that all four investor attention measures have significantly positive coefficient estimates in all regressions (with and without controlling for SEO underpricing), suggesting that a firm which receives more investor attention prior to its SEO is likely to have a greater number of institutional investor shareholders after the SEO. The positive coefficient estimates of SEO underpricing (statistically significant in regression specifications (2) and (4)) provide further support for our theoretical prediction that firms conducting SEOs may leave more money on the table to attract more institutional investors to invest in their firms' equity. These results are also economically significant. For example, a one-standard-deviation increase in the number of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to their SEO issue dates (which correspond to increases in the number of news items of approximately 6, 11, 23, and 46, respectively) increases the number of institutional investors holding the SEO firms' equity by 29, 37, 40, and 39, respectively (i.e., 22.0%, 28.0%, 30.0%, and 29.8% increases in the number of institutional investors, respectively). These results indicate that a greater extent of investor attention paid to issuing firms immediately prior to their SEOs is associated with a greater number of institutional investors holding the issuing firms' equity post-SEO, and support our hypothesis **H4**.

7.3 Investor Attention and the Post-SEO Market Valuation of Issuing Firms

In this subsection, we test our hypothesis **H5** which predicts a positive relation between investor attention received by firms immediately prior to their SEOs and their post-SEO market valuation. We measure post-issue market valuation of SEO firms using industry-adjusted Q ratios computed using either the SEO issue day closing stock price (*QFTDAdj*) or the stock price at the end of the first post-issue fiscal quarter (*QFQAdj*). We define Q ratio as the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and either the SEO issue day closing price (*QFTD*) or the price at the end of the first post-issue fiscal quarter (*QFQ*). We further adjust these ratios for median industry valuation by subtracting contemporaneous 2-digit SIC code industry median Q ratios from the above Q ratios of SEO firms. We regress these two measures of post-SEO market valuation (*QFTDAdj* and *QFQAdj*) on our four investor attention measures (*NumNewsIss*) while controlling for the same set of control variables and fixed effects as described in Subsection 7.2. As discussed in Subsection 7.2, in our regressions we include only those SEOs for which the number of days between the SEO announcement date and the SEO issue date is greater than the number of days that we use to measure investor attention.

The results of our regressions are reported in Panels A (using *QFTDAdj* as the dependent variable) and B (using *QFQAdj* as the dependent variable) of Table 9. In regression specifications (2), (4), (6), and (8) of each panel we include SEO underpricing as an additional control variable in order to control for the potential effect of SEO underpricing on the immediate post-SEO valuation of issuing firms. Both Panels A and B of Table 9 show that all four pre-SEO investor attention measures have significantly positive coefficient estimates in all regressions (both with and without SEO underpricing as a control variable). This suggests that firms receiving more investor attention immediately prior to their SEOs are likely to have higher post-SEO market valuations. These results are also economically significant. For example, a one-standard-deviation increase in the number of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to their SEO issue dates (which correspond to increases in the number of news items of approximately 6, 11, 23, and 46, respectively) increases the magnitude of *QFQAdj* by 0.126, 0.166, 0.184, and 0.182, respectively, which is a sizable increase compared to the mean *QFQAdj* of -0.037 in our sample. These results imply that a greater extent of investor attention paid to issuing firms immediately prior to their SEOs leads to higher post-SEO market valuations, and support our hypothesis **H4**.

7.4 Investor Attention and SEO Underpricing

In this subsection, we study the relation between investor attention and SEO underpricing by regressing SEO underpricing on our investor attention measures and other controls. We compute SEO underpricing as the percentage difference between SEO issue day closing price and SEO offer price (*Underpricing*). We test the above hypothesis by regressing SEO underpricing on our pre-SEO-issue investor attention measures (*NumNewsIss*) while controlling for the same set of control variables and fixed effects as described in Subsection 7.2. As discussed in Subsection 7.2, in our regressions we include only those SEOs for which the number of days between the SEO announcement date and the SEO issue date is greater than the number of days that we use to measure investor attention.

In Table 10, we report the results of our regressions using SEO underpricing (*Underpricing*) as the dependent variable. All four investor attention measures have positive and statistically significant coefficient estimates, suggesting that firms receiving more investor attention prior to their SEOs are associated with greater SEO underpricing. These results are also economically significant.

For example, a one-standard-deviation increase in the number of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to their SEO issue dates (which correspond to increases in the number of news items of approximately 6, 11, 23, and 46, respectively) increases SEO underpricing in magnitude by 0.265, 0.554, 0.760, and 0.683, respectively (i.e., increases the magnitude of underpricing by 7.4%, 15.6%, 21.4%, and 19.2%, respectively). These findings suggest that, indeed, a greater extent of investor attention paid to issuing firms immediately prior to their SEOs is associated with a greater degree of SEO underpricing, and support our hypothesis **H6B**.

7.5 Investor Attention and SEO Valuation of Issuing Firms

In this subsection, we study the effect of investor attention received by firms immediately prior to their SEOs on their firm valuation at the SEO offer price. We measure SEO valuation of issuing firms using industry-adjusted Q ratios computed using SEO offer price (*QOPAdj*). We define Q ratio as the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and SEO offer price (*QOP*). We further adjust these ratios for median industry valuation by subtracting contemporaneous 2-digit SIC code industry median Q ratios from the above Q ratios of SEO firms. We regress SEO valuation (*QOPAdj*) on our four investor attention measures (*NumNewsIss*) while controlling for the same set of control variables and fixed effects as described in Subsection 7.2. As discussed in Subsection 7.2, in our regressions we include only those SEOs for which the number of days between the announcement date and the issue date is greater than the number of days that we use to measure investor attention.

The results of our regressions are reported in Table 11. In regression specifications (2), (4), (6), and (8) of each panel we include SEO underpricing as an additional control variable in order to control for the potential channel of using SEO underpricing as a compensation for investor attention. Table 11 shows that coefficients of all four pre-SEO investor attention measures are significantly positive in all regressions and remain unchanged with and without SEO underpricing as a control variable. This suggests that firms receiving more investor attention immediately prior to their SEOs are likely to have higher SEO valuation. These results are also economically significant. For example, a one-standard-deviation increase in the number of news items covering SEO firms over the 1-week, 2-week, 1-month, and 2-month periods prior to their SEO issue dates (which correspond to increases in the number of news items of approximately 6, 11, 23, and 46, respectively) increases the magnitude of *QOPAdj* by 0.202, 0.266, 0.322, and 0.228, respectively, which is a sizable increase compared to the mean *QOPAdj* of -0.036 in our sample. These results imply that a greater extent of investor attention paid to issuing firms immediately prior to their SEOs leads to higher post-SEO market valuations. Combining results from Subsection 7.4, the results here support our hypothesis **H7B**.

7.6 Identification

In order to deal with the potential endogeneity problems in our analysis of the effect of investor attention on various SEO-related offering and firm characteristics (discussed previously in Subsection 6.4), we perform a similar set of robustness tests and instrumental variable analyses as in Subsection 6.4. First, we regress SEO underpricing, SEO valulation and post-SEO market valuation of issuing firms, and post-SEO institutional investors' participation in issuing firm's equity ownership on our four abnormal investor attention measures while controlling for the same set of control variables and fixed effects as described in Subsection 7.2. For brevity, the results of these regressions are presented in the Internet Appendix of this paper: Tables A.1, A.2, A.3, and A.4. The coefficient estimates of all four abnormal investor attention measures in these regressions have the same signs as those reported in our baseline results in Tables 8, 9, 10, and 11, and are statistically significant in all of the *QOPAdj*, *QFTDAdj* and *InstN* regressions, and in two of the *Underpricing* and *QFQAdj* regressions. Overall, these regression results on the relationship between abnormal investor attention and various SEO-related offering and firm characteristics are consistent with the results of our baseline regressions.

Next, we also implement instrumental variable analyses of the effect of investor attention on various SEO-related offering and firm characteristics making use of the same instrumental variables as described in Subsection 6.4. The results of our instrumental variable analyses for SEO underpricing, post-SEO market valuation, and post-SEO institutional investor participation are reported in Tables 12, 13, 14, and 15, respectively. Our first-stage regressions in all four tables show that our instrumental variables are significantly and positively correlated with our investor attention variables and the F-statistics of the weak instruments test are well above the critical value 8.96. Our second-stage regressions in Tables 12, 13, 14, and 15 show that the coefficient estimates of predicted values of investor attention measures from first-stage regressions have the same signs as those reported in the baseline results in Tables 8, 9, 10, and 11, and are statistically significant (except for regression specifications (4) and (6) in Table 13). These results suggest that, even after controlling for the potential endogeneity of investor attention paid to SEO firms immediately prior to their SEOs, firms which receive a higher level of investor attention prior to their SEOs are associated with greater participation of institutional investors in their post-SEO equity ownership, higher post-SEO market valuations, larger SEO underpricing, and higher firm valuation at the offer price. Overall, our instrumental variable analysis demonstrates the robustness of our baseline findings in previous subsections.

8 Conclusion

Models of seasoned equity offerings (SEOs) such as Myers and Majluf (1984) assume that all investors in the economy pay immediate attention to SEO announcements and the pricing of SEOs. In this paper, we relax the above assumption and analyze, theoretically and empirically, the implications of a fraction of investors in the equity market paying only delayed attention to SEO announcements. We first show theoretically that, in the above setting, the announcement effect of an SEO will be positively related to the fraction of investors paying attention to the announcement and that there will be a post-announcement stock-return drift that is negatively related to investor attention. In the first part of the paper, we test the above predictions using the media coverage of firms announcing SEOs as a proxy for investor attention, and find evidence consistent with the above predictions. In the second part of the paper, we develop and test various hypotheses relating investor attention paid to the issuing firm (between the announcement and the equity issue) to various SEO characteristics. We empirically show that institutional investor participation in SEOs, the post-SEO equity market valuation of firms, SEO underpricing, and SEO valuation are all positively related to investor attention. The results of our identification tests show that the above results are causal.

References

Altınkılıç, Oya, and Robert S Hansen, 2003, Discounting and underpricing in seasoned equity offers, *Journal of Financial Economics* 69, 285 – 323.

Asquith, Paul, and David W. Mullins, 1986, Equity issues and offering dilution, *Journal of Financial Economics* 15, 61 – 89.

Bajo, Emanuele, Thomas J. Chemmanur, Karen Simonyan, and Hassan Tehranian, 2016, Underwriter networks, investor attention, and initial public offerings, *Journal of Financial Economics* 122, 376 – 408.

Benveniste, Lawrence M, and Paul A Spindt, 1989, How investment bankers determine the offer price and allocation of new issues, *Journal of Financial Economics* 24, 343–361.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Chemmanur, Thomas J., Shan He, and Gang Hu, 2009, The role of institutional investors in seasoned equity offerings, *Journal of Financial Economics* 94, 384 – 411.

Chemmanur, Thomas J., and Yawen Jiao, 2011, Institutional trading, information production, and the seo discount: A model of seasoned equity offerings, *Journal of Economics & Management Strategy* 20, 299–338.

Chemmanur, Thomas J, Karthik Krishnan, and Qianqian Yu, 2018, Venture capital backing, investor attention, and initial public offerings, *Unpublished working paper, Boston College* .

Cook, Douglas O, Robert Kieschnick, and Robert A Van Ness, 2006, On the marketing of ipos, *Journal of Financial Economics* 82, 35–61.

Corwin, Shane A., 2003, The determinants of underpricing for seasoned equity offers, *The Journal of Finance* 58, 2249–2279.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In search of attention, *The Journal of Finance* 66, 1461–1499.

Engelberg, Joseph E., and Christopher A. Parsons, 2011, The causal impact of media in financial markets, *The Journal of Finance* 66, 67–97.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fang, Lily, and Joel Peress, 2009, Media coverage and the cross-section of stock returns, *The Journal of Finance* 64, 2023–2052.

Gao, Xiaohui, and Jay R. Ritter, 2010, The marketing of seasoned equity offerings, *Journal of Financial Economics* 97, 33 – 52.

Gerard, Bruno, and Vikram Nanda, 1993, Trading and manipulation around seasoned equity offerings, *The Journal of Finance* 48, 213–245.

Giammarino, Ronald M., and Tracy Lewis, 1988, A theory of negotiated equity financing, *The Review of Financial Studies* 1, 265–288.

