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By

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Abstract

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Frictions affecting information demand play an essential role in equilibrium outcomes of financial markets, and the behavior of investors, managers, and regulators. Demand-side information frictions can be the result of costly information acquisition or psychological factors, and can interact with various behavioral biases resulting in outcomes that would be puzzling in traditional, entirely rational models.

The first chapter models the learning and trading decision of investors in an economy with regular public announcements and costly information. Scheduled public announcements affect the information acquisition decision of traders, who in equilibrium focus their learning on stocks with upcoming announcements. When learning is endogenous, public announcements have a significant effect on information acquisition, price movements, and price informativeness. Using quarterly earnings announcements as regular and major information events, I document a number of patterns consistent with rational allocation of limited learning capacity. In the time-series, I show that costly information acquisition results in lower learning and price movements before announcements on busier weeks. In the cross-section of stocks, I find that learning and price movements are lower when other announcing firms are more valuable to learn about. The results suggest that learning plays a significant role in pre-announcement market movements, previously mainly attributed to leakage of insider information.

In the second chapter, I propose a new approach to model the role of regret and rejoice in dynamic stopping problems; where past outcomes the agent chose not to reach act as reference points. An agent with regret induced reference points exhibits history dependent behavior, and if the stopping decision affects the set of available information, a regret agent is more likely to continue (stop) than a fully rational decision maker when regret level is sufficiently high (low). I show that this approach to regret and rejoice can provide a unified explanation for various previously analyzed phenomena in investor and CEO behavior, such as the disposition effect, the sunk cost fallacy, and the escalation of commitment. In an equilibrium asset pricing framework, regret generates asymmetric price reaction to news, where good information is reflected in prices to a lower extent than bad news.

To whom it may concern.

And to my loved ones, but they are unlikely to read it.

Contents

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Chapter 1

Costly Information Acquisition and Public Announcements

Public announcements play a vital role in financial markets. They provide information to investors, previously only known to insiders. Such announcements can be regular disclosure of company information, like earnings or dividend announcements. They can also inform investors about a firm's planned actions, for example, mergers, or equity issuance. Unsurprisingly, stock prices usually respond strongly to the release of unexpected news (see for example Beaver, 1968; Hite and Owers, 1983). However, in a number of important releases, stock prices respond even prior to the announcement. For example, in the case of earnings announcements (Ball and Kothari, 1991), or before announcements of mergers and acquisitions (Gao and Oler, 2012). The typical interpretation for these reactions, is insider trading (Keown and Pinkerton, 1981; Penman, 1982; Meulbroek, 1992). My paper proposes a different explanation, that pre-announcement trading activity and abnormal returns can be a result of costly information acquisition.

There is a long tradition in finance emphasizing the role of information frictions for asset prices, since Grossman and Stiglitz (1980). These frictions can be a result of costly information acquisition, as trading firms have a finite number of employees working a finite number of hours. Alternatively, they can arise through rational inattention as cognitive constraints act as a fundamental source of information costs. If investor learning is constrained by information costs, focusing the learning and consequently informed trading to short periods before the information becomes public, could arise as a rational outcome. This timing would be counter-intuitive in a frictionless world but can be optimal when costly information poses constraints on learning. Investors with limited capacity to learn, choose to focus on assets where the value of information is most valuable, hence learning about stocks with upcoming announcements.

I construct an infinite horizon model, with three risky assets and the regular release of public information; where private information is costly, and rational traders optimally allocate their constrained learning capacity. Firms' earnings follow AR(1) processes, and in each period some firms publicly announce the next realization of the innovation. Investors with mean-variance preferences can observe noisy private signals, and choose their signal precisions optimally, subject to an entropy constraint. Given the form of the constraint, the investors' capacity allocation decision has a corner solution, so each trader learns only about one of the three risky assets. A firm with higher earnings persistence will observe a more significant price reaction to the announcement; thus it is a more valuable target of learning for investors. However, there are strategic considerations in learning as well. Acquiring information about a stock is more valuable if fewer traders learn about it today, or if investors will learn more about it in the next period. The presence of an upcoming announcement also increases the value of learning. If information costs are sufficiently high, then there exists a focusing equilibrium, where all investors focus their learning, and only obtain information about firms with upcoming announcements. Besides the timing of informed trades, the model provides further predictions that differentiate it from standard models of learning. When there are multiple announcements, and the equilibrium is in mixed strategies, each investor randomize which announcing stock to learn about. The fraction of traders focusing on a stock, therefore the returns and trading volume of that stock, depends on the earning process parameters of both announcing firms.

To empirically test the model's implications, I use quarterly earnings announcements of publicly traded US firms between 1990 and 2017, as regular and important information events. Using data on institutional investor attention calculated by Bloomberg, based on terminal searches for firm-related information; pre-announcement price movements measured by cumulative abnormal returns and trading volume. I show that information appears costly. Investor attention spikes in the weeks before the announcement and the increase is significantly higher before weeks with fewer announcements. In the time-series, the number of announcements in each week has a negative effect on average attention, abnormal returns, and trading volume in the pre-announcement period. In the cross-section, I find that the earnings process parameters of other announcing firms' also have a significant and negative effect on attention and market reactions of an asset. Using regressions of market outcomes of a stock on the firm's own, and other announcing firms' characteristics, I show that returns and trading volume is higher when other firms have lower earnings persistence, thus learning about these other announcements is less valuable.

Findings are consistent with costly information acquisition, and rational investors reacting to constraints in learning. This argument suggests, that the abnormal excess returns observed before anticipated public announcements can, at least partially be a result of focused learning, and informed trading by investors, rather than a consequence of leaked information. Such distinction of causes would have consequences on how price movements before announcements expected to change as technology continues to improve and AI-based methods start to ease human constraints in information discovery. There are also significant implications for price informativeness, asset price movements, and volatility patterns. Assets with upcoming announcements have greater price movements, while other, non-announcing stocks' price informativeness is lower. These results also suggest that the interaction of market structure, regulations and firms' disclosure activity, with investors' information acquisition decision have broader implications. They have significant effects on asset prices and market outcomes in a variety of settings.

Literature review. The pertinence of information frictions in financial markets is well known. Many fundamental papers since Grossman and Stiglitz (1980) and Glosten and Milgrom (1985) have analyzed the effects of learning and information structures. In recent decades, an increasing amount of research has focused on information costs and frictions related to processing and interpreting available information. On the theoretical side, an emerging literature focuses on what effect rational investor reaction to information costs and constraints has on markets, and how said frictions and market structure interact.

Mondria (2010) shows how investor reaction to learning constraints can lead to asset co-movements; Van Nieuwerburgh and Veldkamp (2010) argue these frictions can result in investor specialization and under diversification. Kacperczyk et al. (2016) analyze how attention allocation of mutual fund investors reacts to the market environment and interacts with manager skill. Kacperczyk et al. (2018) show how constrained learning interacts with market structure, and that predictions of models with endogenous learning can have major differences from models with exogenously given information structure. Nezafat et al. (2017) provide a model illustrating how costly information acquisition can interact with short-sale constraints. Under endogenous and costly learning, constraints on portfolios can decrease price and increase volatility. Van Nieuwerburgh and Veldkamp (2009) show how limited attention can explain home stock bias. Mondria (2010) and Mondria and Quintana-Domeque (2012) connect asset co-movements to learning constraints.

The empirical literature on information costs and learning capacities has well established that information processing of market participants is not frictionless. DellaVigna and Pollet (2009) show lower investor attention on Fridays, using variation in firm announcements across days of the week. Fedyk (2018) exhibits evidence that the positioning of news matters, as front page information in Bloomberg gets incorporated to prices faster. Corwin and Coughenour (2008) find that market activities affect NYSE specialists' attention, and this has implications for liquidity provision. Hirshleifer et al. (2009) argue that the number of information events, such as announcements on a given day, affects the speed of information being processed and geting incorporated into prices.

Quarterly earnings announcements are one of the most important, regular, and frequent information events in financial markets. It has been well known for decades, since of the first papers by Beaver (1968) analyzing earnings announcements, that they are a rich source of market puzzles and interesting learning related phenomena. Some examples include abnormal excess returns around the announcements or the post-announcement drift. Ball and Kothari (1991) argue that these price movements are not purely related to compensation to risk, while Drake et al. (2012), using Google search data before earnings announcements, argue that information and learning play an important role in price movements around the announcements. Investor attention spikes, and abnormal market movements are present prior to a various set of public announcements. Da et al. (2011) find similar patterns in Google search volumes before IPOs.

The rest of this paper is organized as follows. Section 1.1 outlines the model and its solution; it also provides comparative statics and discusses implications. Section 1.2 contains the empirical results of both time-series and cross-sectional analyses of model predictions. Finally, Section 1.3 summarizes the results and concludes the paper. All proofs for the model can be found in Appendix A; Appendix B contains supplementary tables for the empirical analysis.

1.1 Model

1.1.1 The economy

An infinite horizon economy is populated with unit measures of finitely lived overlapping generations of traders. Time is discrete and indexed by t. There are four assets in the economy: a risk-free asset with payoff R_f, and with a price normalized to one, and $N = 3$ risky assets with net supply normalized to one. Each asset has an AR(1) earnings process, and for simplicity assume that all earnings are paid out as dividends. Each asset pays dividends in every other period. Denote the earnings process of asset j as

$$\theta_{j,t} = \rho_j \theta_{j,t-2} + \epsilon_{j,t}, \tag{1.1}$$

where the innovations are normally distributed with $\epsilon_{j,t} \sim \mathcal{N}(0, \sigma^2_{\epsilon j})$. The earnings of the three firms are independent. Firms announce earnings one period before the dividends are paid out, and in each period some of the firms have an upcoming announcement, while the others are after the previous announcement. This timing represents the fact that not all companies announce their earnings on the same day; announcements are spread out through the quarter. Without loss of generality assume that firms 1 and 2 pay dividends in even periods, while firm 3 pays in odd periods. Let $p_{j,t}$ be the price of asset j in period t.

1.1.2 Traders

In each period a new generation of a unit mass of traders is born with exogenously given wealth, w and mean-variance utility over terminal wealth with a common risk-aversion parameter, γ. Utility of trader i has the form

$$\gamma E[w_i] - \frac{\gamma^2}{2} Var(w_i). \tag{1.2}$$

Each generation of traders lives for two periods but only actively trades in one. When born, each trader learns about the assets' upcoming dividend payments and trades in the markets. In the next period, the old generation unwinds their position, receives the upcoming dividend, and consumes their wealth. Figure 1.1 summarizes the timing of the model.

Each trader's terminal wealth is the sum of two components: their sale of the four assets, and the dividend paid out by one or two of the risky assets. When traders are born and trade, the value of the upcoming dividend they will receive is already announced, and the only uncertainty pertains to the prices of the three risky assets when they have to unload their positions.

1.1.3 Learning

Before trading, each investor can learn about the upcoming innovation term in the assets' earnings process. Learning takes the form of observing a noisy private signal with a noise term η_{ij} observed by trader i about assets j, normally distributed with $\eta_{ij} \sim \mathcal{N}(0, \sigma_{ij})$ and independent across assets and investors. Each trader has limited information processing

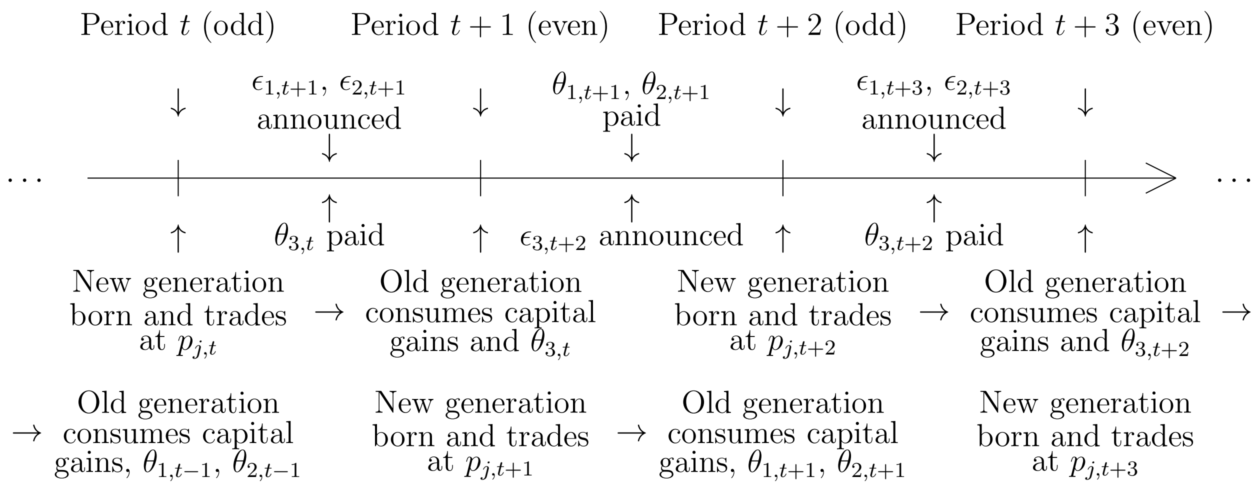

Figure 1.1: Timeline of payoffs, announcements, and trading

capacity, and each chooses how to allocate it across the three signals. She does so by choosing signal precisions. Learning capacity is represented by an entropy constraint, denoted by κ. When making the choice of allocating capacity over the two signals, traders maximize their unconditional expectation of their terminal utility,

$$E[EU(w_i|\{s_{ij}\}_{j=1}^3)] = E\left[\gamma E[w_i|\{s_{ij}\}_{j=1}^3] - \frac{\gamma^2}{2}Var(w_i|\{s_{ij}\}_{j=1}^3)\right] \tag{1.3}$$

Figure 1.2 shows the timeline of traders decision.

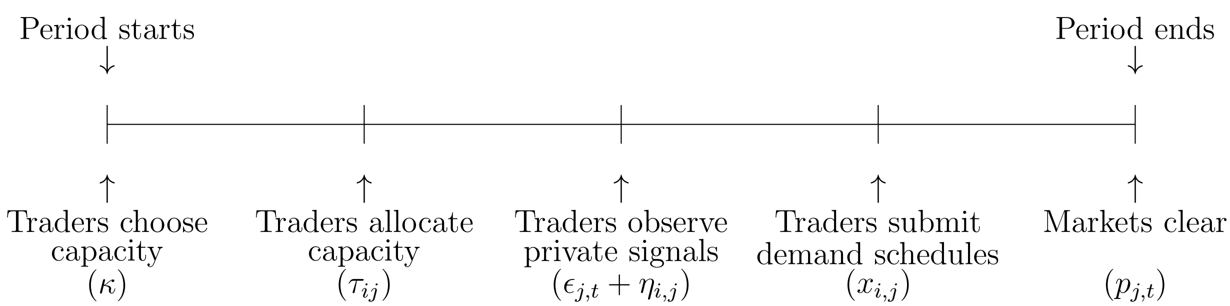

Figure 1.2: Timeline of traders' lifecycle and decisions

After observing their private signals, traders update their beliefs about next period prices using Bayes-rule, then submit their demand functions. Markets clear at a price where the total demand of traders equals the unit net supply for the assets.

1.1.4 Solution

To solve the model by backward induction, first consider the traders' portfolio allocation decision with endogenously given information structure for the three risky assets, and the resulting asset prices as functions of private signal precisions, presented in Section 1.1.4.

Section 1.1.4 provides details on the solution to the learning choice of traders. Finally, Section 1.1.4 outlines an extension where traders' learning capacity is not fixed, but is also an endogenous choice. The focus of this paper is on equilibria, where traders focus their learning on firms with upcoming announcements.

Asset prices with exogenous learning

Given that the risk factors governing each risky asset's payoff are independent, for any given information structure of the traders, the portfolio allocation problem for the three risky assets is independent. In particular, let τ_{ij} be the precision of the private signal, that trader i observes about asset j. The solution for prices is to first conjecture then later verify there exists an equilibrium where prices are linear. The equilibrium of the trading game is described in Lemma 1 and in Appendix A.

Lemma 1 (Asset prices with exogenous private signals) *Suppose that the private signal precisions for a stock are exogenous; τ_{ij} for trader i and asset j. Traders only learn about the asset in the period before the announcement. Then, if t denotes a period where the stock has an upcoming announcement, and $t+1$ is a period with an upcoming dividend payment, the trading game has an equilibrium where prices are linear in the last dividend and the upcoming innovation term. So prices are*

$$p_{j,t} = B_{0j} + B_{1j}\theta_{j,t-1} + B_{2j}\epsilon_{j,t+1}, \tag{1.4}$$

$$p_{j,t+1} = A_{0j} + A_{1j}\theta_{j,t+1}, \tag{1.5}$$

for some coefficients, depending on the earnings process parameters, ρ_j and $\sigma^2_{\epsilon_j}$, and the average signal precision of traders, $\bar{\tau}_j = \int \tau_{ij} di$. For details, see Appendix A.

