REDUNDANT INFORMATION AND PREDICTABLE STOCK PRICE RETURNS

Michael Philip Carniol

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Supervisor of Dissertation

_____

Catherine M. Schrand, Professor, Accounting

Graduate Group Chairperson

_____

Catherine M. Schrand, Professor, Accounting

Dissertation Committee

Catherine M. Schrand, Professor, Accounting

Paul E. Fischer, Professor, Accounting

Brian Bushee, Professor, Accounting

Daniel Taylor, Assistant Professor, Accounting

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ABSTRACT

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Catherine M. Schrand

How well do investors distinguish information that already is priced from genuinely novel and exclusive private information? This paper examines whether investors misweight information that already is in stock prices ("redundant information") in making their trading decisions, and whether this misweighting is associated with investors' information processing frictions or behavioral biases. I extend the Kyle (1985) model to allow for non-Bayesian updating and transaction costs. The model predicts that price changes exhibit a state space process, in which the parameter for investors' non-Bayesian weighting of redundant information is estimable distinctly from information asymmetry and transaction costs. Using this model, I estimate a firm-quarter measure of investors' misweighting of redundant information. I find that, on average, investors behave as if the information content in the immediately prior price change is private information. This overweighting of redundant information appears higher when investors have less time to process information, stock prices are less informative, and industry-wide information is less costly to obtain. Overall, these results suggest one way that information processing frictions contribute to momentum and mean reversion in stock price returns.

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CHAPTER 1 : Introduction

A number of predictable patterns in stock price returns suggest that investors misperceive the amount of information already incorporated into stock prices. For example, extensive survey evidence documents that investors form expectations of future returns by extrapolating from past returns (e.g., Malmendier and Nagel, 2011; Amromin and Sharpe, 2014; Greenwood and Shleifer, 2014; Hoffmann and Post, 2015). These extrapolation-driven beliefs, in combination with frictions to arbitrage, could contribute to momentum in the returns of individual equities, industries, mutual funds, and country-wide equity indices (e.g., Jegadeesh and Titman, 1993, 2001; Carhart, 1997; Asness, Moskowitz, and Pedersen, 2013; Géczy and Samonov, 2015, 2016).

Explanations for this seeming violation of the efficient markets hypothesis are varied (see Harvey, Liu, and Zhu, 2016 and Novy-Marx and Velikov, 2016, for recent reviews). Daniel and Hirshleifer (2015) argue that psychological biases constrain investors' ability to form unbiased expectations of future returns. Bernard and Thomas (1989, 1990) and Novy-Marx (2015), among others, argue that predictable returns in the same direction as earnings surprises reflect that investors underestimate the informativeness of firms' earnings reports relative to the information in prices. Banerjee, Kaniel, and Kremer (2009), Banerjee (2011), and others argue that investors overreact to their own private information and dismiss the information in prices as noise. Abreu and Brunnermeier (2002, 2003) suggest why this misuse of information can persist. They argue that frictions to arbitrage, such as capital constraints, could encourage arbitrageurs to delay exploiting mispricing or even trade in the same direction as, rather than against, mispricing.

Empirical identification of non-Bayesian investor behavior is difficult. Models of non-Bayesian weighting of information signals and models of information asymmetry or trading costs often yield the same empirical predictions about stock price behavior. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) and Odean (1998) present models of non-Bayesian behavior and show that excessive weighting of private information leads to higher stock price volatility and greater trading volume. In a rational expectations setting, Kim and Verrecchia (1997) show that greater dispersion in investors' information precision also leads to greater price volatility and trading volume. Information asymmetry not only generates similar stock price behavior as information processing biases do, but also can facilitate higher equilibrium levels of information processing biases. Fischer and Verrecchia (1999) show that, if given the choice, privately informed investors would trade as if their

private signals were more informative than the signals really are. They find that this exaggeration of information precision is increasingly profitable as information asymmetry increases.

To ascertain the information mechanisms that underlie predictable stock price returns, and distinguish the misweighting of information from information precision, I present an analytical model and structural estimation that identify investors' misweighting of information that is already priced. I label information that is already priced as "redundant information." I choose the term "redundant information" to indicate formerly private information that is impounded into the stock price and no longer could provide an investor with an information advantage.[1]

I extend the standard Kyle (1985) model to allow for trading costs and the possibility that informed investors overreact or under-react to their private signals about the value of a risky asset. Specifically, I assume that informed investors observe a private signal that comprises some private information and some public information, but behave as if the private signal has greater or less private information than the signal truly has. If informed investors exaggerate the novelty and exclusivity of their private signal, they would tend to trade in the same direction as prior informed investors did, and subsequent price changes could exhibit momentum. If informed investors under-react to the novelty and exclusivity of their private signal, they would tend to trade in the opposite direction of prior informed investors, and subsequent price changes would exhibit mean-reversion.