Gibson, Scott, Assem Safieddine, and Ramana Sonti, 2004, Smart investments by smart money: Evidence from seasoned equity offerings, *Journal of Financial Economics* 72, 581–604.

Gustafson, Matthew T., 2018, Price pressure and overnight seasoned equity offerings, *Journal of Financial and Quantitative Analysis* 53, 837866.

Hirshleifer, David, Sonya S. Lim, and Siew Hong Teoh, 2011, Limited investor attention and stock market misreactions to accounting information, *The Review of Asset Pricing Studies* 1, 35–73.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337 – 386.

Huang, Rongbing, and Donghang Zhang, 2011, Managing underwriters and the marketing of seasoned equity offerings, *Journal of Financial and Quantitative Analysis* 46, 141170.

Liu, Baixiao, and John J McConnell, 2013, The role of the media in corporate governance: Do the media influence managers' capital allocation decisions?, *Journal of Financial Economics* 110, 1–17.

Liu, Laura Xiaolei, Ann E. Sherman, and Yong Zhang, 2014, The long-run role of the media: Evidence from initial public offerings, *Management Science* 60, 1945–1964.

Liu, Lauro Xiaolei, Ruichang Lu, Ann E Sherman, and Yong Zhang, 2019, Attracting attention in an IPO, *Unpublished working paper, Peking University* .

Loderer, Claudio F., Dennis P. Sheehan, and Gregory B. Kadlec, 1991, The pricing of equity offerings, *Journal of Financial Economics* 29, 35 – 57.

Masulis, Ronald W., and Ashok N. Korwar, 1986, Seasoned equity offerings: An empirical investigation, *Journal of Financial Economics* 15, 91 – 118.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *The Journal of Finance* 42, 483–510.

Myers, Stewart C., and Nicholas S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187 – 221.

Peng, Lin, 2005, Learning with information capacity constraints, *Journal of Financial and Quantitative Analysis* 40, 307–329.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Pinto-Gutiérrez, Cristian A., 2018, The effect of media coverage on the pricing of seasoned equity offerings, *Canadian Journal of Administrative Sciences / Revue Canadienne des Sciences de l'Administration* .

Smith, Clifford W., 1977, Alternative methods for raising capital: Rights versus underwritten offerings, *Journal of Financial Economics* 5, 273 – 307.

Stock, James H, Jonathan H Wright, and Motohiro Yogo, 2002, A survey of weak instruments and weak identification in generalized method of moments, *Journal of Business & Economic Statistics* 20, 518–529.

Table 1: **Summary statistics**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *NumNewsFile [-60:-1]* and *NumNewsIss [-60:-1]* are the numbers of news items covering SEO firms over a two-month period (from day -60 to day -1) prior to their SEO announcement dates and prior to their SEO issue dates, respectively. *PriorYrNumNewsFile [-60:-1]* is the number of news items covering SEO firms over a two-month period ending one year prior to their SEO announcement dates. *AbnNumNewsFile [-60:-1]* is the abnormal investor attention over a two-month period (from day -60 to day -1) prior to the SEO announcement date, which is defined as the difference between *NumNewsFile [-60:-1]* and *PriorYrNumNewsFile [-60:-1]*. *AbnNumNewsIss [-60:-1]* is the abnormal investor attention over a two-month period (from day -60 to day -1) prior to the SEO issue date, which is defined as the difference between *NumNewsIss [-60:-1]* and *PriorYrNumNewsFile [-60:-1]*. Other investor attention measures are defined in a similar fashion and their precise definitions can be found in Subsection 5.1. *ROA* is the ratio of net income over the book value of total assets at the end of the first post-announcement fiscal quarter. *Cash Flow* is the ratio of income before extraordinary items plus depreciation to the book value of total assets at the end of the first post-announcement fiscal quarter. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *QOPAdj* is the industry-adjusted Q ratios calculated using the SEO offer price. *QFTDAdj* and *QFQAdj* are the industry-adjusted Q ratios calculated using the SEO issue day closing price and the price at the end of the first post-issue fiscal quarter, respectively. Q ratio is defined as the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and either the SEO issue day closing price (*QFTDAdj*) or the price at the end of the first post-issue fiscal quarter (*QFQAdj*). Industry adjustment is performed by subtracting contemporaneous 2-digit SIC code industry median Q ratios from SEO firms' Q ratios. *InstN* is the number of institutional investors holding SEO firms' shares at the end of the first post-issue fiscal quarter. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *MidFilePrice* is the midpoint of initial filing range. *PriorQtrEarnSurpFile* and *PriorQtrEarnSurpIss* are the earnings surprises one quarter prior to the SEO announcement date and prior to the SEO issue date, respectively. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetFile* and *PriorMktRetIss* are the returns on the CRSP value-weighted index over one-month (21-trading-day) periods prior to the SEO announcement date and prior to the SEO issue date, respectively.

Panel A: Summary statistics on investor attention measures

	N	Mean	Median	Min.	Max.	S.D.
NumNewsFile [-7:-1]	6,309	2.148	1	0	173	5.249
NumNewsFile [-14:-1]	6,309	4.044	2	0	287	9.013
NumNewsFile [-30:-1]	6,309	8.329	5	0	18	17.601
NumNewsFile [-60:-1]	6,309	15.620	10	0	31	32.142
NumNewsIss [-7:-1]	4,862	3.016	1	0	176	6.305
NumNewsIss [-14:-1]	4,510	5.100	3	0	355	11.080
NumNewsIss [-30:-1]	3,577	10.135	7	0	20	23.038
NumNewsIss [-60:-1]	2,713	19.602	13	3	35	45.532
PriorYrNumNewsFile [-7:-1]	6,309	1.663	0	0	146	4.506
PriorYrNumNewsFile [-14:-1]	6,309	3.178	1	0	239	7.597
PriorYrNumNewsFile [-30:-1]	6,309	6.524	3	0	15	15.201
PriorYrNumNewsFile [-60:-1]	6,309	12.417	8	0	26	29.007
AbnNumNewsFile [-7:-1]	6,309	0.485	0	-49	126	3.929
AbnNumNewsFile [-14:-1]	6,309	0.866	0	-56	212	5.846
AbnNumNewsFile [-30:-1]	6,309	1.805	0	-5	10	9.835
AbnNumNewsFile [-60:-1]	6,309	3.203	1	-7	15	16.024
AbnNumNewsIss [-7:-1]	4,862	1.616	0	-56	129	5.220
AbnNumNewsIss [-14:-1]	4,510	2.280	1	-119	280	8.422
AbnNumNewsIss [-30:-1]	3,577	3.492	2	-5	12	14.612
AbnNumNewsIss [-60:-1]	2,713	5.608	3	-8	19	26.033

Panel B: Summary statistics on SEO and firm characteristics

	N	Mean	Median	Min.	Max.	S.D.
ROA	6,194	-3.741	0.200	-75.153	11.279	10.572
Cash Flow	5,345	-3.390	0.515	-80.311	12.947	11.251
Underpricing	6,006	3.556	2.227	-20.661	38.321	6.583
QOPAdj	6,189	-0.036	-0.009	-6.873	13.298	2.048
QFTDAdj	5,902	-0.041	-0.005	-7.234	13.749	2.144
QFQAdj	6,182	-0.037	-0.009	-7.902	12.086	1.939
InstN	6,079	131.664	102	1	907	128.516
UndwrtReputation	6,309	0.036	0.007	0	0.193	0.050
FirmSize	6,174	6.225	6.150	1.515	12.506	2.122
MidFilePrice	6,009	24.073	18.700	0.350	158.550	23.017
PriorQtrEarnSurpIss	5,469	-0.077	0.001	-13.393	2.400	1.040
PriorQtrEarnSurpFile	5,382	0.028	0	-4.030	8.889	0.768
PriorMktRetIss	6,300	0.014	0.017	-0.127	0.140	0.039
PriorMktRetFile	6,309	0.012	0.016	-0.164	0.151	0.044

Table 2: **Summary statistics of SEO announcement effect and SEO post-announcement drift**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *CAR [0: 0]* is the abnormal return on SEO firm's equity on the SEO announcement day. CAR [-1:1] is the cumulative abnormal return on SEO firm's equity over a 3-day window (from day -1 to day +1) around the SEO announcement date. *CAR [-2:2]* is the cumulative abnormal return on SEO firm's equity over a 5-day window (from day -2 to day +2) around the SEO announcement date. *CAR [-3:3]* is the cumulative abnormal return on SEO firm's equity over a 7-day window (from day -3 to day +3) around the SEO announcement date. *CAR [1:21]* is the cumulative abnormal return on SEO firm's equity over a 21-day window (from day 1 to day 21) after the SEO announcement date. *CAR [1:42]* is the cumulative abnormal return on SEO firm's equity over a 42-day window (from day 1 to day 42) after the SEO announcement date. Abnormal returns are estimated using the market model with CRSP value-weighted index return as the market return; market model variables (alphas and betas) are estimated over a 150-day period ending 50 days prior to the SEO announcement date. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary statistics of SEO announcement effect

	N	Mean	Median	Min.	Max.	S.D.	t-Statistic (Means= 0)	z-Statistic (Medians= 0)
CAR [0:0]	5,821	-0.761	-0.445	-19.573	17.677	4.302	-13.492***	-15.307***
CAR [-1:1]	5,818	-2.298	-1.698	-34.642	33.101	7.821	-22.411***	-27.192***
CAR [-2:2]	5,815	-2.131	-1.794	-38.164	49.046	9.901	-16.415***	-22.709***
CAR [-3:3]	5,815	-2.068	-1.890	-41.185	62.389	11.425	-13.804***	-20.123***

Panel B: Summary statistics of SEO post-announcement drift

	N	Mean	Median	Min.	Max.	S.D.	t-Statistic (Means= 0)	z-Statistic (Medians= 0)
CAR [1:21]	5,828	-3.530	-2.778	-65.918	68.419	17.546	-15.358***	-18.543***
CAR [1:42]	5,829	-5.625	-4.198	-98.238	101.048	26.018	-16.506***	-18.918***

Table 3: **Relationship between investor attention and SEO announcement effect**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *CAR [0: 0]* is the abnormal return on SEO firm's equity on the SEO announcement day. *NumNewsFile [-7:-1]*, *NumNewsFile [-14:-1]*, *NumNewsFile [-30:-1]*, and *NumNewsFile [-60:-1]* are measures of investor attention prior to the SEO announcement date as described in Table 1. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpFile* is the earnings surprise one quarter prior to the SEO announcement date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetFile* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO announcement date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	CAR [0:0]			
	(1)	(2)	(3)	(4)
NumNewsFile [-7:-1]	-0.051***			
	(-3.15)			
NumNewsFile [-14:-1]		-0.035***		
		(-3.85)		
NumNewsFile [-30:-1]			-0.019***	
			(-4.15)	
NumNewsFile [-60:-1]				-0.009***
				(-3.66)
UndwrtReputation	-1.625	-1.549	-1.568	-1.590
	(-1.11)	(-1.06)	(-1.07)	(-1.09)
FirmSize	0.157***	0.170***	0.176***	0.172***
	(3.00)	(3.23)	(3.35)	(3.26)
PriorQtrEarnSurpFile	0.260***	0.259***	0.257***	0.258***
	(3.23)	(3.21)	(3.18)	(3.20)
PriorMktRetFile	0.662	0.507	0.434	0.512
	(0.43)	(0.33)	(0.28)	(0.33)
MidFilePrice	0.009***	0.009***	0.009***	0.009***
	(2.65)	(2.76)	(2.73)	(2.67)
Constant	-7.308	-7.410	-7.516	-7.395
	(-1.20)	(-1.22)	(-1.24)	(-1.22)
Industry × Year FE	Yes	Yes	Yes	Yes
R^2	0.170	0.171	0.171	0.171
Observations	4735	4735	4735	4735