This result is quite standard for models with continuous double auctions and Bayesian agents. Given that all three assets in the model have linear prices with known coefficients, it is possible to solve for the traders' learning problem. Before doing so, it is worth pointing out a few features of a standard model with exogenously given information structure. In particular, there are three important features that are also standard in rational models with no frictions. First, new information gets incorporated into prices when it becomes available. Second, price reaction to information is constant over time. Third, price informativeness is constant over time. Under these conditions, prices would be fully revealing in all periods. However, as the next section will demonstrate, these implications won't hold anymore, if otherwise rational traders face frictions in information acquisition and rationally react to those constraints.

The learning decision of traders

I focus on the existence of information processing frictions on the investor side, which are costly information acquisitions in the form of constraints on learning capacity. One can think about this as an analyst at a hedge fund or investment bank requiring time to prepare forecasts and evaluate assets. The number of analysts and the hours in any given day are constrained. In this section, the capacity constraint is fixed and exogenous for the traders.

Section 1.1.4 solves for traders' optimal choice of their capacity, subject to some cost function. One interpretation of this choice is to temporarily assign analysts to certain divisions or, as an example, pay out overtime.

The traders' learning decision in each period is to choose their private signal precision for the three assets, subject to their entropy constraint. The capacity constraint is modeled as an entropy constraint following the literature of Mondria (2010), Kacperczyk et al. (2016), or Kacperczyk et al. (2018). Trader i can observe noisy signals with precisions τ_{ij} about asset j's innovation term. The learning constraint is defined as

$$\sum_{i=1}^{3} \ln \frac{\tau_{ij} + \tau_{\epsilon_j}}{\tau_{\epsilon_j}} \leq \kappa. \tag{1.6}$$

Before turning to the analysis of how can learning be concentrated on periods right before the announcements, I will first establish some more general results given the traders' constraints described above.

Lemma 2 (Traders focus on a single stock) *For any fixed signal structure of all traders but one, trader i, that result in the linear price structure described in Lemma 1, the learning problem of trader i with mean-variance preferences and an entropy constraint, as in Equation 1.6, has a corner solution in all periods. In other words, all traders learn about a single asset.*

This corner solution result is a direct consequence of the functional forms in the entropy constraint. After the result in Lemma 2, an intuition for how traders make their learning decision is clear. A trader will choose to learn about a stock where information is the most valuable. The value of information, informally, is determined by three factors. First, it is increasing in the persistence of the firm's earnings. Higher persistence means that the announcement has a higher impact on the net present value of future cash-flows, thus the price reaction to the announcement, is increasing in persistence. Second, the value of learning is increasing in the variance of the earnings. Finally, other traders' learning has a major effect on the value of learning, both today and in the next period. Information about a stock is more valuable if there is less learning about it today in the economy, and more in the next period. If other traders' learning is higher today, then the price will reflect the new information more. This would decrease the expected returns from the assets, thus decreasing the value of learning. However, if there is more learning by other traders in the next period, then there will be greater price reaction, thus information today becomes more valuable. This intuition leads to the equilibrium learning behavior of traders.

Given this result, now it is possible to analyze how capacity constraints can allow for equilibria where learning patterns, returns, and price informativeness are substantially different from a standard, frictionless world.

Proposition 1 (Equilibrium with traders focusing on upcoming announcements) *In the model with endogenous learning, there exist two threshold capacities, $\bar{\kappa}_1 \leq \bar{\kappa}_2$, determining the characteristics of the equilibrium.*

(i) If traders' learning capacity is lower than the higher threshold, $\kappa \leq \bar{\kappa}_2$, then there exists an equilibrium where in each period all traders learn only about stocks with an upcoming

announcement. Each trader plays a mixed strategy and randomizes which stock to learn about. In this equilibrium the mixing probabilities are unique.

(ii) Moreover, if the capacity is lower than the lower threshold, such that $\kappa \leq \bar{\kappa}_1$, then all traders learn about the same announcing stock.

(iii) If learning capacity is sufficiently large, as $\kappa > \bar{\kappa}_2$, then there exists no symmetric equilibrium in which traders only learn about stocks with upcoming announcements.

To understand the intuition behind this equilibrium, consider a scenario with only one announcing firm. If learning capacity is low, all traders focus their learning on the stock where information is more valuable, and an upcoming announcement increases the marginal value of information. Moreover, if capacity is low, then the price movements of firms not announcing now, will be smaller in the next period when they will be before their announcement. Therefore the exploitable pricing error is quite small for these stocks. As capacity increases, the increased learning activity about the stock decreases its expected returns, as the current price becomes more informative. While, the increased capacity results in greater price movements next period for stocks without an announcement today. Both of these effects make it less valuable to learn about the currently announcing firm, and more valuable to learn about a stock without an upcoming announcement. Moreover, as capacity increases, traders' signals become more precise, thus they are willing to trade more agressively to exploit these pricing errors. This factor, affecting the expected portfolio size, amplifies the increasing gains from learning about the non-announcig stock, but mitigates the decreasing gains from learning about the announcing firm. At some point, as capacity increases, these effects make traders indifferent between increasing their precision on their stock of focus or learning about another stock instead. For the case with two announcements, the intuition is similar, but in those periods traders might switch to learn about another announcing firm, before acquiring information on the stock without an announcement. Each trader still learns about only one asset, and they are ex-ante identical and indifferent about which asset to learn. Figure 1.3 presents a graphical representation of the equilibrium in Proposition 1.

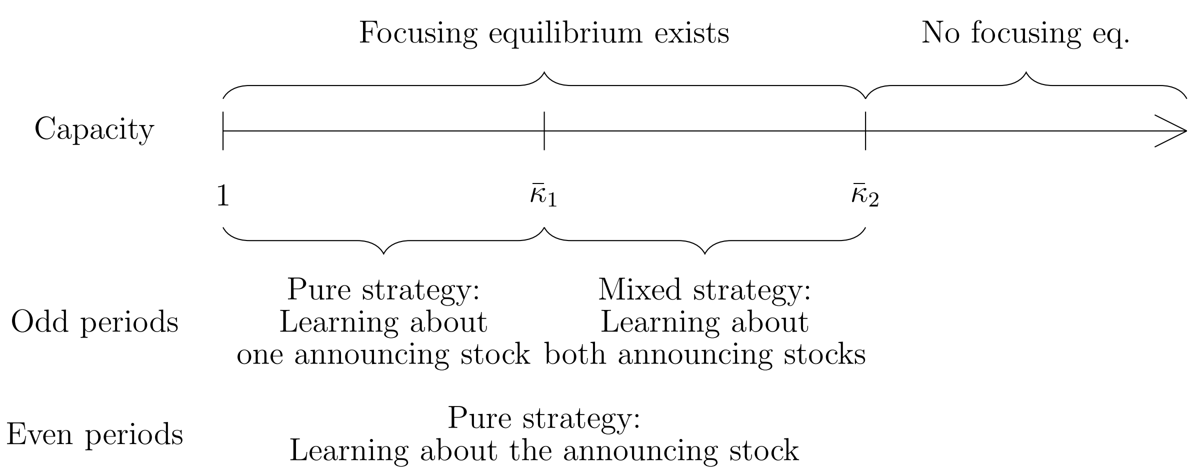

Figure 1.3: Focusing equilibrium

The model's main result is that if traders face constraints in the form of costly information acquisition and capacity constraints, even in an otherwise fully rational setting, an equilibrium can exist where traders focus their learning on stocks with upcoming announcements. This setup also allows me to derive comparative statics on equilibrium learning across stocks and returns, resulting in empirically testable predictions on both the market level across time and in the cross-section of assets.

The most important characteristics of the unique probability, λ_j, can be summarized as follows.

Proposition 2 (Equilibirum mixing probability) *In the equilibrium where traders play a mixed strategy in learning about the stocks with upcoming announcements, λ_j is*

(i) increasing in ρ_j, decreasing in τ_{ϵ_j},

(ii) decreasing in ρ_l, and increasing in τ_{ϵ_l} for any firm l also having an announcement, and $l \neq j$.

In this model pre-announcement returns are easily computed as

$$R_{j,t} = \frac{1}{R_f^2 - \rho_j} \frac{\lambda_j(\kappa - 1)}{\lambda_j(\kappa - 1) + 1} \epsilon_{j,t} + \gamma \frac{1}{(R_f^2 - \rho_j)^2} \frac{(\lambda_j(\kappa - 1))^2}{(\lambda_j(\kappa - 1) + 1)^2} \frac{1}{\tau_{\epsilon_j}}. \tag{1.7}$$

Hence the squared returns net of expectations are

$$E[AR_{j,t}^2] = \frac{1}{(R_f^2 - \rho_j)^2} \frac{(\lambda_j(\kappa - 1))^2}{(\lambda_j(\kappa - 1) + 1)^2} \frac{1}{\tau_{\epsilon_j}}. \tag{1.8}$$

while the average absolute return net of expectations is

$$E[|AR_{j,t}|] = \frac{1}{R_f^2 - \rho_j} \frac{\lambda_j(\kappa - 1)}{\lambda_j(\kappa - 1) + 1} \sqrt{\frac{2}{\pi} \frac{1}{\tau_{\epsilon_j}}}. \tag{1.9}$$

This simple closed form solution of returns, combined with comparative statics on the learning probabilities from Proposition 2, leads to comparative statics on the market level in the time-series, and on the firm level in the cross-section.

Proposition 3 (Pre-announcement price reactions to new information) *In the model, pre-announcement price reactions to new information, as measured by squared or absolute demeaned returns for individual stocks, are*

(i) increasing in own persistence and variance of their earnings process, and

(ii) decreasing in firm characteristics of other announcing firms.

In the case of aggregate results, if all stocks are identical, then average price reactions are

(i) decreasing in the number of announcing stocks, and

(ii) increasing in the common persistence and variance of the earnings process.

While post-announcement returns ex-dividend payments are

$$R_{j,t+1} = \frac{R_f}{R_f^2-\rho_j}\frac{1}{\lambda_j(\kappa-1)+1}\epsilon_{j,t} + \gamma\frac{R_f^2}{(R_f^2-\rho_j)^2}\frac{1}{\lambda_j(\kappa-1)+1}\frac{1}{\tau_{\epsilon_j}}. \tag{1.10}$$

Both pre- and post-announcement returns can be decomposed into two components. The first term is a reaction to new information. The second term is the expected return, which is positive, since with only three assets, even idiosyncratic uncertainty cannot be fully diversified away. To gain more intuition on the equilibrium effect of learning, consider a comparison of expected returns to the case with no learning. Consider returns around the announcement of $\epsilon_{j,t}$.

$$E[R_{j,t}] = \gamma\frac{1}{(R_f^2-\rho_j)^2}\frac{(\lambda_j(\kappa-1))^2}{(\lambda_j(\kappa-1)+1)^2}\frac{1}{\tau_{\epsilon_j}}, \tag{1.11}$$

$$E[R_{j,t+1}] = \gamma\frac{R_f^2}{(R_f^2-\rho_j)^2}\frac{1}{\lambda_j(\kappa-1)+1}\frac{1}{\tau_{\epsilon_j}}. \tag{1.12}$$

What can be written as

$$E[R_{j,t}] = 0+\gamma\frac{1}{(R_f^2-\rho_j)^2}\frac{(\lambda_j(\kappa-1))^2}{(\lambda_j(\kappa-1)+1)^2}\frac{1}{\tau_{\epsilon_j}}, \tag{1.13}$$

$$E[R_{j,t+1}] = \gamma\frac{R_f^2}{(R_f^2-\rho_j)^2}\frac{1}{\tau_{\epsilon_j}} - \gamma\frac{R_f^2}{(R_f^2-\rho_j)^2}\frac{\lambda_j(\kappa-1)}{\lambda_j(\kappa-1)+1}\frac{1}{\tau_{\epsilon_j}}. \tag{1.14}$$

Expected returns can be also considered as the sum of two components. The first term is, what expected return would be without learning. This component represents compensation for risk introduced by the announcements. The second, residual part can be called the compensation for risk introduced by learning. Note that in the pre-announcement period, the learning related expected return is positive, as information acquisition introduces risk. On the other hand, in the post-announcement period, the learning related component is negative, as learning decreases uncertainty.

Finally, consider trading activity before announcements. In the model, the total demand always has to sum up to the unit net supply of the assets. However, a good measure of trading activity would be the total magnitude of submitted demands. This volume can be decomposed into two components: 1, the net supply of assets that needs to be held by traders, and trades between traders due to heterogeneous posteriors. Traders with the highest private signals will buy the asset from the ones with the lowest private signals. The effect of signal precision and learning however is not straightforward at first sight. Traders with mean-variance preferences have demand of the form

$$x_{i,j} = \frac{E_{i,j}-R_f p_j}{\gamma V_{i,j}}, \tag{1.15}$$

where $E_{i,j}$ is trader i's expected payoff from stock j, given her information, and $V_{i,j}$ is her conditional variance of the payoffs. One effect of more learning, and higher private signal precision, is the decrease in conditional variance; what increases individual demands thus increases stock j's volume. On the other hand, increased precision means that the dispersion in beliefs, the variance of conditional expectations, is smaller, which would decrease the magnitude of trading due to heterogeneous beliefs and push volume closer to one. Formally, the following can be said about volume.

Proposition 4 (Pre-announcement trading volume) *In the model, pre-announcement volume of stock j, as measured by the average magnitude of individual demands, is increasing in the fraction of traders learning about the stock, λ_j, thus decreasing in firm characteristics of other announcing firms. Moreover, if all stocks are identical, then average volume is decreasing in the number of announcing firms.*

Endogenous capacity

Consider the case, where traders instead of observing their exogenously set capacity constraint, can optimally choose it. The choice is subject to a cost function, $c(\kappa)$, where $c(\cdot)$ is convex, increasing, $c(1) = 0$, $c'(1) = 0$, and if $x \to \infty$, then $c(x) \to \infty$. The intuition for this constraint is that even if hedge funds cannot change employee numbers from week to week, and definitely cannot vary the number of hours in each day, they still can pay analysts and researchers overtime pay, thus extending their capacity constraints slightly. For simplicity, to focus on the capacity choice, in this part I assume that all assets are identical in the parameters of their earnings processes.

Proposition 5 (Equilibrium information capacity) *If the cost of capacity is sufficiently large, then there exists a symmetric equilibrium where all traders learn only about announcing stocks, as described in Proposition 1. All traders purchase the same capacity, determined by the parameters of the stocks' earnings processes. The equilibrium capacity solves*

$$\gamma^2 \frac{1}{(R_f^2 - \rho)^2} \frac{1}{\tau_\epsilon} + 1 = c'(\kappa)(\lambda(\kappa - 1) + 1)^2 \tag{1.16}$$

for $\lambda = \frac{1}{M}$ when there are M announcing firms in this period.

The equilibrium capacity choice is increasing in the earnings persistence and earnings variance of the firms with upcoming announcements. Moreover the total capacity (κ) is increasing in the number of announcing firms, and the average capacity $\frac{1}{M}\kappa$ is decreasing.

The intuition behind this step is that even though capacity for learning is constrained, it is not completely fixed. Optimal choice of capacity given information costs can be interpreted as analysts at a firm working overtime on certain weeks, or employees with multiple tasks postponing certain activities until later periods while working more on firms with upcoming announcements.

1.1.5 Discussion of the theoretical results

The model has several important implications regarding both price informativeness and comovements. First, consider price informativeness. In the standard model of learning and finance, information gets incorporated into prices when it becomes available. Given the information structure in this model, where new information is ready and available at the time of the announcement of the previous earnings, the standard model of exogenously set learning would predict constant price informativeness over time. In each period, between the information being available to learn and it is released to the public, prices incorporate the same fraction of that information.

However, if traders face constraints in learning due to costly information acquisition, price informativeness changes over time. In this model, prices reflect more information before that information becomes publicly available than in earlier periods. In this model, the availability of information is quite stylized. However, these results would not change qualitatively if there were a temporal pattern for new information availability between two announcements. In that case, the unavailability of information in early periods would reinforce the effects of learning constraints. A more restrictive timing on the availability of new information would favor the existence of focusing equilibria even more.

Another interesting implication of investors reacting rationally to limited learning capacity is that learning and price informativeness are significantly affected by the public release of information. In particular, prices become more informative and more volatile before the relevant information becomes public. The model focuses on periodical reporting of earnings news, but similar effects would take place before the release of any information relevant to the future cash-flows of a firm, whenever the release of information is anticipated by traders.

Resultant from this pattern, an outside observer would find cyclical patterns in stock price volatility, and correlations between volatilities, or between price informativeness of stocks. Costly information and constraints on learning then need to be taken into account when interpreting these patterns in volatility, trading volume, and information content of prices. Otherwise, a naive econometrician would draw incorrect conclusions from the data.