The analytical model predicts that price changes exhibit a state space process in which investors' misweighting redundant information is identifiable separately and distinctly from information asymmetry and trading costs. I estimate the parameters of this price change process by maximum likelihood by firm-quarter. This estimation yields a firm-quarter measure of informed investors' misweighting of redundant information.

I find that informed investors overweight redundant information more often than not. On average, investors appear to behave as if the information content in the immediately prior price change is novel private information. Investors weight redundant information excessively in 83 percent of the 107,300 firm-quarter estimations on five-minute returns (74 percent of the estimations at the 5 percent statistical significance level). Investors weight redundant information excessively in 82 percent of the 159,800 firm-quarter estimations on 30-minute returns (59 percent of the estimations

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[1] Alternatively, Tetlock (2011) defines "stale news" as the similarity of a news story to prior news stories about the same firm. In this sense, the term "stale news" emphasizes the repetition of public information by information intermediaries. In examining "redundant information," I do not distinguish between news that information intermediaries repeated, news that investors accessed repeatedly, etc.

at the 5 percent statistical significance level).

To validate that the estimated measure reflects investors' misweighting of information, I conduct three studies. First, the analytical model predicts that trading on redundant information reduces informed investors' expected profits from trading on genuine private information, but would not completely negate informed investors' expected profits if the misweighting is not too egregious. I estimate that the magnitude of trading on redundant information would not wipe out informed investors' expected profits for at minimum 54 percent of firm-quarters. Second, the analytical model shows that rational arbitrageurs who weight redundant information fairly can profit from informed investors' misweighting of redundant information. These rational arbitrageurs are likely to correct extreme levels of misweighting with some delay (Abreu and Brunnermeier, 2002). Consistent with this prediction, I find evidence that investors' misweighting of redundant information mean reverts by more than 90 over the next two quarters. Third, the analytical model predicts that trading volume is proportional to a linear function of the estimated parameters. I find empirical evidence consistent with this prediction.

Next, I examine cross-sectional and time-series variation in the estimated parameters. These studies are intended to explore whether investors' misweighting of redundant information is associated with information processing frictions or a behavioral bias. I explore the covariation between investors' misweighting of redundant information and investor and information environment characteristics in the following five studies:

First, I re-estimate the measure of investors' misweighting of redundant information when investors have more time to process information. In particular, I modify the analytical model to allow for price changes when stock exchanges are closed (i.e., overnight price changes). Using this structural model, I estimate the extent to which investors' misweight information revealed during the prior trading day.

Second, I consider how investors' misweighting of redundant information varies with price informativeness. Diamond and Verrecchia (1987) show that stock prices are less informative when short sales are restricted. As a proxy for exogenous variation in stock price informativeness, I use the Regulation SHO uptick exemption pilot study.

Third, I consider whether investors' misweighting of redundant information is consistent with self-attribution bias. Gervais and Odean (2001) argue that investors overestimate their information

processing ability more after experiencing positive portfolio returns. I present two studies. First, since most investors have positive exposure to the market portfolio, I assess the correlation between past stock price returns and changes in the estimated misweighting of redundant information. Second, I assess the correlation between institutional investors' past portfolio returns and changes in the average misweighting of redundant information in their portfolios.

Fourth, I examine whether sophisticated institutional investors earn higher portfolio returns when their portfolio has more exposure to the misweighting of redundant information. In expectation, investors who gather and process information more earn above average expected returns, and these returns are increasing in information processing frictions (Grossman and Stiglitz, 1980). If investors' misweighting of redundant information is associated with information processing frictions, investors should earn greater returns by holding greater exposure to firms with greater misweighting of redundant information. Using proxies for institutional investors' information gathering and processing ability from Bushee and Goodman (2007), I study whether sophisticated institutional investors outperform other institutional investors when their portfolio has more exposure to the misweighting of redundant information.

Fifth, I consider how investors' misweighting of redundant information varies with the cost of gathering information. When investors' cost of obtaining information from an information intermediary is below their private cost of acquiring this information, many investors will gather this information (Veldkamp, 2006). Veldkamp (2006) shows that information intermediaries sell industry-wide information to investors at a low price because they have synergies in gathering industry-wide information and selling this information to a wide audience of investors. To examine how investors' misweighting of redundant information varies with the cost of gathering information, I study whether the estimated misweighting of redundant information varies at an industry-wide level, with the similarity of firms within an industry, and as competition among sell-side analysts increases.