Table 4: **Relationship between investor attention and SEO post-announcement drift**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *CAR [1:21]* is the cumulative abnormal return on SEO firm's equity over a 21-day window (from day 1 to day 21) after the SEO announcement date. *NumNewsFile [-7:-1]*, *NumNewsFile [-14:-1]*, *NumNewsFile [-30:-1]*, and *NumNewsFile [-60:-1]* are measures of investor attention prior to the SEO announcement date as described in Table 1. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpFile* is the earnings surprise one quarter prior to the SEO announcement date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetFile* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO announcement date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	CAR [1:21]			
	(1)	(2)	(3)	(4)
NumNewsFile [-7:-1]	0.236***			
	(3.60)			
NumNewsFile [-14:-1]		0.150***		
		(4.09)		
NumNewsFile [-30:-1]			0.060***	
			(3.25)	
NumNewsFile [-60:-1]				0.023**
				(2.28)
UndwrtReputation	-8.611	-8.918	-8.718	-8.592
	(-1.45)	(-1.51)	(-1.47)	(-1.45)
FirmSize	0.649***	0.609***	0.649***	0.697***
	(3.07)	(2.87)	(3.04)	(3.25)
PriorQtrEarnSurpFile	0.706**	0.712**	0.721**	0.718**
	(2.16)	(2.18)	(2.21)	(2.20)
PriorMktRetFile	16.078**	16.806***	17.058***	16.824***
	(2.58)	(2.70)	(2.73)	(2.70)
MidFilePrice	-0.031**	-0.033**	-0.032**	-0.031**
	(-2.37)	(-2.47)	(-2.40)	(-2.33)
Constant	45.202*	45.516*	45.333*	44.661*
	(1.84)	(1.85)	(1.84)	(1.81)
Industry × Year FE	Yes	Yes	Yes	Yes
R^2	0.155	0.156	0.155	0.154
Observations	4742	4742	4742	4742

Table 5: **Relationship between the SEO announcement effect, post-announcement drift, and subsequent operating performance**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000 - 2018. $ROA_{1(2,3,4)}$ is the ratio of net income over the book value of total assets measured over one (two, three, four) quarters after the SEO announcement. *Cash* $Flow_{1(2,3,4)}$ is the ratio of income before extraordinary items plus depreciation to the book value of total assets measured over one (two, three, four) quarters after the SEO announcement. *CAR [0:0]* is the abnormal return on SEO firm's equity on the SEO announcement day. *CAR [1:21]* is the cumulative abnormal return on SEO firm's equity over a 21-day window (from day 1 to day 21) after the SEO announcement date. *NumNewsFile [-7:-1]*, *NumNewsFile [-14:-1]*, *NumNewsFile [-30:-1]*, and *NumNewsFile [-60:-1]* are measures of investor attention prior to the SEO announcement date as described in Table 1. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpFile* is the earnings surprise one quarter prior to the SEO announcement date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetFile* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO announcement date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between the SEO announcement effect, post-announcement drift, and subsequent ROA

Dependent Variable	ROA_1	ROA_2	ROA_3	ROA_4
	(1)	(2)	(3)	(4)
CAR [0:0]	0.042	0.107^{**}	0.183^{**}	0.166^{*}
	(1.56)	(2.16)	(2.54)	(1.76)
CAR [1:21]	0.016^{**}	0.029^{**}	0.049^{***}	0.070^{***}
	(2.42)	(2.39)	(2.79)	(3.05)
UndwrtReputation	3.269	7.207	10.963^{*}	14.924^{*}
	(1.30)	(1.58)	(1.66)	(1.73)
FirmSize	1.262^{***}	2.498^{***}	3.706^{***}	4.862^{***}
	(14.44)	(15.79)	(16.09)	(16.17)
PriorQtrEarnSurpFile	-0.740^{***}	-1.075^{***}	-2.145^{***}	-2.573^{***}
	(-5.33)	(-4.24)	(-5.77)	(-5.29)
PriorMktRetFile	0.497	-0.838	-0.769	-1.638
	(0.19)	(-0.18)	(-0.11)	(-0.18)
MidFilePrice	0.032^{***}	0.064^{***}	0.092^{***}	0.126^{***}
	(5.72)	(6.37)	(6.31)	(6.53)
Constant	-2.313	-7.664	51.963^{*}	-79.156^{***}
	(-0.22)	(-0.41)	(1.93)	(-2.79)
Industry × Year FE	Yes	Yes	Yes	Yes
R^2	0.462	0.514	0.531	0.539
Observations	4724	4688	4561	4438

Panel B: Relationship between the SEO announcement effect, post-announcement drift, and subsequent Cash Flow				
Dependent Variable	Cash Flow_1	Cash Flow_2	Cash Flow_3	Cash Flow_4
	(1)	(2)	(3)	(4)
CAR [0:0]	0.043	0.102*	0.168**	0.108
	(1.38)	(1.80)	(2.03)	(0.98)
CAR [1:21]	0.014*	0.030**	0.051**	0.073***
	(1.78)	(2.12)	(2.52)	(2.72)
UndwrtReputation	2.991	7.494	12.083	17.188
	(0.99)	(1.36)	(1.50)	(1.63)
FirmSize	1.493***	2.985***	4.424***	5.795***
	(14.50)	(15.89)	(16.04)	(16.06)
PriorQtrEarnSurpFile	-0.768***	-1.110***	-2.161***	-2.711***
	(-4.99)	(-3.93)	(-5.17)	(-4.97)
PriorMktRetFile	0.149	-2.389	-3.995	-4.646
	(0.05)	(-0.40)	(-0.46)	(-0.41)
MidFilePrice	0.035***	0.070***	0.102***	0.140***
	(5.06)	(5.59)	(5.59)	(5.83)
Constant	-3.738	-9.113	53.131*	-79.932**
	(-0.33)	(-0.44)	(1.80)	(-2.56)
Industry × Year FE	Yes	Yes	Yes	Yes
R^2	0.472	0.525	0.543	0.553
Observations	4076	4010	3858	3728

Table 6: **Relationship between abnormal investor attention and market reaction upon SEO announcement**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000 - 2018. *CAR [0:0]* is the abnormal return on SEO firm's equity on the SEO announcement day. *CAR [1:21]* is the cumulative abnormal return on SEO firm's equity over a 21-day window (from day 1 to day 21) after the SEO announcement date. *AbnNumNewsFile [-7:-1]*, *AbnNumNewsFile [-14:-1]*, *AbnNumNewsFile [-30:-1]*, and *AbnNumNewsFile [-60:-1]* are measures of abnormal investor attention prior to the SEO announcement date as described in Table 1. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpFile* is the earnings surprise one quarter prior to the SEO announcement date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetFile* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO announcement date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between abnormal investor attention and SEO announcement effect

Dependent Variable	CAR [0:0]			
	(1)	(2)	(3)	(4)
AbnNumNewsFile [-7:-1]	-0.041**			
	(-2.42)			
AbnNumNewsFile [-14:-1]		-0.041***		
		(-3.35)		
AbnNumNewsFile [-30:-1]			-0.019***	
			(-2.73)	
AbnNumNewsFile [-60:-1]				-0.011**
				(-2.44)
UndwrtReputation	-1.672	-1.508	-1.492	-1.471
	(-1.14)	(-1.03)	(-1.02)	(-1.00)
FirmSize	0.120**	0.122**	0.121**	0.121**
	(2.36)	(2.41)	(2.39)	(2.39)
PriorQtrEarnSurpFile	0.260***	0.262***	0.259***	0.258***
	(3.23)	(3.24)	(3.21)	(3.20)
PriorMktRetFile	0.585	0.582	0.491	0.499
	(0.38)	(0.38)	(0.32)	(0.32)
MidFilePrice	0.008***	0.009***	0.009***	0.009***
	(2.60)	(2.68)	(2.69)	(2.64)
Constant	-7.013	-7.014	-7.060	-6.933
	(-1.15)	(-1.15)	(-1.16)	(-1.14)
Industry × Year FE	Yes	Yes	Yes	Yes
R^2	0.169	0.170	0.169	0.169
Observations	4735	4735	4735	4735

Panel B: Relationship between abnormal investor attention and post-announcement drift				
Dependent Variable	CAR [1:21]			
	(1)	(2)	(3)	(4)
AbnNumNewsFile [-7:-1]	0.071			
	(1.06)			
AbnNumNewsFile [-14:-1]		0.079*		
		(1.65)		
AbnNumNewsFile [-30:-1]			0.019	
			(0.70)	
AbnNumNewsFile [-60:-1]				-0.008
				(-0.46)
UndwrtReputation	-7.751	-8.075	-7.936	-7.581
	(-1.34)	(-1.40)	(-1.37)	(-1.31)
FirmSize	0.802***	0.799***	0.804***	0.810***
	(3.98)	(3.96)	(3.98)	(4.01)
PriorQtrEarnSurpFile	2.122	2.123	2.150	2.160
	(1.56)	(1.56)	(1.58)	(1.59)
PriorMktRetFile	18.330***	18.311***	18.473***	18.505***
	(2.92)	(2.92)	(2.95)	(2.95)
MidFilePrice	-0.031**	-0.031**	-0.031**	-0.030**
	(-2.21)	(-2.26)	(-2.22)	(-2.17)
Constant	44.363*	44.370*	44.362*	44.271*
	(1.86)	(1.86)	(1.86)	(1.85)
Industry × Year FE	Yes	Yes	Yes	Yes
R^2	0.155	0.155	0.155	0.155
Observations	4742	4742	4742	4742

Table 7: **Instrumental variable analysis of the relationship between investor attention and market reaction upon SEO announcement**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000 - 2018. *CAR [0: 0]* is the abnormal return on SEO firm's equity on the SEO announcement day. *CAR [1:21]* is the cumulative abnormal return on SEO firm's equity over a 21-day window (from day 1 to day 21) after the SEO announcement date. *NumNewsFileHat [-7:-1]*, *NumNewsFileHat [-14:-1]*, *NumNewsFileHat [-30:-1]*, and *NumNewsFileHat [-60:-1]* are predicted values of investor attention variables as described in Table 1 (*NumNewsFile [-7:-1]*, *NumNewsFile [-14:-1]*, *NumNewsFile [-30:-1]*, and *NumNewsFile [-60:-1]*) from first-stage regressions. *PriorYrNumNewsFile [-7:-1]*, *PriorYrNumNewsFile [-14:-1]*, *PriorYrNumNewsFile [-30:-1]*, and *PriorYrNumNewsFile [-60:-1]* are instrumental variables which measure investor attention one year prior to the SEO announcement date as described in Table 1. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpFile* is the earnings surprise one quarter prior to the SEO announcement date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetFile* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO announcement date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between investor attention and SEO announcement effect

Dependent Variable	1st-stage	CAR [0:0]	1st-stage	CAR [0:0]	1st-stage	CAR [0:0]	1st-stage	CAR [0:0]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PriorYrNumNewsFile [-7:-1]	0.570***							
	(37.31)							
NumNewsFileHat [-7:-1]		-0.031						
		(-1.06)						
PriorYrNumNewsFile [-14:-1]			0.832***					
			(58.28)					
NumNewsFileHat [-14:-1]				-0.022*				
				(-1.79)				
PriorYrNumNewsFile [-30:-1]					0.899***			
					(71.49)			
NumNewsFileHat [-30:-1]						-0.017***		
						(-3.03)		
PriorYrNumNewsFile [-60:-1]							1.003***	
							(87.87)	
NumNewsFileHat [-60:-1]								-0.009***
								(-3.00)
UndwrtReputation	0.562	-1.646	4.127**	-1.597	9.694***	-1.580	19.804***	-1.597
	(0.46)	(-1.22)	(2.20)	(-1.19)	(2.86)	(-1.18)	(3.68)	(-1.19)
FirmSize	0.388***	0.141***	0.366***	0.150***	0.535***	0.170***	0.429**	0.168***
	(8.79)	(2.71)	(5.39)	(2.99)	(4.35)	(3.42)	(2.18)	(3.39)
PriorQtrEarnSurpFile	0.070	0.259***	0.098	0.258***	0.064	0.257***	0.078	0.258***
	(1.02)	(3.50)	(0.95)	(3.49)	(0.34)	(3.47)	(0.26)	(3.48)
PriorMktRetFile	2.777**	0.594	1.981	0.500	-0.204	0.440	0.926	0.510
	(2.14)	(0.42)	(1.00)	(0.35)	(-0.06)	(0.31)	(0.16)	(0.36)

MidFilePrice	0.004	0.009***	0.011***	0.009***	0.024***	0.009***	0.026**	0.009***
	(1.51)	(2.84)	(2.71)	(2.92)	(3.16)	(2.96)	(2.17)	(2.90)
Constant	-2.644	-2.250	-8.475	-2.303	-5.405	-2.229	-10.969	-2.288
	(-0.63)	(-0.49)	(-1.33)	(-0.51)	(-0.47)	(-0.49)	(-0.60)	(-0.50)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.170		0.170		0.171		0.171
Observations	4735	4735	4735	4735	4735	4735	4735	4735
F Statistics	1391.92		3396.03		5110.44		7720.30	

