Reactions to News and Reasoning By Exemplars

Spencer Yongwook Kwon and Johnny Tang*

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Abstract

We propose a model of stock price reaction to corporate news in which investors use significant past observations to evaluate new information. The model predicts that event-types with more extreme distributions of fundamental realizations experience greater overreaction to news. Using a comprehensive database of corporate news events, we identify substantial heterogeneity in both reactions to corporate news and extremenesses of fundamental realizations across types of corporate events. Consistent with our model, we document overreaction to more extreme event-types, such as leadership changes, mergers and acquisitions, and customer-related announcements, and underreaction to less extreme event-types such as earnings announcements. We also document greater trading volume to corporate events with more extreme fundamental realizations conditional on the magnitude of the return. We calibrate the model to quantitatively fit the variation in investor overreaction and underreaction, as well as trading volume, across different event-types.

*Spencer Yongwook Kwon: Harvard Business School and Harvard University, ykwon@hbs.edu. Johnny Tang: Harvard University, jtang01@g.harvard.edu. We thank Malcolm Baker, Nick Barberis, Francesca Bastianello, Michael Blank, John Campbell, Veronica De Falco, Mark Egan, Paul Fontanier, Xavier Gabaix, Robin Greenwood, Sam Hanson, Angela Ma, Yueran Ma, Peter Maxted, Suproteem Sarkar, Josh Schwartzstein, Andrei Shleifer, Jeremy Stein, Adi Sunderam, and seminar participants at Harvard and Yale for helpful comments and feedback.

1 Introduction

How do stock prices react to corporate news? A large literature on post-earnings announcement drift (PEAD) (e.g. Ball and Brown (1968), Bernard and Thomas (1989)), defined as positive autocorrelations in stock returns following earnings announcements, suggests short-term underreaction and sluggishness in price adjustments to news. On the other hand, more recent work (e.g. Antweiler and Frank (2006), Daniel and Titman (2006)) finds overreaction for other types of corporate information.

Why do investors overreact to certain events and underreact to others? We propose a model that explains this cross-section of stock price reaction to news. We posit that investors react to news events by drawing comparisons to significant events that have occurred in the past. Following the psychology literature (Nosofsky (1992)), we refer to these significant past events as exemplars for the event-type (Enron for accounting scandals; Apple's iPhone for product launches), and the dominant use of exemplars as references as *reasoning by exemplars* (RBE).

How does RBE explain the variation in investor reactions to different types of corporate events? When evaluating a new event, investors disproportionately recall exemplars, leading them to overweight extreme outcomes and overreact. Furthermore, the more extreme exemplars are relative to a typical event of the same type, the greater the overreaction. Statistically, this is captured by the fatness of the tail of the distribution of outcomes: the fatter the tail, the farther the extreme, e.g. top 1%, events are from the median event. For instance, the distribution of fundamentals following a CEO change has a fat right tail. Thus, a CEO change today may bring to mind a previous CEO change that led to a dramatic turnaround, causing a strong overreaction. In contrast, the distribution of fundamentals following earnings calls has thin tails. An earnings call today does not bring to mind an extreme event and will be associated with relatively little overreaction. We thus define the *extremeness* of a given event-type as the fat-tailedness of the underlying fundamental distribution, which we measure in several ways, with the Pareto tail index being our preferred measure.[1] The fundamental prediction of our model therefore is that more extreme event-

[1] In the empirical section, we show that the fundamental realizations of corporate events, as measured by event-day returns, are fat-tailed and very well approximated by a power-law distribution. Consequently, our main measure of extremeness is the slope of the log-log rank-size regressions of event-day returns, also known as power-law regressions (Gabaix (2016)). For power-law, or Pareto, distributions, this regression precisely

types are associated with greater overreaction.[2]

To formalize the link between extremeness of fundamentals and investor reactions, we write down a stylized asset pricing model with RBE agents. Investors receive private signals of the fundamentals of an event, which can reflect a combination of different information sources, interpretations, and similarity judgments. We formalize RBE as a distortion in the subjective availability of past events: past events associated with greater absolute fundamentals receive greater subjective availability, with investors otherwise updating based on their signals in a Bayesian manner. We embed RBE agents in an asset market setting with limited arbitrage and derive price and volume predictions.[3] Our model predicts that fatter-tailed, i.e. more extreme, event-types have (1) greater price overreaction and reversals and (2) greater disagreement and trading volume.

In the second part of the paper, we empirically test the predictions generated by the model. First, we confirm that investor reaction to different types of corporate developments is highly heterogeneous. Drawing from a comprehensive database of corporate news events in the US from 2011 to 2018, we find not only drift for earnings announcements, but also significant reversals for a wide range of event-types, including business expansions, mergers, acquisitions, leadership changes, and customer-related events. In particular, short-term overreaction to news seems to be the norm across corporate events that do not frequently coincide with earnings announcements.[4] The cross-section of drift and reversal across event-types is robust to different measurement methods and not driven by sampling variation or

measures the tail fatness, also known as the Pareto index. The measurement of fat tails has received recent attention in economics, from wealth distributions and city size, to stock market returns and trading volume. For a general reference, see Gabaix (2016). We also show that our results are robust to using alternative measures of extremeness, such as skew or quantile ratios. Finally, our measures of extremeness of an event-type are also robust to alternative measures of the fundamental of the event, using longer-horizon returns or realized long-term cash-flow.

[2]While our baseline model predicts varying degrees of overreaction across different event-types, our full model can account for underreaction by allowing RBE to be conditional.

[3]Our theory does not focus on why arbitrageurs cannot price out the distortions by trading against RBE agents. One of the reasons can be that by trading against potentially extreme events, the arbitrageurs are taking on a negative skew-risk, which can command a significant risk premium. Short-sale constraints on the part of the arbitrageur in response to positive company news can also contribute to the limits of arbitrage. To focus on the distortions due to investor psychology, we simplify the arbitrageur response by positing a simple reduced-form asset demand function that captures these risk and capital concerns.

[4]We have chosen 90 days as our main choice of horizon, as it approximately corresponds to the range of post-earnings drift studies (e.g. Bernard and Thomas (1989)). Our findings are robust to the exact horizon of the reversal (from 60 days to 6 months).

non-event-driven forces. In addition to the variation in short-term stock market reaction to different event-types, we also document significant differences in the extremeness of the fundamentals of each event-type. Consistent with earlier findings (Gabaix (2016)), the distribution of fundamentals, as measured by event-day returns, longer-term returns, and realized cash flow growth, are very well fit by the fat-tailed power-law distribution, with substantial variation in the extremeness, i.e. fatness of the tails, across event-types.

Equipped with these baseline results, we then test the core asset-pricing predictions of our model: more extreme event-types are more overreacted to, with greater reversals and trading volume. Consistent with our first prediction, we find that corporate event-types with fatter-tails exhibit more post-announcement return reversals, whereas event-types with thinner tails exhibit more post-announcement drift. We estimate that fatter-tailed events exhibit reversals up to 14% of the event-day return, while thinner-tailed events experience continued drifts of up to 9% of the event-day return. We show that this pattern is robustly found across return horizons and rule out alternative explanations such as familiarity with different event-types, non-linearities in return autocorrelations, or predictability or the recurring nature of certain event types. Turning to our second prediction, we confirm that more extreme corporate events have higher trading volumes conditional on the magnitudes of event-day returns. Conditional on a 10% event-day return, we estimate that turnover for different event-types would range from 4.8% for the thinnest-tailed event-types to 6.3% for the fattest-tailed event-types. This range of estimated conditional turnovers quantitatively matches the range (4.6% to 7.0%) of the actual conditional turnovers across event-types we observe in our data.

In the final part of the paper, we extend our model to account for two limitations: in our simple framework, RBE agents always overreact and do so uniformly within a given event-type. In reality, we expect RBE to be conditional: people only reason by exemplars about news that they judge to be sufficiently important. Thus, we hypothesize that if the subjective fundamentals are lower than an exogenous threshold, investors dismiss the news as a non-event. We develop this extension and show that the full model yields underreaction for sufficiently thin-tailed event-types and overreaction for fat-tailed event-types. We calibrate our full model to quantitatively match the empirical moments, including the full spectrum of the overreaction and underreaction in our data.

Our paper relates to the extensive theoretical (Barberis et al. (1998), Hong and Stein (1999), Daniel et al. (1998)) and empirical literature (De Bondt and Thaler (1985), Lakonishok et al. (1994), La Porta (1996), Daniel and Titman (2006), Bernard and Thomas (1989), Antweiler and Frank (2006), and Bordalo et al. (2019)) studying investor over- and underreactions in asset pricing. A large literature focuses on horizon as the key variation and documents short-term underreaction and long-term overreaction in stock prices (Bernard and Thomas (1989), De Bondt and Thaler (1985), Bordalo et al. (2019)) and in yield curves (Giglio and Kelly (2018)). Recent work in this literature has also connected asset price over- and underreaction to expectations (Bordalo et al. (2019); d'Arienzo (2020); Wang (2019)). While this literature focuses on the variation in horizon, we fix the horizon to the short-term and focus on variations in the types of events. Our focus on event-type variation also relates our work to Daniel and Titman (2006), which focuses on long-run overreaction to intangible and tangible information, and Antweiler and Frank (2006), which uses Wall Street Journal articles and finds short-term overreaction to corporate announcements. Relative to this literature, our work focuses primarily on explaining the variation in overreaction through the lens of the extremeness of fundamentals.

Our model is most closely related to the work on representativeness and diagnostic expectations, which generate overreaction to news (Gennaioli and Shleifer (2010), Bordalo et al. (2020), Bordalo et al. (2019)). There are two differences between our framework and theirs. Conceptually, while diagnostic expectations exaggerate the difference between a given group and a reference group, our model emphasizes the exaggerated availability of exemplars, rather than an explicit contrast to a reference group. Empirically, by extending RBE to be conditional, with investors otherwise dismissing news, our framework is able to deliver both underreaction and overreaction to news, while diagnostic expectations always yield overreaction.

By modelling RBE and its implications on asset price fluctuations, our work also relates to the growing literature that studies psychological foundations of information processing and their applications to financial settings. Overreaction has been attributed to extrapolation (Barberis et al. (2018), Barberis et al. (2015)), cursedness (Eyster et al. (2019)), and representativeness (Bordalo et al., Bordalo et al. (2019), d'Arienzo (2020)). A related recent literature also delves into fundamental mechanisms of memory in asset pricing (Wachter and Kahana (2019); Nagel and Xu (2019)), and in an experimental context (Enke et al. (2020)). While our model also emphasizes the role of availability in memory and the association between a new event and corresponding exemplars, we focus on the variation in short-term asset price reactions to specific news items across different types of events.

Lastly, our work relates to the large literature on asset price reactions to news and media coverage. Prior work on this topic has found that individual investors are prone to buy attention-grabbing stocks which appear in the news or have extreme returns and volume (Barber and Odean (2008)). In general, news and media coverage have an impact on trading volume (Engelberg and Parsons (2011)), returns (Fang and Peress (2009)), and potentially the momentum cycle (Hillert et al. (2014)). Tetlock (2011) finds that investors temporarily overreact to stale news, although the impact can be potentially permanent (Huberman and Regev (2001)). While overreaction to stale news can partially explain our results, our news dataset identifies the exact time at which each piece of news is first publicly announced. In addition, our paper finds only partial reversals of the event day returns, suggesting that investors are genuinely reacting to new information.

The rest of the paper is organized as follows. Section 2 presents the model and discusses its motivation in financial narratives and psychology research. Section 3 describes the data. Section 4 documents heterogeneity in the short-term reaction to different corporate developments and identifies significant differences in the extremeness of the fundamental distribution across different event-types. Section 5 tests the main asset pricing predictions of the model, linking extremeness of fundamentals to overreaction. Section 6 illustrates the full RBE model which accounts for underreaction and reports a numerical calibration. Section 7 concludes.

2 Reaction to events and reasoning by exemplars

An extensive literature since Ball and Brown (1968) and Bernard and Thomas (1989) has used event studies to identify variation in short-term investor reaction to news. Much of the work in this literature points to short-term underreaction, or drift in returns, for earnings announcements and other corporate events (Bernard and Thomas (1989), Bernard (1992)), with underreaction attributed to inattention (DellaVigna and Pollet (2009)) or costly information processing (Engelberg (2008)). On the other hand, other work that considers a broader class of corporate developments finds cases of short-term overreaction (Antweiler and Frank (2006)). Relatedly, investors also systematically overreact to stale news (Tetlock (2011)) or chatter on message boards (Sabherwal et al. (2011)).

In this section, we develop a model of investor psychology that seeks to explain the variation in the investor response to different types of news. Our model relies on two core assumptions drawn from narrative evidence and prior literature in psychology and finance. First, the fundamental impact of corporate developments follows an extreme distribution: while most corporate news tend to have a small, or relatively immaterial impact on the overall valuation of the firm, there are some major events that have significant implications for the company. Formally, the distribution of the fundamentals has a fat tail, consistent with related findings in the literature.[5] While we assume this for now, we will return to validate this assumption in the empirical section.

Our second assumption is that these extreme, or tail, events have an out-sized influence on how investors react to news. Specifically, motivated by a rich literature in psychology pointing to the availability of prominent examples and their role in shaping human judgments (Kahneman (2011), Kahneman and Frederick (2002), Nosofsky (1992)),[6] we hypothesize that investors react to news by comparing them to notable past exemplary events, or exemplars, a behavior we refer to as *reasoning by exemplars* (RBE). Such behavior of comparing current events to past significant examples abound in financial journalism and analyst reports. We note that while we motivate RBE based in investor psychology, such thinking may also reflect information acquisition processes at the institutional level. Fund managers, for instance, may find it easier to access significant events in the past as reference points for new events than accessing an exhaustive database of all events of a given type.

RBE provides a natural way to explain the variation in how people react to news. Not only is the greater availability of past exemplars a typical force for overreaction, the *degree* of overreaction is determined by how far these exemplars are relative to the typical events of the same type. The fatter the tail of the distribution of outcomes, the more agents will disproportionately remember extreme realizations and overreact more to news. Consequently, our model predicts that event-types with more extreme fundamental distributions are associated with greater overreaction.

[5] For example, Gabaix (2016) documents earlier work in econophysics (Plerou et al. (1999)) that shows that the distribution of stock market returns is fat-tailed.

[6] Analogously, in economic settings, Malmendier and Nagel (2011) and Knüpfer et al. (2017) document life-long impacts that experienced economic depressions have on individuals' investment and consumption choices.

2.1 Model

We formalize RBE by combining fat-tailed fundamentals and over-representation of significant events in a simple asset pricing framework. The model yields the novel prediction of greater overreaction, price reversals, and trading volume for more extreme event-types.

2.1.1 Set-up

Let E be an event-type, and θ be the latent fundamentals associated with an event of type E, which is drawn from the distribution π_E. Each investor i receives a noisy, idiosyncratic signal s_i drawn from a distribution $f(s|\theta)$. For simplicity, we shall assume that $\theta \geq 0$: the event has positive impact. The negative case follows analogously.

Assumption 1. We assume the following regarding fundamentals and investor psychology.

1. **Extreme fundamental distribution:** Fundamentals are drawn from a fat-tailed, power-law distribution. In other words,

$$\pi_E(\theta) = \zeta_E^{-1} \frac{\theta_{0,E}^{\zeta_E^{-1}}}{\theta^{\zeta_E^{-1}+1}} \text{ for } \theta \geq \theta_{0,E}. \tag{1}$$

   There are two parameters of the distribution: $\theta_{0,E}$, the scale parameter, and $0 < \zeta_E < 1$, which governs the extremeness of the distribution. To obtain a simple closed form solution, we assume that the idiosyncratic signal s is drawn uniformly from 0 to θ, the conjugate distribution for the power-law distribution.[7]

2. **Reasoning by exemplars:** significant events with extreme returns have greater availability. We model this as a distortion in the subjective base rate:

$$\pi_E^{ex}(\theta) \propto \pi_E(\theta) \cdot w(\theta), \tag{2}$$

   where $w(\theta)$ is increasing in θ: more extreme events have greater availability weight w. The agent then uses π_E^{ex} as a base-rate to interpret his private signal s in a Bayesian way: $\pi_E^{ex}(\theta|s) \propto \pi_E^{ex}(\theta) \cdot f(s|\theta)$.

[7]This can be generalized to a sub-class of the Beta distribution: $f(s|\theta) = \gamma \cdot \frac{s^{\gamma-1}}{\theta^{\gamma}}$.

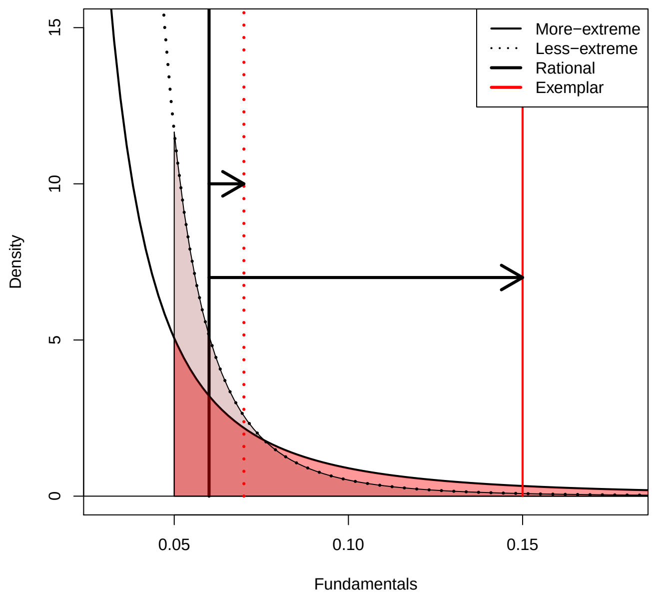

Figure 1: Greater RBE distortion for more extreme event-types

Note: Figure 1 shows the RBE distortion of subjective fundamentals. The solid (dotted) line represents events with more (less) extreme exemplars, which we assume to be events above 5% impact (shaded). The black (red) vertical line is the rational (RBE) expected fundamentals.

Figure 1 provides a visual illustration of the impact of RBE across event-types with different extremeness. Consider two event-types with power-law distributions with the same mean: one more extreme (fatter tails) and the other less extreme (thinner tails). Suppose individuals regard as exemplars events with fundamentals above 5%: $w(\theta) = I(\theta > 0.05)$. The subjective fundamentals, shown in the red vertical bars, are the mean of the exemplars, $E^{ex}[\theta]$. As Figure 1 illustrates, the subjective fundamentals for the fat-tailed distribution overshoots the rational fundamentals (given by the black vertical bar) by more than that of the thin-tailed distribution. RBE thus introduces more distortion when the underlying distribution is more extreme.

For a closed-form solution, we parametrize $w(\theta)$ as a power function increasing in θ: $w(\theta) = \theta^{\nu}$, with $\nu \geq 0$. First, prior to seeing any signal, the expected fundamentals are equal to $\frac{1}{1-\zeta_E}\theta_{0,E}$ for rational agents and $\frac{1-\nu\zeta}{1-(\nu+1)\zeta}\theta_{0,E}$ for RBE agents: RBE agents have a higher ex ante expected fundamentals. Next, upon receiving signal s, rational agents have the following posterior expectations:

$$E^{rat}[\theta|s] = \begin{cases} (\zeta_E + 1)\theta_{0,E} & \text{if } s \leq \theta_{0,E} \\ (\zeta_E + 1)s & \text{if } s > \theta_{0,E}, \end{cases}$$

while the RBE posterior expectation given s is

$$E^{RBE}[\theta|s] = \frac{1-(\nu-1)\zeta_E}{(1-\nu\zeta)(1+\zeta_E)} E^{rat}[\theta|s] = \psi(\zeta,\nu)E^{rat}[\theta|s].$$

The above results can be summarized into the following core implications of RBE:

Proposition 1. RBE investor beliefs satisfy the following.

1. $\psi > 1$: RBE posteriors exceed the rational benchmark.