Evidence from these tests suggests that the misweighting of redundant information is associated with information processing frictions. When investors have more time to process information, the mean and median estimated parameter for the misweighting of redundant information are approximately zero. When short sale constraints are lessened and stock prices are more informative, the estimated parameter for the misweighting of redundant information appears lower. Investors' misweighting of redundant information is not consistently higher after a stock experiences positive returns and institutional investors do not appear to acquire positions in firms with greater misweighting of

redundant information after experiencing positive portfolio returns. Rather, institutional investors appear to earn positive returns on investing in firms with greater misweighting of redundant information. Sophisticated institutional investors – large institutions, blockholders, and transient investors – outperform other institutional investors more when their portfolios have more exposure to the misweighting of redundant information. The misweighting of redundant information covaries at an industry-wide level, and increasingly so when firms within an industry are more similar and competition among sell-side analysts is greater. These associations are consistent with an information processing friction explanation.

Overall, these results suggest an information processing bias that contributes to momentum and mean reversion in stock price returns. In prior literature, identification of information processing biases proved challenging because observable proxies for the presence and magnitude of these biases, such as price volatility and trading volume, also could be influenced by trading costs and information asymmetry. This study addresses the identification challenge by offering an analytical model and structural estimation framework that separate investors' misweighting of information that is already priced from trading frictions and information asymmetry. I estimate this structural model and find that, on average, investors behave as if redundant information is private information. This result extends Tetlock (2011), who finds that firms with more stale news stories in one week exhibit returns reversals in the subsequent week. Further, the cross-sectional studies suggest that the misweighting of redundant information is associated with information processing frictions, rather than behavior biases.

Future work could extend this paper in analytical or empirical domains. Future analytical work could introduce additional investor types, such as investment style chasers (e.g., Barberis and Shleifer, 2003); long-lived information, noisy private signals, and heterogeneous investors (e.g., Foster and Viswanathan, 1996); or, more detailed market microstructure characteristics (e.g., Adrian, Capponi, Vogt, and Zhang, 2016). The challenge for analytical work on information processing biases is to provide an empirical framework in which information processing biases are estimable distinctly from genuine information advantages and frictions to arbitrage. Future empirical work could examine how investors' misperception of the information already in prices varies with communication among capital market participants. For example, corporate managers and information intermediaries might attempt to exploit this information processing bias. Clement, Frankel, and Miller (2003) argue that confirming management guidance reduces investors' uncertainty about future earnings realizations. An alternative explanation could be that investors behave like confirming management guidance

has more novel information than the announcement truly has. If so, the variance of their posterior beliefs could be excessively low. Similarly, corporate managers with equity-linked incentives might take advantage of investors' information processing bias by repeating good news disclosures in multiple venues or formats (e.g., in mandatory filings, conference calls, presentations to investors, and social media channels) while mentioning bad news disclosures only the requisite number of times. Bayesian investors would back out this repetitive disclosure, but investors who misunderstand what information already is reflected in prices might believe that the repeated disclosures contain new news. If sell-side analysts anticipate that investors will respond excessively to the information already in prices, their earnings forecasts are likely to reiterate corporate managers' guidance (e.g., Feng and McVay, 2010). In all, this non-Bayesian investor behavior could affect the quality of communication between corporate managers, information intermediaries, and investors.

The paper proceeds as follows. Chapter 2 presents a review of the precedent literature. Chapter 3 presents the analytical model, structural estimation of the model, and its results. Chapter 4 presents the cross-sectional studies.

CHAPTER 2 : Literature review

2.1. Motivation

2.1.1. Contribution to accounting research

This paper extends prior work on the relation between capital markets efficiency and information. In their pioneering test of the strong form of the efficient markets model, Ball and Brown (1968) and Beaver (1968) asked whether investors use accounting information or whether investors can acquire all valuation-relevant information from stock prices themselves.[1] This and subsequent work has found that investors use both accounting information and the information in stock prices. Moreover, this work established the precedent for accounting research on how market participants use financial information and how this information becomes reflected in securities prices.

Within the accounting literature on capital markets efficiency and information, prior work has asked whether investors exhibit patterns of biased information processing. The maintained null hypothesis is that market participants process information unbiasedly and efficiently such that, on the margin, the cost of gathering and processing information equals its benefit in expected returns (e.g., Grossman and Stiglitz, 1980). Accounting literature that attempts to refute this null hypothesis typically presents associations between publicly available information and subsequent returns. This publicly available information, such as historic stock prices and accounting information from Securities and Exchange Commission filings, costs investors little to gather and process. Under the maintained null hypothesis, gathering and processing this information investors should earn investors negligible returns. Empirically, the correlation between publicly available information and subsequent returns should be indistinguishable from zero on average. Rejection of this null hypothesis could suggest that, on average, investors process information in a biased or inefficient manner.