Panel B: Relationship between investor attention and post-announcement drift								
Dependent Variable	1st-stage	CAR [1:21]	1st-stage	CAR [1:21]	1st-stage	CAR [1:21]	1st-stage	CAR [1:21]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PriorYrNumNewsFile [-7:-1]	0.571***							
	(37.33)							
NumNewsFileHat [-7:-1]		0.389***						
		(3.29)						
PriorYrNumNewsFile [-14:-1]			0.832***					
			(58.30)					
NumNewsFileHat [-14:-1]				0.194***				
				(3.91)				
PriorYrNumNewsFile [-30:-1]					0.899***			
					(71.40)			
NumNewsFileHat [-30:-1]						0.084***		
						(3.75)		
PriorYrNumNewsFile [-60:-1]							1.003***	
							(87.72)	
NumNewsFileHat [-60:-1]								0.041***
								(3.54)
UndwrtReputation	0.503	-8.763	4.020**	-9.077*	9.534***	-8.860	19.483***	-8.754
	(0.41)	(-1.61)	(2.14)	(-1.67)	(2.82)	(-1.63)	(3.62)	(-1.61)
FirmSize	0.391***	0.527**	0.369***	0.541***	0.535***	0.570***	0.437**	0.590***
	(8.85)	(2.50)	(5.44)	(2.67)	(4.35)	(2.83)	(2.22)	(2.94)
PriorQtrEarnSurpFile	0.070	0.697**	0.098	0.710**	0.064	0.722**	0.079	0.718**
	(1.03)	(2.32)	(0.95)	(2.37)	(0.34)	(2.41)	(0.27)	(2.39)
PriorMktRetFile	2.761**	15.559***	1.944	16.785***	-0.299	17.134***	0.744	16.786***
	(2.13)	(2.71)	(0.99)	(2.93)	(-0.08)	(2.99)	(0.13)	(2.93)
MidFilePrice	0.004	-0.032***	0.011***	-0.033***	0.024***	-0.032***	0.026**	-0.031***
	(1.51)	(-2.65)	(2.72)	(-2.75)	(3.17)	(-2.67)	(2.16)	(-2.59)
Constant	-2.645	-0.627	-8.476	-0.796	-5.398	-2.016	-10.968	-1.767
	(-0.63)	(-0.03)	(-1.33)	(-0.04)	(-0.47)	(-0.11)	(-0.60)	(-0.10)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.154		0.156		0.155		0.153
Observations	4742	4742	4742	4742	4742	4742	4742	4742
F Statistics	1393.29		3398.43		5097.53		7693.97	

Table 8: **Relationship between investor attention and post-SEO participation of institutional investors in the ownership of issuing firms' equity**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *InstN* is the number of institutional investors holding SEO firms' shares at the end of the first post-issue fiscal quarter. *NumNewsIss [-7:-1]*, *NumNewsIss [-14:-1]*, *NumNewsIss [-30:-1]*, and *NumNewsIss [-60:-1]* are measures of investor attention prior to the SEO issue date as described in Table 1. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	InstN							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NumNewsIss [-7:-1]	4.593***	4.591***						
	(17.58)	(17.54)						
NumNewsIss [-14:-1]			3.330***	3.326***				
			(18.70)	(18.62)				
NumNewsIss [-30:-1]					1.723***	1.718***		
					(14.74)	(14.64)		
NumNewsIss [-60:-1]							0.866***	0.863***
							(13.16)	(13.06)
Underpricing		0.484**		0.436*		0.355		0.311
		(2.16)		(1.91)		(1.31)		(0.95)
UndwrtReputation	19.050	20.258	22.962	23.691	71.773**	71.129**	79.433**	77.654*
	(0.69)	(0.73)	(0.79)	(0.82)	(2.06)	(2.04)	(1.97)	(1.92)
FirmSize	43.146***	43.206***	42.261***	42.290***	43.815***	43.834***	45.555***	45.535***
	(41.47)	(41.25)	(38.61)	(38.36)	(33.09)	(32.75)	(29.20)	(28.89)
PriorQtrEarnSurpIss	-1.822	-1.602	-1.649	-1.453	-1.459	-1.313	-1.869	-1.731
	(-1.59)	(-1.39)	(-1.45)	(-1.27)	(-1.10)	(-0.99)	(-1.28)	(-1.18)
PriorMktRetIss	-7.902	-11.573	-0.806	-4.363	31.472	28.633	24.887	22.354
	(-0.24)	(-0.36)	(-0.02)	(-0.13)	(0.80)	(0.72)	(0.52)	(0.47)
MidFilePrice	1.032***	1.042***	1.067***	1.076***	1.238***	1.246***	1.336***	1.345***
	(14.31)	(14.42)	(14.02)	(14.12)	(13.26)	(13.32)	(11.84)	(11.88)
Constant	-262.282**	-268.652***	-271.063***	-276.603***	-304.249***	-308.994***	-344.022*	-432.622***
	(-2.53)	(-2.59)	(-2.64)	(-2.70)	(-2.76)	(-2.80)	(-1.77)	(-2.62)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.729	0.728	0.744	0.743	0.766	0.765	0.781	0.780
Observations	3883	3854	3569	3541	2796	2770	2156	2132

Table 9: **Relationship between investor attention and post-SEO market valuation of issuing firms**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *QFTDAdj* and *QFQAdj* are the industry-adjusted Q ratios calculated using the SEO issue day closing price and the price at the end of the first post-issue fiscal quarter, respectively. Q ratio is defined as the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and either the SEO issue day closing price (*QFTDAdj*) or the price at the end of the first post-issue fiscal quarter (*QFQAdj*). Industry adjustment is performed by subtracting contemporaneous 2-digit SIC code industry median Q ratios from SEO firms' Q ratios. *NumNewsIss [-7:-1]*, *NumNewsIss [-14:-1]*, *NumNewsIss [-30:-1]*, and *NumNewsIss [-60:-1]* are measures of investor attention prior to the SEO issue date as described in Table 1. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between investor attention and post-SEO market valuation measured using the first trading day closing price

Dependent Variable	QFTDAdj							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NumNewsIss [-7:-1]	0.033***	0.033***						
	(4.03)	(3.98)						
NumNewsIss [-14:-1]			0.025***	0.024***				
			(4.31)	(4.21)				
NumNewsIss [-30:-1]					0.015***	0.014***		
					(4.26)	(4.14)		
NumNewsIss [-60:-1]							0.005***	0.005***
							(3.03)	(2.99)
Underpricing		0.013*		0.013*		0.014*		0.008
		(1.82)		(1.86)		(1.80)		(0.96)
UndwrtReputation	4.069***	4.141***	3.711***	3.784***	2.759***	2.795***	2.403**	2.412**
	(4.65)	(4.73)	(3.97)	(4.04)	(2.72)	(2.75)	(2.34)	(2.35)
FirmSize	-0.519***	-0.517***	-0.512***	-0.509***	-0.465***	-0.461***	-0.425***	-0.426***
	(-15.92)	(-15.79)	(-14.65)	(-14.51)	(-12.16)	(-12.00)	(-10.81)	(-10.78)
PriorQtrEarnSurpIss	0.016	0.020	0.015	0.019	-0.013	-0.010	-0.027	-0.025
	(0.48)	(0.59)	(0.44)	(0.55)	(-0.37)	(-0.28)	(-0.78)	(-0.70)
PriorMktRetIss	-0.146	-0.177	-0.315	-0.352	-0.391	-0.408	-0.097	-0.072
	(-0.14)	(-0.17)	(-0.29)	(-0.32)	(-0.34)	(-0.35)	(-0.08)	(-0.06)
MidFilePrice	0.031***	0.032***	0.031***	0.031***	0.025***	0.026***	0.022***	0.022***
	(13.79)	(13.88)	(12.57)	(12.66)	(9.44)	(9.51)	(7.68)	(7.74)
Constant	-1.421	-1.590	-1.516	-1.697	-1.194	-1.392	15.880***	15.817***
	(-0.43)	(-0.48)	(-0.46)	(-0.51)	(-0.37)	(-0.43)	(3.76)	(3.75)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.119	0.121	0.117	0.119	0.124	0.126	0.174	0.176

Observations	3915	3911	3597	3593	2813	2809	2163	2161

Panel B: Relationship between investor attention and post-SEO market valuation measured using the price at the end of the first post-issue fiscal quarter

Dependent Variable	QFQAdj							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NumNewsIss [-7:-1]	0.021***	0.020***						
	(2.79)	(2.74)						
NumNewsIss [-14:-1]			0.015***	0.015***				
			(2.90)	(2.86)				
NumNewsIss [-30:-1]					0.008***	0.008**		
					(2.74)	(2.57)		
NumNewsIss [-60:-1]							0.004**	0.004**
							(2.42)	(2.34)
Underpricing		0.004		0.006		0.011		0.003
		(0.68)		(0.92)		(1.55)		(0.42)
UndwrtReputation	4.149***	4.148***	3.571***	3.572***	2.516***	2.499***	2.151**	2.105**
	(5.31)	(5.30)	(4.28)	(4.28)	(2.76)	(2.74)	(2.35)	(2.30)
FirmSize	-0.470***	-0.469***	-0.457***	-0.454***	-0.426***	-0.419***	-0.408***	-0.405***
	(-16.21)	(-16.04)	(-14.71)	(-14.52)	(-12.45)	(-12.15)	(-11.67)	(-11.48)
PriorQtrEarnSurpIss	0.004	0.005	0.003	0.004	-0.014	-0.012	-0.019	-0.018
	(0.12)	(0.16)	(0.10)	(0.15)	(-0.44)	(-0.37)	(-0.60)	(-0.57)
PriorMktRetIss	-0.051	-0.092	-0.090	-0.142	-0.162	-0.311	0.526	0.363
	(-0.06)	(-0.10)	(-0.09)	(-0.15)	(-0.16)	(-0.30)	(0.48)	(0.33)
MidFilePrice	0.021***	0.021***	0.019***	0.020***	0.017***	0.017***	0.014***	0.014***
	(10.54)	(10.57)	(8.95)	(9.00)	(6.98)	(7.04)	(5.51)	(5.55)
Constant	-2.997	-3.064	-3.024	-3.114	-2.864	-3.038	10.584**	15.185***
	(-1.02)	(-1.04)	(-1.02)	(-1.05)	(-0.99)	(-1.05)	(2.38)	(4.03)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.133	0.130	0.133	0.130	0.146	0.142	0.218	0.212
Observations	3934	3905	3615	3587	2829	2803	2180	2156

Table 10: **Relationship between investor attention and SEO underpricing**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *NumNewsIss [-7:-1]*, *NumNewsIss [-14:-1]*, *NumNewsIss [-30:-1]*, and *NumNewsIss [-60:-1]* are measures of investor attention prior to the SEO issue date as described in Table 1. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year $\times$ industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Underpricing			
	(1)	(2)	(3)	(4)
NumNewsIss [-7:-1]	0.042**			
	(2.00)			
NumNewsIss [-14:-1]		0.050***		
		(3.44)		
NumNewsIss [-30:-1]			0.033***	
			(3.52)	
NumNewsIss [-60:-1]				0.015***
				(2.93)
UndwrtReputation	-4.869**	-4.688**	-1.553	1.696
	(-2.22)	(-1.97)	(-0.56)	(0.55)
FirmSize	-0.363***	-0.400***	-0.500***	-0.423***
	(-4.42)	(-4.50)	(-4.78)	(-3.57)
PriorQtrEarnSurpIss	-0.285***	-0.279***	-0.237**	-0.321***
	(-3.44)	(-3.28)	(-2.43)	(-3.04)
PriorMktRetIss	4.582*	4.735*	3.681	1.736
	(1.77)	(1.72)	(1.17)	(0.47)
MidFilePrice	-0.014**	-0.014**	-0.009	-0.011
	(-2.50)	(-2.20)	(-1.23)	(-1.35)
Constant	14.443*	14.525*	15.429*	10.844
	(1.74)	(1.72)	(1.75)	(0.85)
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
R^2	0.228	0.243	0.288	0.326
Observations	3920	3601	2817	2166