2. $\partial\psi/\partial\zeta_E > 0$: the degree of overshooting is increasing in the fatness of the tail.

3. As s increases, $\frac{E^{RBE}[\theta|s]-E^{RBE}[\theta]}{E^{rat}[\theta|s]-E^{rat}[\theta]} \mapsto \psi$ asymptotically. For significant events, there is greater overreaction for more extreme event-types.[8]

To see the intuition, note that even in the rational case, the more extreme the underlying fundamentals (the greater the ζ_E), the greater the rational expectations given any signal s. RBE agents, by over-representing significant events in the base rate, produce an even greater reaction than the rational benchmark.

Next, we shall embed this psychological model into a simple asset market, where arbitrageurs trade against RBE agents. This will allow us to connect RBE to observable quantities such as market price, reversals, and volume.

Assumption 2. We make the following assumptions regarding the asset market.

1. **Arbitrageurs and RBE agents:** There are two types of agents in the economy: RBE agents and arbitrageurs. The latter know the fundamentals θ perfectly.

[8] As $E^{RBE}[\theta] > E^{rat}[\theta]$, for small values of s, there is a competing effect: the ex ante expected fundamentals are also higher than rational.

2. **Limits to arbitrage:** There are limits to arbitrage, which is given by a reduced form linear demand:

$$D^{arb}(p) = \kappa^{arb} \cdot (\theta - p) .$$

The elasticity of demand κ^{arb} reflects the limits to arbitrage: the arbitrageurs need to be guaranteed a premium to be induced to hold the asset, due to various limits to readily available arbitrageur capital. RBE agents similarly have a linear demand in the (subjective) expected returns:

$$D_i(s_i, p) = \kappa^{RBE} \cdot \left(E^{RBE}[\theta|s_i] - p\right) .$$

3. **Asset supply:** The asset is in zero net supply.

Imposing market-clearing and solving for the equilibrium price yields:

$$p(\theta; \nu, \zeta_E, \kappa^{arb}, \kappa^{RBE}) = \frac{\kappa^{arb} \cdot \theta + \kappa^{RBE} \cdot \bar{\theta}^{RBE}(\theta, \zeta_E, \nu)}{\kappa^{arb} + \kappa^{RBE}}, \tag{3}$$

where $\bar{\theta}^{RBE}(\theta, \zeta_E, \nu) = \frac{\zeta_E^{-1} - \nu + 1}{\zeta_E^{-1} - \nu} \cdot \frac{1}{2}\left(\frac{\theta_{0,E}^2}{\theta} + \theta\right)$ is the average valuation of RBE agents. As is standard, we shall also define the total trading volume to be $Vol = \frac{1}{2}\left(\int |D_i(s_i, p)|di + |D^{arb}(p, \theta)|\right)$, or half of the average absolute asset holdings in the economy.

Figure 9 shows the relationship between θ, the fundamentals of the event, and p. For simplicity, we set $\kappa^{arb} = 0$: arbitrageurs simply shrink the curves closer to θ. In the rational ($\nu = 0$) case, the price of the asset starts above the fundamentals θ, and eventually lies below the true fundamentals. This is due to Bayesian forces: as market participants (excluding arbitrageurs) have incomplete information about the fundamentals, they shrink towards the prior mean, causing market prices to overshoot for events below the prior, and undershoot for events above the prior.[9]

As market participants reason by exemplars ($\nu > 0$), prices overreact relative to the Bayesian benchmark. As described in Proposition 1, RBE agents overreact to the signal, driving up prices. As the comparison between Figures 9a and 9b illustrates, the overreaction

[9] If individuals learned from prices, as is standard in REE, in our setting prices will be fully revealing. We are assuming here that individuals are only using their signals, and are agreeing to disagree.

is greater for more extreme event-types. Furthermore, for sufficiently fat-tailed events (ζ_E sufficiently high), there is greater overreaction for events with greater fundamentals, as p asymptotically increases faster than θ: as fundamentals grow, RBE asymptotically dominates Bayesian shrinkage.

One can obtain a similar insight by holding fundamentals θ constant and varying the extremeness of the underlying distribution. As shown in Figures 9c and 9d, as the underlying distribution becomes more extreme, prices and volume increase. Naturally, the same happens for rational agents ($\nu = 0$), but the degree is far more muted, with prices never overshoooting fundamentals. Intuitively, fatter tails lead to greater overreaction by RBE agents which elevates prices and subsequent reversals. Simultaneously, these RBE agents trade aggressively with arbitrageurs and generate heightened volume. The following proposition encapsulates the above insights, with the proofs relegated to the appendix.

Proposition 2. Asset prices with RBE agents satisfy the following.

1. **[Price and Fundamentals]**
   (a) Rational ($\nu = 0$): prices overshoot/undershoot fundamentals for small/big events. Specifically, there is $\theta^*(\kappa^{arb}, \kappa^{RBE})$ such that $p^{rat}(\theta) < \theta$ for $\theta < \theta^*(\kappa^{arb}, \kappa^{RBE})$, and $p^{rat}(\theta) > \theta$ otherwise.
   (b) RBE ($\nu > 0$): if θ is sufficiently large, prices overshoot fundamentals: $p^{RBE}(\theta) > \theta$. If $\zeta_E > \frac{1}{1+\nu}$, the degree of overshooting is greater for bigger events.
2. **[Extremeness, Price, and Volume]**
   (a) Holding fundamentals fixed, prices are increasing in the tail-fatness ζ_E.
   (b) Holding fundamentals fixed, the total trading volume increases monotonically in ζ_E for ζ_E sufficiently large.

To summarize, our theory makes the following testable predictions of RBE:

Prediction 1. Event-types with fatter-tailed distributions are associated with greater price reversals. Conversely, event-types with thinner-tailed distributions are associated with less reversal and greater drift.

Prediction 2. More extreme event-types are associated with greater trading volume, holding fixed the fundamentals of the event.

Remark 1. (Underreaction) For simplicity, our simple model does not capture underreaction, but predicts increasing overreaction for more extreme event-types. This is to draw emphasis to our main finding, which is the cross-sectional variation of market reactions, i.e. less underreaction or more overreaction in more extreme corporate events. In Section 6, we introduce the full model where agents engage in RBE conditionally: they only reason by exemplars for events that they believe to be significant. This force allows our full model to account for both underreaction and overreaction.

Remark 2. (Overshooting and overreaction) Our static model does not fully model eventual price reversals. To connect asset overvaluation with overreaction and reversals, one can assume that RBE agents enter the market with the news (and hence do not previously price the asset)[10], and arbitrageur capital is able to eventually bring prices back to fundamentals (Duffie (2010)). Then, one can translate the above asset price propositions into overreaction and reversals.

Remark 3. (Connection to psychology research and related models) A rich literature on categorization, recognition, and memory (Medin and Schaffer (1978), Rosch (1973), Nosofsky (1992)) points to the role of similarity judgments to prototypes or exemplars in object recognition and evaluation: when evaluating a novel object, individuals recall from memory relevant exemplars to serve as references (Nosofsky (1988)).[11] In particular, these exemplars are not necessarily representative of the category, but can be extreme caricatures (Goldstone (1996), Goldstone et al. (2003)). In our setting, we assume that investors react in a similar fashion to corporate news, by comparing it to past salient events of the same category, as shown in the diagram in Figure 2.

Our description of investor psychology is also intimately linked to the literature on judgments of representativeness (Tversky and Kahneman (1973), Kahneman and Frederick (2002)). Representativeness, as formalized by diagnostic expectations, has been used to

[10]The tendency of retail investors to enter the market after news is documented in Barber and Odean (2008).

[11]The close link between similarity judgments to such exemplars and object recognition has been experimentally documented (Nosofsky (1991)).

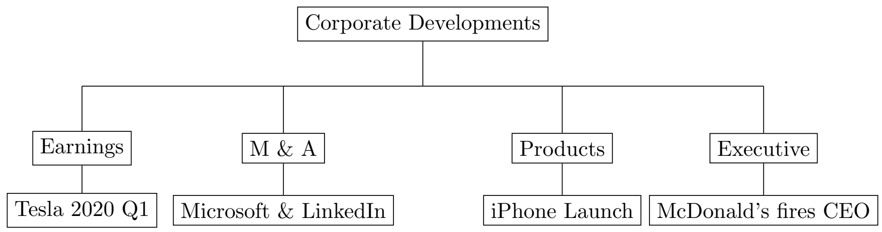

Figure 2: Reasoning by exemplars in corporate news

Note: Figure 2 describes the schema of reasoning by exemplars.

model overreaction to stereotypes and news (Bordalo et al. (2016), Bordalo et al. (2020)). In the diagnostic expectations framework, certain states of the world become more likely in light of new information, because the information is representative of these states. Individuals then exaggerate this difference and overreact. While our model yields a similar intuition, it emphasizes the distortion due to the unconditional availability of exemplars, rather than exaggerating a contrast to a reference group.[12]

3 Data

To bring our theory to the data, we use two main datasets for our news events and stock prices. First, we compile our list of corporate news events from the Capital IQ Key Developments. The Capital IQ dataset tracks major corporate news events such as earnings announcements, product and client announcements, lawsuits/legal issues, leadership changes, and mergers and acquisitions, but excludes macroeconomic news announcements such as interest rates and unemployment rates that may affect stock price returns. Among the corporate events in our dataset, we identify the universe of events associated with US companies listed on a major US stock exchange (Nasdaq, NYSE, and AMEX) that occurred between 2011 and 2018. Second, we obtain daily stock returns and trading volume from CRSP, which we merge onto the Capital IQ dataset.

As noted by the market microstructure literature, short-term price reversals can occur due to liquidity concerns: at extremely short time scales, bid ask bounces generate negative

[12]At a technical level, while diagnostic expectations introduces the distortion in the likelihood ratio, RBE distorts the base rate, capturing the psychological insight that exemplars are far more available than the rest of the population.

return autocorrelation. Even at longer time scales, there may be transient price pressure as market makers demand compensation for liquidity while trading against uninformed flow (Kyle (1985), Nagel (2012)). To ameliorate these concerns, we exclude small-cap stocks for our main analysis, which we define to be companies that have less than 2 billion dollars in market capitalization at the time of the event.[13]

Event categories

We focus our analysis on news events that pertain to the real economic activities of the firm, in particular its corporate and business operations, to filter out extraneous event-types. In other words, we wish to use events that have direct relevance to the firm's valuation and its expected future cash flows. As such, we select event categories based on the following methodology: first, we select categories that have happened at least 1000 times across all US companies in our sample between 2011 and 2018. Second, to focus on news related to the fundamental operations of the firm, we exclude administrative events (such as announcements of earnings release dates, name changes, and address changes), capital structure changes (such as debt and equity issuances including IPOs[14] and SEOs), or trading activities, such as index exclusion, delisting, and delayed SEC filings.

Our final universe of events comprise of 23 different major event-types, including earnings announcements, mergers and acquisitions, leadership changes, product and client-related announcements, labor activities, and business reorganizations. The list of event-types we use in our analysis is shown in Table 1. While we focus our main analyses on these events, we conduct robustness checks on different samples of event categories and show that our results are robust to the precise inclusion/exclusion criteria that we employ.

Basic summary

Table 1 reports the basic summary statistics regarding the events in our sample. In general, corporate announcement days are characterized by significant price movements and trading behavior. The unconditional means across all the event-types are largely centered around zero with a small but notable positive mean: with the exception of lowered earnings guidance,

[13] We repeat our analysis for the small-cap sample, and qualitatively replicate our main findings.

[14] We exclude IPOs in particular to avoid conflating IPO event day returns with the IPO premium.

most event-types are associated with a small positive daily return.

Furthermore, corporate event days tend to matter for stock prices: the standard deviation of returns on the event days for almost all event-types exceed 2.1%, which is the average daily return volatility of stocks in our sample. There is also meaningful variation in stock price movements across types of events as well. Earnings announcements and calls, credit rating downgrades, and leadership changes tend to have higher absolute daily moves, while annual general meetings, credit rating confirmations, and CFO changes tend to have lower absolute daily moves. In addition to returns, event days are also characterized by high trading volume. Finally, there is also meaningful variation in the higher moments of the event day returns for the different event-types. As we shall explore in later sections, the returns associated with most event-types are fat-tailed, or extreme.[15]

Are news announcement days separate?

Given the centrality of earnings announcements, one potential concern may be that the announcement dates in our sample largely coincide with the major earnings announcements. The literature on strategic corporate announcement documents evidence of corporations strategically timing their announcements, such as bunching multiple news events together (e.g. Graffin et al. (2011)). If corporate events significantly co-occur with earnings announcements, isolating the component of event day return attributable to earnings announcement from the effects of other concurrent events could be challenging.

Table A2 presents the percentage of event occurrences in each category that overlaps with an earnings announcement of the same firm. The results suggest that while some corporate announcements are indeed concurrent with earnings announcements, a vast majority of events occur on different dates: 16 of the 23 event-types had less than half of their events occurring on earnings announcement days. In fact, for most of these major events, over 90% of these announcements do not occur on earnings announcement days.

[15] We introduce our measure of extremeness, given by the power-law exponent, in Section 4.

4 Event-Type Heterogeneity

In this section and the next, we take the model to the data. We document three sets of findings. First, the market reacts heterogeneously to different types of news events. Second, the distributions of fundamentals vary in their extremeness across event-types. Third, consistent with the core predictions of our model, event-types with more extreme fundamentals experience more overreaction and greater trading volume.

4.1 Heterogeneous price reaction to corporate announcements

We first document significant heterogeneity in the stock price reactions to corporate news.[16] We estimate return autoregressions (e.g. Campbell et al. (1993)) and find that while stock prices following earnings announcements have post-announcement drift, many other types of corporate events such as mergers, acquisitions, client announcements, and leadership changes have post-announcement reversals. In fact, the majority of corporate events that do not highly coincide with earnings announcements display reversals, with the economic magnitudes of the reversals comparable to that of PEADs. We conduct robustness exercises and show that the drift and reversal patterns are unlikely to be generated by sampling variation or non-event-driven market dynamics, such as unconditional stock price autocorrelations, and are robust to industry effects and alternative return measures.

4.1.1 Cross-section of return drift and reversal

We first present evidence of heterogeneity of drifts and reversals across corporate event-types by estimating the return autocorrelation regressions. For each corporate event-type e, we estimate:

$$r_{e,c,t+1,t+k} = \alpha_e + \beta_e \cdot r_{e,c,t,t+1} + \epsilon_{e,c,t}, \tag{4}$$

[16] These findings relate to prior work in the event-studies literature that jointly study a wider array of corporate events. Antweiler and Frank (2006) classifies WSJ articles into various corporate event-types, and documents overall overreaction. Neuhierl et al. (2013) studies corporate press releases and documents higher return volatility and uncertainty post-announcements, and also finds reversals for a few event-types such as management changes and corporate restructuring. Relative to both works, our paper quantifies the degree of over-and-underreaction and highlights systematic differences across event-types. Most importantly, our paper documents variation in the extremeness of the fundamentals across different event-types, and shows that it can explain the variation in over- and underreaction to news.

where each observation is an occurrence of a corporate event of type e to company c at date t. $r_{e,c,t+1,t+k}$ is the cumulative stock return following the event from date $t+1$ to date $t+k$, where days are restricted to trading days, and $r_{e,c,t,t+1}$ is the event-day stock return on date t.[17] β_e, our measure of interest, reflects the degree of return drift/reversals of event-type e. If $\beta_e = 1$, then roughly half of the stock price movements are realized on the event day, with a predictable drift of equal proportion. If $\beta_e = 0$, excess returns are on average not predictable by event-day returns, as implied by rational expectations. Finally, if $\beta_e = -1$, event-day returns are on average fully reversed. We set $k = 90$ trading days for our baseline specification of the stock price drift/reversal horizon, similar to the horizon considered by the PEAD literature.[18] We benchmark stock price returns relative to the S&P 500 returns and repeat our analysis without benchmarking as robustness checks. To ensure our β_e estimates are not driven by outliers, for each event-type, we winsorize events at the 1% level. Standard errors are computed to account for cross-sectional and serial correlations in the error term.

Figure 3 shows that the estimated β_e coefficients exhibit considerable variation across different types of corporate events. In particular, 11 out of the 23 event-types in our sample exhibit post-announcement reversals. Table 2 reports the coefficient estimates for each event-type e corresponding to eq. (4). Consistent with Figure 3, Table 2 documents significant variation in the magnitudes of post-event drifts and reversals. While we find positive return autocorrelation indicating post-announcement drift for earnings announcements, we also find meaningful reversals for other corporate event-types, including leadership changes, mergers and acquistions, client-related announcements, and business alliances. Table 2 also reports the standard errors corresponding to individual β_e estimates and we find that seven of the individual β_e estimates are statistically distinguishable from zero at the 5% level. These event-types are among the most common event-types in our sample. To evaluate the overall statistical significance of post-announcement drifts and reversals, we estimate a pooled version of eq. (4) across all event-types e:

$$r_{e,c,t+1,t+k} = \alpha + \beta_e \cdot 1(Event_e) \cdot r_{e,c,t,t+1} + \epsilon_{e,c,t}, \tag{5}$$

[17]For example, let e be earnings announcements, c be Apple Inc., t be November 1st, 2018, and k be 90 days. Then the regression captures the relationship between the cumulative logarithmic return to Apple stock price from November 1st, 2018 to 90 trading days in the future (March 18th, 2019), and the Apple stock return on the day of November 1st, 2018.

[18]We also set $k = 30, 60,$ and 120 as robustness checks and obtain qualitatively similar results.

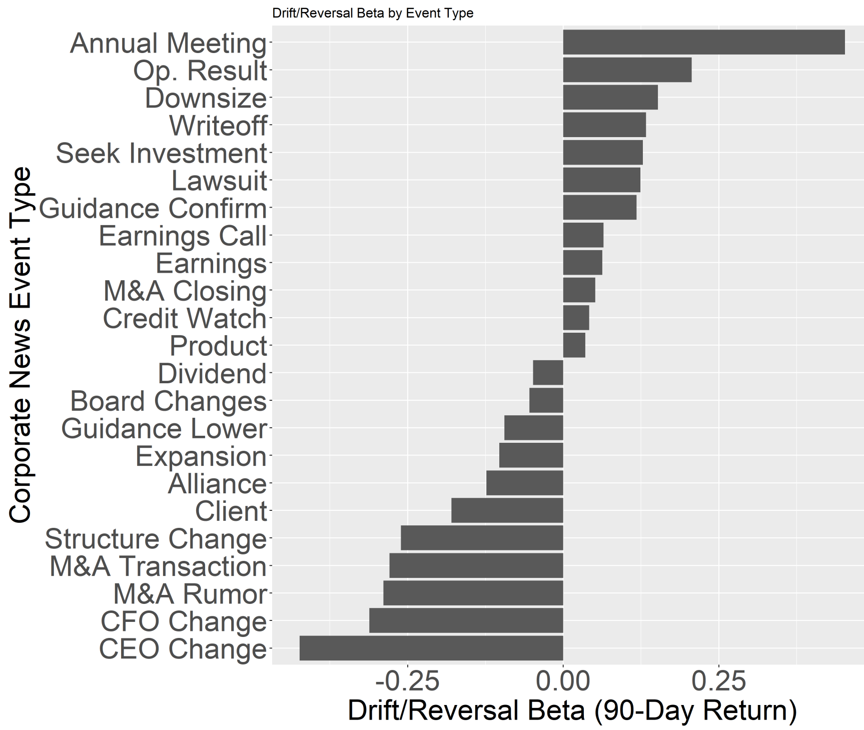

Figure 3: Reversal vs Drift

Note: Figure 3 plots the estimated β_e for each of the 23 event-types corresponding to eq. (4).

where each observation is a corporate event, and $1(Event_e)$ is a dummy variable for event-type e. The joint F-statistic of the pooled specification is 2.74, which strongly rejects the null hypothesis that the event-type-specific β_e's are jointly zero ($p < 0.01$). As such, the analysis indicates significant variation in post-announcement drifts/reversals in stock prices.