In this paper, I attempt to identify an inefficiency in investors' processing private information signals and the information content in stock prices. Prior literature struggles to identify a clear empirical measure of investors' misuse of information as distinct from genuine information advantages and the transaction costs of trading. This paper fills that gap by deriving an analytical model and structural estimation specification that can empirically identify and allow estimation of investors'

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[1] Fama (1970) defines an efficient market as "a market in which security prices 'fully reflect' all available information" and strong form tests of market efficiency as those "concerned with whether given investors or groups have monopolistic access to any information relevant for price formation." (p. 383)

misuse of information as distinct from information asymmetry and the transaction costs of trading. In presenting an analytical model and structural estimation approach, I attempt to provide a "well-developed theory of naive investor behavior that can be subjected to empirical testing" (Kothari, 2001, p. 191). The overarching null hypothesis of this paper is that investors process private information signals unbiasedly. The key contribution of this paper is the derivation and estimation of a structural model, using which one might be able to reject this null hypothesis.

The remainder of this section discusses empirical evidence of predictable securities returns, arguments on how investors process information in a biased or inefficient manner, and the complications in empirically identifying inefficient information processing.

2.1.2. Empirical evidence of predictable returns

A sufficient condition for market efficiency is that existing information cannot be used to predict future securities returns. Empirical evidence suggests, however, that securities returns can be predictable. Past returns, accounting information, and other signals can be used to predict future returns.

Stock price returns exhibit predictable reversals over long and short investment horizons. De Bondt and Thaler (1985) provide evidence that stock prices mean-revert over consecutive three-year windows. They find that, from 1930 to 1975, the 35 stocks with the lowest cumulative excess returns over the preceding 36 months subsequently outperform the 35 stocks with the highest cumulative excess returns over the preceding 36 months by 25 percent over the next three years. Further, they find that the vast majority of these excess returns are realized in January, consistent with a predictable turn-of-the-year effect. Regarding short investment horizons, French and Roll (1986) find that individual stocks exhibit negative autocorrelation in returns over two- to 12-day horizons. In addition, over consecutive days, stocks in the smallest quintile by market value of equity exhibit negative autocorrelation in returns, while those in the largest quintile by market value of equity exhibit positive autocorrelation in returns.

In addition, securities that recently outperformed or underperformed exhibit a tendency to continue to do so. Jegadeesh and Titman (1993) examine trading strategies that select stocks based on their relative returns over the prior one to four quarters and hold these stocks for one to four quarters. They find that a zero-cost portfolio strategy that buys the stocks in the highest decile of returns over the last 12 months, sells the stocks in the lowest decile of returns over the last 12 months, and holds

this portfolio for three months would have yielded average returns of 131 basis points per month from 1965 to 1989. A zero-cost portfolio strategy that selects stocks based on trailing six-month returns would have yielded average returns of 84 basis points per month over the subsequent three months, 95 basis points per month over the subsequent six months, and 86 basis points per month over the subsequent year. The authors rule out that these predictable returns are attributable to risk. First, they show that the beta of this zero-cost portfolio strategy (the exposure of this portfolio's returns to the total market portfolio returns) is on average slightly negative. Second, they show that returns to this strategy are negatively correlated with lagged market volatility. They conclude that the positive average returns to this strategy are attributable to investors' under-reaction to firm-specific information. Investment strategies that seek to exploit this tendency have become known as relative strength strategies or momentum strategies.

Subsequent research has documented profitable relative strength strategies across asset classes, geographies, and time. For example, Carhart (1997) demonstrates that momentum in stock returns accounts for the persistence in mutual fund performance. Asness, Moskowitz, and Pedersen (2013) present evidence of momentum in individual stocks in the United States, the United Kingdom, continental Europe, and Japan, as well as country-wide equity index futures, government bonds, currencies, and commodity futures. Géczy and Samonov (2016) combine databases of U.S. stock price returns from 1800 to 2012, and document that relative strength strategies would have been profitable throughout these 212 years. Moskowitz, Ooi, and Pedersen (2012) document that country equity indexes, currencies, commodities, and sovereign bonds also exhibit momentum with respect to their own trailing 12-month returns.