Table 11: **Relationship between investor attention and SEO valuation of issuing firms**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *QOPAdj* is the industry-adjusted Q ratios calculated using the SEO offer price. Q ratio is defined as the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and the SEO offer price. Industry adjustment is performed by subtracting contemporaneous 2-digit SIC code industry median Q ratios from SEO firms' Q ratios. *NumNewsIss [-7:-1]*, *NumNewsIss [-14:-1]*, *NumNewsIss [-30:-1]*, and *NumNewsIss [-60:-1]* are measures of investor attention prior to the SEO issue date as described in Table 1. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	QOPAdj							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NumNewsIss [-7:-1]	0.032***	0.032***						
	(4.00)	(4.00)						
NumNewsIss [-14:-1]			0.024***	0.024***				
			(4.29)	(4.35)				
NumNewsIss [-30:-1]					0.014***	0.014***		
					(4.23)	(4.25)		
NumNewsIss [-60:-1]							0.005***	0.005***
							(3.04)	(3.13)
Underpricing		-0.010		-0.010		-0.009		-0.015*
		(-1.55)		(-1.43)		(-1.19)		(-1.95)
UndwrtReputation	4.103***	4.019***	3.746***	3.660***	2.737***	2.670***	2.321**	2.278**
	(4.88)	(4.77)	(4.17)	(4.06)	(2.81)	(2.73)	(2.34)	(2.29)
FirmSize	-0.494***	-0.498***	-0.487***	-0.491***	-0.442***	-0.446***	-0.409***	-0.415***
	(-15.78)	(-15.78)	(-14.53)	(-14.53)	(-12.07)	(-12.04)	(-10.78)	(-10.82)
PriorQtrEarnSurpIss	0.022	0.019	0.021	0.018	-0.007	-0.009	-0.019	-0.024
	(0.69)	(0.60)	(0.64)	(0.55)	(-0.20)	(-0.27)	(-0.57)	(-0.71)
PriorMktRetIss	-0.127	-0.071	-0.305	-0.249	-0.209	-0.215	0.176	0.150
	(-0.13)	(-0.07)	(-0.29)	(-0.24)	(-0.19)	(-0.19)	(0.15)	(0.13)
MidFilePrice	0.030***	0.030***	0.030***	0.030***	0.025***	0.025***	0.021***	0.021***
	(13.89)	(13.79)	(12.65)	(12.56)	(9.59)	(9.54)	(7.80)	(7.72)
Constant	-1.815	-1.666	-1.903	-1.759	-1.644	-1.510	10.848**	15.464***
	(-0.57)	(-0.52)	(-0.59)	(-0.55)	(-0.53)	(-0.49)	(2.25)	(3.78)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.120	0.119	0.119	0.118	0.126	0.125	0.173	0.173
Observations	3940	3911	3621	3593	2835	2809	2185	2161

Table 12: **Instrumental variable analysis of the relationship between investor attention and post-SEO participation of institutional investors in the ownership of issuing firms' equity**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *InstN* is the number of institutional investors holding SEO firms' shares at the end of the first post-issue fiscal quarter. *NumNewsIssHat [-7:-1]*, *NumNewsIssHat [-14:-1]*, *NumNewsIssHat [-30:-1]*, and *NumNewsIssHat [-60:-1]* are predicted values of investor attention variables as described in Table 1 (*NumNewsIss [-7:-1]*, *NumNewsIss [-14:-1]*, *NumNewsIss [-30:-1]*, and *NumNewsIss [-60:-1]*) from first-stage regressions. *PriorYrNumNewsFile [-7:-1]*, *PriorYrNumNewsFile [-14:-1]*, *PriorYrNumNewsFile [-30:-1]*, and *PriorYrNumNewsFile [-60:-1]* are instrumental variables which measure investor attention one year prior to the SEO announcement date as described in Table 1. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

	1st-stage	InstN	1st-stage	InstN	1st-stage	InstN	1st-stage	InstN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PriorYrNumNewsFile [-7:-1]	0.566***							
	(22.51)							
NumNewsIssHat [-7:-1]		9.437***						
		(13.98)						
PriorYrNumNewsFile [-14:-1]			0.687***					
			(32.49)					
NumNewsIssHat [-14:-1]				5.386***				
				(16.87)				
PriorYrNumNewsFile [-30:-1]					0.667***			
					(38.12)			
NumNewsIssHat [-30:-1]						2.285***		
						(13.73)		
PriorYrNumNewsFile [-60:-1]							0.840***	
							(42.00)	
NumNewsIssHat [-60:-1]								1.105***
								(13.72)
Underpricing	0.021	0.329	0.053***	0.266	0.113***	0.254	0.165*	0.223
	(1.52)	(1.52)	(2.62)	(1.26)	(2.96)	(1.04)	(1.96)	(0.78)
UndwrtReputation	3.753**	5.929	8.929***	9.600	9.892**	67.705**	21.689**	75.417**
	(2.16)	(0.22)	(3.46)	(0.36)	(2.01)	(2.17)	(2.07)	(2.13)
FirmSize	0.825***	37.479***	1.102***	38.176***	1.898***	41.647***	2.578***	43.646***
	(12.71)	(30.09)	(11.37)	(33.03)	(10.26)	(32.12)	(6.34)	(30.06)
PriorQtrEarnSurpIss	-0.003	-1.492	-0.043	-1.308	-0.091	-1.225	-0.079	-1.643
	(-0.04)	(-1.36)	(-0.42)	(-1.24)	(-0.48)	(-1.03)	(-0.21)	(-1.28)

PriorMktRetIss	3.196	-32.790	2.184	-15.350	2.455	25.656	10.008	18.819
	(1.57)	(-1.05)	(0.73)	(-0.50)	(0.44)	(0.72)	(0.81)	(0.45)
MidFilePrice	-0.000	1.054***	0.005	1.074***	0.006	1.249***	-0.018	1.356***
	(-0.07)	(15.25)	(0.79)	(15.24)	(0.43)	(14.92)	(-0.60)	(13.63)
Constant	-8.597	-217.755**	-7.670	-247.806***	-5.408	-296.564***	-13.311	-416.064***
	(-1.32)	(-2.19)	(-0.84)	(-2.61)	(-0.35)	(-3.01)	(-0.31)	(-2.86)
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.699		0.732		0.763		0.779
Observations	3854	3854	3541	3541	2770	2770	2132	2132
F Statistics	506.58		1055.81		1452.81		1763.62	

Table 13: **Instrumental variable analysis of the relationship between investor attention and post-SEO market valuation of issuing firms**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *QFTDAdj* and *QFQAdj* are the industry-adjusted Q ratios calculated using the SEO issue day closing price and the price at the end of the first post-issue fiscal quarter, respectively. Q ratio is defined as the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and either the SEO issue day closing price (*QFTDAdj*) or the price at the end of the first post-issue fiscal quarter (*QFQAdj*). Industry adjustment is performed by subtracting contemporaneous 2-digit SIC code industry median Q ratios from SEO firms' Q ratios. *NumNewsIssHat [-7:-1]*, *NumNewsIssHat [-14:-1]*, *NumNewsIssHat [-30:-1]*, and *NumNewsIssHat [-60:-1]* are predicted values of investor attention variables as described in Table 1 (*NumNewsIss [-7:-1]*, *NumNewsIss [-14:-1]*, *NumNewsIss [-30:-1]*, and *NumNewsIss [-60:-1]*) from first-stage regressions. *PriorYrNumNewsFile [-7:-1]*, *PriorYrNumNewsFile [-14:-1]*, *PriorYrNumNewsFile [-30:-1]*, and *PriorYrNumNewsFile [-60:-1]* are instrumental variables which measure investor attention one year prior to the SEO announcement date as described in Table 1. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. *t*-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between investor attention and post-SEO market valuation measured using the first trading day closing price

Dependent Variable	1st-stage	QFTDAdj	1st-stage	QFTDAdj	1st-stage	QFTDAdj	1st-stage	QFTDAdj
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PriorYrNumNewsFile [-7:-1]	0.568***							
	(22.77)							
NumNewsIssHat [-7:-1]		0.037*						
		(1.83)						
PriorYrNumNewsFile [-14:-1]			0.681***					
			(32.46)					
NumNewsIssHat [-14:-1]				0.016				
				(1.60)				
PriorYrNumNewsFile [-30:-1]					0.664***			
					(38.13)			
NumNewsIssHat [-30:-1]						0.007		
						(1.39)		
PriorYrNumNewsFile [-60:-1]							0.838***	
							(42.24)	
NumNewsIssHat [-60:-1]								0.004*
								(1.78)
Underpricing	0.020	0.013**	0.052***	0.014**	0.106***	0.015**	0.157*	0.008
	(1.48)	(1.97)	(2.63)	(2.14)	(2.86)	(2.19)	(1.91)	(1.16)
UndwrtReputation	3.550**	4.130***	8.723***	3.840***	10.428**	2.841***	21.760**	2.426***
	(2.06)	(5.18)	(3.40)	(4.52)	(2.13)	(3.14)	(2.10)	(2.70)
FirmSize	0.827***	-0.521***	1.089***	-0.493***	1.857***	-0.433***	2.549***	-0.415***

	(13.03)	(-14.07)	(11.48)	(-13.67)	(10.24)	(-11.64)	(6.43)	(-11.43)
PriorQtrEarnSurpIss	0.006	0.020	-0.001	0.018	-0.076	-0.011	-0.106	-0.025
	(0.09)	(0.65)	(-0.01)	(0.60)	(-0.44)	(-0.35)	(-0.30)	(-0.82)
PriorMktRetIss	3.040	-0.194	2.305	-0.308	2.282	-0.370	9.814	-0.053
	(1.50)	(-0.21)	(0.78)	(-0.31)	(0.41)	(-0.36)	(0.80)	(-0.05)
MidFilePrice	-0.000	0.032***	0.004	0.031***	0.006	0.026***	-0.019	0.022***
	(-0.07)	(15.26)	(0.65)	(13.99)	(0.49)	(10.65)	(-0.66)	(8.81)
Constant	-8.597	-1.547	-7.520	-1.807	-5.114	-1.552	-12.899	15.723***
	(-1.32)	(-0.52)	(-0.82)	(-0.60)	(-0.33)	(-0.54)	(-0.30)	(4.25)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.121		0.118		0.125		0.176
Observations	3911	3911	3593	3593	2809	2809	2161	2161
F Statistics	518.49		1053.76		1453.65		1783.83	

Panel B: Relationship between investor attention and post-SEO market valuation measured using the price at the end of the first post-issue fiscal quarter

Dependent Variable	1st-stage	QFQAdj	1st-stage	QFQAdj	1st-stage	QFQAdj	1st-stage	QFQAdj
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PriorYrNumNewsFile [-7:-1]	0.568***							
	(22.75)							
NumNewsIssHat [-7:-1]		0.039**						
		(2.13)						
PriorYrNumNewsFile [-14:-1]			0.681***					
			(32.42)					
NumNewsIssHat [-14:-1]				0.016*				
				(1.72)				
PriorYrNumNewsFile [-30:-1]					0.664***			
					(38.07)			
NumNewsIssHat [-30:-1]						0.007		
						(1.55)		
PriorYrNumNewsFile [-60:-1]							0.838***	
							(42.17)	
NumNewsIssHat [-60:-1]								0.004**
								(2.16)
Underpricing	0.020	0.004	0.052***	0.006	0.106***	0.011*	0.156*	0.003
	(1.47)	(0.65)	(2.62)	(1.00)	(2.84)	(1.77)	(1.90)	(0.45)
UndwrtReputation	3.434**	4.098***	8.638***	3.567***	10.292**	2.506***	21.607**	2.101***
	(1.99)	(5.75)	(3.36)	(4.71)	(2.10)	(3.08)	(2.08)	(2.62)
FirmSize	0.826***	-0.490***	1.088***	-0.456***	1.856***	-0.415***	2.550***	-0.408***
	(13.00)	(-14.80)	(11.45)	(-14.18)	(10.21)	(-12.43)	(6.42)	(-12.60)