To interpret the economic magnitudes of the post-announcement drifts and reversals, we construct sorted portfolios based on the event-day returns for each type of corporate news. We divide our event-types into two categories based on the overlap of each event-type with earnings announcements. We define an event-type as *earnings-overlapping* if more than 50% of the events of the event-type occur within a 5-day window around the same firm's earnings announcements and *non-earnings-overlapping* otherwise. Table A2 reports each event-type's overlap with earnings announcements, which is bimodal: certain types of news are frequently announced around earnings announcements, including announcements of operating results, dividends, and corporate guidances, while other types of news, such as mergers and acquisitions, client and product announcements, and legal issues, are rarely announced around earnings announcements. For each of the two categories, we sort all events within the category by the event day returns and create ten sorted portfolios based on the event-day returns. For example, portfolio 1 in each category represents the 10% of events that had the lowest event day returns and portfolio 10 represents the 10% with the highest event day returns. We calculate the cumulative abnormal returns to an equal-weighted winner-minus-loser trading strategy where we buy portfolio 10 and sell portfolio 1. If events have post-announcement drift (reversals), this winner-minus-loser strategy should deliver positive (negative) cumulative abnormal returns.

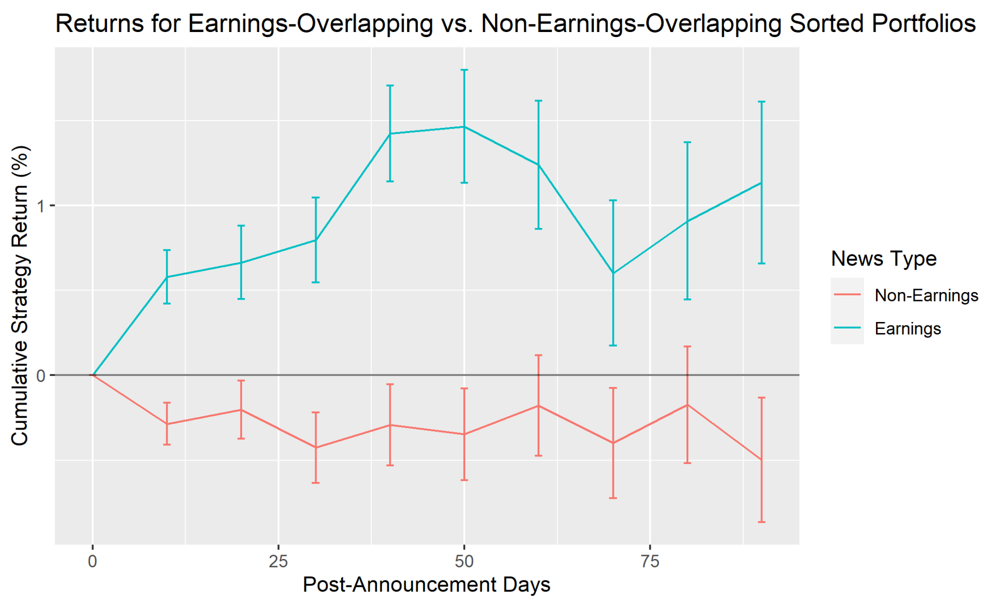

Figure 4: Sorted Portfolios of Earnings-Overlapping vs. Non-Earnings-Overlapping Events

Note: Figure 4 plots the cumulative abnormal returns to winner-minus-loser strategies for sorted portfolios created on earnings-overlapping events (blue) and non-earnings-overlapping events (red). The stocks are sorted based on the event-day returns into ten equally-sized portfolios. The winner-minus-loser strategy buys the portfolio with the highest event-day returns and shorts the portfolio with the lowest event-day returns.

Figure 4 presents the results. Consistent with Bernard and Thomas (1989) and the PEAD literature, for earnings-overlapping events, a top-minus-bottom strategy generates

113 basis points of cumulative returns over a 90 day period. On the other hand, for non-earning-overlapping events, the same strategy loses 50 basis points over a 90 day period. The evidence thus suggests that while post-announcement drift occurs for earnings, post-announcement reversals of similar magnitude are prevalent for other event-types.

4.1.2 Robustness exercises

We now conduct a series of robustness checks to test for alternative hypotheses that could generate our results.

A. Sampling variation and placebo exercises

To ensure that the cross-sectional variation in β_e estimates is not driven by sampling variation or latent autocorrelation in stock returns, we perform two bootstrap exercises. First, we take the sample of all firm-days on which no corporate event occurred for each given firm, which we call the *no-event-placebo* sample. For example, if company c did not have a corporate event occur on date t, we include firm-day c, t in the non-event sample. Second, to contrast the market reaction to our event-types with that to earnings announcements, we also construct the *earnings-placebo* sample, where we similarly sample from earnings-announcements days. For both approaches, we bootstrap 1000 draws with replacement, with each bootstrapped draw having the same number of events as the pooled sample of all actual events. We compute the $\beta_i^{bootstrap}$ coefficients for each bootstrapped draw following eq. (4), for $1 \leq i \leq 1000$, and compare the estimated β_e coefficients to the distribution of $\beta_i^{bootstrap}$.

Figure 5 shows the results. As depicted by the blue no-event-placebo histogram of β estimates, the 95% interval of no-event-placebo is $[-0.06, 0.11]$. We find that 61% (14 out of 23) of the observed β_e estimates lie outside of the 95% interval, which is significantly more than 5% implied by the null hypothesis that our drift/reversal patterns for event days are statistically indistinguishable from non-event-days. For our earnings-placebo exercise, we similarly find that 81% (13 out of 16) of the non-earnings-overlapping event-types have post-announcement drift/reversal coefficients outside the 95% interval of the boostrapped earnings estimates $\beta^i_{earnings}$. Furthermore, all but one of the 13 have β_e estimates that are more negative than the 95% interval of $\beta^i_{earnings}$, indicating that there is less post-announcement drift and more post-announcement reversal for these event-types. Overall,

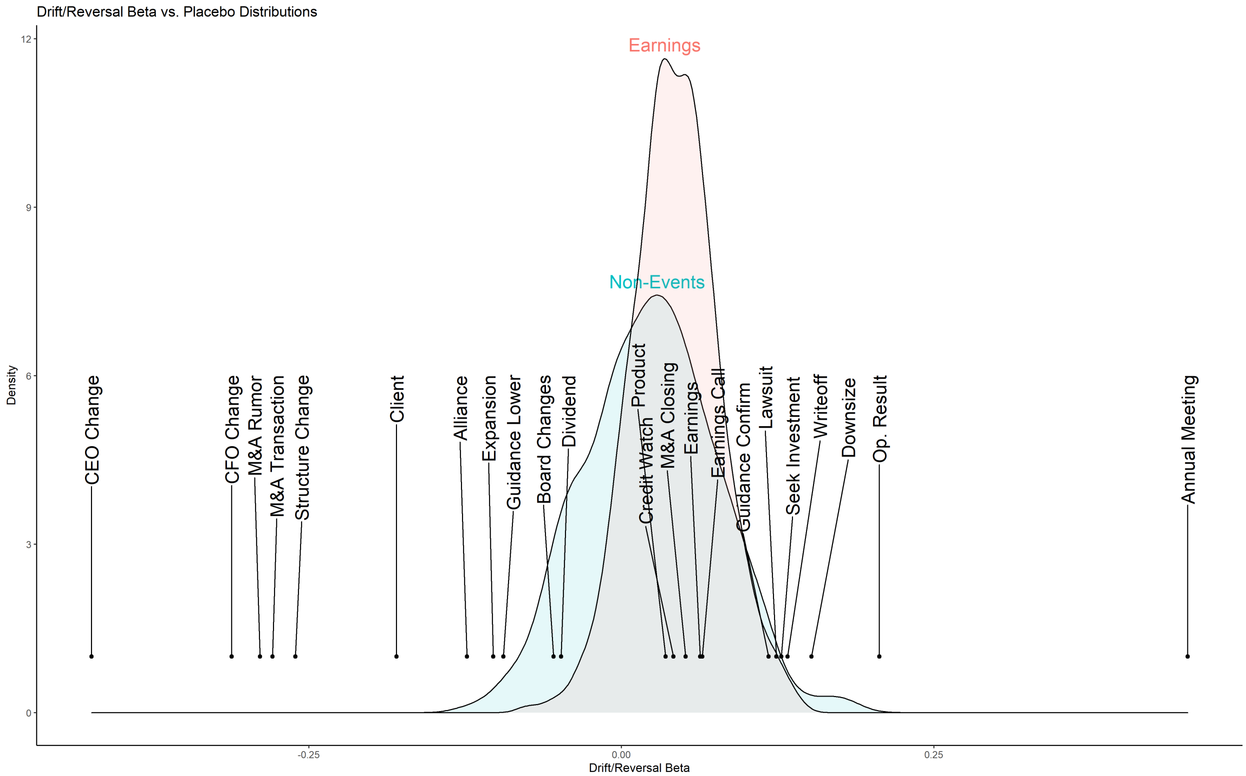

Figure 5: Reversal vs Drift: Non-Event and Earnings Permutation Tests

Note: Figure 5 plots the density distributions of placebo β_i's estimated according to a bootstrap for days where no corporate events occurred for the firms (Non-Events, in blue) and days where earnings were announced for the firms (Earnings, in red). The point estimates of β_e coefficients for each event-type are plotted as labeled points on the line.

our placebo exercise suggests that there is an economically and statistically significant cross-sectional variation in stock price reactions to a wide range of event-types.

B. Controlling for Unconditional Market Reaction

Another potential concern is that our results may be driven by unconditional market dynamics unrelated to corporate news. For example, suppose there are unconditional reversals to large returns. Then event-types with larger event-day returns may mechanically experience more post-event reversals and not because market participants overreact more to those event-types.

To address this concern, we estimate our return autoregression on the full firm-day panel, which includes the unconditional market response to non-event-day returns:

$$r_{c,t+1,t+90} = \alpha + f(r_{c,t}) + \sum_{e \in E} \beta_e \cdot 1(e_{ct}) \cdot r_{c,t} + \epsilon_{ct}, \tag{6}$$

where $1(e_{ct})$ is an indicator variable for whether a corporate event of type e occurred for firm c on day t.[19] The term $f(r_{c,t})$ captures the component of future market returns predictable by unconditional returns, regardless of whether it is due to a particular event-type. β_e therefore identifies the drift and reversal attributed to event-type e in excess of the component predictable by unconditional returns. We implement two versions of $f(r_{c,t})$. First, we set $f(r_{c,t}) = \gamma \cdot r_{c,t}$, with γ capturing the unconditional drift or reversals. Second, to address potential non-linearities in the autocorrelation of unconditional returns, we set $f(r_{c,t}) = \sum_{i=1}^{10} \gamma_i \cdot 1(r_{c,t} \in \Delta_i)$, where $1(r_{c,t} \in \Delta_i)$ is an indicator variable for whether $r_{c,t}$ is in the i-th decile of event-day returns.

Table A4 reports the corresponding results. Across all specifications, we find that the heterogeneity in the cross-section of drift and reversal to different types of corporate events are quantitatively consistent across specifications controlling for event-day returns. The β_e estimates in the full firm-day panel regression range from 0.41 to -0.38 (based on the non-parametric specification of f), and are quantitatively similar to our previous β_e estimates from eq. (4). Overall, the results of the firm-day panel specification with flexible event-day return controls suggest that our β estimates reflect true heterogeneity in responses to different event-types.

C. Drifts and Reversals as Sorted Portfolios

Two additional concerns may be raised about our choice of the regression coefficient β_e as the measure of drift and reversal. First, the regression coefficients may not be robust to outliers even after winsorizing. Second, β_e is a relative measure, which may not capture the economic magnitude of the drifts and reversals. While we have partially addressed the second point by comparing the earnings-overlapping and non-earnings-overlapping sorted portfolios, we now extend the sorted portfolio approach to all of our event-types by estimating the

[19] To avoid potential collinearities, the set of events E excludes the six event-types that co-occur within five days of earnings announcements at least 50% of the time, so there are 17 total event-type indicators. We compute standard errors following Driscoll and Kraay (1998) to account for overlaps and autocorrelated errors.

following regression specification:

$$UMD_e = E[r_{e,c,t+1,t+k}|r_{e,c,t} > 5\%] - E[r_{e,c,t+1,t+k}|r_{e,c,t} < -5\%].^{20} \tag{8}$$

UMD_e can be interpreted as the returns to a winner-minus-loser portfolio that buys the firms whose event-day returns are greater than 5% and sells the firms whose event-day returns are less than -5%. We set $k = 90$ days following eq. (4). UMD_e is positive (negative) if there is drift (reversal), i.e. event-day winners (losers) have future positive (negative) returns. UMD_e not only measures the absolute magnitudes of drifts and returns, but also equally weighs the observations in the portfolio rather than assigning more weight to the extremes, as is done in the regression specification.

Figure A1 plots the estimated UMD_e's against the estimated β_e's. The UMD_e measures are highly positively correlated with the β_e estimates with a correlation coefficient of 0.80 (p-value < 0.01). The drifts and reversals from the β_e estimates exactly coincide with the sign of the UMD_e measure (with the exception of lawsuits, for which the β_e is slightly positive and the UMD_e is slightly negative). In particular, the returns on the UMD_e portfolios of events with reversals are of a comparable magnitude to those of drifts. For instance, the median return on the UMD_e portfolio for event-types with reversals is -7.1% annualized, compared to 4.0% annualized for the median event-type with drift. For reference, the UMD_e portfolio for earnings announcements earns 2.4% annualized returns. Overall, these results suggest that our β_e estimates are closely linked to the returns to a standard sorted portfolio, with the reversals of a comparable economic magnitude to that of PEAD.

D. Additional Robustness Exercises

In Section B in the Online Appendix, we include additional robustness exercises. We show that our results are robust to using log-returns and absolute returns, to controlling for industry effects, and to both large and small-cap stocks.

[20] We estimate UMD_e from the following regression:

$$r_{e,c,t+1,t+k} = \alpha_e + D_e \cdot 1(r_{e,c,t} < -5\%) + U_e \cdot 1(r_{e,c,t} > 5\%) + \epsilon_{e,c,t}, \tag{8}$$

with $\widehat{UMD}_e = \hat{U}_e - \hat{D}_e$.

4.2 Corporate news are heterogeneously extreme

Having documented the cross-sectional variation in short-term reaction to corporate developments, we now turn to the second key variation: the distribution of the fundamental impact of events are extreme (fat-tailed), and differentially so across event-types.

We measure the fundamental impact of an event by its event-day return as the main measure and repeat our analysis using alternative measures, such as long-run returns and realized cash-flow growths. For our main measure of extremeness, we draw on the extremal distribution literature (e.g. Embrechts et al. (2013) and Gabaix (2016)) and measure the relationship between the log-rank and the log-value of the top 10% absolute event-day returns for each event-type. This relationship is negative by design: the value decreases as one moves down the rank. A flatter relationship indicates a greater increase in the value as one moves up the rank, and hence a fatter tail, or more extreme distribution. In particular, the relationship is exactly linear for the case of power-law distributions.[21]

Figure 6 plots the relationship for earnings and M&A announcements as well as for a simulated normal distribution with a similar standard deviation. As is evident from the plot and previous work (Gabaix (2016)), the tail of the event-day returns is far better fit by a power-law than a normal distribution, whose log-rank log-value curve decays faster than any linear fit. While we have shown only two event-types for simplicity, the conclusion holds generally: the R^2 associated with the linear fit is close to 1 for all types of corporate events, suggesting that the distribution of fundamentals for all event-types are extreme and described well by a power-law.[22]

Furthermore, there is significant variation in extremeness across the event-types. We estimate log rank-value regressions of absolute event-day returns for each event-type[23]:

$$\log(Rank_{i,e}) = \xi_e - \zeta_e^{-1} \log(|r_{i,e}|),\ |r_{i,e}| > |r_{e,90}|. \tag{9}$$

[21] To see this, note that $1 - F(x) = (x/x_{min})^{-k}$ for power-law distributions, which implies $\log(1 - F(x))$ is affine in $\log(x)$.

[22] The extremal distribution literature has a precise way of categorizing thin-tailed (such as log-normal, normal, exponential) distributions and fat-tailed (such as power-law, Student-t, Cauchy, etc) distributions. The limit of $\max\{x_1, x_2, ...x_n\}$, suitably normalized, converges to the Gumbel distribution for thin-tailed distributions, and the Frechet distribution for heavy-tailed distributions. For more details, see Embrechts et al. (2013).

[23] We also perform two robustness checks. First, we vary the horizons of the returns in the tail regression to 30 and 100 day horizons. Second, we also estimate the power-law exponent separately for the positive

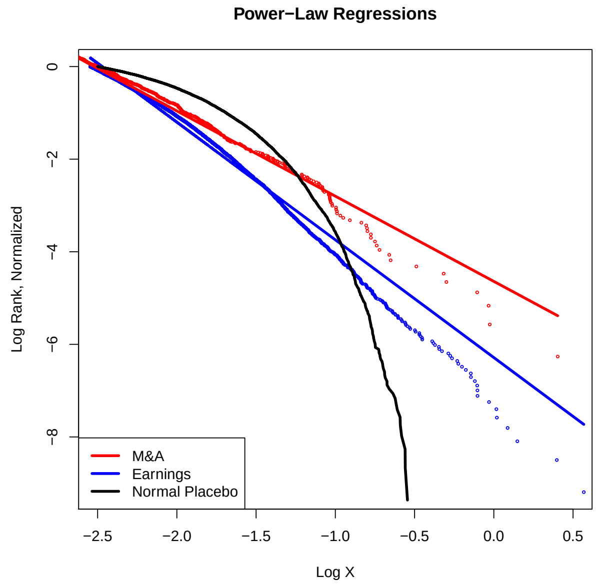

Figure 6: Tail Regressions

Note: Figure 6 plots the estimates corresponding to eq. (9) for M&A events (red), Earnings events (blue), and a simulated normally-distributed return distribution (black). The x-axis shows the normalized log value of event-day absolute returns, while the y-axis shows the normalized log rank. The solid lines plot the linear best fit corresponding to eq. (9).

The higher the ζ_e, the farther the tails are from the median and thus the more extreme the distribution. Table 1 reports the estimated ζ_e coefficients for each of the corporate event-types. The coefficients estimates suggest significant variation in the tail fatness of stock returns across different event-types: ζ_e ranges from 0.32 (earnings calls) to 0.51 (CEO changes). To give a sense of the economic magnitudes of these difference in ζ_e, one can translate these results into a statement about the magnitude of tail event returns: the average return of events with greater than 5 percentage point (p.p.) returns is 8.3 p.p. for earnings calls and 9.7 p.p., or 17% greater, for CEO changes. As such, the distribution of

and the negative parts of the distribution:

$$\log(Rank_{i,e,pos}) = \xi_{pos,e} - k_{pos,e} \log(r_{i,e}),\ r_{i,e} > r_{e,90}$$
$$\log(Rank_{i,e,neg}) = \xi_{neg,e} - k_{neg,e} \log(-r_{i,e}),\ r_{i,e} < r_{e,10}.$$

The qualitative conclusions of our analysis remain robust to both exercises.

returns associated with earnings announcements are consistently less extreme than that of other corporate news such as business expansions and leadership changes.

Two advantages of the ζ_e power law coefficients are that the goodness of fit is very high and that the tail coefficients are extremely precisely estimated across event types: the median standard error across all event types is 0.02 (Table 1).[24] Importantly, this shows that the coefficient estimates are not driven by a small number of data points, and that there are an economically and statistically significant differences in the extremity of the fundamentals of each event-type.