2.1.3. Explanations for predictable returns

The origins of these predictable patterns in returns remain debated. Explanations for predictable returns generally conjecture a way in which investors misuse information, a dynamic in investors' higher order beliefs, or a friction to arbitrage. The leading hypotheses for predictable returns are the following:

1. Investors have psychological constraints on processing information.

2. Investors with limited attention fixate on easily accessible information.

3. Investors underestimate the persistence of fundamental news.

4. Investors believe that other investors are trading on noise.

5. Investors are rationally herding.

6. Rational bubbles induce the appearance of momentum and mean reversion in securities prices retrospectively.

7. Frictions to arbitrage, such a short sale constraints, impede investors' use of information.

2.1.3.1. Behavioral economics

Behavioral economists argue that psychological biases constrain investors' ability to form unbiased beliefs about the distribution of future returns (Daniel and Hirshleifer, 2015; Thaler, 2016). Among possible psychological biases, survey evidence documents that investors form expectations of future returns by extrapolating from past returns during salient periods. Using data from the Survey of Consumer Finances from 1960 to 2007, Malmendier and Nagel (2011) find that individuals who experienced low stock market returns over their lifetimes subsequently participate less in the stock market, and, conditional on participating, invest less of their liquid assets in stocks. Greenwood and Shleifer (2014) draw data from surveys of individual investors, investment newsletters, and surveys of executives, and find that all of these market participants express expectations of market returns that extrapolate from recent past returns. Hoffmann and Post (2015) find similar extrapolative beliefs about expected returns and risk for a sample of individual investors from the Netherlands, based on brokerage records and surveys. Similarly, Griffin, Harris, and Topaloglu (2003) find that institutional investors trade in the same direction as past stock returns.

DeLong et al. (1990), Barberis and Shleifer (2003), Barberis et al. (2015), and others present theoretical models in which certain investors hold extrapolative beliefs – expectations of future returns that extrapolate from recent past returns. In DeLong et al. (1990), a class of investors, labeled "positive feedback" investors, learn only from past price changes and trade in the same direction as past price changes. In their model, if rational arbitrageurs are risk averse, they trade less aggressively than they would if the positive feedback investors were pure noise traders, because the positive feedback investors' trades cause prices to overshoot the rational arbitrageurs' valuation of the asset. In Barberis et al. (2015), "extrapolators" believe that mean future returns are a weighted average of recent past returns. Their model predicts that the dividend-to-price ratio predicts stock price returns, which is consistent with empirical evidence. Their model, however, also predicts that price changes exhibit negative autocorrelation at all horizons, which is not consistent with empirical evi-

dence. In Barberis and Shleifer (2003), investors allocate funds based on relative past performance by moving into categories of securities, such as large or small capitalization stocks, that recently outperformed and out of categories that recently underperformed. These flows of funds, which might or might not be correlated with securities' expected cash flows or exposure to risk factors, increase the correlation between securities in the same category and lowers the correlation between securities in different categories. In addition, a shock to cash flow news to any security in a category can lead to momentum in returns for the whole category in the short term.

Theoretical models that allow investors to hold extrapolation-driven beliefs generally find that, although these investors lose money on average, they can survive long enough to affect securities returns. Barberis and Shleifer (2003) and Barberis et al. (2015) present simulation evidence to this effect. Kogan et al. (2006) show that trend-following investors' trading activity affects prices even as their wealth deteriorates toward zero. Similarly, Yan (2008) shows that investors who hold miscalibrated beliefs about the distribution of market returns can survive in equilibrium if their risk tolerance is sufficiently high. In simulations, he finds that investors who overestimate risk-adjusted market returns by 50 percent can survive if their time discount rate is approximately 1 percent less than that of correctly calibrated investors. In all, investors who misweight information can survive for sufficiently long durations to affect the time series properties of returns.

Behavioral economists also have examined whether investors behave as if the precision of their information is greater than it truly is. In repeated surveys over a 10-year period, Ben-David, Graham, and Harvey (2013) asked chief financial officers for forecasts of 80% confidence intervals of S&P 500 index returns over the next 12 months. They found that realized market returns were within the executives' 80% confidence intervals only 36% of the time, suggesting that these chief financial officers overestimated the precision of their forecasts. In a field experiment on professional traders and business school students in Germany, Glaser, Langer, and Weber (2013) asked subjects to state upper and lower bounds of 90% confidence intervals for returns on two German equity market indexes and three individual stocks. All median volatility estimates were lower than the historical volatilities over a forecast horizon of one month.