PriorQtrEarnSurpIss	0.006	0.005	-0.001	0.004	-0.075	-0.012	-0.106	-0.018
	(0.10)	(0.19)	(-0.01)	(0.16)	(-0.44)	(-0.42)	(-0.30)	(-0.65)
PriorMktRetIss	3.002	-0.167	2.249	-0.146	2.198	-0.306	9.894	0.357
	(1.48)	(-0.20)	(0.76)	(-0.17)	(0.39)	(-0.33)	(0.80)	(0.37)
MidFilePrice	-0.000	0.022***	0.004	0.020***	0.006	0.017***	-0.019	0.014***
	(-0.06)	(11.64)	(0.65)	(9.95)	(0.49)	(7.89)	(-0.66)	(6.34)
Constant	-8.592	-2.873	-7.512	-3.103	-5.100	-3.063	-12.882	15.215***
	(-1.32)	(-1.07)	(-0.82)	(-1.16)	(-0.33)	(-1.19)	(-0.30)	(4.61)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.129		0.130		0.142		0.212
Observations	3905	3905	3587	3587	2803	2803	2156	2156
F Statistics	517.55		1051.18		1449.09		1778.37	

Table 14: **Instrumental variable analysis of the relationship between investor attention and SEO underpricing**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *NumNewsIssHat [-7:-1]*, *NumNewsIssHat [-14:-1]*, *NumNewsIssHat [-30:-1]*, and *NumNewsIssHat [-60:-1]* are predicted values of investor attention variables as described in Table 1 (*NumNewsIss [-7:-1]*, *NumNewsIss [-14:-1]*, *NumNewsIss [-30:-1]*, and *NumNewsIss [-60:-1]*) from first-stage regressions. *PriorYrNumNewsFile [-7:-1]*, *PriorYrNumNewsFile [-14:-1]*, *PriorYrNumNewsFile [-30:-1]*, and *PriorYrNumNewsFile [-60:-1]* are instrumental variables which measure investor attention one year prior to the SEO announcement date as described in Table 1. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

	1st-stage	Underpricing	1st-stage	Underpricing	1st-stage	Underpricing	1st-stage	Underpricing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PriorYrNumNewsFile [-7:-1]	0.569***							
	(22.83)							
NumNewsIssHat [-7:-1]		0.090*						
		(1.78)						
PriorYrNumNewsFile [-14:-1]			0.683***					
			(32.60)					
NumNewsIssHat [-14:-1]				0.064**				
				(2.49)				
PriorYrNumNewsFile [-30:-1]					0.666***			
					(38.28)			
NumNewsIssHat [-30:-1]						0.031**		
						(2.32)		
PriorYrNumNewsFile [-60:-1]							0.840***	
							(42.41)	
NumNewsIssHat [-60:-1]								0.016**
								(2.53)
UndwrtReputation	3.468**	-5.000**	8.479***	-4.778**	10.361**	-1.540	22.102**	1.689
	(2.02)	(-2.49)	(3.31)	(-2.22)	(2.12)	(-0.62)	(2.14)	(0.62)
FirmSize	0.817***	-0.420***	1.069***	-0.427***	1.809***	-0.492***	2.496***	-0.429***
	(12.94)	(-4.53)	(11.30)	(-4.68)	(10.02)	(-4.87)	(6.32)	(-3.93)
PriorQtrEarnSurpIss	0.000	-0.284***	-0.016	-0.278***	-0.101	-0.237***	-0.159	-0.321***
	(0.01)	(-3.76)	(-0.17)	(-3.61)	(-0.59)	(-2.74)	(-0.45)	(-3.46)
PriorMktRetIss	3.240	4.366*	2.695	4.653*	2.606	3.693	10.054	1.726
	(1.60)	(1.85)	(0.91)	(1.87)	(0.47)	(1.31)	(0.82)	(0.54)
MidFilePrice	-0.001	-0.014***	0.004	-0.014**	0.005	-0.009	-0.021	-0.011
	(-0.15)	(-2.72)	(0.54)	(-2.43)	(0.42)	(-1.38)	(-0.73)	(-1.54)
Constant	-8.291	14.931**	-6.765	14.699*	-3.482	15.388**	-11.290	10.892
	(-1.28)	(1.98)	(-0.74)	(1.92)	(-0.22)	(1.96)	(-0.26)	(0.97)

Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.227		0.243		0.288		0.326
Observations	3920	3920	3601	3601	2817	2817	2166	2166
F Statistics	521.35		1062.51		1465.18		1798.93	

Table 15: **Instrumental variable analysis of the relationship between investor attention and SEO valuation of issuing firms**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *QOPAdj* is the industry-adjusted Q ratios calculated using the SEO offer price. Q ratio is defined as the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and the SEO offer price. Industry adjustment is performed by subtracting contemporaneous 2-digit SIC code industry median Q ratios from SEO firms' Q ratios. *NumNewsIssHat [-7:-1]*, *NumNewsIssHat [-14:-1]*, *NumNewsIssHat [-30:-1]*, and *NumNewsIssHat [-60:-1]* are predicted values of investor attention variables as described in Table 1 (*NumNewsIss [-7:-1]*, *NumNewsIss [-14:-1]*, *NumNewsIss [-30:-1]*, and *NumNewsIss [-60:-1]*) from first-stage regressions. *PriorYrNumNewsFile [-7:-1]*, *PriorYrNumNewsFile [-14:-1]*, *PriorYrNumNewsFile [-30:-1]*, and *PriorYrNumNewsFile [-60:-1]* are instrumental variables which measure investor attention one year prior to the SEO announcement date as described in Table 1. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	1st-stage	QOPAdj	1st-stage	QOPAdj	1st-stage	QOPAdj	1st-stage	QOPAdj
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PriorYrNumNewsFile [-7:-1]	0.568***							
	(22.77)							
NumNewsIss [-7:-1]		0.037*						
		(1.89)						
PriorYrNumNewsFile [-14:-1]			0.681***					
			(32.46)					
NumNewsIss [-14:-1]				0.016*				
				(1.67)				
PriorYrNumNewsFile [-30:-1]					0.664***			
					(38.13)			
NumNewsIss [-30:-1]						0.007		
						(1.47)		
PriorYrNumNewsFile [-60:-1]							0.838***	
							(42.24)	
NumNewsIss [-60:-1]								0.004*
								(1.89)
Underpricing	0.020	-0.011*	0.052***	-0.009	0.106***	-0.008	0.157*	-0.015**
	(1.48)	(-1.72)	(2.63)	(-1.48)	(2.86)	(-1.15)	(1.91)	(-2.15)
UndwrtReputation	3.550**	4.005***	8.723***	3.714***	10.428**	2.715***	21.760**	2.291***
	(2.06)	(5.21)	(3.40)	(4.54)	(2.13)	(3.11)	(2.10)	(2.63)
FirmSize	0.827***	-0.503***	1.089***	-0.476***	1.857***	-0.418***	2.549***	-0.404***
	(13.03)	(-14.09)	(11.48)	(-13.69)	(10.24)	(-11.68)	(6.43)	(-11.47)
PriorQtrEarnSurpIss	0.006	0.019	-0.001	0.017	-0.076	-0.010	-0.106	-0.025
	(0.09)	(0.66)	(-0.01)	(0.60)	(-0.44)	(-0.33)	(-0.30)	(-0.83)

PriorMktRetIss	3.040	-0.091	2.305	-0.207	2.282	-0.179	9.814	0.169
	(1.50)	(-0.10)	(0.78)	(-0.22)	(0.41)	(-0.18)	(0.80)	(0.16)
MidFilePrice	-0.000	0.030***	0.004	0.030***	0.006	0.025***	-0.019	0.021***
	(-0.07)	(15.17)	(0.65)	(13.89)	(0.49)	(10.68)	(-0.66)	(8.78)
Constant	-8.597	-1.616	-7.520	-1.866	-5.114	-1.664	-12.899	15.372***
	(-1.32)	(-0.56)	(-0.82)	(-0.64)	(-0.33)	(-0.60)	(-0.30)	(4.28)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.119		0.117		0.123		0.172
Observations	3911	3911	3593	3593	2809	2809	2161	2161
F Statistics	518.49		1053.76		1453.65		1783.83	

Online Appendices

A.1 List of Constants in Propositions and Proofs

$$A_a \equiv f^a(\sigma_1^a)^{-2}[1+\rho^{-2}(\sigma_1^a)^{-2}\sigma_x^{-2}] > 0, \tag{A.1}$$

$$A_u \equiv f^u\sigma_0^{-2}[1+\frac{\frac{1}{2}\sigma_0^{-2}}{\rho^2\sigma_x^2+\frac{1}{2}\sigma_e^{-2}}] > 0, \tag{A.2}$$

$$B_0 \equiv \frac{A_a(\sigma_1^a)^2+A_u\sigma_0^2}{A_a+A_u} > 0, \tag{A.3}$$

$$B_1 \equiv \frac{A_a(\sigma_1^a)^2+f^u}{A_a+A_u} > 0, \tag{A.4}$$

$$E \equiv \frac{A_a}{f^a}(\frac{A_u}{A_a+A_u})^2+(\sigma_1^a)^{-2}\sigma_e^2\sigma_0^{-2} > 0, \tag{A.5}$$

$$F_0 = \frac{A_u}{A_a+A_u}[\frac{A_a}{f^a}B_0-\frac{A_a}{f^a}(\sigma_1^a)^2+1], \tag{A.6}$$

$$F_1 = \frac{A_u}{A_a+A_u}[\frac{A_a}{f^a}B_1-\frac{A_a}{f^a}(\sigma_1^a)^2+1], \tag{A.7}$$

$$G \equiv \frac{A_a}{f^a}[B_1-(\sigma_1^a)^2]^2+2B_1-(\sigma_1^a)^2-\frac{F_1^2}{E}+\rho^{-2}\sigma_x^{-2}, \tag{A.8}$$

$$H_0 \equiv B_1+\frac{A_a}{A_a+A_u}\frac{F_1}{E}, \tag{A.9}$$

$$H_1 \equiv -\frac{A_a}{f^a}B_0B_1+\rho^{-2}(\sigma_1^a)^{-2}\sigma_x^{-2}(B_0+B_1)-\rho^{-2}\sigma_x^{-2}+\frac{F_0F_1}{E}, \tag{A.10}$$

$$J \equiv \frac{A_u}{f^u}(\frac{A_a}{A_a+A_u})^2+(\sigma_1^a)^{-2}\sigma_e^2\sigma_0^{-2} > 0, \tag{A.11}$$

$$K \equiv \frac{A_u}{f^u}\frac{B_1^2}{J}(\sigma_1^a)^{-2}\sigma_e^2\sigma_0^{-2}+\rho^{-2}\sigma_x^{-2} > 0, \tag{A.12}$$

$$L_0 \equiv \frac{B_1}{J}(\sigma_1^a)^{-2}\sigma_e^2\sigma_0^{-2}, \tag{A.13}$$

$$P_a \equiv f^a[\frac{1}{E}(\frac{A_a}{A_a+A_u})^2+\frac{H_0^2}{G}]^{-1}, \tag{A.14}$$

$$Q_a \equiv f^a[\frac{1}{E}(\frac{A_a}{A_a+A_u})^2+\frac{H_0^2}{G}]^{-1}(B_0+\frac{A_a}{A_a+A_u}\frac{F_0}{E}+\frac{H_0H_1}{G}), \tag{A.15}$$

$$P_u \equiv f^u[\frac{1}{J}(\frac{A_a}{A_a+A_u})^2+\frac{L_0^2}{K}]^{-1}, \tag{A.16}$$

$$Q_u \equiv f^u\{B_0[\frac{1}{J}(\frac{A_a}{A_a+A_u})^2+\frac{L_0^2}{K}]^{-1}-\frac{A_u}{f^u}(B_0-\sigma_0^2)1\}. \tag{A.17}$$

Both A_a and A_u are positive because they both consist of sums and products of variances terms (σ's) and positive parameters (ρ, f^a, and f^u). This further confirms the positivity of B_0, B_1, E, J, and K.

A.2 Proof of Propositions

Proof of Proposition 1. We solve the investors' utility maximization problems (UMP) backwards.