The comparative statics on equilibrium learning as measured by (λ_j and κ_t), and price reactions, as measured by squared demeaned returns ($E[AR_{j,t}^2]$), are quite intuitive given the model, but worth further discussion. These results allow me to distinguish this model from other models of learning, or insider trading, and testing if traders face constraints in learning and if they react optimally to them. In particular, the average learning capacity devoted to a stock, average squared abnormal returns, and average trading volume is decreasing in the number of announcements in that period. This is a feature, which is unique to models with costly information acquisition, and thus can be used to provide empirical support for the model. Moreover, comparative statics on the market level average learning capacity, with respect to firm characteristics, are unique to models with information frictions and learning constraints that also feature traders' optimal reaction to these constraints.

In the cross-section of firms, results on price reactions and a firm's own characteristics are consistent with any model of informed trading and learning. On the other hand, the comparative statics of price reactions and learning, with respect to the characteristics of other announcing firms, are unique to this model and would be zero in models with exogenous private information, models of inattention without a rational reaction, or in a model of insider trading. The next section utilizes these differences to provide empirical analysis of the questions: do traders face constraints due to costly information acquisition, and if so, do they react optimally to these constraints?

1.2 Empirical analysis

My framework presents a simple way to analyze investor reaction to learning constraints and costly information. However, to do so, first I argue that quarterly earnings announcements are indeed an efficient way to analyze capacity constraints in learning. Using investor attention data from Bloomberg, I document the rise of investor attention in the weeks before the announcements. This increase is heterogeneous across announcements and higher for stocks that announce in weeks where the number of announcements is in the lower quintile. For announcements in weeks with the most announcements, there is no statistically significant increase detectable. Moreover, in the time series, I document that both average attention, average squared cumulative abnormal return before announcements, and average trading volume, are lower on weeks with more announcements. These results suggest investors facing constraints due to costly information acquisition.

The second part focuses on a subset of firms and announcements where attention data is available. It shows how firm characteristics and characteristics of other announcing firms affect the attention of investors. Finally, I use a broader set of firms and announcements to further analyze the connection between firm characteristics, announcement patterns, and abnormal returns before the announcement.

These cross-sectional results show that both attention and price reaction are affected by the characteristics of other announcing firms. However, the effects are stronger for the firms' earning persistence than for earnings variance. This evidence suggests that the traders' reaction is not fully optimal, possibly due to the use of approximations in determining the importance of announcements. These approximations are based on variables more convenient and suitable for observing and understanding than the ones in the model.

1.2.1 Data

The data is based on three sources. Institutional investor attention proxy is available from Bloomberg for the years 2010-2017. This variable is constructed and published by Bloomberg based on all subscribers' reading and search activity on Bloomberg terminals. Bloomberg records this activity through their subscription service, and the data is aggregated to an integer between 0 and 4 based on activity compared to a 30 day moving average of activity on the firm level, by comparing current activity to specific threshold percentiles in the past. Ben-Rephael et al. (2016) find, that this variable possibly a better proxy to institutional investor attention, than Google search volume. The two variables are correlated, but especially before earnings announcements, the Bloomberg measure reacts faster to news, and results in a greater price reaction.

Announcement characteristics, moments of the analyst forecasts, earnings surprises, dates, and the number of analysts covering a firm are from the I/B/E/S for the years 1990-2017. Firm fundamentals are used for the same time period from CRSP/Compustat merged quarterly fundamentals files. Announcement surprises are computed from the actual EPS value and the mean forecast, normalized by the stock price at the end of the corresponding fiscal quarter. Earnings process characteristics showed in this section are estimated using a rolling window estimate, where the parameter in each year and quarter is estimated using the previous 20 quarters. The variable used for persistence is the first order autocorrelation coefficient of earnings per share, while for the variance of earnings, the variable used is the sample variance of the earnings surprises. Following the literature in accounting, surprises are relative to the mean analyst forecast normalized by price.

Trading volume is based on data from CRSP/Compustat. My measure is based on turnover adjusted for market average, similar to Garfinkel and Sokobin (2006) and Garfinkel (2009). To compute turnover, reported trading volume for each stock and for the market, is normalized by the number of common shares outstanding. Then stock level turnover is adjusted with the market turnover to receive a measure of unexpected trading volume. Finally, abnormal returns are calculated for each announcement in the 1990-2017 period via the WRDS event study tool Eventus. Abnormal returns used in this section are computed with respect to a three factor Fama-French estimate. The models were estimated on one year of trading data, ending a month before the announcement, given that at least half a year of data was available for the estimation.

1.2.2 Investor attention and capacity constraints

In the past decades, multiple papers have analyzed how the attention of investors can be affected by various factors. For example, DellaVigna and Pollet (2009) show that investor attention is lower on Fridays, Fedyk (2018) show that the location of news in the Bloomberg terminal affects how fast information gets incorporated into asset prices, and Drake et al. (2012), using Google search data, document a spike in searches before firm related announcements.

These results indicate that investors' information processing is imperfect. However, it resists tests to discern if investor behavior is an optimal reaction to constraints in learning capacity, or if it is driven by exogenous factors related to attention or the salience of the information. The clearest evidence of capacity constraints is by Hirshleifer et al. (2009), who show that the number of other announcements on the same day has a negative effect on how fast the information contained in the surprise gets incorporated into prices. This first part of my analysis is closest to their results.

Adding to this literature, I provide evidence that investors are indeed constrained in their capacity for learning. Using institutional investor attention, measured by Bloomberg for the 2010–2017 period on the stock-announcement level, Figure 1.4 shows that average attention significantly increases in the weeks before the announcements. This pattern is consistent with the intuition of the model, that investors focus their learning on stocks with upcoming announcements. Moreover, as Figure 1.5 shows, the increase in attention is much higher if there will be fewer announcements on the same week. The graph compares attention before the announcement for stocks that are in the top and bottom quintile by the number of announcements. Important to note, the sorting is based on the number of announcements in the same week when the stock is announcing, but there is already a statistically significant difference in attention two to three weeks before the announcement. This difference cannot be attributed to naive, attention-based explanations, but is consistent with the model where traders focus their learning on announcing stocks in the weeks before the announcement, and allocate their capacity, subject to their constraints. Figure 1.6 shows the same difference on the daily frequency rather than weekly.

To provide further evidence that this institutional investor attention variable from Bloomberg

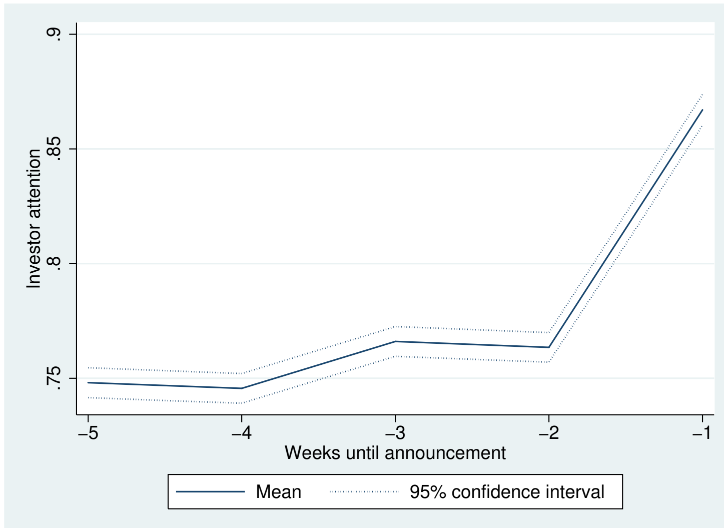

Figure 1.4: Investor attention before earnings announcements. Average attention of firms during the k-th week before the announcement day. Sample period is 2010–2017, investor attention is from Boomberg.

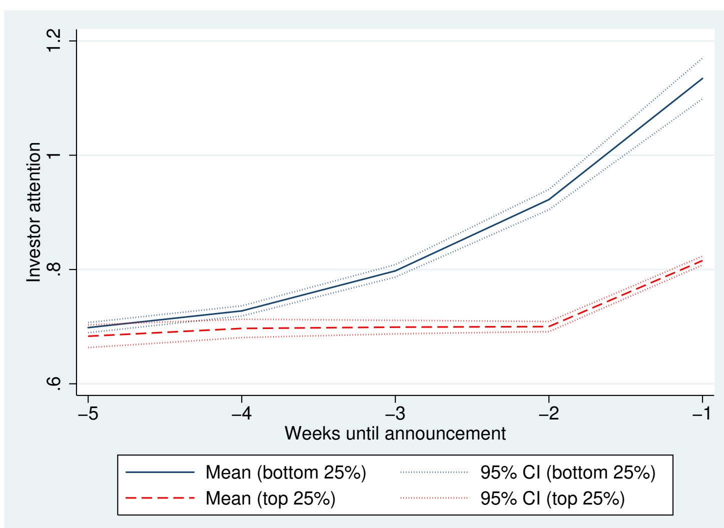

Figure 1.5: Investor attention for firms with many and few other announcing firms. Average attention during the k-th week before the announcement day. Observations are sorted basedon the number of announcing firms on each week. Solid line represents the top 25%, and dashed line the bottom 25%. Dotted lines are 95% confidence intervals. Sample period is 2010–2017, investor attention is measured and reported by Bloomberg.

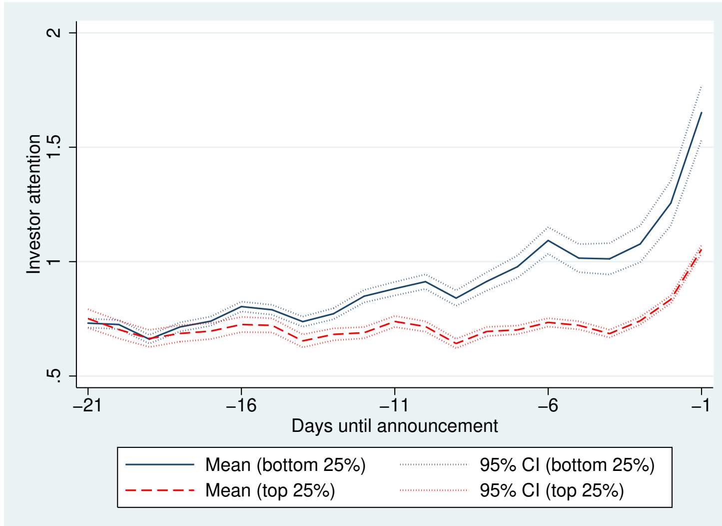

Figure 1.6: Investor attention for firms with many and few other announcing firms. Average attention k trading days before the announcement day. Observations are sorted basedon the number of announcing firms on each week. Solid line represents the top 25%, and dashed line the bottom 25%. Dotted lines are 95% confidence intervals. Sample period is 2010–2017, investor attention is measured and reported by Bloomberg.

indeed captures aspects of traders' information acquisition and learning, a simple test can be performed, to see if attention in the weeks before the announcements has a significant effect on pre-announcement price movements. Regressions of the form

$$(CAR^2_{-5d})_{j,t} = \delta_t + \sum_{k=1}^{4} \beta_k Att_{-kw,j,t} + \gamma X_{j,t} + \xi_{j,t}. \tag{1.17}$$

Where the outcome variable is the squared cumulative abnormal returns for firm j announcing on week t. The regressors are $Att_{-kw,j,t}$, the average attention for firm j in period t, k weeks before the announcement $(5(k-1)+1$ to $5(k-1)+5$ trading days), $X_{j,t}$ is a set of controls, such as firm size, number of analysts covering the firm, and number of announcements in week t, while δ_t is a time fixed-effect.

The results in Table 1.1 indicate, as expected, price movements in the five days prior to the announcement are significantly affected by attention in that same week and are not affected by attention in previous weeks.

1.2.3 Market level time-series analysis

Let's continue the analysis using the time series variation on the market level. The goal of this section is to show that information is costly, and learning is subject to capacity constraints. Thus, average investor attention, average squared abnormal returns, and average trading volume for firms before the announcements are lower in weeks with more announcements. The second set of regressions are motivated by results of the model showing that the average characteristics of announcing firms have an effect on the equilibrium allocation of capacity,

Table 1.1: Cross-sectional regression of cumulative abnormal returns:

$$(CAR^2_{-5d})_{j,t} = \delta_t + \sum_{k=1}^{4} \beta_k Att_{-kw,j,t} + \gamma X_{j,t} + \xi_{j,t}.$$

Where $(CAR^2_{-5d})_{j,t}$ is the squared cumulative abnormal returns for firm j announcing on week t, compared to a three factor Fama-French forecast. The regressors are $Att_{-kw,j,t}$, the average attention for firm j in period t, k weeks before the announcement ($5(k-1)+1$ to $5(k-1)+5$ trading days), $X_{j,t}$ is a set of controls, such as firm size, number of analysts covering the firm, and number of announcements in week t, while γ_t is a time fixed-effect. All standard errors are two-way clustered on firm and time level. Sample period is 2010–2017, investor attention is measured and computed by Bloomberg.

	(1) CAR^2_{-5d}	(2) CAR^2_{-5d}	(3) CAR^2_{-5d}
Att_{-1w}	0.000173***	0.000289***	0.000282***
	(6.14)	(9.87)	(10.45)
Att_{-2w}	-0.0000969***	-0.0000291	-0.0000384
	(-4.55)	(-1.24)	(-1.69)
Att_{-3w}	-0.0000560**	0.00000690	-0.0000114
	(-2.55)	(0.31)	(-0.53)
Att_{-4w}	-0.0000623***	0.0000129	0.00000840
	(-3.30)	(0.70)	(0.52)
Controls	None	Firm	Firm
Observations	21703	21700	21700

t statistics in parentheses

All regressions with time fixed effects

Standard errors two-way clustered on firm and time level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and subsequently on the equilibrium level or squared abnormal returns and trading volumes. The first set of regressions in this part have the form

$$Y_t = \beta_0 + \beta_1 \ln NA_t + \delta_{yq} + \xi_t, \tag{1.18}$$

where Y_t is either mean squared abnormal returns, mean trading volume, or mean investor attention in the five trading days preceding the announcement, NA_t is the number of announcing firms in week t, δ_{yq} is a year and quarter level fixed effect.

The sample for regressions with the attention measure is $\sim 20,000$ firm-announcement level observation between 2010 and 2017, while with regard to returns and volume, it is a set of $\sim 150,000$ firm-announcement observations between 1990 and 2017. The results shown in Table 1.2 for market level averages are consistent with investors facing capacity constraints in learning and rationally reacting to these limits. Both investor attention, price reaction, and trading volume are smaller when more firms are announcing on a certain week.

Table 1.2: Time-series regression on number of announcements:

$$Y_t = \beta_0 + \beta_1 \ln NA_t + \delta_{yq} + \xi_t,$$

Where Y_t is either mean squared abnormal returns, mean trading volume, or mean investor attention in the five trading days preceding the announcement, for firms announcing on week t. NA_t is the number of announcing firms in week t, δ_{yq} is a year and quarter level fixed effect. Regression (1) is for the 2010–2017 period, regressions (2) and (3) for the 1990–2017 period.

	(1)	(2)	(3)
	$\bar{A}tt_{-5d}$	$C\bar{A}R^2_{-5d}$	$\bar{V}ol_{-5d}$
$\ln(NA_t + 1)$	-0.0574***	-0.000195***	-0.0002647***
(# announcements)	(-2.92)	(-3.18)	(-4.98)
Observations	348	1411	1403

t statistics in parentheses

Year and quarter fixed effects

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.2.4 Firm level cross-sectional results

The next step is to turn to the analysis of investors' behavior, given their capacity constraints in learning, and the effect of their allocation of learning capacity on pre-announcement price movements. Using investor attention data, pre-announcement price movements, and trading volume in the cross-section. The theoretical framework provides clear predictions on how rational investors would react to capacity constraints generated by costly information. If investors react in a rational fashion, adjust and allocate their capacity optimally, then characteristics of other announcing firms have an effect on the fraction of attention each firm receives, and subsequently, pre-announcement abnormal price movements will also be affected by characteristics of other announcing firms, not just own characteristics of the stock.

The first set of regressions is a direct test on how investor attention is affected by firm and announcement related characteristics. Here the regressions have the form of

$$Att_{-1w,j,t}\% = \delta_t + \beta_1\rho_{j,t} + \beta_2\sigma^2_{\epsilon_{j,t}} + \gamma X_{j,t} + \xi_{j,t}, \quad (1.19)$$

$$Att_{-1w,j,t}\% = \delta_t + \beta_1\rho_{j,t} + \beta_2\sigma^2_{\epsilon_{j,t}} + \beta_3\bar{\rho}_{-j,t} + \beta_4\bar{\sigma}_{\epsilon-j,t} + \gamma_1 X_{j,t} + \gamma_2 X_{-j,t} + \xi_{j,t}. \quad (1.20)$$

The variable of interest is the share of attention for firm j compared to total attention that same week, in period t in the 1 to 5 trading days prior to the announcement. Explanatory variables are ρ_j, the persistence of earnings for firm j, $\sigma^2_{\epsilon_j}$, the variance of the earnings surprise for firm j, $\bar{\rho}_{-j}$, the average persistence of firms that announce the same week as firm j, $\bar{\sigma}^2_{\epsilon-j}$, the average earnings surprise variance of firms that announce the same weeks as firm j, δ_t, a time fixed effect, $X_{j,t}$ and $X_{-j,t}$, a set of controls, such as size and analyst coverage of own and other announcing firms, and industry dummies.