Other studies have used proprietary data on investor attributes to identify proxies for cross-sectional variation in investors' misperception of their own information processing ability. Barber and Odean (2001) access monthly statements for 78,000 households from a retail brokerage firm. The authors use the gender of the individual who opened the account as their proxy for overconfidence, as psychology

research shows that men tend to be overconfident in financial matters. They find that men trade more frequently than women do and earn lower profits by the differential in their total transaction costs due to this additional trading. Grinblatt and Keloharju (2009) combine Finnish records of individuals' equities trades, driving records, and the Finnish military's mandatory psychological tests. The authors find that individuals who received more speeding tickets traded more frequently. Døskeland and Hvide (2011) study whether individual investors in Norway earn greater profits when investing in firms in the industry in which they work. Individuals might invest in such professionally close firms due to a genuine information advantage or an overestimation of the precision of their knowledge of an industry. The authors find that these investors do not earn excess profits from holdings in professionally close firms, but do trade in these firms' shares more often, which suggests an overestimation of the precision of their information.

Chan, Frankel, and Kothari (2004) examine whether investors exhibit "representativeness" and "conservatism" biases. Representativeness is the tendency to over-extrapolate from salient experiences in forming beliefs about the distribution of future outcomes, whereas conservatism is the tendency for individuals to update their beliefs excessively slowly after observing new evidence. An investor who applies the representativeness heuristic might observe a sequence of repeated returns and incorrectly believe that these returns imply a persistent trend. Oppositely, an investor who applies the conservatism bias might not update his beliefs about future earnings after observing an earnings announcement. The authors find that seasonally-differenced growth in sales, operating income, and net income are predictive of three-month to six-month returns. The outperformance becomes statistically insignificant at 12-month investment horizons and using longer term growth rates in sales or profits. In addition, the authors do not find evidence of mean reversion in returns subsequent to outperformance. The authors conclude that this evidence is not consistent with representativeness and conservatism biases because those biases would predict mean reversion in returns when the events about which investors' beliefs were miscalibrated realize.

2.1.3.2. Limited attention and functional fixation

The functional fixation hypothesis conjectures that investors with limited attention exaggerate the precision of easily accessible information in forming their beliefs about the value of risky assets (Watts and Zimmerman, 1986). In theoretical models, Hirshleifer and Teoh (2003) and Hirshleifer, Lim, and Teoh (2011) consider environments in which some investors have limited attention and can overweight certain signals. Since prices are a weighted average of all investors' beliefs, however formed, this

misweighting of signals affects prices. Hirshleifer and Teoh (2003) find that in such an environment corporate managers have an incentive to produce more precise signals and/or manipulate the signals on which investors fixate. Peng and Xiong (2006) consider a similar environment in which investors can allocate attention to firm-specific, industry-wide, or market-wide information and overweight whichever information they acquire. Investors can learn more about the correlation among securities by acquiring market-wide or sector-wide information. Accordingly, investors tend to acquire market-wide or sector-wide information more as attention constraints increase or risk-aversion increases. When investors allocate more attention to market-wide or sector-wide information and investors exaggerate the precision of this information, securities prices tend to overreact to public signals of market-wide or sector-wide information and underreact to public signals of firm-specific information.

In these models, exaggerating the precision of certain information is necessary for limited attention to lead to predictable returns. If investors allocate their attention according to their information processing abilities and recognize the precision of their information properly, limited attention would not lead to predictable returns (e.g., Merton, 1987).

Empirical studies of functional fixation often hypothesize that investors overemphasize reported earnings and underweight other accounting information. Hand (1990) studies investors' response to firms' reporting of debt-equity swaps in 1981-1984. When a firm undertook a debt-equity swap, the firm reported the amount of gain immediately and publicly, and repeated this announcement with its subsequent earnings report. Hand (1990) finds positive stock price responses to both announcements, which is consistent with investors fixating on earnings announcements. Sloan (1996) finds abnormal returns associated with the reversal of abnormal accruals, and argues that investors fixate on earnings and underweight operating cash flows in forecasting future earnings. The profitability of trading on this mispricing declined over the 15 years following the publication of Sloan (1996), suggesting that investors learned over time to weight operating cash flows relative to earnings properly (Green, Hand, and Soliman, 2011). Green, Hand, and Zhang (2013) provide a meta-analysis of publicly available signals that predict returns. The authors identify 330 accounting-based (e.g., abnormal accruals), finance-based (e.g., return momentum), and other (e.g., a stock's ticker symbol) signals from the academic business literature from 1970-2010. They document that the mean annualized return and Sharpe ratio of these signals were 12.1 percent and 1.04, whereas the CRSP U.S. equal-weighted (value-weighted) market portfolio annualized return and Sharpe ratio were 9.5 percent and 0.50 (6.6 percent and 0.44) over the same time period. Further, the authors find that portfolios formed on these signals exhibit an average cross-correlation of 0.05, suggesting that an investor can reduce his

portfolio volatility by combining these signals.