Power law index vs. other tail measures

We use ζ_e as the main measure of extremeness given the impressive fit of the power law specifications. However, our results are robust to the exact tail measure we use. For example, one can alternatively use quantile-ratios (such as the 1%/50% percentile ratios) or conditional mean ratios (e.g. $E[\theta|\theta > C]/E[\theta|\theta > 0]$). As a robustness check, we report in Figure A4 the 1%/50% quantile-ratio of each event-type and verify that it is highly correlated with the fatness of the tail ζ_e. We also compute the skew as an alternative measure and find that skew is also highly correlated with ζ_e.[25]

On the other hand, we emphasize that our measure of extremeness is distinct from other potentially intuitive measures, such as variance or the absolute frequency of big events. These measures do not properly proxy for extremeness because they are not normalized measures: theoretically, RBE is distortive because exemplars are outliers *relative* to the base distribution. Earnings announcements provide an illustrative example. While earnings announcements tend to be quite significant, with relatively frequent large event-day returns, they are among the least extreme event-types in our sample. An outstanding earnings announcement is simply not so big relative to other significant earnings announcements. Empirically, we confirm in Section 5.1.2 that these alternative measures do not predict investor reaction whereas tail fatness does.

[24] We used the standard error correction in Gabaix and Ibragimov (2011) as well as a simple bootstrap standard error.

[25] One major drawback of skew, however, is that higher-order moments such as skew or kurtosis cannot be reliably measured for fat-tailed distributions.

Alternative Measures of Fundamentals

While we use the event day returns as our main measure of fundamentals, it is possible that event-day returns may be a biased measure of fundamentals given that we documented predictable drift and reversions. In Table A6 in the Online Appendix, we alternatively measure the extremeness of fundamentals by computing the tail fatness of long-run returns and realized cash flow growth over one- to five-year horizons, and find all of our measures of fundamentals to be highly correlated. However, given that the latter two measures are measured at a longer horizon and can be confounded by other developments that are unrelated to the event, we use the extremeness of the event-day returns as our main measure, and provide robustness checks showing that our results are robust to using alternative fundamental measures.

5 Asset Pricing Implications of RBE

In the previous section, we documented significant heterogeneity in the short-term market reaction and the extremeness of the fundamental impact across a wide range of corporate developments. We now turn to the key asset pricing implications of RBE outlined in Section 2: more extreme event-types are associated with greater overreaction, reversals, and trading volume. We document evidence consistent with these predictions and test and rule out several alternative explanations of these results.

5.1 Prediction 1: Overreaction and Extremeness

We test Prediction 1 by comparing the fatness of the tail of each type of corporate events, ζ_e against its degree of post-announcement drift or reversal.

We first present our main result in a scatterplot in Figure 7. The figure illustrates a striking relationship between the tail fatness ζ_e and the post-announcement drift/reversal β_e across event-types: fatter-tailed event-types have more reversal; thinner-tailed events have more drift. The correlation coefficient is -0.61 and is statistically significant at the 1% level.

Next, we formally estimate the relationship in a regression specification as follows:

$$r_{e,c,t+1,t+k} = \alpha + \beta_0 \cdot r_{e,c,t,t+1} + \gamma \cdot \zeta_{e,t} \cdot r_{e,c,t,t+1} + \epsilon_{e,c,t}. \tag{10}$$

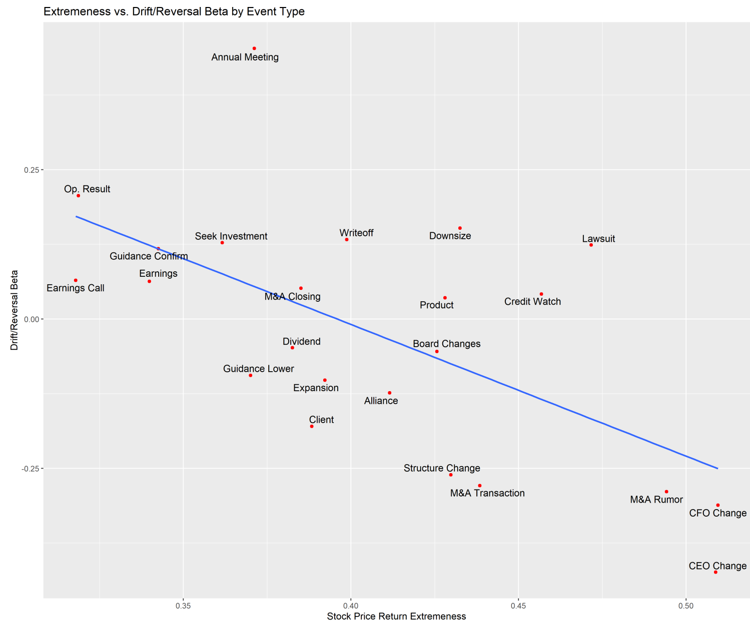

Figure 7: Post-Announcement Price Drift/Reversal vs. Extremeness

Note: Figure 7 plots the relationship between tail fatness and post-announcement drift/reversal β_e for each event-type e. Tail fatness is the inverse power-law index ζ_e estimated following eq. (9), and drift/reversal β_e is estimated following eq. (4).

Observations are at the corporate event level. $r_{e,c,t+1,t+k}$ is the cumulative stock price return for a corporate event e for company c from date $t+1$ to $t+k$, where days are restricted to trading days. $r_{e,c,t,t+1}$ is the event-day stock return for event e of company c. γ, the coefficient of interest, captures the correlation between the future drift/reversal and the tail fatness of each event-type. To ensure that our tail fatness measurements are not contaminated by future event returns, we estimate ζ_e both over the entire sample period as well as using a trailing window of three years, for which we exclude the first three years of the sample to ensure we have full three-year windows of returns.[26]

Table 3 reports the results corresponding to eq. (10). In each specification, we estimate a negative and statistically significant γ coefficient. For reference, the time-varying $\zeta_{e,t}$ measure ranges from 0.19 to 1.22 (sd = 0.08), while the fixed $\zeta_{e,t}$ measure ranges from 0.32 to 0.51

[26] As with our baseline results in Section 3, we use a 90-day horizon, and show that we obtain quantitatively similar results with different horizons in the Appendix (Tables A7 and A8).

(sd = 0.05).[27] In column (2), the estimated β coefficients imply that the differences in the tail-fatness can explain the range of post-announcement stock price movements from drifts of 9% ($= -1.24 \times 0.32 + 0.49$) to reversals of 14% ($= -1.24 \times 0.51 + 0.49$). This finding is consistent with the model prediction that overreaction is increasing in the tail fatness.

5.1.1 Robustness exercises

In this section, we report results on several robustness exercises related to Prediction 1.

A. Reverse causality

One alternative hypothesis is that the results are driven by reverse causality. For example, there may be a general underlying force for overreaction that is unrelated to our mechanism, which impacts event-day returns, and mechanically generates fat tails for the event-day return distribution. We address this concern using our alternative measures of fundamental extremeness unrelated to the event-day return, by using the extremeness of the cash flow growth distribution over multi-year horizons and of the long-run return distributions. If these alternative measures of fundamental extremeness also predict reversals, then it is unlikely that our results are driven by reverse causality of stock price reversals generating fat-tailed event-day returns.

We define the k-year cash flow growth subsequent to each corporate news event experienced by firm i in year t as $\Delta EPS_{i,t+k} = EPS_{i,t-1+k}/EPS_{i,t-1} - 1$, which is the percentage change in earnings per share of firm i from the fiscal year immediately preceding the event to k years later. We use horizons of 1 to 5 years subsequent to the events.[28] For our long-run return distribution, we use the distribution of the cumulative stock price returns up to 100 days after the event. We estimate the extremeness of each of these distributions for each event type following eq. (9), where we replace the event-day returns with the cash flow growths and long-run returns, respectively. We note here that these alternative estimates are based on the same sample as the extremeness estimated on the event-day return distribution, and that these estimates are similarly precise.

We repeat our analysis in eq. (10) with the extremeness of cash flow growths and long-

[27] Note that $\zeta < 1$ for a proper distribution. In our estimates, $\zeta \geq 1$ for only 0.2% of rolling windows in our sample.

[28] To avoid dividing by quantities close to zero, we estimate our cash flow growth measure based on firms with earnings per share in year $t-1$ of at least 10 cents.

run returns instead of the extremeness of the event-day returns as the explanatory variable. In other words, we estimate:

$$r_{e,c,t+1,t+k} = \alpha + \beta_0 \cdot r_{e,c,t,t+1} + \gamma \cdot \zeta_{F,e} \cdot r_{e,c,t,t+1} + \epsilon_{e,c,t}, \tag{11}$$

where $\zeta_{F,e}$ is the extremeness of the cash flow growths and long-run returns, respectively. Table A9 reports the estimates. We estimate a negative γ coefficient for each of the alternative measures of extremeness of fundamentals. As such, the analysis using alternative measures of fundamentals suggests that our results are not driven by reverse causality.

B. Generated regressor problem

The empirical estimation of ζ_e coefficients poses a generated regressor problem (Pagan (1984) and Murphy and Topel (2002)) in the estimation of eq. (10). To address this, we use the block bootstrap procedure (Politis and Romano (1994)). We draw 100 bootstrap samples and estimate the γ coefficient on each bootstrap sample following eq. (10). Figure A5 presents the density plot of the γ estimates from the bootstrap samples. The mean is -1.10 and the empirical 95% interval is $[-2.22, -0.05]$, which is quantitatively in line with the estimated γ coefficients reported in Table 3. As such, our estimation of the γ coefficient in eq. (10) is quantitatively unchanged when we account for the generated regressor.

5.1.2 Testing alternative explanations

In the following section, we test alternative hypotheses that could explain the cross-sectional variation in post-announcement drifts and reversals.

Our main econometric specification follows eq. (10) and includes additional explanatory variables corresponding to each alternative hypothesis. We individually test whether each additional variable is either quantitatively meaningful or has incremental explanatory power in explaining the variation in post-announcement drift and reversal beyond the tail fatness ζ_e. Formally, we estimate regression specifications as follows:

$$r_{e,c,t+1,t+k} = \alpha + \beta \cdot r_{e,c,t,t+1} + \gamma \cdot \zeta_{e,t} \cdot r_{e,c,t,t+1} + \phi \cdot X_{e,c,t} \cdot r_{e,c,t,t+1} + \epsilon_{e,c,t}. \tag{12}$$

Observations are at the event level as in eq. (10). $X_{e,c,t}$ denotes the additional explanatory variable of interest, with ϕ measuring whether the additional explanatory variable can explain the cross-sectional variation in post-announcement drift and reversal beyond tail fatness ζ_e. We report the results of this exercise using time-varying $\zeta_{e,t}$ estimates and also find that all results are unchanged using ζ_e's estimated over the full sample.

A. Familiarity with events

One alternative explanation for why investors react differently to different event-types is that investors may be more accustomed to some event-types than others. For instance, investors may be very familiar with earnings announcements as they are frequent and regular, whereas investors may not know how to react when the CEO gets fired because they are unfamiliar with CEO firings. To address this concern, we compute the number of times an event of each type has occurred $N_{e,t}$ as a proxy for investors' familiarity with each event-type, and estimate eq. (12) with $X_{e,c,t} = N_{e,t}$.

B. Lower-order moments of stock returns

Another alternative hypothesis is that our results are driven by either the mean or variance of fundamentals, rather than the extremeness. For example, if investors mechanically overreact to event-types with big returns, then differences in event-day return variance may instead drive variations in post-announcement drift or reversal. In a similar vein, if investors react differently to good and bad news, differences in the mean returns across different event-types could instead generate the observed variation. To test these alternative hypothesis, we compute the mean $\mu_{e,t}$ and the variance $Var_{e,t}$ of event-day returns for each type of corporate events,, and estimate eq. (12) with $X_t = \mu_{e,t}$ and $Var_{e,t}$ respectively.

C. Price impact

A third alternative explanation could be that the differences in post-announcement drift or reversal are generated by differential price impacts of event-day returns. For example, there may be an unconditional reversal for events with larger event-day returns, regardless of the event-type, due to market-maker inventory or reasons unrelated to fundamental news. To test this explanation, we add a term that is the event-day return, $X_{e,c,t} = |r|_{e,c,t+1,t+k}$, which controls for potential non-linearities in price impact that may confound our results.

D. Event Predictability

A final alternative explanation could be that certain types of events in the sample are either regularly occurring or are predictable in when they occur, and that the market reacts differently to these predictable events compared to unpredictable events.[29] To test

[29]For example, Hartzmark and Solomon (2018) documents mispricings in the market reaction to predictable

this, we classify the event types into Predictable and Not Predictable, where Predictable events are defined as those that regularly occur for a firm (i.e. operating results, earnings announcements, corporate guidances, dividends, earnings calls, and annual general meetings). We add a term $X_{e,c,t} = 1(e \text{ is Predictable})$ which is an indicator variable for whether the event type is predictable.

5.1.3 Testing for alternative hypotheses

We test all of the above alternative explanations by estimating eq. (12) by setting $X_{e,c,t}$ as each of the alternative explanatory variables. Table 4 reports the corresponding estimates. We find that the estimated coefficients ϕ for none of the alternative explanatory variables are economically and statistically insignificant, whereas the coefficient corresponding to tail fatness ζ_e, γ, is negative and both economically and statistically significant for all specifications, as is consistent with our baseline result. This suggests that none of the alternative explanations are likely to be driving our findings, and that tail fatness is indeed driving the cross section of investor reaction to news.

5.2 Prediction 2: Volume and Extremeness

We next test Prediction 2, the relationship between tail fatness and trading volume. Our model implies that more extreme event-types trigger greater disagreement between those who receive high private signals and those who do not. Therefore, events with more extreme return distributions should generate more trading conditional on the same fundamentals.

We measure trading volume as the turnover, defined as the number of shares traded times the share price divided by total market cap. We take two approaches to measure trading volume conditional on the fundamentals. First, we compute the event-day turnover for each event-type conditional on the event-day returns, which is a proxy for the magnitude of the fundamental news. For each event-type, we estimate a conditional turnover, $\overline{Turnover}_{e,10}$, for an event of each type with a 10% absolute event-day return. We then examine how $\overline{Turnover}_{e,10}$ correlates with tail fatness ζ_e across event-types.

Second, we estimate the relationship between trading volume and tail fatness in a panel regression and control for the absolute value of the event-day return as a proxy for the

events.

fundamentals of each event. The regression specification mirrors eq. (10) and is as follows:

$$Turnover_{i,e,t} = \alpha + \beta \cdot |r_{i,e,t}| + \delta \cdot |r_{i,e,t}| \cdot \zeta_{e,t} + \mu_t + \mu_e + \epsilon_{i,e,t}, \tag{13}$$

where observations are at the individual event level, $Turnover_{i,e,t}$ is the event-day turnover for the stock of firm i that occurred at date t, $r_{i,e,t}$ is the associated event-day return, and $\zeta_{e,t}$ is the return tail fatness for each event-type as defined before. We also include μ_t and μ_e as trading day and event-type fixed effects. Finally, δ, the coefficient of interest, measures the impact of the tail on the conditional turnover.

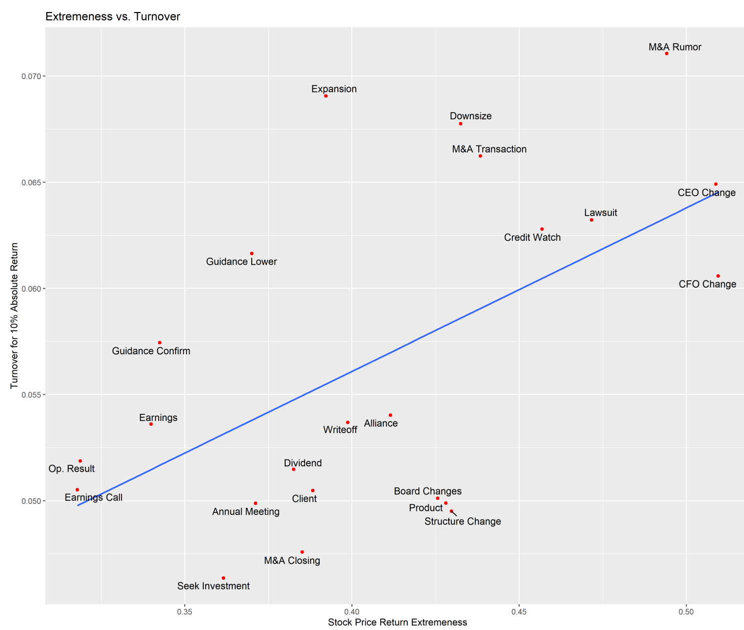

Figure 8: Volume and Extremeness

Note: Figure 8 plots the relationship between tail fatness and conditional turnover $\overline{Turnover}_{e,10}$ for each event-type e. Tail fatness is the inverse power-law index ζ_e estimated following eq. (9) and conditional turnover $\overline{Turnover}_{e,10}$ is estimated following eq. (13).

Figure 8 plots the relationship between tail fatness ζ_e and the conditional turnover $\overline{Turnover}_{e,10}$, which ranges from 4.6% to 7.0%. The correlation coefficient is 0.56 (p-value $<$ 0.01). Consistent with Prediction 2, event-types with fatter tails are associated with higher turnovers conditional on the absolute event-day return. Table 5 presents the estimated coefficients of our second approach. In each specification, we estimate a positive and statistically significant δ coefficient, indicating that events with fatter-tailed returns generate higher trading volume. Conditional on a constant 10% event-day return, the predicted turnover $\widehat{Turnover}_{e,10}$ ranges from 4.8% to 6.3%[30], spanning almost the entire range of the conditional turnovers. Our results thus suggest that tail fatness ζ_e can quantitatively explain the observed differences in average trading volume across event-types.[31]

6 Extension to underreaction and calibration

In this section, we extend our model to address two important limitations. First, our baseline framework does not predict underreaction and hence drift events, but rather only differing degrees of overreaction. We extend our model to account for underreaction in thin-tailed, or less extreme event-types. Second, our simple model implies an equal degree of overreaction for all events of a given event-type. This implication is unrealistic as not all corporate events warrant equal degrees of overreaction. For instance, not every investor thinks every new product launch is the next iPhone.

Our extension therefore accounts for the idea that reasoning by exemplars is conditional. In particular, we hypothesize that investors only reason by exemplars for events that they regard as sufficiently important. Conversely, if an event is not judged to be sufficiently important, they are dismissed by investors as a non-event. This leads to a dichotomy in reactions to news: individuals will either dismiss the news as a non-event if they judge it to be inconsequential, or compare it to notable exemplars if they judge it to be important.[32]

We formalize the thresholding of news as events or non-events as agents categorizing corporate news according to a decision boundary: corporate news with subjective returns greater than θ^* will be considered as an event and compared to relevant exemplars. Otherwise, it will be categorized as a non-event and perceived to have minimal impact.[33]

[30] Explicitly, $4.8\% = 0.23 \times 10 + 0.79 \times 10 \times 0.32 + 0.0058$ and $6.3\% = 0.23 \times 10 + 0.79 \times 10 \times 0.51 + 0.0058$ based on Column (4) of Table 5.

[31] The variation in trading volume we document across event types is the trading volume *holding fixed* the event-day returns. The relationship between volume and the extremeness of the underlying event-day returns is therefore not mechanically driven by differences in the magnitudes of returns.

[32] Intuitively, there are many reasons why non-events may be ignored: investors may not pay attention to non-events because they have limited capital and trade only on sufficiently large news; financial media may not report on non-events so they are less widely disseminated; investors may not remember these non-events because they did not trade on them nor did anyone talk about them.

[33] This idea of a sharp decision boundary is commonly featured in many theories in the literature on coarse

Figure 10a illustrates the extension of this decision boundary to reasoning by exemplars. The figure highlights that RBE is conditional: when an investor judges a corporate news to be insignificant, she dismisses the event as a non-event. It is only when she deems the event to be sufficiently important that she compares the event to exemplars. We show that our extended model can deliver both over- and underreaction depending on the event. We conclude by calibrating our full model to quantitatively match the empirical moments, including the full spectrum of overreaction and underreaction.