The reason why the persistence seems to be the important factor, as it was discussed in the theoretical section, is that its interpretation, the effect of news on the NPV of all future dividends, is easy to understand. As Figure 1.7 shows, it is easy to proxy with the firms' price reaction to earnings surprises.

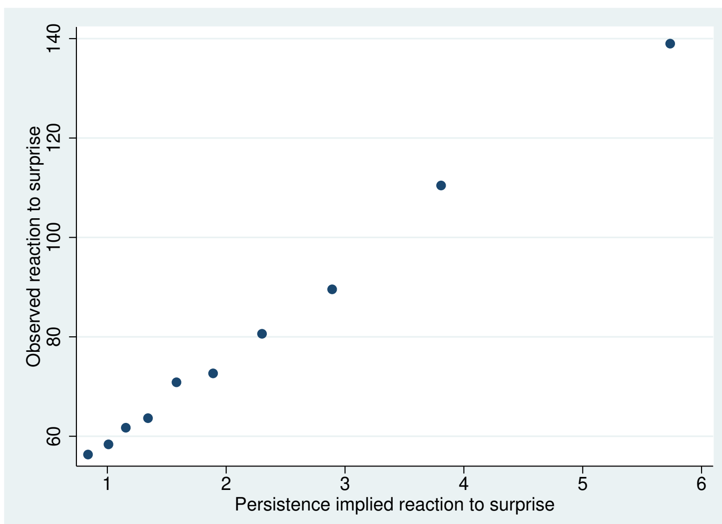

Figure 1.7: Earnings persistence and stock price reaction to surprises. On the vertical axis observe reaction to earnings surprise is computed as the absolute value of cumulative abnormal returns around the announcement ($t-2$ to $t+2$ days), divided by the standardized earnings surprise relative to the mean analyst forecast. On the horizontal axis implied reactions is cimputed from the AR(1) coefficient of earnings, as $\frac{1}{1-\rho}$. The sample contains all firm-announcement observations for the entire 1990–2017 period.

Regressions in Table 1.3 have this form. The main coefficients of interest are the average characteristics of other announcing firms, β_3 and β_4. In the case when investors are not constrained in their learning capacity, or if they would not react to their constraints in any rational fashion, those coefficients should be zero. However if traders behave as predicted by the model in this paper, one would expect a negative value for β_3 and β_4. The significant and negative coefficient on the average persistence of other announcing firms indicates that investors do allocate their attention rationally. The small significance of variables related to earnings surprise variance can be interpreted in multiple ways. One possible explanation: it is a result of limitations of the attention data, both in terms of available firms and years, and also in terms of the quality of attention measure. Another possible explanation is, that though investors react to capacity constraints in a rational fashion, their attention allocation is not fully optimal. In other words, it seems that investors do not fully incorporate all characteristics in the environment, which would be consistent with using simplifying rules in their decisions.

Table 1.3: Cross-sectional regression of investor attention on firm characteristics:

$$Att_{-1w,j,t}\% = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \gamma X_{j,t} + \xi_{j,t},$$

$$Att_{-1w,j,t}\% = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \beta_3 \bar{\rho}_{-j,t} + \beta_4 \bar{\sigma}_{\epsilon-j,t} + \gamma_1 X_{j,t} + \gamma_2 X_{-j,t} + \xi_{j,t}.$$

The outcome variable $Att_{-1w,j,t}\%$, is the share of attention for firm j compared to total attention that same week, prior to the announcement. Explanatory variables are ρ_j, the persistence of earnings for firm j, $\sigma^2_{\epsilon_j}$, the variance of the earnings surprise for firm j, $\bar{\rho}_{-j}$, the average persistence of firms that announce the same week as firm j. $\bar{\sigma}^2_{\epsilon-j}$, the average earnings surprise variance of firms that announce the same weeks as firm j. δ_t, a time fixed effect, $X_{j,t}$ and $X_{-j,t}$, a set of controls, such as size and analyst coverage of own and other announcing firms, and industry dummies.

	(1) $Att_{-5d}\%$	(2) $Att_{-5d}\%$	(3) $Att_{-5d}\%$
ρ_j	-0.0000295	-0.0000956*	-0.0000902*
(own persistence)	(-0.37)	(-1.82)	(-1.78)
$\sigma^2_{\epsilon_j}$	-0.000166***	0.0000994*	0.000116*
(own variance)	(-3.14)	(1.73)	(2.04)
$\bar{\rho}_{-j}$			-0.00202***
(other persistence)			(-4.83)
$\bar{\sigma}^2_{\epsilon-j}$			0.00140
(other variance)			(1.40)
Controls	None	Firm	Firm
Observations	21703	21700	21697

t statistics in parentheses

All regressions with time fixed effects

Standard errors two-way clustered on firm and time level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The same analysis is performed for various time frames before the announcement. Frames start from one week and range up to four weeks prior. These regressions also test an important implication of the model. As expected based on the theoretical results, other firm characteristics only have a significant effect on investor attention in the weeks before the announcement, but not earlier. The intuition is straightforward, as in early weeks, learning is focused on other announcing firms. Therefore, the relevant factor would be the characteristics of those firms. These results are summarized in Table 1.4.

Table 1.4: Cross-sectional regression of investor attention on firm characteristics for various time horizons:

$$Att_{-1k,j,t}\% = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \beta_3 \bar{\rho}_{-j,t} + \beta_4 \bar{\sigma}_{\epsilon-j,t} + \gamma_1 X_{j,t} + \gamma_2 X_{-j,t} + \xi_{j,t}.$$

The outcome variable $Att_{-1k,j,t}\%$, is the share of attention for firm j compared to total attention that same week, k weeks prior to the announcement. Explanatory variables are ρ_j, the persistence of earnings for firm j, $\sigma^2_{\epsilon_j}$, the variance of the earnings surprise for firm j, $\bar{\rho}_{-j}$, the average persistence of firms that announce the same week as firm j. $\bar{\sigma^2_{\epsilon}}_{-j}$, the average earnings surprise variance of firms that announce the same weeks as firm j. δ_t, a time fixed effect, $X_{j,t}$ and $X_{-j,t}$, a set of controls, such as size and analyst coverage of own and other announcing firms, and industry dummies.

	(1)	(2)	(3)	(4)
	$Att_{-1w}\%$	$Att_{-2w}\%$	$Att_{-3w}\%$	$Att_{-4w}\%$
ρ_j	-0.0000902*	-0.0000412	-0.0000668	-0.000105**
(own persistence)	(-1.78)	(-1.05)	(-1.61)	(-2.48)
$\sigma^2_{\epsilon_j}$	0.000116*	0.000101***	0.000150**	0.0000287
(own variance)	(2.04)	(2.85)	(2.21)	(0.32)
$\bar{\rho}_{-j}$	-0.00202***	-0.00103***	-0.000351*	-0.0000319
(other persistence)	(-4.83)	(-4.48)	(-1.89)	(-0.16)
$\bar{\sigma^2_{\epsilon}}_{-j}$	0.00140	0.00110	-0.000471	-0.000888
(other variance)	(1.40)	(1.23)	(-0.67)	(-1.21)
Observations	21697	21697	21697	21697

t statistics in parentheses

All regressions with time fixed effects and firm controls

Standard errors clustered on firm and time level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The analysis of a richer dataset contains $\sim 150,000$ firm-announcement level observations between 1990 and 2017. This section addresses the two main concerns regarding the direct analysis of investor attention data. One issue is purely statistical, due to limited availability of the Bloomberg institutional investor attention variable, a direct analysis of cumulative abnormal returns and trading volume allows for a much greater sample size. Any effect between returns and characteristics of other announcing firms is a direct test of the model, even without the direct measure of attention. The other issue is, that the available attention measures are proxies to learning capacity in the model. However, these cannot be mapped one-to-one. The closest real-world quantity to the capacity spent on a stock in the model would be the number of hours analysts work on a firm. This measure is clearly correlated with the attention measure from Bloomberg, but the correlation need not be close to one.

There can be a possible scenario where an analyst accesses the data of two firms exactly once, then spends one hour forming beliefs on earnings for one of the firms, and eight hours on the other. However, patterns present in the model discussed in this paper related to returns and other firm characteristics which are hard to reconcile with other models of learning or information acquisition of any sort, including leakage of insider information. This allows a more powerful analysis using pre-announcement returns and trading volumes for almost over three decades.

The regressions used here have the same form as before, but using squared cumulative abnormal returns and fraction of a stocks volume of total volume that day, instead of fraction of investor attention. Formally, they have the form

$$Y_{-5d,j,t}\% = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma_{\epsilon_{j,t}} + \gamma X_{j,t} + \xi_{j,t}, \quad (1.21)$$

$$Y_{-5d,j,t}\% = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma_{\epsilon_{j,t}} + \beta_3 \bar{\rho}_{-j,t} + \beta_4 \bar{\sigma}_{\epsilon-j,t} + \gamma_1 X_{j,t} + \gamma_2 X_{-j,t} + \xi_{j,t}, \quad (1.22)$$

for both outcome variables mentioned. The main results are summarized in Table 1.5 and Table 1.6. Regressions (1) and (2) exclude other firm characteristics, while regression (3) includes them. The results are strongly significant and support the hypothesis of the model. Pre-announcement price movements and trading volume, are highly influenced by information discovered in this period by traders, and traders need to allocate limited learning capacity across assets.

The significant and negative coefficient on other announcing firms' persistence indicates that investors capacity allocation is happening in a rational fashion. However, the not significant coefficients on the variance of earnings surprises suggests that investor reaction is not fully optimal. In this analysis, squared cumulative abnormal returns five trading days prior announcement, excluding announcement days, were used. In Appendix B, Table B.1 repeats the main specification for various time horizons between two and ten trading days, while Table B.2 uses the absolute value of returns instead of squared ones. Table B.3 repeats the analysis for the level of trading volume, instead of fraction of total daily volume. Both the sign, magnitude, and significance of results seem to be stable across specifications.

1.3 Conclusions

Costly information acquisition and capacity constraints in processing new information can have significant effects on investor behavior, trading, and price informativeness. I presented a model where private information is costly, and rational traders allocate their learning capacity optimally. The model shows how public announcements interact with these information frictions, resulting in the existence of focusing equilibria, where traders allocate their learning capacity to assets with upcoming announcements. This equilibrium behavior results in higher volatility and trading volume in periods before public announcements, but decreased price informativeness, price discovery, and lower volatility for stocks that are not affected by

Table 1.5: Cross-sectional regression of squared cumulative abnormal returns on firm characteristics:

$$CAR^2_{-5d,j,t} = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \gamma X_{j,t} + \xi_{j,t},$$

$$CAR^2_{-5d,j,t} = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \beta_3 \bar{\rho}_{-j,t} + \beta_4 \bar{\sigma}_{\epsilon-j,t} + \gamma_1 X_{j,t} + \gamma_2 X_{-j,t} + \xi_{j,t}.$$

The outcome variable $CAR^2_{-5d,j,t}$, is squared cumulative abnormal return for firm j, in the five trading days prior the announcement, relative to a three factor Fama-French prediction. Explanatory variables are ρ_j, the persistence of earnings for firm j, $\sigma^2_{\epsilon_j}$, the variance of the earnings surprise for firm j, $\bar{\rho}_{-j}$, the average persistence of firms that announce the same week as firm j. $\bar{\sigma}^2_{\epsilon-j}$, the average earnings surprise variance of firms that announce the same weeks as firm j. δ_t, a time fixed effect, $X_{j,t}$ and $X_{-j,t}$, a set of controls, such as size and analyst coverage of own and other announcing firms, and industry dummies.

	(1) CAR^2_{-5d}	(2) CAR^2_{-5d}	(3) CAR^2_{-5d}
ρ_j	0.000473***	0.000323***	0.000282***
(own persistence)	(7.94)	(5.77)	(4.97)
$\sigma^2_{\epsilon_j}$	0.000395***	0.000330***	0.000340***
(own variance)	(5.50)	(5.43)	(5.13)
$\bar{\rho}_{-j}$			-0.00418**
(other persistence)			(-2.51)
$\bar{\sigma}^2_{\epsilon-j}$			0.000965
(other variance)			(0.50)
Controls	None	Firm	Firm
Observations	151115	150328	150328

t statistics in parentheses

All regressions with time fixed effects

Standard errors two-way clustered on firm and time level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Cross-sectional regression of trading volume on firm characteristics:

$$Vol_{-5d,j,t}\% = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \gamma X_{j,t} + \xi_{j,t},$$

$$Vol_{-5d,j,t}\% = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \beta_3 \bar{\rho}_{-j,t} + \beta_4 \bar{\sigma}_{\epsilon-j,t} + \gamma_1 X_{j,t} + \gamma_2 X_{-j,t} + \xi_{j,t}.$$

The outcome variable $Vol_{-5d,j,t}\%$, is fraction of trading volume of firm j, in the five trading days prior the announcement, relative to the total market trading volume. Explanatory variables are ρ_j, the persistence of earnings for firm j, $\sigma^2_{\epsilon_j}$, the variance of the earnings surprise for firm j, $\bar{\rho}_{-j}$, the average persistence of firms that announce the same week as firm j. $\bar{\sigma^2_{\epsilon}}_{-j}$, the average earnings surprise variance of firms that announce the same weeks as firm j. δ_t, a time fixed effect, $X_{j,t}$ and $X_{-j,t}$, a set of controls, such as size and analyst coverage of own and other announcing firms, and industry dummies.

	(1) $Vol_{-5d}\%$	(2) $Vol_{-5d}\%$	(3) $Vol_{-5d}\%$
ρ_j	0.000311***	0.000101***	0.0000576**
(own persistence)	(9.98)	(3.85)	(2.12)
$\sigma^2_{\epsilon_j}$	0.000122**	0.000168***	0.000174***
(own variance)	(2.04)	(3.77)	(4.00)
$\bar{\rho}_{-j}$			-0.00441***
(other persistence)			(-3.38)
$\bar{\sigma^2_{\epsilon}}_{-j}$			0.00103
(other variance)			(0.34)
Controls	None	Firm	Firm
Observations	104424	103963	103963

t statistics in parentheses

All regressions with time fixed effects

Standard errors two-way clustered on firm and time level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the announcement.

I use quarterly earnings announcements as regular, frequent, and important information events to empirically test the model's implications. I find patterns consistent with the model, both in the time-series and the cross-section of assets. Average institutional investor attention, average abnormal price movements, and average trading volume are lower on weeks with more announcements, suggesting that learning capacity is indeed a scarce resource. However, measures are higher on weeks with more informative announcements, which is consistent with investors rationally reacting to information costs.

The cross-sectional analysis shows that attention, return movements, and volume are negatively affected by the importance of other announcing stocks. Results are consistent with my model of costly information acquisition and rational investor reaction to these frictions, and hard to reconcile with other models of learning or leakage of insider information. The results also suggest that investor reaction to information frictions is rational, however not fully optimal, and on average there could be improvements in efficiency.

Chapter 2

Regret Induced Reference Points in Stopping Problems

Regret is the feeling of an individual induced by comparing the outcome of a decision to a counterfactual outcome that could have happened had the individual made another decision in the past. The role of regret on decision making is in the focus of economic research since Loomes and Sugden (1982) and Bell (1982). Anticipated regret showed to be the source of many well known behavioral phenomena. (Loomes and Sugden, 1987) shows how regret can generate the endowment effect in static decision problems, (Michenaud and Solnik, 2008) analyze the effect of regret in currency hedging decisions, while (Muermann et al., 2006) describe the effect of regret on portfolio choice.

The main question of modeling regret is what makes a counterfactual outcome relevant to the decision maker. The importance of a counterfactual is determined by many factors, and analyzed widely in psychology, for example in Kahneman and Varey (1990). Following Loomes and Sugden (1982) and Loomes and Sugden (1987) economic modeling treats the ex-post best possible outcome as the relevant counterfactual. Even though this is an approximation, however, Quiggin (1994) showed that under conditions that are reasonable for static decision problems, this is a valid representation of regret preferences.

The case is vastly different for dynamic decision settings, where decisions made in different points in time perceived differently by the acting agent, thus a simple maximum representation leads to predictions that are different from observed data. For example, Strack and Viefers (2019) shows that experimental results in a dynamic stopping problem cannot be matched with predictions from the classic models of regret.

This paper presents a new framework, in the spirit of Kőszegi and Rabin (2006) to capture the effect of regret on decisions in dynamic settings. After describing the general theoretical setup, Section 2.2 outlines models to illustrate how counterfactual induced utility and temporal changes can provide a unifying framework to explain several phenomena observed in finance. Regret induced reference points can micro found behavior of individual stock investors, such as the disposition effect, previously analyzed by Odean (1998). Furthermore, it can explain multiple CEO (mis)behaviors during investment decision, such as the escalation of commitment or the sunk cost fallacy. Section 2.3 then outlines implications of regret on asset prices, showing how it generates asymmetric price reaction to news about fundamentals.