- At $t = 2$, an investor of type i (for both $i = a$ and $i = u$) solves the following UMP

$$\max_{D_2^i} E_2^i[-\exp(-\rho W_3^i)], \text{ where } W_3^i = W_2^i + D_2^i(f - S_2) \tag{A.18}$$

The only random component here is $f = \mu + z$, which follows normal distribution, hence the above UMP is equivalent to

$$\max_{D_2^i} D_2^i(\mu + E_2^i[z] - S_2) - \frac{\rho}{2} D_2^i V_2^i[z] D_2^i = D_2^i(\mu + \hat{z}_2 - S_2) - \frac{\rho}{2}(D_2^i)^2 \sigma_2^2 \tag{A.19}$$

By the standard optimization procedure, the optimal demand is therefore

$$D_2^i = \frac{\mu + \hat{z}_2 - S_2}{\rho \sigma_2^2}, \text{ for } i = a, u. \tag{A.20}$$

To clear the markets, $\sum_{i=a,u} D_2^i = \bar{x} + x_1 + x_2$, hence

$$\bar{x} + x_1 + x_2 = \frac{\mu + \hat{z}_2 - S_2}{\rho \sigma_2^2}, \tag{A.21}$$

and the equilibrium price at $t = 2$ is therefore

$$S_2 = \mu + \hat{z}_2 - \rho \sigma_2^2 (\bar{x} + x_1 + x_2). \tag{A.22}$$

The consequent value function (optimized utility), after substituting in (A.20) and (A.22), is

$$E_2^i[-\exp(-\rho W_3^i)] \quad = \quad -\exp\{-\rho W_2^i - \frac{1}{2}\rho^2 \sigma_2^2 (\bar{x} + x_1 + x_2)^2\} \tag{A.23}$$

- At $t = 1$, an investor of type i maximizes the following expected utility

$$E_1^i[-\exp(-\rho W_3^i)] = E_1^i[-\exp\{-\rho W_2^i - \frac{1}{2}\rho^2 \sigma_2^2 (\bar{x} + x_1 + x_2)^2\}]. \tag{A.24}$$

Since the information set of an investor (and thus the corresponding posterior belief on z) depends on the type of the investor, the calculation for (A.24) is carried out separately for type $i = a$ and type $i = u$.

Type-a investors. As to be confirmed, the equilibrium price follows a linear structure that combines the public signal e_1 and the supply shock x_1. Once an attentive investor correctly observes the public signal e_1, he/she can back out the contemporaneous supply shock x_1 from the equilibrium price. Hence, the supply shock x_1 is essentially "known" to a type-a investor and not a random variable in his/her UMP at $t = 1$, and the only relevant random variable here is $x_2 \sim (0, \sigma_x^2)$. Therefore, continuing from (A.24), we get

$$E_1^a[-\exp(-\rho W_3^a)] \;\; \propto \;\; -\exp\Big(-\rho\{W_1^a + D_1^a[\mu + \hat{z}_1^a - \rho(\sigma_1^a)^2(\bar{x} + x_1) - S_1] + \frac{\rho}{2}(\sigma_1^a)^2(\bar{x} + x_1)^2\} + \frac{1}{2}\rho^2(\sigma_1^a)^2[1 + \rho^{-2}(\sigma_1^a)^{-2}\sigma_x^{-2}]^{-1}[D_1^a - (\bar{x} + x_1)]^2\Big) \tag{A.25}$$

The standard optimization procedure derives the optimal demand by an attentive investor as

$$D_1^a \;\; = \;\; \rho^{-1}\frac{A_a}{f^a}(\mu + \hat{z}_1^a - S_1) - [\frac{A_a}{f^a}(\sigma_1^a)^2 - 1](\bar{x} + x_1), \tag{A.26}$$

where we applied the constants A_a and A_u as defined in Appendix A.1.

Type-u investors. Inattentive investors are not aware of the SEO announcement immediately at $t = 1$, thus they are unable to back out the exact number of x_1 from the equilibrium price contemporaneously either.[20] Therefore, the calculation of (A.24) for $i = u$ involves taking two expectations: one with respect to the random variable $\hat{z}_2 = \sigma_2^2\sigma_e^{-2}e_1 \sim N(0, \sigma_2^4\sigma_e^{-4}(\sigma_0^2 + \sigma_e^2))$, the other with respect to the random variable $x_1 + x_2 \sim N(0, 2\sigma_x^2)$. Indeed,

$$E_1^u[-\exp(-\rho W_3^u)] \;\; \propto \;\; -\exp\Big(-\rho\{W_1^u + D_1^u[\mu - \rho\sigma_2^2\bar{x} - S_1] + \frac{\rho}{2}\sigma_2^2\bar{x}^2\} + \frac{\rho^2}{2}(D_1^u)^2\sigma_2^2\sigma_e^{-2}\sigma_0^2 + \frac{1}{2}[\rho^2\sigma_2^2 + \frac{1}{2}\sigma_x^{-2}]^{-1}\rho^4\sigma_2^4(D_1^u - \bar{x})^2\Big) \tag{A.27}$$

The standard optimization procedure implies the optimal demand by an inattentive investor as

$$D_1^u \;\; = \;\; \rho^{-1}\frac{A_u}{f^u}(\mu - S_1) - [\frac{A_u}{f^u}\sigma_0^2 - 1]\bar{x}. \tag{A.28}$$

The equilibrium price of the risky asset at $t = 1$ is thus

$$S_1 \;\; = \;\; \mu + \frac{A_a}{A_a + A_u}\hat{z}_1^a - \rho(B_0\bar{x} + B_1 x_1), \tag{A.29}$$

assuming the market clearing condition $\bar{x} + x_1 = f^a D_1^a + f^u D_1^u$ holds.

- At $t = 0$, all investors maximize their expected utility based on their prior belief on the

[20] At $t = 2$, however, as inattentive investors realized that they missed the SEO announcement at $t = 1$, they could retroactively find the value of x_1 when they looked back at S_1, and thus when they make their portfolio rebalance decision at $t = 2$, x_2 (rather than $x_1 + x_2$ as a whole) is the only random component they do not know directly (but then can be learned from the equilibrium price S_2, same as for type-a investors).

fundamental value of the firm's stock. The calculation is in principle similar to the one for $t = 1$.

Type-a investors. The calculation of $E_0^a[-\exp(-\rho W_3^a)]$ consists of two expectations of $E_1^a[-\exp(-\rho W_3^a)]$: one with respect to $\hat{z}_1^a \sim N(0, \sigma_2^4 \sigma_e^{-4}(\sigma_0^2 + \sigma_e^2))$, the other with respect to $x_1 \sim N(0, \sigma_x)$. In fact,

$$\begin{aligned} & E_0^a[-\exp(-\rho W_3^a)] \\ \propto & -\exp\Big(-\rho D_0^a(\mu - \rho B_0 \bar{x} - S_0) + \frac{1}{2E}[\rho^2 (D_0^a)^2 (\frac{A_a}{A_a + A_u})^2 + 2\rho^2 D_0^a \frac{A_a}{A_a + A_u} F_0 \bar{x}] \\ & + \frac{\rho^2}{2G}(H_0 D_0^a + H_1 \bar{x})^2 \Big) \end{aligned} \tag{A.30}$$

By maximizing (A.30), we obtain the optimal demand of a type-a investor at $t = 0$ as

$$D_0^a = \rho^{-1} \frac{P_a}{f^a}(\mu - S_0) - \frac{Q_a}{f^a}\bar{x}. \tag{A.31}$$

Type-u investors. The calculation for $E_0^u[-\exp(-\rho W_3^u)]$ is in essence similar to that for $E_0^a[-\exp(-\rho W_3^a)]$, and we eventually obtain the UMP as

$$E_0^u[-\exp(-\rho W_3^u)] = -\exp\{-\rho D_0^u(\mu - \rho B_0 \bar{x} - S_0) + \frac{\rho^2}{2K}(L_0 D_0^u + L_1 \bar{x})^2\}, \tag{A.32}$$

and the optimal demand of a type-u investor at $t = 0$ as

$$D_0^u = \rho^{-1} \frac{P_u}{f^u}(\mu - S_0) - \frac{Q_u}{f^u}\bar{x}, \tag{A.33}$$

The market clearing condition $f^a D_0^a + f^u D_0^u = \bar{x}$ implies that the equilibrium price at $t = 0$ is

$$S_0 = \mu - \rho \frac{Q_a + Q_u + 1}{P_a + P_u}\bar{x}. \tag{A.34}$$

This completes the proof for Proposition 1.

Proof of Proposition 2.

(i) The calculation of (19) is straightforward by taking the difference between (11) and (12) and then setting both of $\bar{x}$ and x_1 to zero, i.e.,

$$(S_1 - S_0)|_{\bar{x}=x_1=0} = \frac{A_a}{A_a + A_u} \frac{\sigma_0^{-2} + \sigma_e^{-2}}{\sigma_e^{-2}} e_1. \tag{A.35}$$

From the discussion in Appendix A.1, both A_a and A_u are positive, and thus the coefficient of e_1 is positive. Since $e_1 < 0$, the right hand side of (A.35) is negative.

(ii) For any given e_1, the magnitude of the abnormal stock return (A.35) depends on the coefficient of e_1, and it suffices to show that this coefficient is an increasing function of f^a. In fact,

$$\frac{\partial}{\partial f^a}\Big(\frac{A_a}{A_a+A_u}\frac{\sigma_0^{-2}+\sigma_e^{-2}}{\sigma_e^{-2}}\Big) = \frac{A_a A_u}{f^a f^u (A_a+A_u)^2}\frac{\sigma_0^{-2}+\sigma_e^{-2}}{\sigma_e^{-2}} > 0, \tag{A.36}$$

where we apply the fact that $f^u = 1 - f^a$ and the positivity of constants A_a and A_u (as discussed in Appendix A.1).

This completes the proof of Proposition 2.

Proof of Proposition 3.

(i) The calculation of (21) is by taking the difference between (10) and (11) and then setting all of $\bar{x}$, x_1, and x_2 to zero, i.e.,

$$(S_2 - S_1)|_{\bar{x}=x_1=x_2=0} = \frac{A_u}{A_a+A_u}\frac{\sigma_0^{-2}+\sigma_e^{-2}}{\sigma_e^{-2}} e_1. \tag{A.37}$$

From the discussion in Appendix A.1, both A_a and A_u are positive, and thus the coefficient of e_1 is positive. Since $e_1 < 0$, the right hand side of (A.37) is negative.

(ii) For any given e_1, the magnitude of the post-announcement drift (A.37) depends on the coefficient of e_1, and it suffices to show that this coefficient is a decreasing function of f^a. In fact,

$$\frac{\partial}{\partial f^a}\Big(\frac{A_u}{A_a+A_u}\frac{\sigma_0^{-2}+\sigma_e^{-2}}{\sigma_e^{-2}}\Big) = -\frac{A_a A_u}{f^a f^u (A_a+A_u)^2}\frac{\sigma_0^{-2}+\sigma_e^{-2}}{\sigma_e^{-2}} < 0, \tag{A.38}$$

where we apply the fact that $f^u = 1 - f^a$ and the positivity of constants A_a and A_u (as discussed in Appendix A.1).

This completes the proof of Proposition 3.