Remark 4. (Alternative forces for short-term underreaction) The extensive literature on PEAD has previously attributed other forms of drift and short-term underreaction in asset prices to many forces, from investor inattention and costly information processing (DellaVigna and Pollet (2009), Engelberg (2008)) to institutional frictions, such as sluggish capital (Duffie (2010)). While our full RBE framework allows for a psychologically intuitive force for underreaction, we do not wish to rule out these alternative explanations for underreaction. The main focus of our model is to explain the cross-sectional variation in the relative degree of over- and underreaction. The average level of over- and underreaction, on the other hand, may be determined by a variety of forces and frictions, including forces that generate short-term underreaction for all events.

6.1 Full model

Our full RBE model thus incorporates the event/non-event categorization into our pre-existing framework. Following exemplar-based categorization models (Nosofsky (1992)), the investor only uses as exemplars events that he has categorized to be an event in the past. Thus, the exemplar distribution plays a dual role. First, it informs the event/non-event categorization. In turn, the categorization further exaggerates the prevalence of extreme events available to the investor. In other words, what comes to mind as a result are not the overwhelming majority of the instances in which the event had negligible impact, which are discarded as non-events, but extreme cases that serve as exemplars.

thinking and categorization (Mullainathan (2002)); Mullainathan et al. (2008)). Perhaps most explicitly similar to our framework is Nosofksy's exemplar-based categorization model (Nosofsky (1992)), where the decision boundary between two categories is where the net similarity to the exemplars of a given category is the same as the net similarity to the exemplars of a competing category.

Figure 10b summarizes the full RBE process. Upon receiving a signal s, the investor forms a subjective expectation, $\bar{\theta}_E^{RBE}(s)$, using his subjective exemplar distribution π_E^{ex}. If the subjective fundamentals exceed the category boundary θ^*, the investor regards the news as an event, and stores it as an exemplar with weight $a(s) = s^{\nu}$[34]. The weight of an exemplar of fundamentals θ is the net availability averaged across signals: $w(\theta) = \int a(s)f(s|\theta)ds$. Assumption 3 summarizes the extension.

Assumption 3. [Event vs. Non-event] The investor regards e as an event if and only if his subjective fundamental $\bar{\theta}_E^{RBE}(s) = \int \theta \cdot \pi_E^{ex}(\theta|s)d\theta$ is above a fixed threshold θ^*, which can be interpreted as the category boundary between events and non-events. The individual assigns zero fundamental impact, $\theta^d = 0$, to non-events. The investor's exemplar distribution, or his subjective base rate, is $\pi_E^{ex} \propto \pi_E \cdot w(\theta)$, where the availability weight $w(\theta)$ is given by $\int f(s|\theta)a(s)ds$, the availability averaging across the signals.

Proposition 3 modifies Propositions 1 and 2 in light of the model extension.

Proposition 3. The extended model yields the following predictions.

1. **[Non-Events and underreaction]** Investors discard signals lower than an endogenous threshold $s_E^*(\theta^*, \zeta_E)$, and only retain events whose signals exceed this threshold. In other words, $\bar{\theta}_E^{RBE}(s) = 0$ for $s < s_E^*(\theta^*, \zeta_E)$. $s_E^*(\theta^*, \zeta_E)$ is decreasing in ζ_E: holding fixed s, investors are likelier to retain an event for more extreme event-types.

2. **[Events and overshooting]** For events categorized as exemplars ($s > s_E^*(\theta^*, \zeta_E)$), the RBE posterior $\bar{\theta}_E^{RBE}(s)$ exceeds the rational benchmark, and is increasing in ζ_E. As s increases, the ratio between the RBE and rational expectations converges to

$$\frac{\bar{\theta}_E^{RBE}(s)}{E^{rational}[\theta|s]} \mapsto \psi(\zeta_E, \nu), \tag{14}$$

   as in Proposition 1, with greater overreaction for more extreme event-types.

3. **[Price and Volume]** Suppose $\theta > s_E^*$ and $\nu \geq 1$: the availability weight sufficiently favors extreme events. Then, there exists a threshold ζ^* such that there is overreaction

[34] To proxy for individual attention and availability, we let the availability be a function of the signal s, rather than the latent fundamentals θ directly.

for $\zeta > \zeta^*$, and underreaction for $\zeta < \zeta^*$, and the degree of overreaction is increasing in ζ. Furthermore, holding the fundamentals θ constant, the total trading volume increases in ζ for ζ sufficiently large.

The first two predictions of Proposition 3 are analogous to those of Proposition 1. With non-events added, however, there is now underreaction for smaller events, which are likelier to be regarded as non-events. Figure 11a compares the exemplar distribution with the true base rate: the exemplar distribution is indeed fatter-tailed than the true base rate, and is censored below. Figure 11b displays RBE posteriors as a function of the private signal. The black curves represent the thin-tailed case, while the red curves represent the fat-tailed case, with the dotted lines showing the rational benchmark. RBE posteriors start at 0 – individuals treat the news as a non-event – and jump above the rational benchmark as agents categorize the news as an event, with greater overreaction for more extreme event-types. Individuals are also likelier to cross the threshold and classify a signal as an event for more extreme event-types.

The asset price formula, eq. (3), is now modified to:

$$p(\theta;\nu,\zeta_E,\kappa^{arb},\kappa^{RBE}) = \frac{\kappa^{arb}\theta + \kappa^{RBE}\left(1-\left(\frac{s_E^*(\theta^*,\zeta_E)}{\theta}\right)\right)\cdot\bar{\theta}^{RBE}(\theta,\zeta_E,\nu) + \kappa^{RBE}\left(\frac{s_E^*(\theta^*,\zeta_E)}{\theta}\right)\cdot\theta^d}{\kappa^{arb}+\kappa^{RBE}}. \tag{15}$$

The above expression encapsulates two opposing forces that determine whether asset prices react sensitively or sluggishly to news. First, there is the force for overreaction from RBE, as shown in our simple model. However, there is now an additional force for underreaction from investors who dismiss the event as a non-event. It is now ex ante not clear which force dominates: intuitively, the average valuation of the excited individuals, $\bar{\theta}^{RBE}(\theta,\zeta_E,\nu)$, must be sufficiently high relative to fundamentals θ for the aggregate market prices to overreact, which occurs for sufficiently extreme event-types.

Lastly, the volume prediction remains unchanged, save for a subtle non-monotonicity. The absolute mispricing of the asset is now non-monotonic in ζ: there is underreaction for sufficiently thin-tailed events, and overreaction for sufficiently fat-tailed events. Consequently, the relationship between volume and tails can be non-monotonic, as arbitrageurs trade against underreactors for thin-tailed events, and then against overreactors for fat-tailed events. Nevertheless, if the event-type is sufficiently extreme such that there is aggregate overreaction, total trading volume will increase with extremeness.

6.2 Calibration

In this final section, we take our full model directly to the data and calibrate the parameters of our model to quantitatively match the key moments. The target moments are the drift-reversal regression coefficients β_e and the conditional turnovers τ_e given a 10% movement in the market, across our main event-types.

We have four main parameters. The first two are the RBE parameters, θ^* and ν. We shall fix $\theta^* = 0.05$, roughly corresponding to the top 10% among the event-day returns. We shall directly fit the availability parameter ν. The next two parameters are market parameters: κ_{arb} and κ_{RBE}. While only the relative ratio of the two governs the price and hence the reversals, we need the absolute magnitudes to predict the turnover.

As we do not have closed form expressions for β_e or τ_e, we estimate the coefficients given our parameter values through simulation.[35] We choose the parameters $(\nu, \kappa_{arb}, \kappa_{RBE})$ that minimize the following expression:

$$(\hat{\nu}, \hat{\kappa}_{arb}, \hat{\kappa}_{RBE}) = \text{argmin} \frac{1}{\sigma_\beta} \left(\sum_{e=1}^{N} |\hat{\beta}_e(\nu, \kappa_{arb}, \kappa_{RBE}) - \beta_e| \right) + \frac{1}{\sigma_\tau} \left(\sum_{e=1}^{N} |\hat{\tau}_e(\nu, \kappa_{arb}, \kappa_{RBE}) - \tau_e| \right),$$

where β_e is the reversal coefficient and τ_e is the conditional turnover. In other words, we minimize the absolute deviation of the predicted and observed moments, normalizing by the scale parameters, σ_β and σ_τ, which are the dispersions in the observed empirical coefficients.[36]

Figure 12 shows the results of our calibration. Figure 12a plots the model-predicted β_e's against the actual β_e's in the data. Figure 12b plots the model-predicted τ_e's against the

[35]Specifically, given a guess for our parameters $(\nu, \kappa_{arb}, \kappa_{RBE})$, we generate 40,000 draws of the fundamentals for each event-type E: $\theta \sim Pareto(\theta_{0,E}, \zeta_E^{-1})$, where ζ_E is computed using the tails estimated in our power regressions, and $\theta_{0,E}$ is estimated to fit the average absolute value of the event-day returns in our data. For each draw of θ, we compute $p(\theta)$, and compute $\hat{\beta}_E(\nu, \kappa_{arb}, \kappa_{RBE}) = \frac{cov(p(\theta), \theta - p(\theta))}{var(p(\theta))}$ across the simulations. To reduce sampling error, we finally then smooth our simulated regression coefficient $\hat{\beta}_E$ across the event-types using the standard loess regression. We numerically integrate the expression for trading volume to obtain the estimated turnover, $\hat{\tau}_E$.

[36]The reason we minimize absolute differences rather than the squared errors is to reduce the influence of outliers in the regression coefficients. The general performance of our calibration remains largely unchanged when we instead minimize mean-squared-error.

actual τ_e's in the data. In Table 6, we also regress our calibrated β_e's and τ_e's on the observed values,

$$\begin{aligned} \tau_e &= \alpha_\tau + \lambda_\tau \cdot \widehat{\tau_e} + \epsilon_{e,\tau} \\ \beta_e &= \alpha_\beta + \lambda_\beta \cdot \widehat{\beta_e} + \epsilon_{e,\beta}, \end{aligned} \tag{16}$$

and find that our calibrated model fits the observed drift/reversal coefficients and conditional turnovers. The final calibrated parameters are given by $(\nu, \kappa_{RBE}/\kappa_{arb}) = (1.11, 2.72)$. Note that $\nu > 0$, and in particular $\nu \geq 1$, indicating there is substantially greater availability of more extreme events. Quantitatively, this implies that events with 10% event-day returns are roughly twice as available as exemplars than events with 5% returns.

7 Conclusion

To explain the variation in investor reactions to different types of news, we develop a model of investor psychology, where investors compare new events to available exemplars, or significant past occurrences of the same category of events. We then empirically document significant heterogeneity in the short-term market response to different event-types, as well as in the extremeness of the fundamental distribution of these event-types. We then test and confirm the two key novel predictions of our model: corporate event-types with more extreme fundamental distributions are associated with more overreaction and disagreement-driven trading volume.

The application of exemplar-based reasoning in financial settings merits future work. In particular, the true scope of RBE should be more precisely ascertained: in other words, which exemplars come to mind? The reaction to an event should depend on factors beyond event-types, such as richer firm and event characteristics. Measuring these features and linking them to market reactions will ultimately help improve our understanding of how investors react to news.

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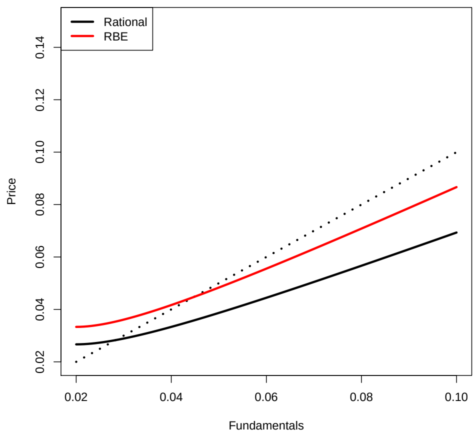
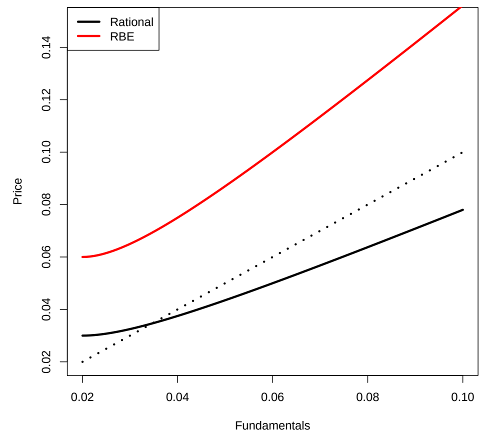
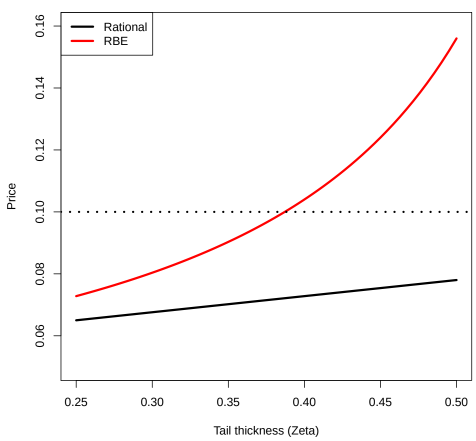
8 Figures and Tables



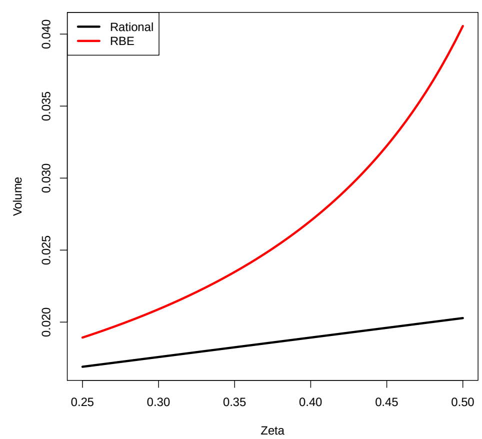
(a) Price vs Fundamentals, thin-tailed



(b) Price vs Fundamentals, fat-tailed



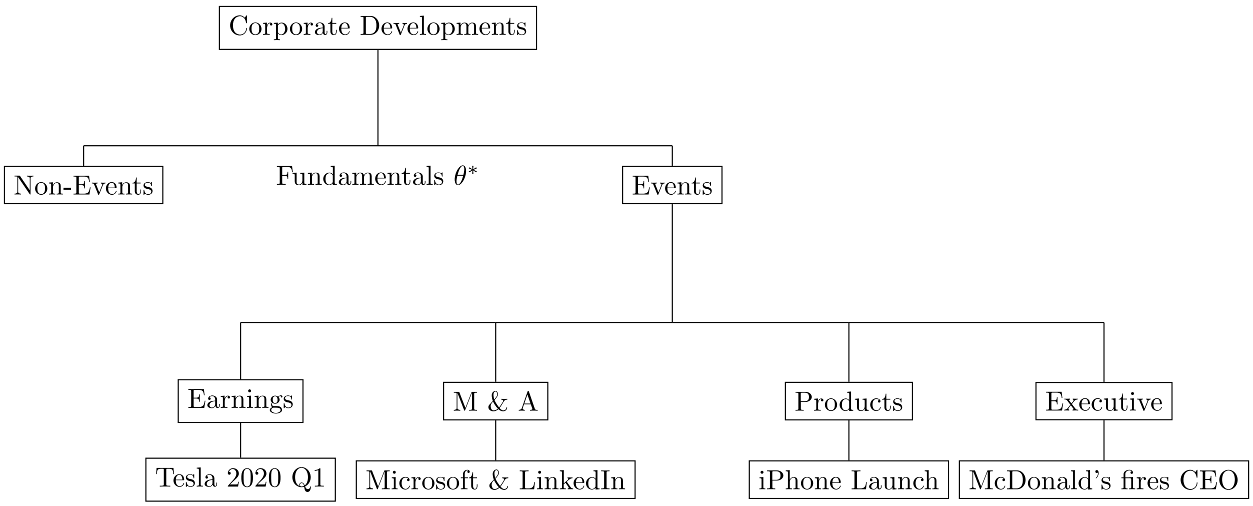
(c) (Normalized) Prices vs Tail Fatness



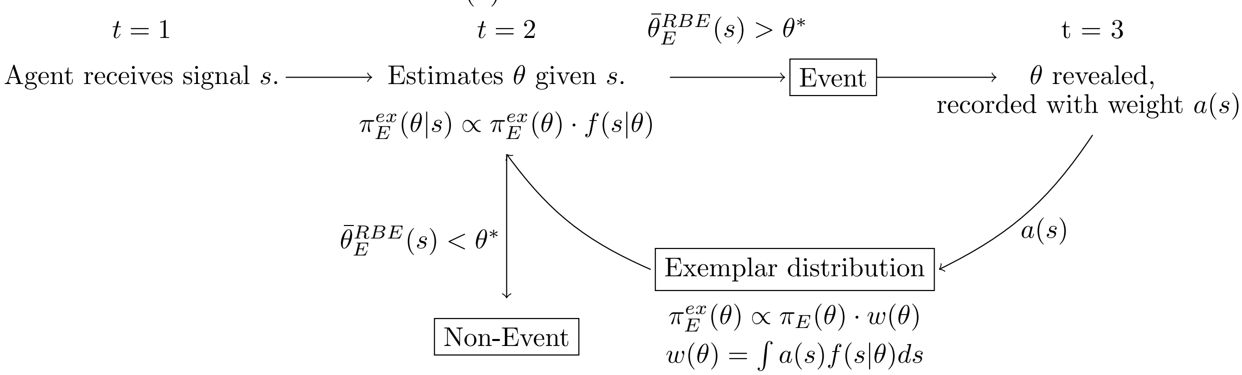
(d) Volume vs Tail Fatness

Figure 9: RBE predictions: price, volume, and extremeness

Note: Figure 9 summarizes the theoretical predictions in our basic RBE framework. First, Figures 9b and 9a plot the market price as a function of the fundamental signal for the rational agents in black and the RBE agents in red, separately for thin-tailed events (a) and fat-tailed events (b). Next, Figures 9c and 9d plot the market price and volume as a function of the tail fatness, holding fixed true fundamentals (at 10%) for a market with only rational agents in black and a market with both rational and RBE agents in red.



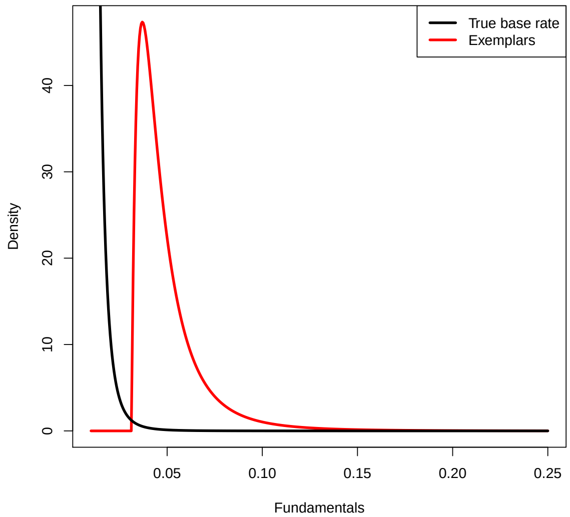
(a) Events vs Non-Events



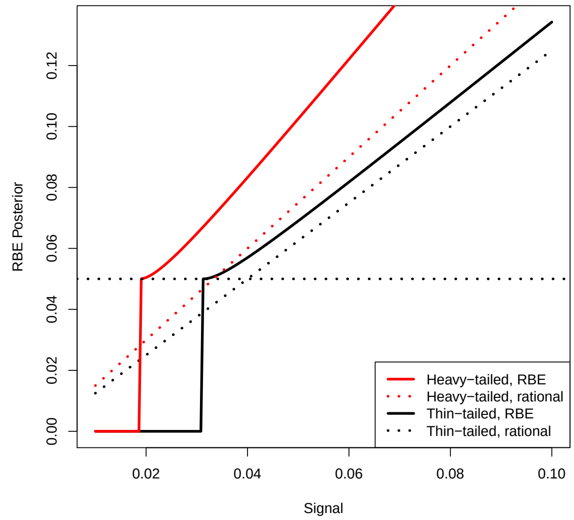
(b) Reasoning by exemplars, full model

Figure 10: RBE predictions: price, volume, and extremeness

Note: Figure 10 describes the full RBE process. Figure 10a presents the full diagram of reasoning by exemplars with the decision boundary threshold extension of events vs. non-events added to the simple framework in Section 4. Figure 10b diagrams the reasoning by exemplars process with belief updating and the decision boundary threshold of event vs. non-event.