2.1 Theoretical framework

This section presents a framework that allows to model regret in certain types of dynamic decisions in the spirit of the reference-dependence framework by Kőszegi and Rabin (2006), with multiple reference points that are induced by counterfactual outcomes the agent choose not to reach. More precisely, consider a dynamic stopping problem in discrete time, where time indexed by $t \geq 0$. There is an underlying value process $\{x_t\}_{t\geq 0}$ representing the outcomes the agent receive if decides to stop in period t, a Markov process defined on a filtered space $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t\geq 0}, \mathbf{P})$. Moreover assume that $\{x_t\}_{t\geq 0}$ is real valued and adapted to $\{\mathcal{F}_t\}_{t\geq 0}$.

2.1.1 Regret induced reference points

The agent observes the value of the process and can decide to exit in any period. She receives a payout x_t in the period when she chooses to stop or in the period when the process ends exogenously, whichever happens first. If the agent chooses to stop at period t, she does not observe the values x_s for $s > t$. As a benchmark, consider a rational agent, whose utility, when the process ends in period t is $u(x_t)$ for some increasing, continuous and continuously differentiable utility function $u(\cdot)$.

Now consider an agent resembling more to human decision makers, whose utility is affected by regret and rejoice, counterfactual outcomes that she could have chosen. In case of a regret agent, her utility of stopping time $t > 0$ has a standard reference dependent formulation,

$$u(x_t) + \kappa \sum_{s=0}^{t-1} (u(x_t) - u(x_s)), \tag{2.1}$$

where $\kappa > 0$ is a parameter governing the weight of regret, and the reference-dependent components are linear in the utility difference relative to the reference point. Therefore, since linear scaling does not affect the representation, the agent's utility can be written as

$$U(x_t, R_t) = u(x_t) - KR_t, \tag{2.2}$$

with

$$R_t = \begin{cases} \frac{1}{t}\sum_{s=0}^{t-1} u(x_s) & \text{if } t > 0 \\ u(x_0) & \text{if } t = 0, \end{cases} \tag{2.3}$$

and $K = \frac{\kappa}{1+\kappa}$. This setup is analogous to Strack and Viefers (2019), with the only difference is the definition of the relevant counterfactual. In Strack and Viefers (2019) the model follows the standard set up by Loomes and Sugden (1982), where the relevant counterfactual is the utility ex-post best outcome the decision maker could have achieved. While in this model, the relevant counterfactual is the average utility the decision maker decided not to reach in previous periods.

An agent whose preferences are described by Equations 2.2 and 2.3 behaves differently as a rational decision-maker. The key driver of the changes is the anticipated change in regret in future periods. The intuition behind the behavior of a regret agent is the following. Besides the standard, rational trade-off between the current value and the expected value from continuation, regret enters into the decision through two channels. A choice to continue will affect regret both through changes in the next period payoff, but also through changes in the reference point. These changes lead to behavior that regret agents are more likely to exit after good states, than a rational decision maker, in order to receive the additional positive utility. While after bad states, individuals with regret preferences are more likely to continue, than a rational agent, to avoid the negative utility from the regret component of preferences. The exact behavioral differences depend on how the underlying process and beliefs about future values formed; however, the central intuition can be summarized easily. Formally the following can be said.

Proposition 6 (Behavior with regret induced reference points) *For any x_t and $\mathcal{F}_t$, there exists a unique level of $\bar{R}_t$ such that the agent is indifferent between stopping and continuation. Moreover, if $R_t > \bar{R}_t$ then the agent strictly prefers to continue, while if $R_t < \bar{R}_t$ then the agent strictly prefers to stop.*

Depending on what is the optimal behavior of a rational agent, the stopping implications of regret can explain behavior such as the escalation of commitment (stopping too late after adverse outcomes) and the disposition effect (stopping too early after good outcomes). The path dependence introduced by the backward-looking reference-point makes the agent's decision dependent on previous values and decision, generating behavior similar to the sunk cost fallacy.

2.1.2 The role of information frictions

Information plays a crucial role in this framework. When the agent exits, she not just realizes the utility $U(x_t, R_t)$, but also stops observing future realizations of the process. Depending on the economic situation this could be a result of how the process is defined, for example in case of an R&D project, when a CEO decides to shut down the project, the outcomes would have been realized if the project had been continued, are not observable anymore. Alternatively, not observing the process after stopping could be physically possible in some cases, for example, if an investor decides to liquidate her position in an asset, she could choose to observe asset prices after the sale if she wishes to. In these situations, the assumption of not observing the process is an assumption on the decision-makers' behavior rather than on the physical environment. However, independently from the reason, this assumption on information is crucial, as explained by the following result.

Proposition 7 (Role of information frictions) *If the full history of the process x_t is observed by the agent, independently of her stopping decision, then the behavior of an agent with regret preferences is identical to the behavior of a rational agent.*

The role of information is clear. When the agent's action affects the information available to her, she might choose different action from the rational decision maker, in order to stop observing the process earlier or to observe the process longer, and change her reference point.

2.2 Examples and implications

To show the implications of regret and counterfactual thinking in dynamic decisions, consider a few example finite period problems. For the purposes of these examples, consider risk-neutral agents. Therefore the consumption utility is linear,

$$U(x_t, R_t) = x_t - KR_t. \tag{2.4}$$

The linearity of the utility function is not crucial for the results. However, it keeps the calculations tractable.

These examples show how reference dependence generated by foregone alternatives the agent choose not to take can unify multiple psychologically well known, and economically important phenomena, such as the disposition effect, the sunk cost fallacy, and the escalation of commitment.

2.2.1 Disposition effect

Consider a simple investment problem. There is one unit of a risky asset for purchase in period $t = 0$ for a price normalized to one. Moreover, if purchased, the investor can either sell it in period $t = 1$ or in period $t = 2$ the asset is liquidated. The gross return on the asset in both periods are iid, D with probability q and $\frac{1}{D}$ with probability $1 - q$ for some $D > 1$ and $0 < q < 1$. Moreover, assume that the investor has initial wealth $w > 1$ that can be used for this trade.

As a benchmark, first consider the decision of a rational risk-neutral investor, who only invests if her expected value is positive, and if invested, always holds the asset until expiration. Given the iid return distribution, a rational investor either invests in both period or does not invest at all. The requirement for investment is to have a positive expected net return,

$$qD + (1 - q)\frac{1}{D} > 1. \tag{2.5}$$

Therefore, a rational investor invests at $t = 0$ if and only if

$$q > \frac{1}{1 + D}, \tag{2.6}$$

and if purchased the asset, the investor holds it until period $t = 2$.

Now consider a regret investor with preferences described above. Regret investors' interim valuation will become history dependent. Therefore actions after bad and good returns might differ, affecting investors' initial actions as well.

First, analyze the investor's interim decision, conditional on buying the asset in period zero. After a positive return, the investor can sell the asset for D, hence her current reference utility is $R_1 = w$, while after continuation, it will be $R_2 = \frac{w+w-1+D}{2} = w + \frac{D-1}{2}$. Therefore, she holds the asset if and only if

$$w - 1 + qD^2 + 1 - q - Kw - K\frac{D-1}{2} > w - 1 + D - Kw, \tag{2.7}$$

or equivalently if

$$q > \frac{2+K}{2}\frac{1}{1+D}. \tag{2.8}$$

This result immediately provides the first results, since $t\frac{2+K}{2}\frac{1}{1+D} > \frac{1}{1+D}$, the regret investor is more likely to sell the asset after positive returns, than the rational investor.

Now consider the decision after negative returns. Similarly $R_1 = w$, while if she chooses to hold on to the asset, $R_2 = \frac{w+w-1+\frac{1}{D}}{2} = w + \frac{1-D}{2D}$. Therefore she keeps the asset if and only if

$$w - 1 + q + (1-q)\frac{1}{D^2} - Kw - K\frac{D-1}{2D} > w - 1 + \frac{1}{D} - Kw, \tag{2.9}$$

or equivalently

$$q > \frac{2-KD}{2}\frac{1}{1+D}. \tag{2.10}$$

Note, that the cutoff probability after negative movements, just as the intuition of the general model suggests, lower than if the investor would be rational. Therefore this model already provides the main component of the disposition effect, that investors are more likely to sell the asset after positive returns than after negative returns.

The results in this example are conditional on the agent choosing to invest in the asset during the initial period. Finally, it is easy to show that there are beliefs, such that the regret agent invests in the asset indeed, then holds onto it only after negative first period returns. There can be three possibilities depending on the relation of q to $\frac{2+K}{2}\frac{1}{1+D}$ and $\frac{2-KD}{2}\frac{1}{1+D}$, the two cutoff values in period $t = 1$. It is easy to see, that if the investor is optimistic enough that she would hold the asset even after good news, then she always invest in this asset. Similarly, if she is pessimistic, that she would sell the asset in period $t = 1$ for sure, then she does not invest. For these investors, the observed behavior is the same as the behavior of rational investors with the same beliefs. The difference comes in the domain, where the disposition effect is observed. In this case, the condition for original investment is that

$$w - 1 + qD - qKw + (1-q)q + (1-q)^2\frac{1}{D^2} - (1-q)Kw - (1-q)K\frac{1-D}{2D} > w - Kw, \tag{2.11}$$

or equivalently

$$qD + (1-q)q + (1-q)^2\frac{1}{D^2} - (1-q)K\frac{1-D}{2D} > 1. \tag{2.12}$$

Given that the marginal investor's beliefs must be on this domain, and expected utility of investment in monotonic in p, the condition has a unique solution on $\left(\frac{2-KD}{2}\frac{1}{1+D}, \frac{2+K}{2}\frac{1}{1+D}\right)$. Therefore there exist agents who would invest into assets, then sell it only after positive returns.

Regret has two effects on investor decision. One is that after good outcomes, investors more likely to sell the asset than rational investors, while after adverse outcomes they would be more likely to hold on to the asset, however in a setting with iid returns the observed actions of entirely rational investors and those of with regret preferences, observationally equivalent. The reason is that investors who would sell after negative returns do not invest in the asset in the first place. This behavior, the disposition effect is analyzed by Odean (1998).

2.2.2 Sunk cost fallacy

Consider an investment problem of a firm, where the firm runs a trial test before the development of a product. There are three periods, and in $t = 0$ the firm can invest I_0 in the trial. After the trial, the firm can invest I_1 to develop the final project, that could yield to a payoff of D. The probability of success, p_1 depends on the outcome of the trial, observed by the firm before the additional investment decision. Moreover, assume that the firm's budget fur such projects are greater than the required investment, $B >> I_0 + I_1$.

Focus the analysis on the interesting case, when the firm starts the trial. The rational CEO does the period $t = 1$ investment if her expected payoff is higher than the investment amount of I_1. Therefore if

$$p_1 D > I_1, \tag{2.13}$$

or equivalently if

$$p_1 > \frac{I_1}{D}. \tag{2.14}$$

However, a CEO with regret preferences has a different continuation criteria. After the trial, stopping would result in regret regarding the previous period decision to invest. The current reference point of the CEO is $R_1 = B$, thus the utility of terminating the project after the trial is

$$B - I_0 - KB. \tag{2.15}$$

If the CEO decides to invest after the trial result, her reference point will change to

$$R_2 = \frac{B + B - I_0}{2} = B - \frac{I_0}{2}, \tag{2.16}$$

in the final period. Thus her expected utility from investment is

$$B - I_0 - I_1 + p_1 D - KR_2 = B - I_0 - I_1 + p_1 D - K\left(B - \frac{I_0}{2}\right). \tag{2.17}$$

Therefore a regret CEO would invest after the trial if and only if the expected utility of investment is greater than the utility of stopping, or equivalently if

$$p_1 D > I_1 - K\frac{I_0}{2}. \tag{2.18}$$

Therefore, if the probability of success based on the trial is greater than some cutoff value,

$$p_1 > \frac{I_1}{D} - K\frac{I_0}{2D}. \tag{2.19}$$

There are several consequences of regret for the CEO's decision. First, just as in the previous example for disposition effect, the CEO with regret preferences is more likely to continue after bad outcomes, as the cutoff value for p_1 is lower for a regret CEO than for a rational agent. Second, the CEO with regret exhibits behavior usually referred to as the sunk cost fallacy. Her decision in period $t = 1$ depends on the amount already invested in the project previously. This value I_0 is a sunk cost in the interim period, thus should not be a factor in the continuation decision. However, the CEO's willingness to invest further, as captured by the cutoff value for p_1 is decreasing in the already invested amount of I_0.

Sunk cost fallacy is a commonly known behavior that decision-makers' actions depend on costs that occurred in past periods, that cannot be reversed. It has important implications in a variety of decision problems, for example during specific auction mechanisms, as analyzed by Augenblick (2015). This example shows how regret, and regret induced reference dependence can explain, and micro found such behavior in a fairly general context.

2.2.3 Escalation of commitment

Consider a similar problem, where a firm has to invest in a project that involves research and development, but now in multiple periods. Formally, there are a finite number of periods indexed by $t = 0, \cdots, T$. At period $t = 0$ the firm can invest an initial amount of I in starting the project. If they do so, then with probability p_0 the project ends and pays off D in the next period. In each consecutive periods, if the project did not end before, then the firm has a binary choice. Either abandon the project with no further cash flows, or to invest another amount I and succeed with probability p_t, where $p_t < t_{t-1}$ and $p_{T+1} = 0$. Moreover, just as before assume that the firm's budget is much higher than the total amount of investment, $B >> (T+1)I$, and again, focus on the interesting case, where $p_0 D > I$ and $p_T D < I$.

The rational CEO invests into the project initially, and continue to fund it as long as $p_t D > I$. The solution can be obtained by backward induction and is a direct consequence of $p_t D$ being decreasing in t. Note, that the only purpose for the two conditions is to rule out the two uninteresting cases, where the rational CEO does not invest, or when the investment is continued until the final period.

Now consider the decision of a CEO with regret preferences. One can solve the problem using backward induction, however in any period t where continued investment is beneficial for the CEO. Then it is also beneficial in any earlier period $s < t$. The last period where the CEO still invests has a continuation value only $p_t D$, as no further investment will follow even after a negative outcome, however, the utility of investment is higher than the utility of stopping. At period t, the CEO's reference utility is $R_t = B - (t-1)I$, hence utility of stopping is

$$B - tI - K(B - (t-1)I), \tag{2.20}$$

while the expected utility of another round of investment is

$$B - (t+1)I + p_t D - K(B - tI). \tag{2.21}$$

Therefore the CEO invests indeed, if and only if

$$-I + p_t D + KI > 0, \tag{2.22}$$

or equivalently

$$p_t D > (1-K)I \tag{2.23}$$

Given that $(1-K)I < I$, this result implies that whenever there exists some period t, such that $(1-K)I < p_t D < I$, then after a series of unsuccessful rounds, the probability of success dropped too low, and the rational CEO would already be stopped investing in the project. However, the CEO with regret preferences exhibits escalation of commitment, and so to speak doubles down on the investment and still continues until the success probability drops below another threshold. The intuition of the example is straightforward. Decision makers with regret preferences would hold onto a project and consequently overinvest to have a chance of voiding the negative utility (feeling of regret) associated with failure and abandoning a project they already started. This result is consistent with executive behavior observed in many cases.

2.3 Asset prices in equilibrium

The examples in the previous section show how regret induced reference dependence can affect investor and CEO behavior, explaining various behavioral biases commonly associated with situations that can be described as dynamic stopping problems. However, those examples treated the environment as exogenously given. Another interesting question is the analysis of the general equilibrium effect of regret. To analyze the general equilibrium asset pricing implications of regret induced reference points, consider a simple asset pricing problem. There is a three period economy with a single risky asset and two types of agents. Time is indexed by $t = 0, 1, 2$, and the risky asset has a single payoff in $t = 2$ with value of $\theta_1\theta_2$, where θ_i are iid random variables with value either D or $\frac{1}{D}$. There is an $\alpha > 1$ mass of unconstrained investors, who can both buy or sell short one unit of the asset (institutional investors), while there is a β mass of constrained investors who can only hold long positions (retail investors). Moreover, each investor has heterogeneous beliefs about the probability of a positive outcome of D, what is uniformly distributed, $q_i\ U[0,1]$. All investors initially endowed with period $t = 0$ wealth $w > D^2$, and in period $t = 0$ agents can trade the asset.

Those who do not trade exit the market, while those who trade will observe θ_1 in $t = 1$, then have the possibility to trade again. In $t = 2$ all investors receive payoffs.

First consider the case when all investors are rational, which is the $K = 0$ limit of the preferences in Equation 2.4. In this situation, the marginal investor, who is indifferent to take a long or a short position, is the same as the marginal constrained investor, who is indifferent between investing and leaving the market. Moreover, according to Lemma **??**, these marginal investors will be the same in all periods and all states of the economy. If beliefs for a positive per period return for the marginal investor are $\bar{q}$, then market clearing implies

$$\alpha(1-\bar{q}) + \beta(1-\bar{q}) = 1 + \alpha\bar{q}. \tag{2.24}$$

This condition reveals the identity of the marginal investor. Then the asset prices can be calculated by the beliefs $\bar{q}$ and the fact that the marginal investors' expected utility from a long position is the same as the utility of not trading. The results can be summarized as follows.