Functional fixation studies generally assume that investors correct their information processing error in time, usually at some future event. When investors correct their beliefs, securities prices correct. This price correction allows investors who originally processed information properly to collect abnormal returns. Empirical accounting and finance researchers often present associations between such price corrections and publicly available information as evidence that investors had misprocessed information in the past. If price corrections occur around an event date, such as an earnings announcement, predictable price changes would appear as jumps around the event date. Most empirical tests of the functional fixation hypothesis examine returns across an event date (See Kraft, Leone, and Wasley, 2006 and Richardson, Tuna, and Wysocki, 2010 for reviews). If price corrections occur gradually over time, price changes could exhibit momentum or mean reversion.

2.1.3.3. Post-earnings announcement drift

Post-earnings-announcement drift – predictable abnormal returns following earnings announcements and having the same sign as the earnings change – suggests that investors under-react to the information in earnings announcements. Ball and Brown (1968) first observe these predictable abnormal returns. To understand the information processing error underlying these predictable returns, Bernard and Thomas (1990) ask whether abnormal returns surrounding earnings announcements are associated with misspecified expectations of earnings. The authors predict that investors underestimate the persistence of quarterly earnings news and overestimate the seasonality of quarterly earnings. They find that abnormal returns surrounding earnings announcements are positively associated with earnings news in the three preceding quarters and negatively associated with earnings news four quarters prior. This result suggests that investors do not fully process the time series properties of quarterly earnings. Subsequent work debates the exact form of investors' average expectations of earnings, but often finds that investment strategies based on extended models can be profitable (See Richardson, Tuna, and Wysocki, 2010 for a review).

Chan, Jegadeesh, and Lakonishok (1996) find that "earnings momentum" – the tendency of stocks with recently announced strong earnings to outperform stocks with recently announced weak earnings – has incremental explanatory power to relative strength/momentum in predicting future returns. Nevertheless, Chordia and Shivakumar (2006) and Novy-Marx (2015) argue that relative strength/momentum is driven entirely by earnings momentum. Novy-Marx (2015) finds that earnings surprises subsume the power of past price performance to predict cross sectional vari-

ation in expected returns. Moreover, earnings momentum trading strategies that avoid relative strength/momentum have lower volatility and less negative skewness. Overall, these papers suggest that investors systematically underestimate the full implications of earnings news.

2.1.3.4. Differences of opinion

Other work considers the possibility that investors dismiss the information content of other investors' trading activity and misunderstand the informativeness of stock prices. Varian (1989) labeled circumstances in which agents know one another's beliefs but regard others' beliefs as lacking information content as "differences of opinion." Harrison and Kreps (1978) present a "differences of opinion" environment in which investors have heterogeneous, subjective beliefs about the value of a risky asset and the risky asset cannot be sold short. In such an environment, investors who value the risky asset the highest acquire the asset. The price of the asset tends toward the highest subjective belief and speculative bubbles can occur. Xiong (2013) reviews numerous theoretical models with differences of opinion and short sale constraints that predict speculative bubbles.

In Hong and Stein (1999), a class of investors, labeled "newswatchers," do not condition on the information in prices. In addition, independent pieces of private information arrive to the newswatchers in a staggered manner over time, such that some newswatchers learn the same private information elements later than others do. Since the newswatchers do not condition on the information in prices, each responds to the private information as if he were the first to receive it. The combination of the gradual arrival of private information and newswatchers' ignoring the information content in prices leads price changes to exhibit momentum.

Banerjee, Kaniel, and Kremer (2009) posit a differences of opinion environment in which informed investors behave as if other informed investors' private signals are noise. In this environment, informed investors rely only on their own private information and do not condition on prices when updating their beliefs. With a static setup, prices would exhibit drift because each risk-averse informed investor updates his posterior belief about the variance of the asset inadequately relative to if the investors also had conditioned on prices. In a dynamic setting, investors would anticipate this type of mispricing, and trade to arbitrage it away. This exploitation of the mispricing would eliminate price drift. Nevertheless, price drift could appear if investors believe that other investors hold miscalibrated beliefs about the aggregate signal (i.e., the average of all investors' beliefs as reflected in prices). The authors describe this kind of miscalibration as "higher-order disagreement." By not recognizing that other investors' information has been incorporated into prices, these investors

are likely to trade in the same direction as past price changes. This repeated trading on the same information could induce price drift. Banerjee (2011) and Banerjee and Green (2015) posit similar "differences of opinion" environments in which informed investors behave as if other informed investors' private signals are noise or are uncertain of the quality of other informed investors' private signals. These models yield empirical predictions of how stock price volatility and trading volume vary with investors' dispersion in beliefs.