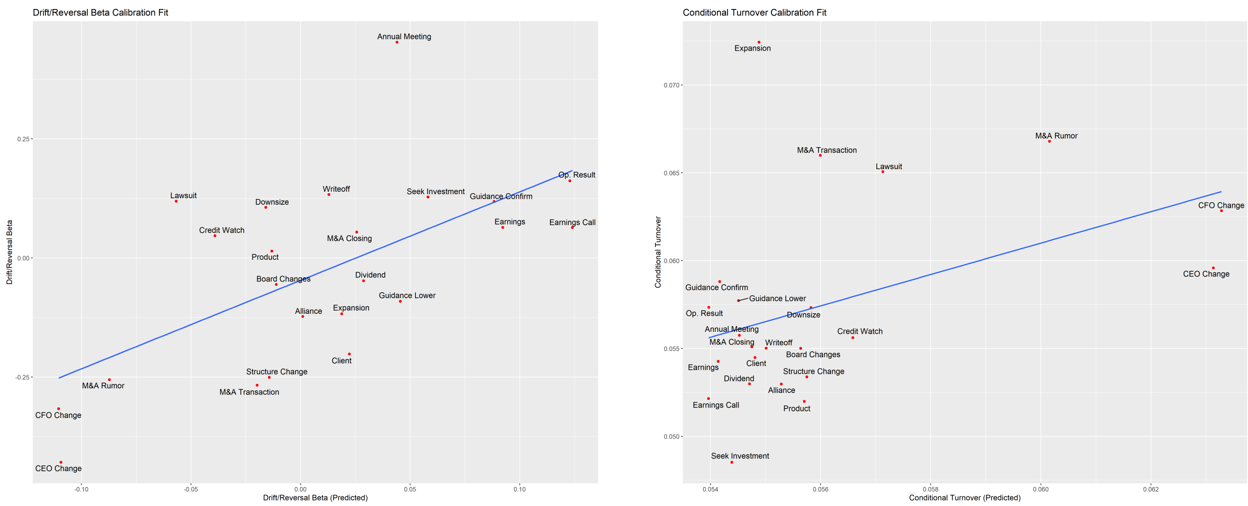
(a) Subjective base rate



(b) Conditional posterior

Figure 11: Modified RBE distribution

Note: Figure 11a plots the subjective beliefs of the RBE agents and true base rates of the fundamentals. Figure 11b plots the RBE and rational agents' conditional posteriors for heavy- and thin-tailed event distributions.



(a) Drift/Reversal fit

(b) Turnover fit

Figure 12: Calibration results

Note: Figure 12 presents the results of the calibration exercise. Panel (a) plots the empirically estimated drift/reversal β_e against the model-predicted β_e. Panel (b) plots the empirically estimated $\overline{Turnover}_{e,10}$ against the model-predicted conditional turnovers as estimated following eq. (13).

Table 1: Event Summary Statistics

Event	N	Mean	|Mean|	SD	Median	Turnover	ζ	ζ (s.e.)
Alliance	3281	0.14	1.29	2.20	0.09	1.10	0.41	0.02
Annual Meeting	4109	0.05	1.20	1.79	0.05	1.03	0.37	0.02
Board Changes	21779	0.07	1.35	2.14	0.08	1.12	0.43	0.01
CEO Change	1132	0.03	2.12	3.75	0.02	2.23	0.51	0.06
CFO Change	1428	-0.07	1.66	3.20	0.05	1.80	0.51	0.05
Client	19638	0.10	1.27	2.01	0.10	1.00	0.39	0.01
Credit Watch	1323	0.28	2.38	4.00	0.10	2.26	0.46	0.04
Dividend	1093	0.14	2.37	3.59	0.19	1.86	0.38	0.04
Downsize	2823	0.01	1.57	2.77	0.05	1.46	0.43	0.03
Earnings	23561	0.13	2.59	4.01	0.12	1.99	0.34	0.01
Earnings Call	15912	0.26	3.00	4.40	0.23	2.21	0.32	0.01
Expansion	9995	0.06	1.36	2.21	0.06	1.25	0.39	0.01
Guidance Confirm	19505	0.08	2.66	4.16	0.11	2.13	0.34	0.01
Guidance Lower	1172	-1.54	3.47	5.64	-0.64	2.53	0.37	0.04
Lawsuit	5511	0.04	1.36	2.25	0.04	1.33	0.47	0.02
M&A Closing	11152	0.10	1.29	1.98	0.08	1.10	0.39	0.01
M&A Rumor	4797	0.33	1.65	2.87	0.13	1.44	0.49	0.03
M&A Transaction	5108	0.33	1.71	3.01	0.16	1.46	0.44	0.02
Op. Result	1454	0.00	2.37	3.38	0.00	1.97	0.32	0.03
Product	22099	0.14	1.40	2.60	0.08	1.07	0.43	0.01
Seek Investment	7880	0.15	2.01	3.20	0.09	1.50	0.36	0.01
Structure Change	2596	0.10	1.30	2.10	0.14	1.20	0.43	0.03
Writeoff	3102	0.02	2.49	3.91	0.07	1.93	0.40	0.03
No Events	2803401	0.07	1.26	2.13	0.07	0.99	0.35	0.00

Note: Table 1 reports the summary statistics of event-day stock price returns and volume for each event-type in our event dataset. The sample is all firms listed on the major US stock exchanges with at least $2 billion in market capitalization between January 1, 2011 and December 31, 2018. |Mean| is the mean of the absolute event-day return. Mean, |Mean|, SD, and Median are all returns measured in percentage points. Vol is the event-day trading volume defined as the number of shares traded times the share price divided by total market capitalization times 100. ζ is the inverse power-law index corresponding to eq. (9). A higher value of ζ corresponds to fatter tails. ζ (s.e.) is the standard error associated with the estimation of ζ.

Table 2: β_e Drift/Reversal Estimates

Event	β_e	β_e s.e.
Alliance	-0.12	0.15
Annual Meeting	0.45	0.12
Board Changes	-0.05	0.09
CEO Change	-0.42	0.25
CFO Change	-0.31	0.32
Client	-0.18	0.08
Credit Watch	0.04	0.14
Dividend	-0.05	0.06
Downsize	0.15	0.18
Earnings	0.06	0.04
Earnings Call	0.06	0.05
Expansion	-0.10	0.14
Guidance Confirm	0.12	0.04
Guidance Lower	-0.09	0.11
Lawsuit	0.12	0.13
M&A Closing	0.05	0.08
M&A Rumor	-0.29	0.16
M&A Transaction	-0.28	0.08
Op. Result	0.21	0.08
Product	0.04	0.10
Seek Investment	0.13	0.06
Structure Change	-0.26	0.33
Writeoff	0.13	0.06
Joint F Statistic	2.74	

Note: Table 2 reports the β_e drift/reversal estimates for each corporate event-type corresponding to eq. (4). Standard errors are computed to account for both serial and cross-sectional correlations in the error term. The Joint F statistic corresponds to an F-test of overall significance of the pooled version of eq. (4), i.e. eq. (5).

Table 3: Prediction 1: Price and Tail Fatness

VARIABLES	(1)	(2)	(3)	(4)
Event-Day Return	0.55**	0.49**	0.61***	0.50***
	(0.23)	(0.23)	(0.14)	(0.15)
Event-Day Return × Tail Fatness	−1.46**	−1.24**	−1.50***	−1.21***
	(0.58)	(0.62)	(0.40)	(0.44)
Constant	0.02	−0.01*	0.01	−0.01***
	(0.02)	(0.01)	(0.02)	(0.01)
Time-Varying Tails	No	No	Yes	Yes
Return Benchmark	No	Yes	No	Yes
Observations	189,737	189,737	106,525	106,525

Note: Table 3 presents the estimated results corresponding to eq. (10). Observations are at the event level. The dependent variable is the cumulative return from day 1 to day 90 subsequent to the event. Event-Day Return is the stock price return of the firm on the day of the event and is measured in percentage points. Tail Fatness is $\zeta_{e,t}$, the inverse power-law index. Time-Varying Tails indicates whether the $\zeta_{e,t}$ is computed over a rolling window (Yes) or over the entire sample (No). Return Benchmark indicates whether the Event-Day Return and dependent variable are abnormal returns benchmarked against the S&P 500. Standard errors are computed to account for both serial and cross-sectional correlations in the error term. *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Prediction 1: Alternative Explanations

VARIABLES	(1) 90-Day	(2) 90-Day	(3) 90-Day	(4) 90-Day	(5) 90-Day	(6) 90-Day
Event-Day Return	0.57***	0.62*	0.60*	0.56***	0.63***	0.70**
	(0.20)	(0.37)	(0.34)	(0.20)	(0.24)	(0.29)
Event-Day Return × Tail Fatness	-1.36***	-1.46**	-1.41**	-1.31**	-1.45***	-1.63**
	(0.49)	(0.67)	(0.59)	(0.51)	(0.53)	(0.66)
Event-Day Return × Alternative Var.	-8.02	-0.76	-0.31	-0.13	-2.6e-06	-0.042
	(10.9)	(5.76)	(4.34)	(0.16)	(4.7e-06)	(0.076)
Observations	106,524	106,524	106,524	106,524	106,524	106,524
Alternative Hypothesis	Mean	IQR	St.Dev.	Abs. Sq.	N	Predict

Note: Table 4 presents the estimated results corresponding to eq. (12). Observations are at the event level. The dependent variable is the cumulative return from day 1 to day 90 subsequent to the event. Event-Day Return is the stock price return of the firm on the day of the event and is measured in percentage points. Tail Fatness is $\zeta_{e,t}$, the inverse power-law index, and are computed over rolling windows. Alternative Hypothesis indicates the alternative variable that is the explanatory regressor: Mean is the average event-day return. IQR is the inter-quartile range of the event-day return. St.Dev. is the standard deviation of the event-day return. Abs. Sq. is the absolute value of the event-day return. N is the number of total occurrences of the event. Predict is an indicator variable for whether the occurrence of the event is predictable. Returns are benchmarked to the S&P500. Standard errors are computed to account for both serial and cross-sectional correlations in the error term. *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Prediction 2: Volume and Extremeness

VARIABLES	(1) Turnover	(2) Turnover	(3) Turnover	(4) Turnover
Event-Day Return	0.32***	0.29***	0.24**	0.23**
	(0.094)	(0.091)	(0.093)	(0.093)
Event-Day Return × Tail Fatness	0.46*	0.58**	0.77***	0.79***
	(0.26)	(0.26)	(0.26)	(0.26)
Constant	0.0054***	0.0051***	0.0058***	0.0058***
	(0.00026)	(0.00026)	(0.00023)	(0.00023)
Observations	189,735	189,734	189,735	189,734
Trading Day FEs	No	Yes	No	Yes
Return Benchmark	No	No	Yes	Yes

Note: Table 5 presents the estimated results corresponding to eq. (13). Observations are at the event level. The dependent variable is the event-day turnover, defined as the volume of shares traded times the share price divided by the market capitalization. Event-day Return is the absolute stock price return of the firm on the day of the event and is measured in percentage points. Tail Fatness is $\zeta_{e,t}$, the inverse power-law index. Return Benchmark indicates whether the Event-Day Return and the day 1 to day 90 cumulative returns are abnormal returns benchmarked against the S&P 500. Standard errors are computed to account for both serial and cross-sectional correlations in the error term. *** p<0.01, ** p<0.05, * p<0.10.

Table 6: Calibration results

VARIABLES	(1) Drift/Reversal	(2) Turnover
Drift/Reversal (Predicted)	1.86***	
	(0.53)	
Turnover (Predicted)		0.89*
		(0.43)
Constant	-0.047	0.0074
	(0.034)	(0.024)
Observations	23	23
R-squared	0.369	0.170

Note: Table 6 presents the coefficient estimates corresponding to eq. (16). Observations are at the event-type level. The dependent variables are the actual drift/reversal and conditional turnovers for each event-type. Drift/Reversal (Predicted) is the model-predicted value of β_e for each event-type based on its tail fatness ζ_e. Turnover (Predicted) is the model-predicted value of τ_e for each event-type based on its tail fatness ζ_e. Standard errors are heteroskedasticity robust. *** p<0.01, ** p<0.05, * p<0.10.

Online Appendix

Reaction to News and Reasoning By Exemplars

Spencer Kwon and Johnny Tang

March 29, 2021

A Proofs

A.1 Proofs

The proof of Propositions 1 and 2 is a special application of the full model, given by Proposition 3. Thus we shall describe the general proof of Proposition 3.

Let us assume the decision rule given by s_E^*: for signals bigger than s_E^*, the individual places the event in the exemplar distribution, and discards them for signals smaller than s_E^*.

One can easily obtain $w(\theta)$ in closed form:

$$w(\theta) \propto \int_{s^*}^{\theta} a(s) f(s|\theta) ds \propto \int_{s^*}^{\theta} s^{\nu+\gamma-1}/\theta^{\gamma} ds = \frac{1}{\nu+\gamma}\left(1 - \left(\frac{s^*}{\theta}\right)^{\nu+\gamma}\right)\theta^{\nu} \tag{17}$$

In particular, standard power integrals show that conditional on observing the signal $s > s^*$, the RBE posterior mean is given by:

$$\bar{\theta}_E^{RBE}(s) = \frac{\frac{1}{\gamma+\zeta_E^{-1}-\nu-1} - \frac{1}{2\gamma+\zeta_E^{-1}-1}\left(\frac{s^*}{s}\right)^{\gamma+\nu}}{\frac{1}{\gamma+\zeta_E^{-1}-\nu} - \frac{1}{2\gamma+\zeta_E^{-1}}\left(\frac{s^*}{s}\right)^{\gamma+\nu}} s \tag{18}$$

From the expression, one can easily obtain that $\bar{\theta}_E^{RBE}(s)$ is increasing in s, and furthermore converges to $\frac{\gamma+\zeta_E^{-1}-\nu}{\gamma+\zeta_E^{-1}-\nu-1} s$ as $s \mapsto \infty$. Given such monotonicity, we thus confirm that $\bar{\theta}_E^{RBE}(s) > \theta^*$ if and only if $s > s_E^*$, which is implicitly defined by $\bar{\theta}_E^{RBE}(s) = \theta^*$. Indirectly, this is given by the above equation:

$$\theta^* = \frac{\gamma+\zeta_E^{-1}-\nu}{\gamma+\zeta_E^{-1}-\nu-1} \cdot \frac{2\gamma+\zeta_E^{-1}}{2\gamma+\zeta_E^{-1}-1} s_E^*, \tag{19}$$

or in other words, the endogenous decision boundary s^* is given by:

$$s_E^* = \frac{\gamma+\zeta_E^{-1}-\nu-1}{\gamma+\zeta_E^{-1}-\nu} \cdot \frac{2\gamma+\zeta_E^{-1}-1}{2\gamma+\zeta_E^{-1}} \theta^*. \tag{20}$$

One can easily thus see that $\frac{\partial s_E^*}{\partial \zeta_E} < 0$ for all parameters. A particularly simple case sets $\nu = 0$ and $\gamma = 1$, which yields:

$$s_E^* = \frac{1}{2\zeta_E + 1}, \tag{21}$$

the heavier the tail, the faster the tendency to jump to concluding that the event is significant.

Lemma 1. *The posterior expectation $E^{ex}[\theta|s]$ as a function of s is convex for $s \geq s^*$.*

Proof. Note that $E^{ex}[\theta|s]$ is increasing in s. We further wish to prove that $E^{ex}[\theta|s]$ is convex in s. After subtracting suitable affine functions, and noting that $\frac{1}{\gamma+\alpha-\nu-1} > \frac{1}{\gamma+\alpha-\nu} \cdot \frac{2\gamma+\alpha}{2\gamma+\alpha-1}$, it suffices to prove that the following expression:

$$\frac{1}{1 - \frac{\gamma+\alpha-\nu}{2\gamma+\alpha}\left(\frac{s^*}{s}\right)^{\gamma+\nu}} \cdot \frac{s}{s^*} \tag{22}$$

is a convex function of s, for $s > s^*$. After expanding the power-series of the former fraction (which trivially converges for our case), we can see that as $\gamma \geq 1$, $\nu \geq 0$, the above expression is an infinite sum of individually convex functions, which yields a convex function, as desired. □

Corollary 1. *The subjective posterior valuation $E^{ex}[\theta|s]$ is monotonically increasing in ζ.*

Proof. From the above discussion, we find that s^* is decreasing as a function of ζ_E. Thus, comparing two functions $E_i^{ex}[\theta|s]$ as a function of s with ζ_i satisfying $\zeta_E^1 < \zeta_E^2$, we have that the second function jumps to θ^* at $s^*(\zeta_E^2)$. This means that $E_2^{ex}[\theta|s] > E_i^{ex}[\theta|s]$ for $s_2^* < s < s_1^*$. Next, from the lemma, we have two convex functions, whose slopes increase monotonically to $\frac{\gamma+(\zeta_E^i)^{-1}-\nu}{\gamma+(\zeta_E^i)^{-1}-\nu-1}$ for $i = 1, 2$.

Suppose for the sake of contradiction that the thinner-tailed posterior expectation curve ever crosses the thicker-tailed posterior expectation curve. Locally, this implies that the instantaneous slope for the former is higher than the latter. However, as both curves are convex, this contradicts the observation that the asymptotic slopes as $s \mapsto \infty$ is higher for the thicker-tailed posterior expectation curve, as desired. □

Furthermore, relative to the rational posterior expectation of fundamentals given signal s, which is $E[\theta|s] = \frac{\zeta_E^{-1}+\gamma}{\zeta_E^{-1}+\gamma-1}s$, for $s > \theta_0$, we obtain the following coefficient of relative overreaction for individuals:

$$\psi(s;\zeta_E,\gamma,\nu) = \frac{E^{RBE}[\theta|s]}{E[\theta|s]} = \frac{\frac{\gamma+\zeta_E^{-1}-1}{(\gamma+\zeta_E^{-1}-1)-\nu} - \frac{\zeta_E^{-1}+\gamma-1}{2\gamma+\zeta_E^{-1}-1}\left(\frac{s^*}{s}\right)^{\gamma+\nu}}{\frac{\gamma+\zeta_E^{-1}}{\gamma+\zeta_E^{-1}-\nu} - \frac{\gamma+\zeta_E^{-1}}{2\gamma+\zeta_E^{-1}}\left(\frac{s^*}{s}\right)^{\gamma+\nu}} \tag{23}$$

From the expression, it is clear that term by term, $\frac{\gamma+\zeta_E^{-1}-1}{(\gamma+\zeta_E^{-1}-1)-\nu} > \frac{\gamma+\zeta_E^{-1}}{\gamma+\zeta_E^{-1}-\nu}$, and $\frac{\zeta_E^{-1}+\gamma-1}{2\gamma+\zeta_E^{-1}-1}\left(\frac{s^*}{s}\right)^{\gamma+\nu} < \frac{\gamma+\zeta_E^{-1}}{2\gamma+\zeta_E^{-1}}\left(\frac{s^*}{s}\right)^{\gamma+\nu}$, which implies that $\psi > 0$.