Lemma 3 (Asset prices with rational investors) *If all investors are rational, then in all periods and states the marginal investors' beliefs for a positive per period return are*

$$\bar{q} = \frac{\alpha + \beta - 1}{2\alpha + \beta} \tag{2.25}$$

and if the asset's price in period $t = 0$, p_0, in period $t = 1$ after observing positive information, p_u and after negative information p_d satisfy

$$\begin{aligned} p_u &= \bar{q}D^2 + 1 - \bar{q} && (2.26)\\ p_d &= \bar{q} + (1-\bar{q})\frac{1}{D^2} && (2.27)\\ p_0 &= \bar{q}p_u + (1-\bar{q})p_d. && (2.28) \end{aligned}$$

Now analyze the effect of regret on equilibrium. Formally assume, that institutional investors have rational preferences, however, regret investors' utility is affected by regret induced reference points, as defined in Equation 2.4. The solution of the model is similar to the rational case, however slightly more complicated. Formally there are six marginal investors, one retail and one institutional in each period and state. In the rational case, the results were simple, as all these investors held the same beliefs, which is not the case anymore. Let's denote $\bar{q}_j$ the marginal institutional investor, while $\hat{q}_j$ the marginal retail investor for $j \in \{0, u, d\}$.

First, consider the equations resulting from the fact that markets have to clear, therefore

$$\alpha(1-\bar{q}_j) + \beta(1-\hat{q}_j) = 1 + \alpha\bar{q}_j \tag{2.29}$$

for all $j \in \{0, u, d\}$. The second observation one can make is that according to Proposition **??**, every retail investor who purchased the asset would like to hold it after negative news in period $t = 1$. This implies that $\hat{q}_d$ does not play a role in the asset pricing, while market clearing now dictates that $\bar{q}_d = \bar{q}_0$, the marginal institutional investor is the same in period

$t = 0$ as in period $t = 1$ after a negative first-period realization of θ_1. Finally, just as before, the marginal investors' expected utility from taking a long position has to be the same as the utility of not trading. This way the marginal institutional investor dictates the price, while the marginal retail investors' conditions complete the set of equations. The results can be summarized as follows.

Proposition 8 (Asset prices with regret investors) *If institutional investors are rational, while retail investors have regret preferences as defined in Equation 2.4, then the marginal investors' beliefs and asset prices are the unique solution over $\hat{q}_i, \bar{q}_i \in [0, 1]$ of the system consisting of equations related to market clearing,*

$$2\alpha\bar{q}_0 + \beta\hat{q}_0 = \alpha + \beta - 1 \tag{2.30}$$

$$2\alpha\bar{q}_u + \beta\hat{q}_u = \alpha + \beta - 1 \tag{2.31}$$

$$\bar{q}_0 = \bar{q}_d. \tag{2.32}$$

Equations related to valuation of marginal institutional investors in all periods and states,

$$p_u = \bar{q}_u D^2 + 1 - \bar{q}_u \tag{2.33}$$

$$p_d = \bar{q}_d + (1 - \bar{q}_d)\frac{1}{D^2} \tag{2.34}$$

$$p_0 = \bar{q}_0 p_u + (1 - \bar{q}))p_d, \tag{2.35}$$

and valuation of marginal retail investors in $t = 0$ and in $t = 1$ after positive news,

$$\hat{q}_u D^2 + 1 - \hat{q}_u - K\frac{p_u - p_0}{2} = p_u, \tag{2.36}$$

$$\hat{q}_0 p_u + (1 - \hat{q}_0)\hat{q}_0 + (1 - \hat{q}_0)^2\frac{1}{D^2} - (1 - \hat{q}_0)K\frac{p_d - p_0}{2} > p_0. \tag{2.37}$$

The reatail investor who would be marginal in period $t = 1$ after negative news, did not trade in period $t = 0$ and exited the market.

In the equilibrium described in Proposition 8, the initial price of the asset and the price after negative news in the first period, p_0 and p_d are higher than with only rational investors. The price impact of news, measured by changes in the marginal institutional investor is the same for negative news, but smaller for positive news, compared to the model with only rational investors. In other words, regret in retail investors mitigate the effect of good news and create an asymmetric response in prices.

The intuition behind the result is quite straightforward after the example in Section 2.2.1. After bad news, just as in the simple investment problem, regret and rational investors' actions are observationally equivalent, therefore after bad news, the marginal investor setting the price remains the same. However, after good news, regret agents with an increased willingness to sell, introduce a supply side pressure, decreasing the prices, thus mitigating the effect of information. The resulting equilibrium prices thus exhibit this asymmetric feature, that negative price reaction to information will be higher than positive movements.

2.4 Conclusions

This paper presents a new framework to model the effects of anticipated regret on decision making in dynamic settings, based on the reference-dependence framework of Kőszegi and Rabin (2006). Some simple examples illustrate how regret can explain psychological phenomena such as the disposition effect, escalation of commitment, and the sunk cost fallacy. Regret can also explain asymmetric price reactions to news about financial assets. In general regret-induced reference points introduce path dependence to decision making. Investors with regret preferences are more likely to stop projects after positive outcomes, and more likely to continue after negative outcomes, than an otherwise identical rational decision maker.

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Appendix A

Proofs and Derivations for Chapter 1

Proof of Lemma 1 Conjecture the linear price structure with τ_{ij} being the private signal precision of trader i bout asset j, and $\bar{\tau}_j$ being the average private signal precision of traders learning about stock j. Then let $E_{ij,t}$ be the expected payoff of trader i from holding one unit of asset j before the announcement, and E_{t+1} the expected payoff of all traders for holding one unit of the asset after the announcement. Then,

$$E_{ij,t} = A_{0j} + A_{1j}\rho_j\theta_{j,t-1} + A_{1j}\frac{\tau_{ij}}{\tau_{ij}+\tau_{\epsilon_j}}\epsilon_{j,t+1}, \tag{A.1}$$

$$E_{j,t+1} = B_{0j} + B_{1j}\theta_{j,t-1} + \theta_{j,t+1}, \tag{A.2}$$

and the conditional variances after observing the signals are

$$V_{ij,t} = A_{1j}^2\frac{1}{\tau_{ij}+\tau_{\epsilon_j}}, \tag{A.3}$$

$$V_{j,t+1} = B_{2j}^2\frac{1}{\tau_{\epsilon_j}}. \tag{A.4}$$

Then for all periods, market clearing implies

$$\int_0^1 \frac{E_{ij,t} - R_f p_{j,t}}{V_{ij,t}}di = \gamma, \tag{A.5}$$

$$\frac{E_{j,t+1} - R_f p_{j,t+1}}{V_{j,t+1}} = \gamma, \tag{A.6}$$

which are linear in θ and ϵ, and has to hold for any value of these variables. So matching coefficients gives

$$
\begin{aligned}
A_{1j}\rho_j &= R_f B_{1j}, && \text{(A.7)}\\
A_{1j}\bar{\tau}_j &= R_f B_{2j}(\bar{\tau}_j + \tau_{\epsilon_j}), && \text{(A.8)}\\
A_{0j} - R_f B_{0j} &= \gamma A_{1j}^2 \frac{1}{\bar{\tau}_j + \tau_{\epsilon_j}}, && \text{(A.9)}\\
1 + B_{1j} &= R_f A_{1j}, && \text{(A.10)}\\
B_{j0} - R_f A_{0j} &= \gamma V_{j,t+1}. && \text{(A.11)}
\end{aligned}
$$

Which solves for

$$
\begin{aligned}
B_{1j} &= \frac{\rho_j}{R_f^2 - \rho_j}, && \text{(A.12)}\\
A_{1j} &= \frac{R_f}{R_f^2 - \rho_j}, && \text{(A.13)}\\
B_{2j} &= \frac{1}{R_f^2 - \rho_j}\frac{\bar{\tau}_j}{\bar{\tau}_j + \tau_{\epsilon_j}}, && \text{(A.14)}\\
V_{bj} &= A_{1j}^2 \frac{1}{\bar{\tau}_j + \tau_{\epsilon_j}}, && \text{(A.15)}\\
V_{aj} &= B_{2j}^2 \frac{1}{\tau_{\epsilon_j}}, && \text{(A.16)}\\
B_{0j} &= -\gamma \frac{R_f V_{bj} + V_{aj}}{R_f^2 - \rho_j}, && \text{(A.17)}\\
A_{0j} &= -\gamma \frac{R_f V_{aj} + V_{bj}}{R_f^2 - \rho_j}. && \text{(A.18)}
\end{aligned}
$$

■

Lemma 4 (Expected utility for the attention allocation) *The expected utility for the attention allocation problem of trader i is*

$$
E[EU(w_i|\{s_{ij}\}_{j=1}^3)] = \sum_{j=1}^{3} \frac{1}{2V_{ij}} \left(Var(E_{ij} - p_j) + E[E_{ij} - p_j]^2\right). \qquad \text{(A.19)}
$$

where E_{ij} is trader i's conditional expectation of her payoff from holding one unit of asset j, after observing her private signals, while V_{ij} is her conditional variance.

Proof of Lemma 4 Trader i's problem is, leaving the t subscript,

$$
\max_{\{\tau_{ij}\}_{j=1}^3} E[EU(w_i|\{s_{ij}\}_{j=1}^3)], \qquad \text{(A.20)}
$$

and let x_{ij} be the demand of trader i in asset j. Then expected utility given the private signals can be written as (using d_j for the total payoff resulting from holding one unit of asset j),

$$EU(w_i|\{s_{ij}\}_{j=1}^3) = \sum_{j=1}^3 \gamma E[x_{ij}(d_j - p_j)|s_{ij}] - \sum_{j=1}^3 \frac{\gamma^2}{2} Var(x_{ij}(d_j - p_j)|s_{ij}) \quad (A.21)$$

$$= \sum_{j=1}^3 \frac{1}{V_{ij}} E[(E_{ij} - p_j)(d_j - p_j)|s_{ij}] \quad (A.22)$$

$$- \sum_{j=1}^3 \frac{1}{2V_{ij}^2} Var((E_{ij} - p_{bj})(d_j - p_{bj})|s_{ij}) \quad (A.23)$$

$$= \sum_{j=1}^3 \frac{1}{V_{ij}} (E_{ij} - p_j)^2 - \sum_{j=1}^3 \frac{1}{2V_{ij}} (E_{ij} - p_j)^2 \quad (A.24)$$

$$= \sum_{j=1}^3 \frac{1}{2V_{ij}} (E_{ij} - p_j)^2, \quad (A.25)$$

therefore the unconditional expected utility before observing the signal is

$$E[EU(w_i|\{s_{ij}\}_{j=1}^3)] = \sum_{j=1}^3 \frac{1}{2V_{ij}} E\left[(E_{ij} - p_j)^2\right] \quad (A.26)$$

$$= \sum_{j=1}^3 \frac{1}{2V_{ij}} \left(Var(E_{ij} - p_j) + (E[E_{ij} - p_j])^2\right). \quad (A.27)$$

■

Proof of Lemma 2 Consider first the case where stocks 1 and 2 have an upcoming announcement. Let $\bar{\tau}_j$ be the average precision of other traders' signals for stock j. Then let's consider trader i's choice and let τ_{ij} be the precision of trader i's signals for stocks $j \in \{1, 2, 3\}$. Then, dropping the time subscript, first compute the difference between trader i's conditional expected payoff, and the discounted price, using the price structure from

Lemma 1.

$$
\begin{aligned}
E_{i1} - R_f p_1 &= A_{01} + A_{11}\rho_1\theta_1 + A_{11}\frac{\tau_{i1}}{\tau_{i1}+\tau_{\epsilon_1}}(\eta_{i1}+\epsilon_1) &\text{(A.28)}\\
&- R_f B_{01} - R_f B_{11}\theta_1 - R_f B_{21}\epsilon_1 &\text{(A.29)}\\
&= A_{11}\frac{\tau_{i1}}{\tau_{i1}+\tau_{\epsilon_1}}\eta_{i1} + A_{11}\left(\frac{\tau_{i1}}{\tau_{i1}+\tau_{\epsilon_1}} - \frac{\bar{\tau}_1}{\bar{\tau}_1+\tau_{\epsilon_1}}\right)\epsilon_1 + \gamma V_{b1}, &\text{(A.30)}\\
E_{i2} - R_f p_2 &= A_{02} + A_{12}\rho_1\theta_2 + A_{12}\frac{\tau_{i2}}{\tau_{i2}+\tau_{\epsilon_2}}(\eta_{i2}+\epsilon_2) &\text{(A.31)}\\
&- R_f B_{02} - R_f B_{12}\theta_2 - R_f B_{22}\epsilon_2 &\text{(A.32)}\\
&= A_{12}\frac{\tau_{i2}}{\tau_{i2}+\tau_{\epsilon_2}}\eta_{i2} + A_{12}\left(\frac{\tau_{i2}}{\tau_{i2}+\tau_{\epsilon_2}} - \frac{\bar{\tau}_2}{\bar{\tau}_2+\tau_{\epsilon_2}}\right)\epsilon_2 + \gamma V_{b2}, &\text{(A.33)}\\
E_{i3} - R_f p_3 &= B_{03} + B_{13}\theta_3 + B_{23}\frac{\tau_{i3}}{\tau_{i3}+\tau_{\epsilon_3}}(\eta_{i3}+\epsilon_3) + \theta_3 - R_f A_{03} - R_f A_{13}\theta_3 &\text{(A.34)}\\
&= B_{23}\frac{\tau_{i3}}{\tau_{i3}+\tau_{\epsilon_3}}\eta_{i3} + B_{23}\frac{\tau_{i3}}{\tau_{i3}+\tau_{\epsilon_3}}\epsilon_3 + \gamma V_{a3}, &\text{(A.35)}
\end{aligned}
$$

and trader i's variances are

$$
\begin{aligned}
V_{i1} &= A_{11}^2\frac{1}{\tau_{i1}+\tau_{\epsilon_1}}, &\text{(A.36)}\\
V_{i2} &= A_{12}^2\frac{1}{\tau_{i2}+\tau_{\epsilon_2}}, &\text{(A.37)}\\
V_{i3} &= B_{23}^2\frac{1}{\tau_{i3}+\tau_{\epsilon_3}}. &\text{(A.38)}
\end{aligned}
$$

So $\frac{E^2[E_{ij}-R_f p_j]}{\gamma V_{ij}}$ terms in the expected utility are

$$
\begin{aligned}
\frac{(E[E_{i1}-R_f p_1])^2}{V_{i1}} &= \gamma^2 A_{11}^2\frac{\tau_{i1}+\tau_{\epsilon_1}}{(\bar{\tau}_1+\tau_{\epsilon_1})^2}, &\text{(A.39)}\\
\frac{(E[E_{i2}-R_f p_2])^2}{V_{i2}} &= \gamma^2 A_{12}^2\frac{\tau_{i2}+\tau_{\epsilon_2}}{(\bar{\tau}_2+\tau_{\epsilon_2})^2}, &\text{(A.40)}\\
\frac{(E[E_{i2}-R_f p_2])^2}{V_{i2}} &= \gamma^2 B_{23}^2\frac{\tau_{i3}+\tau_{\epsilon_3}}{\tau_{\epsilon_3}^2}, &\text{(A.41)}
\end{aligned}
$$

and the $\frac{Var(E_{ij}-R_f p_j)}{V_{ij}}$ terms are

$$
\begin{aligned}
\frac{Var(E_{i1}-R_f p_1)}{V_{i1}} &= \frac{\tau_{i1}}{\tau_{i1}+\tau_{\epsilon_1}} + \left(\frac{\tau_{i1}}{\tau_{i1}+\tau_{\epsilon_1}} - \frac{\bar{\tau}_1}{\bar{\tau}_1+\tau_{\epsilon_1}}\right)^2\frac{\tau_{i1}+\tau_{\epsilon_1}}{\tau_{\epsilon_1}}, &\text{(A.42)}\\
\frac{Var(E_{i2}-R_f p_2)}{V_{i2}} &= \frac{\tau_{i2}}{\tau_{i2}+\tau_{\epsilon_2}} + \left(\frac{\tau_{i2}}{\tau_{i2}+\tau_{\epsilon_2}} - \frac{\bar{\tau}_2}{\bar{\tau}_2+\tau_{\epsilon_2}}\right)^2\frac{\tau_{i2}+\tau_{\epsilon_2}}{\tau_{\epsilon_2}}, &\text{(A.43)}\\
\frac{Var(E_{i3}-R_f p_3)}{V_{i3}} &= \frac{\tau_{i3}}{\tau_{i3}+\tau_{\epsilon_3}} + \frac{\tau_{i3}^2}{\tau_{i3}+\tau_{\epsilon_3}}\frac{1}{\tau_{\epsilon_3}}. &\text{(A.44)}
\end{aligned}
$$