A.3 Additional Empirical Results

Table A.1: **Relationship between abnormal investor attention and post-SEO participation of institutional investors in the ownership of issuing firms' equity**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *InstN* is the number of institutional investors holding SEO firms' shares at the end of the first post-issue fiscal quarter. *AbnNumNewsIss [-7:-1]*, *AbnNumNewsIss [-14:-1]*, *AbnNumNewsIss [-30:-1]*, and *AbnNumNewsIss [-60:-1]* are measures of abnormal investor attention prior to the SEO issue date as described in Table 1. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	InstN							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AbnNumNewsIss [-7:-1]	2.421***	2.440***						
	(8.70)	(8.74)						
AbnNumNewsIss [-14:-1]			1.550***	1.558***				
			(7.37)	(7.39)				
AbnNumNewsIss [-30:-1]					0.504***	0.505***		
					(3.45)	(3.44)		
AbnNumNewsIss [-60:-1]							0.361***	0.359***
							(3.70)	(3.67)
Underpricing		0.599**		0.647***		0.620**		0.580*
		(2.58)		(2.71)		(2.19)		(1.70)
UndwrtReputation	21.500	23.189	29.579	31.053	76.068**	75.535**	79.412*	76.987*
	(0.75)	(0.81)	(0.97)	(1.02)	(2.09)	(2.07)	(1.88)	(1.82)
FirmSize	47.181***	47.285***	47.740***	47.854***	49.835***	49.989***	51.592***	51.704***
	(45.33)	(45.16)	(43.51)	(43.38)	(37.98)	(37.79)	(33.20)	(33.00)
PriorQtrEarnSurpIss	-2.003*	-1.736	-1.924	-1.642	-1.796	-1.549	-2.280	-2.036
	(-1.69)	(-1.46)	(-1.61)	(-1.37)	(-1.30)	(-1.12)	(-1.50)	(-1.33)
PriorMktRetIss	7.363	2.939	17.214	12.219	41.214	37.114	35.144	31.680
	(0.22)	(0.09)	(0.49)	(0.35)	(1.00)	(0.90)	(0.70)	(0.63)
MidFilePrice	1.017***	1.028***	1.058***	1.069***	1.221***	1.231***	1.301***	1.312***
	(13.62)	(13.75)	(13.25)	(13.38)	(12.51)	(12.59)	(11.02)	(11.08)
Constant	-291.507***	-299.458***	-307.050***	-315.648***	-339.162***	-348.055***	-379.480*	-490.675***

	(-2.72)	(-2.79)	(-2.86)	(-2.94)	(-2.95)	(-3.02)	(-1.86)	(-2.84)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.709	0.709	0.718	0.718	0.744	0.744	0.760	0.759
Observations	3883	3854	3569	3541	2796	2770	2156	2132

Table A.2: **Relationship between abnormal investor attention and post-SEO market valuation of issuing firms**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *QFTDAdj* and *QFQAdj* are the industry-adjusted Q ratios calculated using the SEO issue day closing price and the price at the end of the first post-issue fiscal quarter, respectively. Q ratio is defined as the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and either the SEO issue day closing price (*QFTDAdj*) or the price at the end of the first post-issue fiscal quarter (*QFQAdj*). Industry adjustment is performed by subtracting contemporaneous 2-digit SIC code industry median Q ratios from SEO firms' Q ratios. *AbnNumNewsIss [-7:-1]*, *AbnNumNewsIss [-14:-1]*, *AbnNumNewsIss [-30:-1]*, and *AbnNumNewsIss [-60:-1]* are measures of abnormal investor attention prior to the SEO issue date as described in Table 1. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship between abnormal investor attention and post-SEO market valuation measured using the first trading day closing price

Dependent Variable	QFTDAdj							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AbnNumNewsIss [-7:-1]	0.026***	0.025***						
	(3.00)	(2.98)						
AbnNumNewsIss [-14:-1]			0.023***	0.023***				
			(3.55)	(3.49)				
AbnNumNewsIss [-30:-1]					0.015***	0.014***		
					(3.60)	(3.53)		
AbnNumNewsIss [-60:-1]							0.006**	0.006**
							(2.37)	(2.34)
Underpricing		0.013*		0.015**		0.015**		0.009
		(1.91)		(2.01)		(1.97)		(1.09)
UndwrtReputation	4.056***	4.130***	3.659***	3.735***	2.666***	2.703***	2.319**	2.326**
	(4.63)	(4.71)	(3.90)	(3.98)	(2.62)	(2.66)	(2.26)	(2.26)
FirmSize	-0.494***	-0.492***	-0.479***	-0.477***	-0.422***	-0.419***	-0.395***	-0.396***
	(-15.68)	(-15.56)	(-14.33)	(-14.22)	(-11.67)	(-11.54)	(-10.56)	(-10.54)
PriorQtrEarnSurpIss	0.014	0.018	0.013	0.017	-0.015	-0.011	-0.029	-0.026
	(0.43)	(0.55)	(0.38)	(0.50)	(-0.43)	(-0.32)	(-0.84)	(-0.75)
PriorMktRetIss	-0.059	-0.095	-0.194	-0.239	-0.326	-0.349	-0.076	-0.054
	(-0.06)	(-0.09)	(-0.18)	(-0.22)	(-0.28)	(-0.30)	(-0.06)	(-0.04)
MidFilePrice	0.031***	0.031***	0.031***	0.031***	0.025***	0.025***	0.021***	0.022***

	(13.73)	(13.82)	(12.51)	(12.60)	(9.33)	(9.41)	(7.62)	(7.69)
Constant	-1.576	-1.751	-1.737	-1.926	-1.536	-1.745	15.561***	15.490***
	(-0.48)	(-0.53)	(-0.52)	(-0.58)	(-0.48)	(-0.54)	(3.68)	(3.67)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.117	0.119	0.115	0.117	0.122	0.125	0.173	0.175
Observations	3915	3911	3597	3593	2813	2809	2163	2161

Panel B: Relationship between abnormal investor attention and post-SEO market valuation measured using the price at the end of the first post-issue fiscal quarter								
Dependent Variable	QFQAdj							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AbnNumNewsIss [-7:-1]	0.011	0.012						
	(1.49)	(1.51)						
AbnNumNewsIss [-14:-1]			0.010*	0.011*				
			(1.82)	(1.90)				
AbnNumNewsIss [-30:-1]					0.006	0.006		
					(1.56)	(1.51)		
AbnNumNewsIss [-60:-1]							0.002	0.002
							(1.01)	(1.00)
Underpricing		0.005		0.007		0.012*		0.004
		(0.75)		(1.03)		(1.69)		(0.55)
UndwrtReputation	4.157***	4.157***	3.570***	3.569***	2.496***	2.479***	2.137**	2.087**
	(5.32)	(5.31)	(4.27)	(4.26)	(2.73)	(2.71)	(2.32)	(2.27)
FirmSize	-0.453***	-0.451***	-0.435***	-0.433***	-0.399***	-0.394***	-0.384***	-0.381***
	(-16.13)	(-15.97)	(-14.64)	(-14.48)	(-12.32)	(-12.07)	(-11.53)	(-11.38)
PriorQtrEarnSurpIss	0.003	0.004	0.002	0.003	-0.015	-0.013	-0.020	-0.019
	(0.09)	(0.13)	(0.06)	(0.12)	(-0.48)	(-0.40)	(-0.65)	(-0.61)
PriorMktRetIss	0.013	-0.033	-0.013	-0.072	-0.120	-0.277	0.559	0.391
	(0.01)	(-0.04)	(-0.01)	(-0.07)	(-0.12)	(-0.27)	(0.51)	(0.36)
MidFilePrice	0.021***	0.021***	0.019***	0.020***	0.017***	0.017***	0.014***	0.014***
	(10.50)	(10.54)	(8.92)	(8.97)	(6.92)	(6.98)	(5.45)	(5.49)
Constant	-3.123	-3.192	-3.169	-3.266	-3.048	-3.226	10.440**	14.953***
	(-1.06)	(-1.08)	(-1.07)	(-1.10)	(-1.05)	(-1.12)	(2.34)	(3.97)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.131	0.129	0.131	0.129	0.144	0.141	0.215	0.209
Observations	3934	3905	3615	3587	2829	2803	2180	2156

Table A.3: **Relationship between abnormal investor attention and SEO underpricing**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000 - 2018. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *AbnNumNewsIss [-7:-1]*, *AbnNumNewsIss [-14:-1]*, *AbnNumNewsIss [-30:-1]*, and *AbnNumNewsIss [-60:-1]* are measures of abnormal investor attention prior to the SEO issue date as described in Subsection 5.1. *UndwrtReputation* is the reputation measure of the lead underwriter, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in the previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO issue date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean estimates of earnings and actual earnings adjusted by price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year $\times$ industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	Underpricing			
	(1)	(2)	(3)	(4)
AbnNumNewsIss [-7:-1]	0.021			
	(0.97)			
AbnNumNewsIss [-14:-1]		0.032*		
		(1.95)		
AbnNumNewsIss [-30:-1]			0.021*	
			(1.86)	
AbnNumNewsIss [-60:-1]				0.010
				(1.45)
UndwrtReputation	-4.842**	-4.661*	-1.613	1.593
	(-2.20)	(-1.95)	(-0.58)	(0.51)
FirmSize	-0.326***	-0.324***	-0.394***	-0.326***
	(-4.11)	(-3.81)	(-3.97)	(-2.88)
PriorQtrEarnSurpIss	-0.287***	-0.283***	-0.242**	-0.327***
	(-3.45)	(-3.31)	(-2.48)	(-3.09)
PriorMktRetIss	4.717*	4.997*	3.844	1.855
	(1.83)	(1.81)	(1.22)	(0.50)
MidFilePrice	-0.014**	-0.014**	-0.009	-0.012
	(-2.52)	(-2.22)	(-1.28)	(-1.42)
Constant	14.172*	14.020*	14.711*	9.903
	(1.71)	(1.65)	(1.67)	(0.78)
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
R^2	0.227	0.241	0.285	0.324
Observations	3920	3601	2817	2166

Table A.4: **Relationship between abnormal investor attention and SEO valuation of issuing firms**

The sample consists of seasoned equity offerings (SEOs) conducted in 2000-2018. *QOPAdj* is the industry-adjusted Q ratios calculated using the SEO offer price. Q ratio is defined as the market value of assets over the book value of assets, where the market value of assets is equal to the book value of assets minus the book value of equity plus the product of the number of shares outstanding and the SEO offer price. Industry adjustment is performed by subtracting contemporaneous 2-digit SIC code industry median Q ratios from SEO firms' Q ratios. *AbnNumNewsIss [-7:-1]*, *AbnNumNewsIss [-14:-1]*, *AbnNumNewsIss [-30:-1]*, and *AbnNumNewsIss [-60:-1]* are measures of abnormal investor attention prior to the SEO issue date as described in Table 1. *Underpricing* is the percentage difference between the issue day closing price and the SEO offer price. *UndwrtReputation* is the lead SEO underwriter's reputation measure, which is defined as the lead underwriter's share of total proceeds raised in the SEO market in previous five years. *FirmSize* is the natural logarithm of the book value of total assets at the end of the fiscal quarter prior to the SEO announcement date. *PriorQtrEarnSurpIss* is the earnings surprise one quarter prior to the SEO issue date. Earnings surprise is defined as the difference between the mean earnings estimate and actual earnings divided by the stock price. *PriorMktRetIss* is the return on the CRSP value-weighted index over one-month (21-trading-day) period prior to the SEO issue date. *MidFilePrice* is the midpoint of initial filing range. Year × industry (two-digit SIC code) fixed effects are included in all regressions. t-statistics are in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	QOPAdj							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AbnNumNewsIss [-7:-1]	0.024***	0.024***						
	(2.97)	(2.97)						
AbnNumNewsIss [-14:-1]			0.022***	0.022***				
			(3.54)	(3.60)				
AbnNumNewsIss [-30:-1]					0.014***	0.014***		
					(3.61)	(3.58)		
AbnNumNewsIss [-60:-1]							0.006**	0.006**
							(2.39)	(2.42)
Underpricing		-0.010		-0.009		-0.008		-0.014*
		(-1.46)		(-1.29)		(-1.02)		(-1.81)
UndwrtReputation	4.090***	4.009***	3.695***	3.612***	2.645***	2.582***	2.238**	2.193**
	(4.85)	(4.75)	(4.10)	(4.00)	(2.71)	(2.64)	(2.25)	(2.20)
FirmSize	-0.471***	-0.474***	-0.456***	-0.459***	-0.402***	-0.404***	-0.380***	-0.384***
	(-15.53)	(-15.54)	(-14.21)	(-14.21)	(-11.58)	(-11.55)	(-10.52)	(-10.54)
PriorQtrEarnSurpIss	0.021	0.018	0.019	0.016	-0.009	-0.011	-0.021	-0.026
	(0.65)	(0.56)	(0.59)	(0.50)	(-0.26)	(-0.31)	(-0.62)	(-0.76)
PriorMktRetIss	-0.043	0.009	-0.186	-0.137	-0.140	-0.156	0.200	0.169
	(-0.04)	(0.01)	(-0.18)	(-0.13)	(-0.13)	(-0.14)	(0.17)	(0.14)
MidFilePrice	0.030***	0.030***	0.030***	0.029***	0.025***	0.024***	0.021***	0.021***
	(13.83)	(13.73)	(12.59)	(12.51)	(9.49)	(9.44)	(7.74)	(7.66)
Constant	-1.963	-1.824	-2.113	-1.987	-1.969	-1.858	10.666**	15.131***
	(-0.62)	(-0.57)	(-0.66)	(-0.62)	(-0.64)	(-0.60)	(2.21)	(3.69)

Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.118	0.117	0.117	0.116	0.124	0.123	0.172	0.171
Observations	3940	3911	3621	3593	2835	2809	2185	2161