A.2 Proof of volume result

Proof. We prove the case for the uniform distribution $\gamma = 1$. The proof for the more general case proceeds analogously. For simplicity, we assume zero arbitrageurs: the proof is not effected by this assumption. We start by proving that $\bar{\theta}^{RBE}$ is increasing in ζ:

$$\bar{\theta}_E^{RBE} = \frac{1}{\theta - s_E^*}\int_{s_E^*}^{\theta} \bar{\theta}_E^{RBE}(s)ds \tag{24}$$

From Proposition 1, we note that the integrand is monotonically increasing in ζ, which implies that $\bar{\theta}^{RBE} \cdot \frac{\theta - s_E^*}{\theta}$ is increasing monotonically in ζ, which implies that the market equilibrium price p is monotonically increasing in ζ.

Next, consider the case where $\zeta \mapsto 0$: in this case, one can easily see that $\bar{\theta}_E^{RBE}(s) \mapsto s$, and $s_E^* \mapsto \theta^*$, which implies that for $\theta > \theta^*$, $p \mapsto \left(1 - \frac{\theta^*}{\theta}\right)\frac{\theta+\theta^*}{2} < \theta$: for sufficiently thin tails, the non-event thinking dominates, resulting in an underreaction.

In the other extreme, consider the case when the tail gets arbitrarily large. First, suppose that the availability is sufficiently distorted to favor extreme events $\nu \geq 1$. In this case, one can show that there exists $\zeta^* < 1$, such that as $\zeta \mapsto \zeta^*$, $\psi \mapsto \infty$, or in other words, $\bar{\theta}^{RBE}(s)$ increases arbitrarily holding s fixed. Consequently, this implies that $\bar{\theta}^{RBE}$, which is the aggregate over the signal realizations, increases arbitrarily, resulting in arbitrary overreaction and reversals.

As for volume, the following is the proof outline. First, from the proof of the first part of the proposition, as ζ gets sufficiently high, we are in the zone of aggregate overreaction, which implies that the arbitrageurs are trading against the RBE traders. Furthermore, as ζ continues to increase, one can show that the dominant share of the volume can be characterized by the arbitrageurs trading against the most optimistic RBE investors. Then, most of the total volume can be captured by the arbitrageur shorting, which is increasing in price, and we are done by the first part of the proposition. □

B Additional Robustness Exercises

B.1 Cross-section of β robustness exercises

A. Industry variations

Another potential concern is that the observed heterogeneity in post-event drift/reversal magnitudes does not reflect differences in reactions to events of different types, but to events occurring in different industries. To put it in extreme words, if all of our non-earnings events happen for tech companies, it may be that the reversals we are finding reflect overreaction to tech sector news, rather than differences in reactions to different types of events.

To test this hypothesis, we estimate modified versions of eqs. (4) and (5) to include industry-specific slopes as follows:

$$\begin{aligned} r_{e,c,t+1,t+k} &= \alpha_e + \beta \cdot r_{e,c,t,t+1} + \beta_d \cdot 1(Ind_d) \cdot r_{e,c,t,t+1} + \epsilon_{e,c} \\ r_{e,c,t+1,t+k} &= \alpha_e + \beta \cdot r_{e,c,t,t+1} + \beta_e \cdot 1(Event_e) \cdot r_{e,c,t,t+1} + \beta_d \cdot 1(Ind_d) \cdot r_{e,c,t,t+1} + \epsilon_{e,c}, \end{aligned} \tag{25}$$

where β_d is an industry-specific slope for each industry. As such, comparing the two specifications in eq. (25) tests for the differences in fit of adding event-type slopes to a model that already includes industry-specific slopes. Column (3) of Table A3 reports the estimates corresponding to the two specifications in eq. (25) respectively. We find that the F-test for nested models has a test statistic of 2.63 (p-value < 0.01), which strongly rejects the industry-specific slopes only model in favor of the model including event-type-specific slopes. This is consistent with the idea that there is significant variation in drifts and reversals across event-types, even after accounting for industry variations.

B. Stability of β_e estimates across time

Another potential concern is that the β_e estimates at the event-level may not be stable across time. We address this concern by re-estimating eq. (4) on two subsets of our sample period split by time. The first subset is all events before 2013 and the second subset is all events after 2013, which approximately corresponds to splitting the number of events in our sample in half. We use the same methodology as in eq. (4) and keep β_e estimates with at least 1000 observations in each subset. We then compute the correlation coefficient of β_e across all e's. The correlation coefficient is 0.53 and highly significant ($p < 0.05$), which indicates that the β_e estimates are fairly stable but have some noise across time. Figure A3 plots the coefficients across the two time periods and demonstrates the positive correlation of the β_e estimates across time.

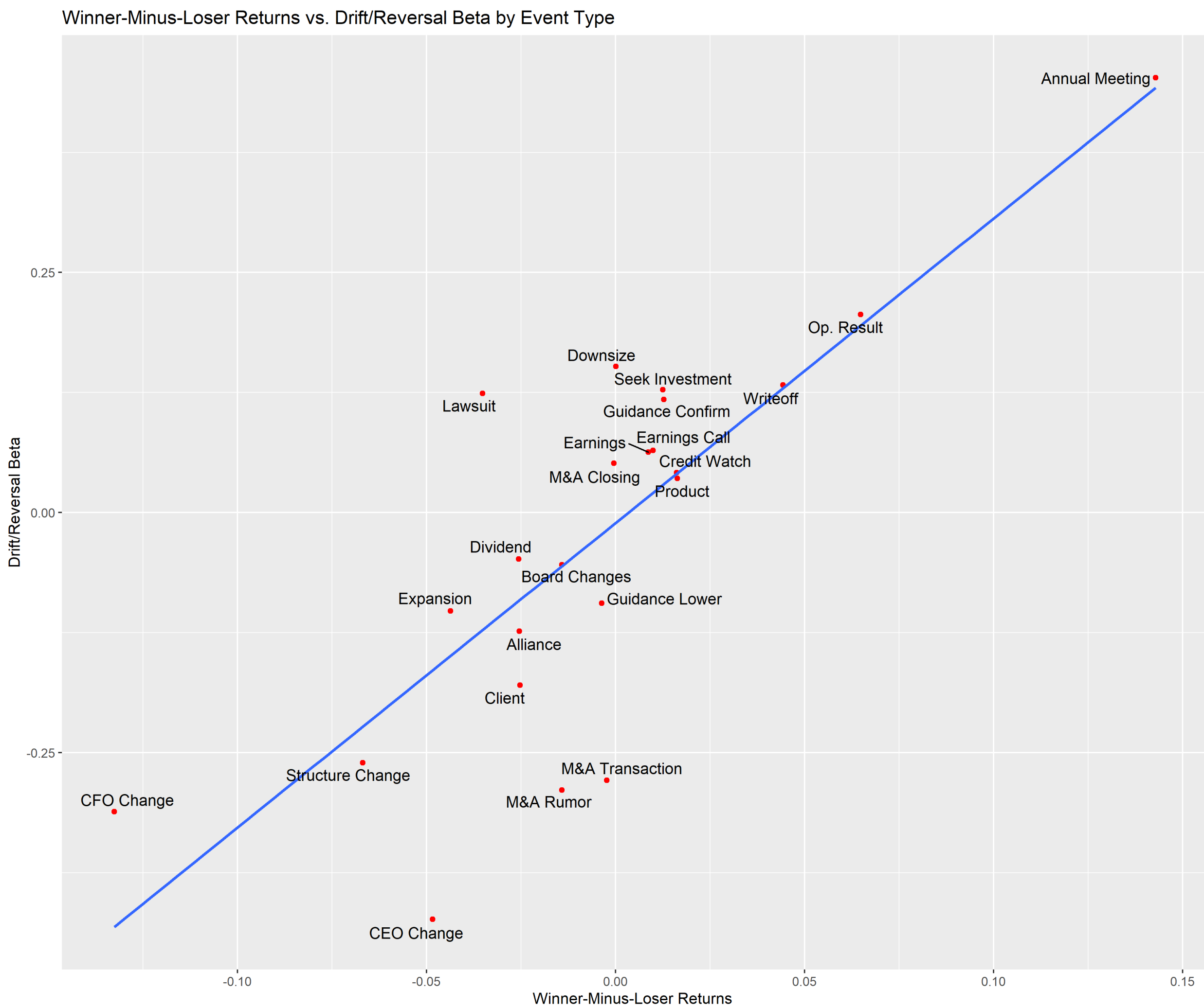
C. Logarithmic vs. linear returns

A final concern is that estimating return drifts and reversals in log returns rather than linear returns can bias the results due to convexity. Theoretically, since the return magnitudes for 99% of our sample is between -0.10 and 0.10, the bias due to convexity is orders of magnitudes smaller than the magnitudes of the returns. Nonetheless, we also estimate the β_e's in linear returns corresponding to eq. (4).

Figure A2 plots the β_e estimates for log returns and for linear returns. The linear return β_e's are highly positively correlated with the log return β_e estimates with a correlation coefficient of 0.83 (p-value < 0.01). Furthermore, the magnitudes of the dispersions in β_e estimates across event-types is almost identical between log returns and linear returns. Overall, these results suggest that our main measure of drifts and reversals, β_e, is robust to alternative measures in absolute returns.

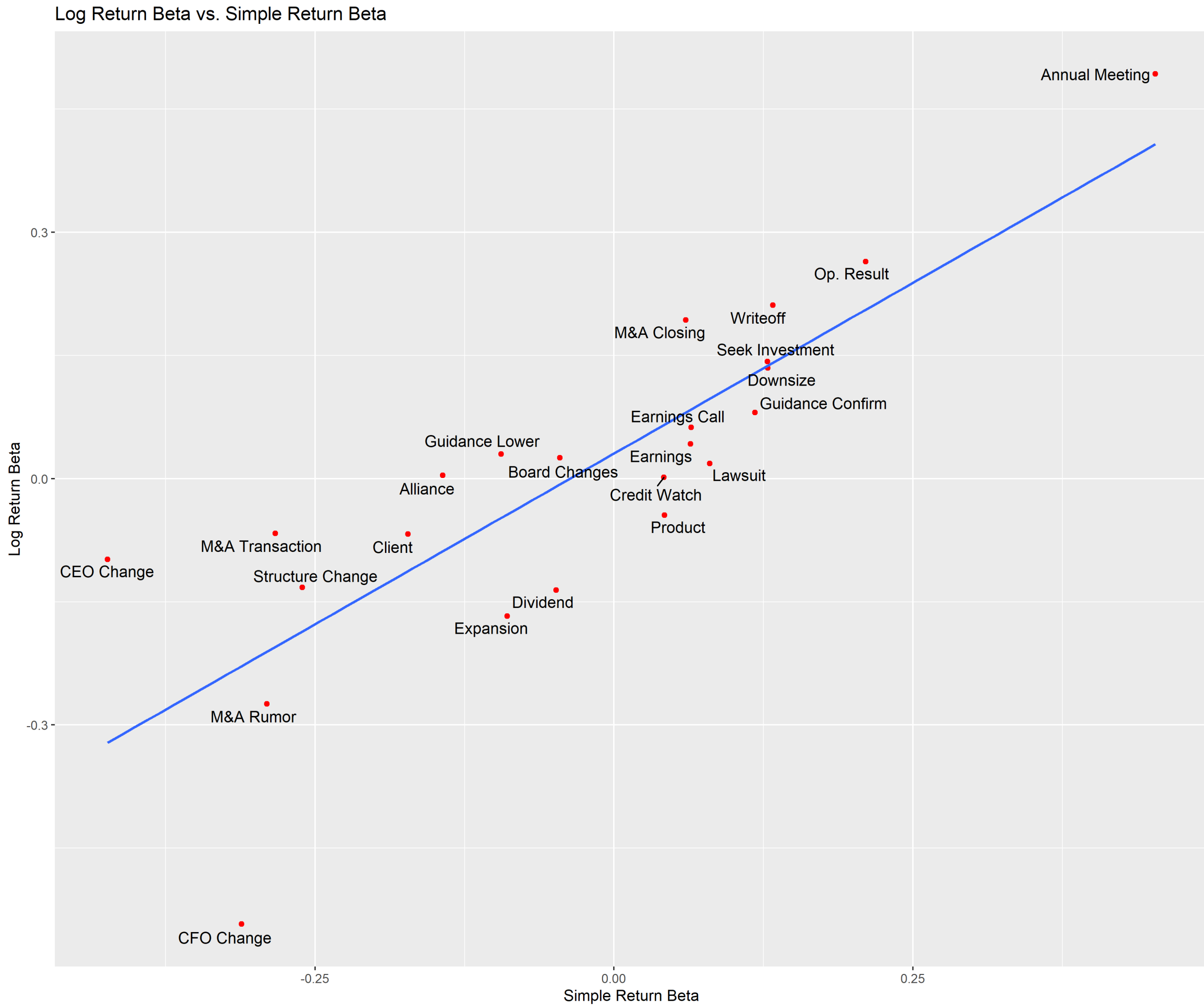
C Additional Figures and Tables

Figure A1: Reversal vs Drift β_E's vs. Winner-Minus-Loser Portfolios



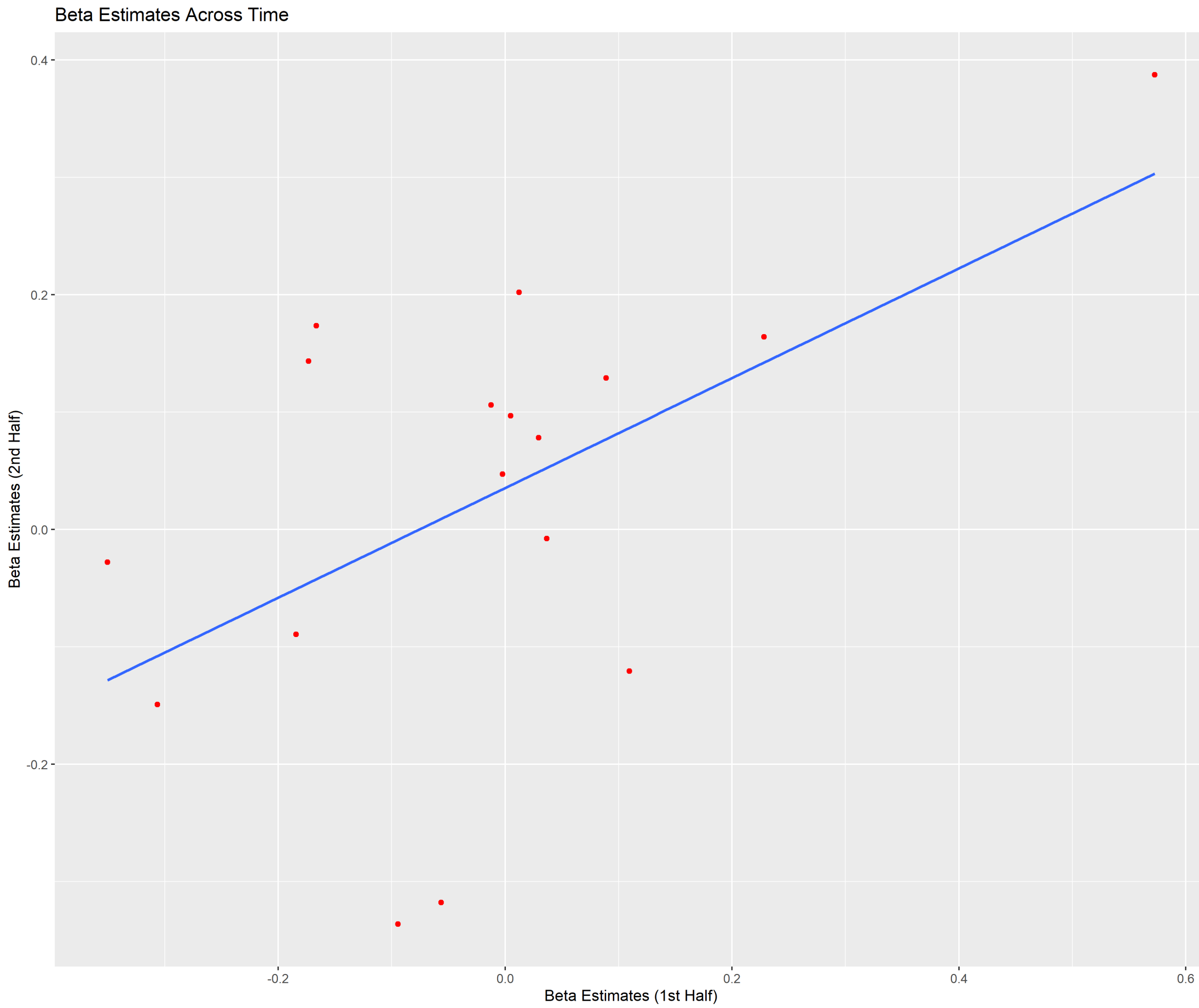
Note: Figure A1 plots the drift/reversal β_e coefficients against the drift/reversal UMD_e coefficients for each event-type e. The β_e coefficients are estimated for each event-type corresponding to eq. (4). The winner-minus-loser return coefficients UMD_e are estimated for each event-type e corresponding to eq. (8).

Figure A2: Reversal vs Drift β_E's: Logarithmic Returns vs. Simple Returns



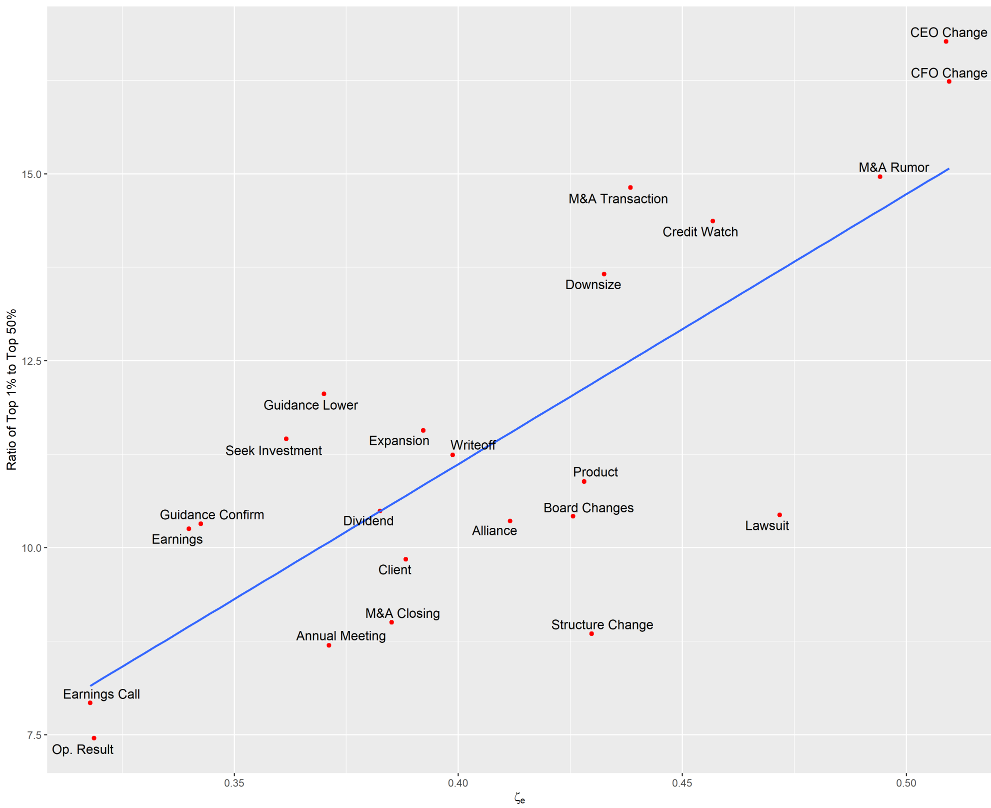
Note: Figure A1 plots the drift/reversal β_e coefficients estimated using logarithmic returns against the drift/reversal β_e coefficients estimated using linear returns for each event-type e. The log-return and linear-return β_e coefficients are all estimated for each event-type corresponding to eq. (4).