Then rewrite the problem in terms of allocated capacity. Let K_{ij} be the allocated capacity to asset j by investor i, so

$$K_{ij} = \ln \frac{\tau_{ij} + \tau_{\epsilon_j}}{\tau_{\epsilon_j}}, \tag{A.45}$$

and the constraint is now linear

$$K_{i1} + K_{i2} + K_{i3} = \ln \kappa. \tag{A.46}$$

Moreover,

$$\tau_{ij} + \tau_{\epsilon_j} = e^{K_{ij}} \tau_{\epsilon_j}, \tag{A.47}$$

$$\tau_{ij} = (e^{K_{ij}} - 1)\tau_{\epsilon_j}. \tag{A.48}$$

Hence, the six terms in trader i's utility are

$$\frac{(E[E_{i1} - R_f p_1])^2}{V_{i1}} = \gamma^2 A_{11}^2 \frac{e^{K_{i1}} \tau_{\epsilon_1}}{(\bar{\tau}_1 + \tau_{\epsilon_1})^2}, \tag{A.49}$$

$$\frac{(E[E_{i2} - R_f p_2])^2}{V_{i2}} = \gamma^2 A_{12}^2 \frac{e^{K_{i2}} \tau_{\epsilon_2}}{(\bar{\tau}_2 + \tau_{\epsilon_2})^2}, \tag{A.50}$$

$$\frac{(E[E_{i2} - R_f p_2])^2}{V_{i2}} = \gamma^2 B_{23}^2 \frac{e^{K_{i3}} \tau_{\epsilon_3}}{\tau_{\epsilon_3}^2}, \tag{A.51}$$

$$\frac{Var(E_{i1} - R_f p_1)}{V_{i1}} = \frac{(e^{K_{i1}} - 1)\tau_{\epsilon_1}}{e^{K_{i1}} \tau_{\epsilon_1}} + \left(\frac{(e^{K_{i1}} - 1)\tau_{\epsilon_1}}{e^{K_{i1}} \tau_{\epsilon_1}} - \frac{\bar{\tau}_1}{\bar{\tau}_1 + \tau_{\epsilon_1}} \right)^2 \frac{e^{K_{i1}} \tau_{\epsilon_1}}{\tau_{\epsilon_1}}, \tag{A.52}$$

$$\frac{Var(E_{i2} - R_f p_2)}{V_{i2}} = \frac{(e^{K_{i2}} - 1)\tau_{\epsilon_2}}{e^{K_{i2}} \tau_{\epsilon_2}} + \left(\frac{(e^{K_{i2}} - 1)\tau_{\epsilon_2}}{e^{K_{i2}} \tau_{\epsilon_2}} - \frac{\bar{\tau}_2}{\bar{\tau}_2 + \tau_{\epsilon_2}} \right)^2 \frac{e^{K_{i2}} \tau_{\epsilon_2}}{\tau_{\epsilon_2}}, \tag{A.53}$$

$$\frac{Var(E_{i3} - R_f p_3)}{V_{i3}} = \frac{(e^{K_{i3}} - 1)\tau_{\epsilon_3}}{e^{K_{i3}} \tau_{\epsilon_3}} + \frac{(e^{K_{i3}} - 1)^2 \tau_{\epsilon_3}^2}{e^{K_{i3}} \tau_{\epsilon_3}} \frac{1}{\tau_{\epsilon_3}}. \tag{A.54}$$

Therefore, the Lagrangian of trader i is now additively separable in K_{ij}. Thus, the Hessian is diagonal, moreover, all diagonal elements are positive. This implies that the maximization problem has a corner solution.

The case when t is odd and only asset 3 has an upcoming announcement has an identical proof.

■

Proof of Proposition 1 Consider first the period where only stock 3 has an upcoming announcement. Then the two thresholds are the same, so $\bar{\kappa}_1 = \bar{\kappa}_2$ and the condition under which focusing equilibrium exists is that trader i's utility from allocating all her capacity to asset 3 is greater than if she were to choose assets 1 or 2. Therefore,

$$\gamma^2 B_{2j}^2 \frac{1}{\tau_{\epsilon_j}} + \gamma^2 A_{13}^2 \frac{1}{\kappa \tau_{\epsilon_3}} + \frac{\kappa - 1}{\kappa} \geq \gamma^2 B_{2j}^2 \frac{\kappa}{\tau_{\epsilon_j}} + \gamma^2 A_{13}^2 \frac{1}{\kappa^2 \tau_{\epsilon_3}} + \kappa - 1 + \frac{(\kappa - 1)^2}{\kappa^2}, \tag{A.55}$$

which is equivalent to, using that here $\bar{\tau}_j = \lambda_j \tau_j$ for the symmetric signal precision τ_j,

$$\gamma^2 \frac{1}{R_f^2} A_{1j}^2 \frac{\lambda_j^2(\kappa-1)^2}{(\lambda_j(\kappa-1)+1)^2} \frac{1}{\tau_{\epsilon_j}} + \gamma^2 A_{13}^2 \frac{1}{\kappa \tau_{\epsilon_3}} + \frac{\kappa-1}{\kappa} \tag{A.56}$$

$$\geq \gamma^2 \frac{1}{R_f^2} A_{1j}^2 \frac{\lambda_j^2(\kappa-1)^2}{(\lambda_j(\kappa-1)+1)^2} \frac{\kappa}{\tau_{\epsilon_1}} + \gamma^2 A_{13}^2 \frac{1}{\kappa^2 \tau_{\epsilon_3}} + \kappa - 1 + \frac{(\kappa-1)^2}{\kappa^2}. \tag{A.57}$$

Given that both sides equal at $\kappa = 1$ and the derivative of the left side is greater at $\kappa = 1$, for small values of κ, this inequality holds for both stocks $j = 1, 2$, and therefore the focusing equilibrium exists. The threshold capacity, $\bar{\kappa}_1 = \bar{\kappa}_2$, is the unique solution of Equation A.55 on $(1, \infty)$.

Now consider the time period where firms 1 and 2 have an upcoming announcement. Without the loss of generality, assume that the expected utility of traders is higher if they only learn about stock 1 than if they would only learn about stock 2, so that

$$\frac{\sigma_{\epsilon_1}^2}{(R_f^2 - \rho_1)^2} \geq \frac{\sigma_{\epsilon_2}^2}{(R_f^2 - \rho_2)^2}. \tag{A.58}$$

This implies that for a small κ, the unique focusing equilibrium is to learn about firm 1.

Now I discuss the conditions where the focusing equilibrium is in mixed strategies. In this equilibrium, traders ex-ante have to be indifferent between learning about stock 1 or stock 2, thus,

$$\gamma^2 A_{11}^2 \frac{1}{\tau_{\epsilon_1}} \frac{\kappa}{(\lambda_1(\kappa-1)+1)^2} + \left(\frac{\kappa-1}{\kappa} - \frac{\lambda_1(\kappa-1)}{\lambda_1(\kappa-1)+1} \right)^2 \kappa \tag{A.59}$$

$$+ \gamma^2 A_{12}^2 \frac{1}{\tau_{\epsilon_2}} \frac{1}{(\lambda_2(\kappa-1)+1)^2} + \frac{\lambda_2^2(\kappa-1)^2}{(\lambda_2(\kappa-1)+1)^2} \tag{A.60}$$

$$= \gamma^2 A_{12}^2 \frac{1}{\tau_{\epsilon_2}} \frac{\kappa}{(\lambda_2(\kappa-1)+1)^2} + \left(\frac{\kappa-1}{\kappa} - \frac{\lambda_2(\kappa-1)}{\lambda_2(\kappa-1)+1} \right)^2 \kappa \tag{A.61}$$

$$+ \gamma^2 A_{11}^2 \frac{1}{\tau_{\epsilon_1}} \frac{1}{(\lambda_1(\kappa-1)+1)^2} + \frac{\lambda_1^2(\kappa-1)^2}{(\lambda_1(\kappa-1)+1)^2}, \tag{A.62}$$

or equivalently,

$$\gamma^2 A_{11}^2 \frac{1}{\tau_{\epsilon_1}} \frac{1}{(\lambda_1(\kappa-1)+1)^2} + \frac{\lambda_1^2(\kappa-1)^2}{(\lambda_1(\kappa-1)+1)^2} - 2\frac{\lambda_1(\kappa-1)}{\lambda_1(\kappa-1)+1} \tag{A.63}$$

$$= \gamma^2 A_{12}^2 \frac{1}{\tau_{\epsilon_2}} \frac{1}{(\lambda_2(\kappa-1)+1)^2} + \frac{\lambda_2^2(\kappa-1)^2}{(\lambda_2(\kappa-1)+1)^2} - 2\frac{\lambda_2(\kappa-1)}{\lambda_2(\kappa-1)+1}, \tag{A.64}$$

where

$$\lambda_2 = 1 - \lambda_1. \tag{A.65}$$

Therefore the left side of the condition is decreasing in λ_1, while the right side is increasing in λ_1. Since both sides are monotonic, the unique equilibrium mixing probability exists if at

$\lambda_1 = 0$, the left side is greater than or equal to the right side, while the opposite holds for $\lambda_1 = 1$. Formally after rearranging

$$\gamma^2 A_{11}^2 \frac{1}{\tau_{\epsilon_1}} \kappa^2 - \gamma^2 A_{12}^2 \frac{1}{\tau_{\epsilon_2}} \geq -(\kappa - 1)^2(\kappa + 1), \tag{A.66}$$

$$\gamma^2 A_{12}^2 \frac{1}{\tau_{\epsilon_2}} \kappa^2 - \gamma^2 A_{11}^2 \frac{1}{\tau_{\epsilon_1}} \geq -(\kappa - 1)^2(\kappa + 1), \tag{A.67}$$

where both left sides are increasing in κ, and both right sides are decreasing and monotonic. Moreover, exactly one of the right sides is greater for $\kappa = 1$, and the left sides limit is infinite while the right side limit is negatively infinite as $\kappa \to -\infty$. This implies that there must exist two thresholds, κ_1 and κ_2, such that between the threshold a unique mixing probability, that satisfies the utility equivalence condition, exists.

Therefore, below κ_1, the only possible focusing equilibrium is where traders only learn about stock 1. Between κ_1 and κ_2, traders randomize which announcing stock to learn about. While above κ_2, no focusing equilibrium exists. Moreover, the first part of the proof reveals that there exists a threshold, $\tilde{\kappa}_1$, above which learning about the non-announcing stock rather than only stock 1 would be a profitable deviation. Similarly, a condition for the focusing equilibrium in mixed strategies, that learning about the non-announcing stock is not a profitable deviation, exists, like in Equation A.55,

$$\gamma^2 A_{1j}^2 \frac{1}{\tau_{\epsilon_j}} \frac{\kappa}{(\lambda_j(\kappa - 1) + 1)^2} + \gamma^2 B_{23}^2 \frac{1}{\tau_{\epsilon_3}} + \left(\frac{\kappa - 1}{\kappa} - \frac{\lambda_j(\kappa - 1)}{\lambda_j(\kappa - 1) + 1} \right)^2 \kappa \tag{A.68}$$

$$\geq \gamma^2 A_{1j}^2 \frac{1}{\tau_{\epsilon_j}} \frac{1}{(\lambda_j(\kappa - 1) + 1)^2} + \gamma^2 B_{23}^2 \frac{\kappa}{\tau_{\epsilon_3}} + \frac{\lambda_j^2(\kappa - 1)^2}{(\lambda_j(\kappa - 1) + 1)^2} + \frac{(\kappa - 1)^2}{\kappa}, \tag{A.69}$$

for $j \in \{1, 2\}$. Or, equivalently,

$$\gamma^2 A_{1j}^2 \frac{1}{\tau_{\epsilon_j}} \frac{\kappa - 1}{(\lambda_j(\kappa - 1) + 1)^2} + \frac{\lambda_j^2(\kappa - 1)^3}{(\lambda_j(\kappa - 1) + 1)^2} - 2\frac{\lambda_j(\kappa - 1)^2}{\lambda_j(\kappa - 1) + 1} \tag{A.70}$$

$$\geq \gamma^2 A_{23}^2 \frac{1}{\tau_{\epsilon_3}} \frac{(\kappa - 1)^3}{\kappa^2}. \tag{A.71}$$

Easy to see that, like in the first part, there exists a unique threshold, $\tilde{\kappa}_2$, such that the condition is satisfied if and only if capacity is below the threshold.

Now it is easy to define the thresholds in the proposition.

(i) If $\tilde{\kappa}_1 \leq \kappa_1$, then let

$$\bar{\kappa}_1 = \bar{\kappa}_2 = \tilde{\kappa}_1, \tag{A.72}$$

(ii) if $\tilde{\kappa}_1 > \kappa_1$, then let

$$\bar{\kappa}_1 = \kappa_1, \tag{A.73}$$

$$\bar{\kappa}_2 = \min\{\tilde{\kappa_2}, \kappa_2\}. \tag{A.74}$$

■

Proof of Proposition 2 The comparative statics on the equilibrium mixing probability are straightforward from Equation A.66.

■

Proof of Proposition 3 The individual results are easy to see, given the results of Proposition 2, and that the price reactions of stock j are increasing in the equilibrium mixing probability of stock j. The aggregate results are straightforward, given that if all stocks are identical, then $\lambda_1 = \lambda_2$ is the unique focusing equilibrium, and

$$\frac{(\kappa-1)^2}{\kappa^2} > \frac{\frac{1}{4}(\kappa-1)^2}{\left(\frac{1}{2}(\kappa-1)+1\right)^2} \tag{A.75}$$

for all $\kappa \geq 1$.

■

Proof of Proposition 5 First, consider the period with one announcement, and let κ be all other trader's symmetric capacity in this period, and κ_i the choice of trader i. Then, trader i's expected utility is

$$\sum_{j=1}^{3}\left(\frac{(E[E_{ij}-R_f p_j])^2}{V_{ij}} + \frac{Var(E_{ij}-R_f p_{ij})}{V_{ij}}\right) - c(\kappa_i), \tag{A.76}$$

where the only term that depends on κ_i is regarding the announcing firm, $j=3$. Hence, her choice is equivalent to maximizing

$$\gamma^2 A_1^2 \frac{1}{\tau_\epsilon}\frac{\kappa_i}{\kappa^2} + \frac{\kappa_i - 1}{\kappa_i} + \left(\frac{\kappa_i-1}{\kappa_i} - \frac{\kappa-1}{\kappa}\right)^2 \kappa_i - c(\kappa_i). \tag{A.77}$$

Which leads to a FOC

$$\gamma^2 A_1^2 \frac{1}{\tau_\epsilon}\frac{1}{\kappa^2} + \frac{1}{\kappa^2} - c'(\kappa_i) = 0, \tag{A.78}$$

which, given that in a symmetric equilibrium $\kappa = \kappa_i$, leads to the condition in the proposition.

In the period with two announcing firms, again let κ be the capacity of all traders but i, who chooses κ_i. Then maximizing her expected utility is equivalent to maximizing

$$\gamma^2 A_1^2 \frac{1}{\tau_\epsilon}\frac{\kappa_i}{\left(\frac{1}{2}(\kappa-1)+1\right)^2} + \frac{\kappa_i-1}{\kappa_i} + \left(\frac{\kappa_i-1}{\kappa_i} - \frac{\frac{1}{2}(\kappa-1)}{\frac{1}{2}(\kappa-1)+1}\right)^2 \kappa_i - c(\kappa_i), \tag{A.79}$$

leading to a FOC

$$\gamma^2 A_1^2 \frac{1}{\tau_\epsilon}\frac{1}{\left(\frac{1}{2}(\kappa-1)+1\right)^2} + \frac{1}{\left(\frac{1}{2}(\kappa-1)+1\right)^2} - c'(\kappa_i) = 0, \tag{A.80}$$

which, given that in a symmetric equilibrium $\kappa = \kappa_i$, leads to the condition in the proposition.

■

Proof of Proposition 4 Comparative statics in terms of signs are identical to the sum of absolute and squared demands. The average squared demand of an announcing firm j is

$$E[x_{i,j}^2] = 1 + \lambda_j \frac{1}{\gamma} \tau_{\epsilon_j} A_{11}^2 (\kappa - 1)\kappa + \frac{1}{\gamma} \frac{\tau_{\epsilon_j}}{A_{11}^2} \frac{\lambda_j^2 (\kappa - 1)^2}{(\lambda_j(\kappa - 1) + 1)^2} \tag{A.81}$$

$$= 1 + \lambda_j \frac{1}{\gamma} \tau_{\epsilon_j} (R_f^2 - \rho_j)^2 (\kappa - 1)\kappa + \frac{1}{\gamma} \tau_{\epsilon_j} (R_f^2 - \rho_j)^2 \frac{\lambda_j^2 (\kappa - 1)^2}{(\lambda_j(\kappa - 1) + 1)^2} \tag{A.82}$$

what is increasing in λ_j, thus Proposition 2 gives the results.