Figure A3: Beta Estimates Across Time



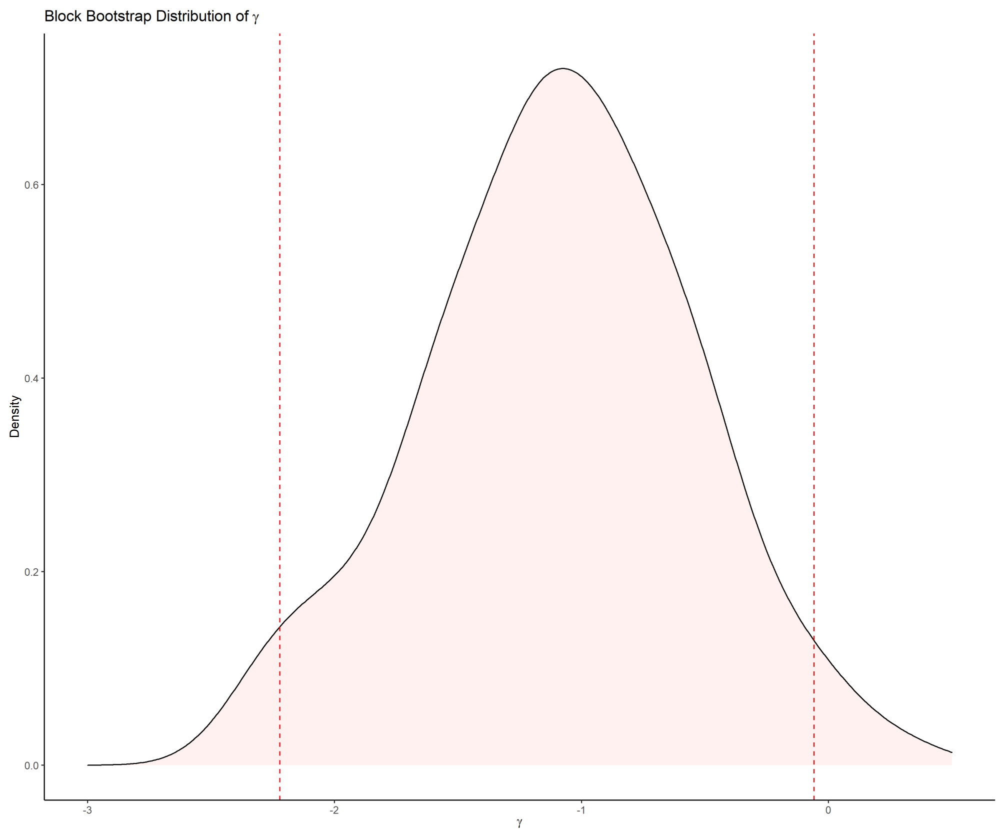
Note: Figure A3 reports the drift/reversal β_e coefficients for each event-type corresponding to eq. (4) described in Section 3.2 split by time. For each event-type, we construct two sub-samples: one of all event occurrences of the event-type before or during 2013 and one of all event occurrences of the event-type after 2013.

Figure A4: Ratio of Top 1% to Top 50% vs. Tail Fatness



Note: Figure A4 plots the relationship between the ratio of the top 1% to the top 50% of the absolute event-day stock returns against the tail fatness ζ_e's. The correlation coefficient is 0.78 (p-value < 0.01).

Figure A5: Bootstrap γ Coefficients



Note: Figure A5 plots the density of γ coefficients from the bootstrap test in Section 5.1.1. The γ coefficients are estimated on moving block bootstraps following eq. (10) across 1000 samples. The red dotted lines plot the 2.5% and 97.5% percentiles of the bootstrapped γ coefficients.

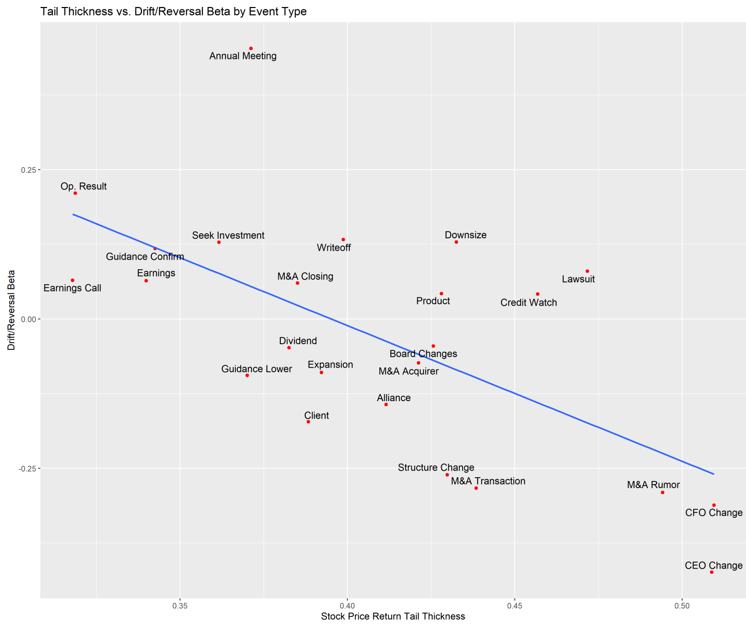


Figure A6: Tail Fatness vs. Post-Announcement Drift/Reversal Beta

Note: Figure A6 plots the relationship between tail fatness and post-announcement drift/reversal β_e for each event-type e with a separate event-type for acquirers in acquisitions. Tail fatness is the inverse Pareto index ζ_e estimated following eq. (9), and drift/reversal β_e is estimated following eq. (4).

Table A1: Corporate Event Sample Headlines

Event	Headline
Alliance	ChinaNet-Online Holdings, Inc Announces Strategic Partnership with Wuxi Jingtum Network Technology
Annual Meeting	STAAR Surgical Company, Annual General Meeting, Jun 11, 2009
Board Changes	Cellectar Biosciences, Inc. Announces Board Changes
CEO Change	MYOS Corporation Announces Executive Changes
CFO Change	Tetraphase Pharmaceuticals, Inc. Announces Resignation of Kamalam Unninayar as CFO, Effective March 16, 2018
Client	Ocean Power Technologies Enters Into First Commercial PB3 Agreement with Mitsui Engineering and Shipbuilding
Credit Watch	Issuer Credit Rating: BBB/Watch Neg/– From BBB/Negative/–: Local Currency Rating
Dividend	Johnson Controls International plc Approves Quarterly Cash Dividend, Payable on Jan. 6, 2017
Downsize	Pier 1 Imports Inc. Plans to Close 16 Stores
Earnings	Fonar Corp. Reports Unaudited Consolidated Earnings Results for the Third Quarter and Nine Months Ended March 31, 2009
Earnings Call	AtriCure, Inc., Q1 2009 Earnings Call, May-05-2009
Expansion	Aemetis, Inc. Completes Construction of Advanced Biodiesel Pre Treatment Unit Required for BP Supply Agreement
Guidance Confirm	Pareteum Corporation Provides Revenue Guidance for the Second Quarter Ended June 30, 2017
Guidance Lower	Crestwood Revises Earnings Guidance for the Year 2016
Lawsuit	Hospitality Properties Trust Announces Settlement of Litigation with TravelCenters of America LLC
M&A Closing	Appliance Recycling Centers of America, Inc. (NasdaqCM:ARCI) acquired GeoTraq Inc. for $16 million.
M&A Rumor	PZU Eyes AIG Assets
M&A Transaction	Differential Brands Group Inc. (NasdaqCM:DFBG) entered into a definitive purchase agreement to acquire majority of North American licensing business of GBG USA, Inc. for $1.4 billion.
Op. Result	Delta Air Lines, Inc. reports operating results for the 2014 Q4
Product	Inovio Biomedical Corporation influenza vaccines demonstrate 100% protection against current pandemic A/ H1N1 influenza viruses in animal studies
Seek Investment	Insmed seeks acquisitions
Structure Change	Diffusion Pharmaceuticals Inc. approves amendment to Certificate of Incorporation
Writeoff	Manitowoc Co. Inc. announces impairment charges for 2009 Q1

Note: Table A1 reports example news headlines for each of the corporate event-types in the dataset.

Table A2: Corporate Event Overlap with Earnings Announcements

Event	Closest	Next	Previous	Day Of	5 Days Of
Alliance	30	47	48	0.12	0.10
Annual Meeting	20	22	73	0.13	0.21
Board Changes	31	44	52	0.13	0.13
CEO Change	31	49	53	0.21	0.19
CFO Change	30	45	55	0.20	0.21
Client	30	45	48	0.10	0.11
Credit Watch	31	43	55	0.18	0.14
Dividend	5	90	87	0.88	0.88
Downsize	28	47	52	0.20	0.21
Earnings	0	90	91	1.00	1.00
Earnings Call	2	90	92	0.90	0.98
Expansion	27	49	51	0.18	0.18
Guidance Confirm	6	90	84	0.88	0.87
Guidance Lower	11	90	73	0.76	0.73
Lawsuit	31	45	50	0.11	0.10
M&A Closing	32	49	52	0.30	0.17
M&A Rumor	33	48	50	0.11	0.12
M&A Transaction	31	49	53	0.20	0.18
Op. Result	10	85	77	0.78	0.72
Product	30	44	48	0.10	0.10
Seek Investment	22	47	70	0.42	0.43
Structure Change	29	39	55	0.15	0.15
Writeoff	1	91	88	0.98	0.98

Note: Table A2 reports the average proximity to earnings announcements of each corporate event type in the database. Closest, Next, and Previous are the average numbers of days between each corporate event-type and the closest, next, and previous earnings announcement of the same firm, respectively. Day Of and ± 5 Days Of measure the probability that events of each corporate event-type occurred on the exact day and within 5 days of an earnings announcement of the same firm.

Table A3: F Tests

	(1)	(2)	(3)
Observations	198,540	2,783,030	198,172
Event-Type Slopes	Yes	Yes	Yes
Full Firm-Day Panel	No	Yes	No
F Statistic	2.74	1.94	2.63

Note: Table A3 reports the F statistics corresponding to testing eq. (4) against eq. (5) in Column (1), an F-test for overall significance for eq. (6) in Column (2), and testing the two specifications in eq. (25) in Column 3, respectively.

Table A4: Firm-Day Panel

Event	β	β (s.e.)	β	β (s.e.)	β	β (s.e.)
Alliance	0.06	0.11	0.06	0.11	0.09	0.1
Annual Meeting	0.43	0.06	0.43	0.07	0.41	0.06
Board Changes	-0.04	0.03	-0.04	0.03	-0.04	0.03
CEO Change	-0.37	0.1	-0.37	0.1	-0.38	0.11
CFO Change	0.11	0.09	0.11	0.09	0.09	0.09
Client	-0.14	0.07	-0.14	0.06	-0.11	0.06
Credit Watch	-0.13	0.1	-0.13	0.1	-0.11	0.1
Downsize	0.01	0.13	0.01	0.13	0	0.13
Earnings	0.06	0.01	0.06	0.01	0.06	0.01
Expansion	-0.04	0.06	-0.04	0.06	-0.03	0.07
Lawsuit	-0.02	0.1	-0.02	0.1	-0.04	0.1
M&A Closing	0.08	0.04	0.07	0.03	0.09	0.04
M&A Rumor	-0.32	0.14	-0.32	0.14	-0.26	0.14
M&A Transaction	-0.15	0.03	-0.15	0.03	-0.11	0.04
Product	0.07	0.04	0.06	0.04	0.09	0.04
Seek Investment	0.06	0.03	0.06	0.02	0.07	0.02
Structure Change	-0.1	0.15	-0.1	0.16	-0.11	0.16
$f(r_{c,t})$	Baseline		Linear		Non-Parametric	

Note: Table A4 reports the estimated results corresponding to eq. (6). $f(r_{c,t})$ is the function for controlling for event-day returns. Baseline indicates no $f(r_{c,t})$ function. Linear indicates $f(r_{c,t}) = \gamma \cdot r_{c,t}$. Non-Parametric indicates $f(r_{c,t}) = \sum_{i=1}^{10} \gamma_i \cdot 1(r_{c,t} \in \Delta_i)$, where $1(r_{c,t} \in \Delta_i)$ is an indicator variable for whether $r_{c,t}$ is in the i-th decile of all event-day returns. Standard errors are computed based on Driscoll and Kraay (1998) to account for both serial and cross-sectional correlations in the error term.

Table A5: Alternative Horizons

Event	$\beta_{e,30}$	$\beta_{e,30}$ s.e.	$\beta_{e,60}$	$\beta_{e,60}$ s.e.	$\beta_{e,120}$	$\beta_{e,120}$ s.e.
Alliance	-0.01	0.10	0.05	0.15	0.08	0.19
Annual Meeting	0.16	0.06	0.43	0.09	0.44	0.20
Board Changes	-0.05	0.04	-0.10	0.07	-0.06	0.11
CEO Change	-0.26	0.15	-0.34	0.17	-0.43	0.33
CFO Change	-0.14	0.14	-0.04	0.26	-0.33	0.37
Client	-0.04	0.04	-0.11	0.08	-0.10	0.08
Credit Watch	0.03	0.06	0.09	0.09	0.04	0.19
Dividend	0.06	0.02	0.05	0.08	-0.10	0.06
Downsize	0.08	0.08	0.15	0.12	0.23	0.23
Earnings	0.04	0.02	0.07	0.03	0.12	0.05
Earnings Call	0.06	0.02	0.08	0.03	0.12	0.07
Expansion	-0.03	0.08	-0.06	0.12	-0.07	0.14
Guidance Confirm	0.05	0.02	0.10	0.03	0.17	0.05
Guidance Lower	-0.09	0.05	-0.01	0.09	-0.04	0.13
Lawsuit	0.03	0.07	0.19	0.10	0.32	0.18
M&A Closing	0.08	0.05	0.08	0.08	-0.01	0.12
M&A Rumor	-0.14	0.05	-0.24	0.11	-0.36	0.22
M&A Transaction	0.02	0.04	0.00	0.06	-0.31	0.10
Op. Result	0.07	0.05	0.18	0.07	0.34	0.15
Product	0.03	0.05	0.05	0.08	0.16	0.10
Seek Investment	0.03	0.03	0.08	0.04	0.23	0.06
Structure Change	-0.14	0.20	0.04	0.15	-0.40	0.37
Writeoff	0.05	0.04	0.13	0.06	0.21	0.06

Note: Table A5 reports the β_e drift/reversal estimates for each corporate event-type corresponding to eq. (4) for varying time horizons (30 days, 60 days, and 120 days). Standard errors are computed to account for both serial and cross-sectional correlations in the error term.

Table A6: Alternative Measures of Fundamentals

Event-Day Return	1	0.74	0.37	0.53	0.48	0.39	0.22
Long-Run Return	0.74	1	0.21	0.25	0.23	0.14	0.06
Cash Flow 1yr	0.37	0.21	1	0.53	0.52	0.63	0.65
Cash Flow 2yr	0.53	0.25	0.53	1	0.92	0.91	0.73
Cash Flow 3yr	0.48	0.23	0.52	0.92	1	0.96	0.70
Cash Flow 4yr	0.39	0.14	0.63	0.91	0.96	1	0.82
Cash Flow 5yr	0.22	0.06	0.65	0.73	0.70	0.82	1

Note: Table A6 reports the correlation between the extremeness of event-day stock price returns (ζ_e) with alternative measures of fundamentals: (1) the extremeness of the long-run stock price returns, defined as the power law index of the distribution of the stock price returns of each corporate news event type over a 100-day period; (2) the extremeness of the cash flow growth, defined as the percentage change in earnings per share between the respective number of years after the event and the fiscal year immediately preceding the event. For instance, the k-year cash flow growth associated with an event of firm i in year t is defined as $\Delta EPS_{i,t+k} = EPS_{i,t-1+k}/EPS_{i,t-1} - 1$. The cash flow growth sample is restricted to firms whose earnings per share in the year $t-1$ are at least 10 cents. Observations are at the event-type level.

Table A7: Prediction 1: 30 Days

VARIABLES	(1)	(2)	(3)	(4)
Event-Day Return	0.35***	0.34***	0.27**	0.24**
	(0.12)	(0.11)	(0.12)	(0.11)
Event-Day Return × Tail Thickness	-0.92***	-0.83***	-0.67**	-0.55*
	(0.33)	(0.32)	(0.31)	(0.30)
Observations	189,737	189,737	106,525	106,525
Time-Varying Tails	No	No	Yes	Yes
Return Benchmark	No	Yes	No	Yes

Note: Table A7 presents the estimated results corresponding to eq. (10). Observations are at the event level. The dependent variable is the cumulative return from day 1 to day 30 subsequent to the event. Event-Day Return is the stock price return of the firm on the day of the event and is measured in percentage points. Tail Fatness is $\zeta_{e,t}$, the Pareto index tail fatness measure. Time-Varying Tails indicates whether the $\zeta_{e,t}$ is computed over a rolling window (Yes) or over the entire sample (No). Return Benchmark indicates whether the Event-Day Return and the day 1 to day 30 cumulative returns are abnormal returns benchmarked against the S&P 500. Standard errors are computed to account for both serial and cross-sectional correlations in the error term. *** p<0.01, ** p<0.05, * p<0.10.

Table A8: Prediction 1: 60 Days

VARIABLES	(1)	(2)	(3)	(4)
Event-Day Return	0.46***	0.46***	0.40**	0.41***
	(0.16)	(0.16)	(0.16)	(0.16)
Event-Day Return × Tail Thickness	-1.16**	-1.08**	-0.94**	-0.91**
	(0.45)	(0.45)	(0.40)	(0.39)
Observations	189,737	189,737	106,525	106,525
Time-Varying Tails	No	No	Yes	Yes
Return Benchmark	No	Yes	No	Yes

Note: Table A8 presents the estimated results corresponding to eq. (10). Observations are at the event level. The dependent variable is the cumulative return from day 1 to day 60 subsequent to the event. Event-Day Return is the stock price return of the firm on the day of the event and is measured in percentage points. Tail Fatness is $\zeta_{e,t}$, the Pareto index tail fatness measure. Time-Varying Tails indicates whether the $\zeta_{e,t}$ is computed over a rolling window (Yes) or over the entire sample (No). Return Benchmark indicates whether the Event-Day Return and the day 1 to day 60 cumulative returns are abnormal returns benchmarked against the S&P 500. Standard errors are computed to account for both serial and cross-sectional correlations in the error term. *** p<0.01, ** p<0.05, * p<0.10.

Table A9: Prediction 1: Reverse Casusality Tests

	(1)	(2)	(3)	(4)	(5)	(6)
Event-Day Return	0.40*	0.91**	0.94***	0.76***	0.64***	0.31
	(0.24)	(0.41)	(0.34)	(0.26)	(0.24)	(0.21)
Event-Day Return × Tail Thickness	−1.16*	−1.18**	−1.24***	−0.96***	−0.76**	−0.34
	(0.63)	(0.55)	(0.46)	(0.34)	(0.30)	(0.26)
Constant	0.02	−0.01*	−0.01*	−0.01*	−0.01*	−0.01*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Horizon	100 Days	1 Year	2 Year	3 Year	4 Year	5 Year
Measure	Returns	CF	CF	CF	CF	CF
Observations	189,737	189,737	189,737	189,737	189,737	189,737

Note: Table A9 presents the estimated results corresponding to eq. (11). Observations are at the event level. The dependent variable is the cumulative abnormal return from day 1 to day 90 subsequent to the event. Event-Day Return is the abnormal stock return of the firm on the day of the event and is measured in percentage points. Tail Fatness is the measure of extremeness of the distributions of long-run returns or cash flow growths of each event type e. Horizon is the time period over which the extremeness of the distributions of returns (Returns) or cash flow growths (CF) is measured. Measure is the long-run stock returns (Returns) or cash flow growths (CF). The k-year cash flow growth is defined as $\Delta EPS_{i,t+k} = EPS_{i,t-1+k}/EPS_{i,t-1} - 1$, which is the percentage change in earnings per share of firm i from the fiscal year immediately preceding the event, $t-1$, to year $t+k$. We exclude firms with earnings per share in year $t-1$ less than 10 cents from our sample. Standard errors are computed to account for both serial and cross-sectional correlations in the error term. *** p<0.01, ** p<0.05, * p<0.10.