■

Appendix B

Supplementary Tables for Chapter 1

Table B.1: Cross-sectional regression of squared cumulative abnormal returns on firm characteristics:

$$CAR^2_{-kd,j,t} = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \beta_3 \bar{\rho}_{-j,t} + \beta_4 \bar{\sigma}_{\epsilon-j,t} + \gamma_1 X_{j,t} + \gamma_2 X_{-j,t} + \xi_{j,t}.$$

The outcome variable $CAR^2_{-5k,j,t}$, is squared cumulative abnormal return for firm j, in the k trading days prior the announcement, relative to a three factor Fama-French prediction. Explanatory variables are ρ_j, the persistence of earnings for firm j, $\sigma^2_{\epsilon_j}$, the variance of the earnings surprise for firm j, $\bar{\rho}_{-j}$, the average persistence of firms that announce the same week as firm j. $\bar{\sigma^2_{\epsilon-j}}$, the average earnings surprise variance of firms that announce the same weeks as firm j. δ_t, a time fixed effect, $X_{j,t}$ and $X_{-j,t}$, a set of controls, such as size and analyst coverage of own and other announcing firms, and industry dummies.

	(1) CAR^2_{-3d}	(2) CAR^2_{-4d}	(3) CAR^2_{-5d}	(4) CAR^2_{-6d}	(5) CAR^2_{-7d}
ρ_j	0.000210***	0.000292***	0.000282***	0.000385***	0.000416***
(own persistence)	(4.55)	(5.58)	(4.97)	(4.25)	(3.38)
$\sigma^2_{\epsilon_j}$	0.000266***	0.000339***	0.000340***	0.000477***	0.000629***
(own variance)	(4.04)	(4.94)	(5.13)	(3.95)	(3.99)
$\bar{\rho}_{-j}$	-0.00418**	-0.00378**	-0.00418**	-0.00522**	-0.00533
(other persistence)	(-2.37)	(-2.46)	(-2.51)	(-2.03)	(-1.62)
$\bar{\sigma^2_{\epsilon-j}}$	-0.000617	0.00102	0.000965	-0.000250	0.000217
(other variance)	(-0.32)	(0.59)	(0.50)	(-0.08)	(0.05)
Observations	150328	150328	150328	150328	150328

t statistics in parentheses

All regressions with time fixed effects and firm level controls

Standard errors clustered on firm and time level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Cross-sectional regression of absolute cumulative abnormal returns on firm characteristics:

$$|CAR_{-kd,j,t}| = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \beta_3 \bar{\rho}_{-j,t} + \beta_4 \bar{\sigma}_{\epsilon-j,t} + \gamma_1 X_{j,t} + \gamma_2 X_{-j,t} + \xi_{j,t}.$$

The outcome variable $|CAR_{-5k,j,t}|$, is absolute cumulative abnormal return for firm j, in the k trading days prior the announcement, relative to a three factor Fama-French prediction. Explanatory variables are ρ_j, the persistence of earnings for firm j, $\sigma^2_{\epsilon_j}$, the variance of the earnings surprise for firm j, $\bar{\rho}_{-j}$, the average persistence of firms that announce the same week as firm j. $\bar{\sigma^2_{\epsilon}}_{-j}$, the average earnings surprise variance of firms that announce the same weeks as firm j. δ_t, a time fixed effect, $X_{j,t}$ and $X_{-j,t}$, a set of controls, such as size and analyst coverage of own and other announcing firms, and industry dummies.

	(1)	(2)	(3)	(4)	(5)
	$\lvert CAR_{-3d}\rvert$	$\lvert CAR_{-4d}\rvert$	$\lvert CAR_{-5d}\rvert$	$\lvert CAR_{-6d}\rvert$	$\lvert CAR_{-7d}\rvert$
ρ_j	0.00227***	0.00277***	0.00278***	0.00312***	0.00329***
(own persistence)	(5.86)	(6.42)	(5.97)	(5.83)	(5.43)
$\sigma^2_{\epsilon_j}$	0.00206***	0.00242***	0.00275***	0.00306***	0.00361***
(own variance)	(5.80)	(6.04)	(6.49)	(6.63)	(7.19)
$\bar{\rho}_{-j}$	-0.0331***	-0.0285**	-0.0336***	-0.0286*	-0.0291*
(other persistence)	(-2.91)	(-2.41)	(-2.62)	(-1.93)	(-1.84)
$\bar{\sigma^2_{\epsilon}}_{-j}$	-0.000160	0.00452	0.00659	0.00388	0.00982
(other variance)	(-0.01)	(0.37)	(0.44)	(0.20)	(0.49)
Observations	150328	150328	150328	150328	150328

t statistics in parentheses

All regressions with time fixed effects and firm level controls

Standard errors clustered on firm and time level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Cross-sectional regression of squared cumulative abnormal returns on firm characteristics:

$$Vol_{-5d,j,t} = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \gamma X_{j,t} + \xi_{j,t},$$

$$Vol_{-5d,j,t} = \delta_t + \beta_1 \rho_{j,t} + \beta_2 \sigma^2_{\epsilon_{j,t}} + \beta_3 \bar{\rho}_{-j,t} + \beta_4 \bar{\sigma}_{\epsilon-j,t} + \gamma_1 X_{j,t} + \gamma_2 X_{-j,t} + \xi_{j,t}.$$

The outcome variable $Vol_{-5d,j,t}$, is trading volume of firm j, in the five trading days prior the announcement. Explanatory variables are ρ_j, the persistence of earnings for firm j, $\sigma^2_{\epsilon_j}$, the variance of the earnings surprise for firm j, $\bar{\rho}_{-j}$, the average persistence of firms that announce the same week as firm j. $\bar{\sigma^2_{\epsilon}}_{-j}$, the average earnings surprise variance of firms that announce the same weeks as firm j. δ_t, a time fixed effect, $X_{j,t}$ and $X_{-j,t}$, a set of controls, such as size and analyst coverage of own and other announcing firms, and industry dummies.

	(1)	(2)	(3)
	Vol_{-5d}	Vol_{-5d}	Vol_{-5d}
ρ_j	0.00234***	0.000756***	0.000617**
(own persistence)	(9.20)	(3.35)	(2.58)
$\sigma^2_{\epsilon_j}$	0.00138*	0.00177***	0.00172***
(own variance)	(1.95)	(3.02)	(3.19)
$\bar{\rho}_{-j}$			-0.0141**
(other persistence)			(-2.05)
$\bar{\sigma^2_{\epsilon}}_{-j}$			-0.00642
(other variance)			(-0.25)
Observations	104424	103963	103963

t statistics in parentheses
All regressions with time fixed effects
Standard errors clustered on firm and time level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C

Proofs and Derivations for Chapter 2

Proof of Proposition 6 The proof consists of two steps. The first one to show that the value of stopping, $U(x_t, R_t)$ and the continuation value $CV(x_t, R_t, \mathcal{F}_t)$ are both monotonically decreasing in R_t, and the value of stopping is continuous. The second to show that there exists a sufficiently low level of R_t such that the value of stopping is greater than the value of continuation and a sufficiently high level of R_t such that it is optimal to continue.

Step 1. $U(x_t, R_t)$ is clearly monotonically decreasing and continuously differentiable, since

$$U(x_t, R_t) = u(x_t) - KR_t. \tag{C.1}$$

Regarding the continuation value, let $k(\omega)$ defined such that on the trajectory corresponding to $\omega \in \Omega$, the agent optimally stops in period $t + k(\omega)$. Then the continuation value is

$$E[U(x_{t+k(\omega)}(\omega), R_{t+k(\omega)}(\omega))|\mathcal{F}_t]. \tag{C.2}$$

Therefore it is sufficient to show that if $R_t < R'_t$, then for each ω, $U(x_{t+k(\omega)}(\omega), R_{t+k(\omega)}(\omega)) < U(x_{t+k'(\omega)}(\omega), R'_{t+k'(\omega)}(\omega))$. Note that the two agents not need to stop at the same time on the trajectory corresponding to ω. Assume by contradiction that for some ω the opposit holds, and $U(x_{t+k(\omega)}(\omega), R_{t+k(\omega)}(\omega)) \geq U(x_{t+k'(\omega)}(\omega), R'_{t+k'(\omega)}(\omega))$. Note that, if the second agent with R'_t would sttop at $k(\omega)$ periods later, insetead of $k'(\omega)$ periods, he could have achieved

$$\begin{aligned}
U(x_{t+k(\omega)}(\omega), R'_{t+k(\omega)}(\omega)) &= u(x_{t+k(\omega)}(\omega)) - KR'_{t+k(\omega)}(\omega) && \text{(C.3)}\\
&> u(x_{t+k(\omega)}(\omega)) - KR_{t+k(\omega)}(\omega) && \text{(C.4)}\\
&= U(x_{t+k(\omega)}(\omega), R_{t+k(\omega)}(\omega)) && \text{(C.5)}\\
&\geq U(x_{t+k'(\omega)}(\omega), R'_{t+k'(\omega)}(\omega)) && \text{(C.6)}
\end{aligned}$$

what is a contradiction, since $k'(\omega)$ is the agent's optimal stopping on the trajectory. The continuation value is just the expectation of optimal stopping values across all trajectories, hence the expectation also has to be smaller. Therefore both the continuation value, and the value of stopping are decreasing in R_t.

Step 2. First, for every $\omega \in \Omega$, construct an upper and lower bound on the utility the agent can achieve through that trajectory. The utility of stopping in period $t + k$ is

$$U(x_{t+k}(\omega), R_{t+k}(\omega)) = u(x_{t+k}(\omega)) - K \frac{tR_t + k \sum_{s=1}^{k} u(x_{t+s}(\omega))}{t + k}, \tag{C.7}$$

where the optimal stopping time might also depend on the trajectory. Now, let

$$U_{max}(x_t, R_t, \omega) = \max_k u(x_{t+k}(\omega)) - K \min_k \frac{k}{t+k} \sum_{s=1}^{k} u(x_{t+k}(\omega)), \tag{C.8}$$

$$U_{min}(x_t, R_t, \omega) = \min_k u(x_{t+k}(\omega)) - K \max_k \frac{k}{t+k} \sum_{s=1}^{k} u(x_{t+k}(\omega)) - K \frac{t}{t+1} R_t. \tag{C.9}$$

Clearly the value of stopping at the optimal time $k(\omega)$ is bounded, for all $\omega \in \Omega$

$$U_{min}(x_t, R_t, \omega) \leq U(x_{t+k}(\omega), R_{t+k}(\omega)) \leq U_{max}(x_t, R_t, \omega). \tag{C.10}$$

Since the continuation value is the expected optimal stopping values across all trajectories, if

$$CV_{max}(x_t, R_t, \mathcal{F}_t) = E[U_{max}(x_t, R_t, \omega) | \mathcal{F}_t], \tag{C.11}$$

$$CV_{min}(x_t, R_t, \mathcal{F}_t) = E[U_{min}(x_t, R_t, \omega) | \mathcal{F}_t], \tag{C.12}$$

then

$$CV_{min}(x_t, R_t, \mathcal{F}_t) \leq CV(x_t, R_t, \mathcal{F}_t) \leq CV_{max}(x_t, R_t, \mathcal{F}_t). \tag{C.13}$$

Now it's sufficient to show, that there exists a sufficiently high R_t such that $U(x_t, R_t) < CV_{min}(x_t, R_t, \mathcal{F}_t)$, and there exists a sufficiently low R_t that $U(x_t, R_t) > CV_{max}(x_t, R_t, \mathcal{F}_t)$. Since all three quantities are monotonically decreasing in R_t, it is the case when the derivatives are such that

$$\frac{\partial CV_{min}(x_t, R_t, \mathcal{F}_t)}{\partial R_t} < \frac{\partial U(x_t, R_t)}{\partial R_t} < \frac{\partial CV_{max}(x_t, R_t, \mathcal{F}_t)}{\partial R_t}. \tag{C.14}$$

The last two terms are easy, as $CV_{max}(x_t, R_t, \mathcal{F}_t)$ is independent from R_t, and $U(x_t, R_t)$ is linear in R_t, so

$$\frac{\partial CV_{max}(x_t, R_t, \mathcal{F}_t)}{\partial R_t} = 0, \tag{C.15}$$

$$\frac{\partial U(x_t, R_t)}{\partial R_t} = -K. \tag{C.16}$$

which immediately satisfies the second inequality. Finally, for the first one,

$$\frac{\partial CV_{min}(x_t, R_t, \mathcal{F}_t)}{\partial R_t} = \frac{\partial E[U_{min}(x_t, R_t, \omega)|\mathcal{F}_t]}{\partial R_t}, \tag{C.17}$$

$$= E\left[\frac{\partial U_{min}(x_t, R_t, \omega)}{\partial R_t}|\mathcal{F}_t\right], \tag{C.18}$$

$$= -K\frac{t}{t+1} > -K, \tag{C.19}$$

providing the first inequality in the condition.

This implies that for sufficiently low R_t, the stopping value is higher than an upper bound for the continuation value, while for sufficiently high R_t, the stopping value is lower than a lower bound of the continuation value.

■

Proof of Proposition 7 If the agent observes the full history of the process x_t, then her reference point, the average value of x become independent of her chosen action. Therefore, the utility component related to the reference point is just a constant in the decision maker's maximization, problem. Effectively such agent would maximize $u(x_t) - KR$, with R being a constant, resulting in the same action as the rational agent maximizing $u(x_t)$.

■

Proof of Lemma 3 Since investors are rational and risk-neutral, the price of the asset in each period is determined by the expected value of the marginal investor. The marginal retail investor is indifferent between buying the asset or not participating in the market, while the marginal institutional investor is indifferent between a long and a short position. The following can be said about the marginal investors.

The beliefs of the marginal investors determine supply and demand for the asset. Hence market clearing provides conditions on those beliefs. Given that preferences of retail and institutional investors are identical, the beliefs of the marginal investors are the same for the two types. Also, given that preferences are not affected by the time or state of the economy, the marginal investors are the same in all periods.

These conditions allow to easily identify the beliefs of the marginal investors from market clearing. The demand for the asset is all investors who are more optimistic than the marginal, while the supply is the institutional investors who are more pessimistic than the marginal investor, plus the net supply of the asset. Therefore if $\bar{q}$ denotes the beliefs of the marginal investors, then

$$\alpha(1-\bar{q}) + \beta(1-\bar{q}) = \alpha\bar{q} + 1, \tag{C.20}$$

what gives

$$\bar{q} = \frac{\alpha+\beta-1}{2\alpha+\beta}. \tag{C.21}$$

Then since all investors are risk-neutral, prices are determined by the expected value of the marginal investors, giving the expressions from the lemma.

■

Proof of Proposition 8 The logic of the solution if retail investors have regret preferences is the same as in the proof of Lemma 3, however, the exact expressions differ. The equations defining the equilibrium are the same, formally markets clear in all states, and all marginal investors are indifferent, which leads to prices be determined by the marginal institutional investor's beliefs. However now preferences of retail and institutional investors are different, just as preferences of retail investors across states are different. Therefore the marginal investor is not necessarily the same across states or investor types.

Let $\bar{q}_j$ and $\hat{q}_j$ the beliefs of marginal institutional and retail investors in state $j \in \{0, u, d\}$. Then market clearing implies

$$\alpha(1 - \bar{q}_j) + \beta(1 - \hat{q}_j) = \alpha\bar{q}_j + 1, \tag{C.22}$$

for states $j \in \{0, u\}$. This gives two equations in the proposition. However, in state $j = d$, after negative news, the example in Section 2.2.1 with the same distribution implies that the marginal retail investor would be more pessimistic than the marginal retail investor in $t = 0$; therefore she is not participating in the market. Therefore, Equation C.22 does not hold in this state. However this also implies that all retail investors still hold the asset, and institutional investor preferences are stable across periods, so the marginal institutional investor after negative news is the same as the marginal institutional investor in period $t = 0$. This provides the proposition's third equation,

$$\bar{q}_0 = \bar{q}_d. \tag{C.23}$$

Finally, the marginal investors in markets where they participate have to be indifferent resulting in the final five equations. For the rational investor

$$p_u = \bar{q}_0 D^2 + 1 - \bar{q}_0, \tag{C.24}$$

$$p_d = \bar{q}_d + (1 - \bar{q}_d)\frac{1}{D^2}, \tag{C.25}$$

$$p_0 = \bar{q}_0 p_u + (1 - \bar{q}_0) p_d. \tag{C.26}$$

While for the marginal retail investor,

$$w - p_0 + \hat{q}_u D^2 + 1 - \hat{q}_u - Kw - K\frac{p_u - p_0}{2} = w - p_0 + p_u - Kw, \tag{C.27}$$

and

$$w - p_0 + \hat{q}_0 p_u - \hat{q}_0 Kw + (1 - \hat{q}_0)\hat{q}_0 + (1 - \hat{q}_0)^2 \frac{1}{D^2} \tag{C.28}$$

$$- (1 - \hat{q}_0)Kw - (1 - \hat{q}_0)K\frac{p_d - p_0}{2} = w - Kw. \tag{C.29}$$

Now the system of eight equations can be solved to recover the beliefs of the five marginal investors and three asset prices.

■