Empirical measures of dispersion in investors' beliefs often have tenuous construct validity; see discussions in Abarbanell, Lanen, and Verrecchia, 1995, Kim and Verrecchia, 1997, and Barron et al., 1998. These construct validity concerns limit the applicability of empirical predictions from differences of opinion models.

2.1.3.5. Rational herding

Momentum in returns also could be attributable to rational herding.[2] Avery and Zemsky (1998) and Park and Sabourian (2011) show that informed investors rationally should underweight their private information and overweight the information content of prices when extreme payoffs are more likely than moderate ones (i.e., the distribution of possible payoffs is U-shaped). Park and Sabourian (2011) suggest that such payoff distributions could arise when a firm experiences a major transition, such as an unexpected CEO change or major acquisition, or during highly uncertain macroeconomic periods. As a result, rational herding predicts that momentum would occur only rarely, which contrasts with the empirical evidence on momentum in returns.

2.1.3.6. Rational bubbles

Rational bubbles in securities prices can lead to the appearance of momentum and mean-reversion in returns data retrospectively. Blanchard and Watson (1982) describe how securities prices can deviate from their fundamental value for an indeterminate period of time in an efficient market. Suppose that the price of firm's equity in period t, P_t, equals the fundamental value of the asset – the sum of expected dividends, d_s, discounted at the appropriate rate, r – plus a speculative component, S_t. That is, $P_t = \sum_{s=t+1}^{\infty} \left(\frac{1}{(1+r)^{s-t}} d_s \right) + S_t$. The speculative component evolves over

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[2]Rational herding is similar to information cascades (e.g., Bikhchandani, Hirshleifer, and Welch, 1992). The quintessential example of an information cascade is the following story: An individual receives a recommendation for a restaurant privately. Upon arriving at the restaurant, the individual notices that the restaurant has few diners, but the restaurant next door is full of customers. Based on these signals, the individual decides to ignore his private information and dine at the full restaurant. If all individuals act this way, the more popular option becomes an absorbing state. Models of information cascades typically assume that the cost of adopting the popular option or privately preferred option is exogenous. In models of behavior in financial markets, however, the cost of acting on private and public information is endogenous (Avery and Zemsky, 1998).

time by the process

$$S_t = \frac{1+r}{\pi} S_{t-1} Z_t + \epsilon_t \tag{2.1.1}$$

where ϵ_t is a mean-zero random shock, $\pi \in (0,1)$ is the probability that the speculative component persists, and

$$Z_t = \begin{cases} 1 & \Pr = \pi \\ 0 & \Pr = 1 - \pi \end{cases} \tag{2.1.2}$$

In expectation, prices are a martingale with a mean rate of return of r. Retrospectively, the time series of returns might appear to exhibit momentum and mean reversion because $\mathrm{E}\left[S_t - S_{t-1} | Z_t = 1\right] \propto S_{t-1}$ and $\mathrm{E}\left[S_t - S_{t-1} | Z_t = 0\right] \propto -S_{t-1}$. In sum, retrospectively returns exhibit momentum while the speculative component persists and mean reversion when the speculative component collapses, even though prices are a martingale.

Similarly, Fischer, Heinle, and Verrecchia (2016) consider an overlapping generations setting in which investors speculate on the valuation multiple (e.g., price to earnings ratio) that future generations of investors will use. The authors also find that returns could exhibit momentum and mean reversion in retrospective data, even though prices are a martingale.

2.1.3.7. Frictions to arbitrage

Frictions to arbitrage – such as short sale restrictions and capital constraints – can explain the persistence of predictable patterns in returns, but not their origins. Harrison and Kreps (1978) and Diamond and Verrecchia (1987) consider markets in which investors hold heterogeneous beliefs about the value of a risky asset and short sales are restricted. The authors show that, under these conditions, price is an upwardly biased measure of investors' average belief of the value of the risky asset. Harrison and Kreps (1978) show that an investor would be willing to pay more than his expectation of the value of the risky asset because he anticipates reselling the asset. This resale option could drive prices higher than the most optimistic belief by any investor. As empirical evidence of the resale option theory, Xiong and Yu (2011) document speculative trading in 18 put warrants in China in 2005–2008. These warrants were almost certain to expire worthless and short sales of these warrants were prohibited. The warrants exhibited an average daily turnover rate of 328 percent and an average daily volume of 1.29 billion yuan. The authors find that the price of the warrants was correlated with the turnover rate and the return volatility, which is consistent with the predictions from Harrison and Kreps (1978).

Shleifer and Vishny (1997) explain that real-world arbitrage opportunities typically require traders to post collateral and expose traders to short-term volatility in prices. If traders face potential capital constraints or collateral shortfalls, they must be selective in which arbitrage opportunities they attempt to exploit (Amihud and Mendelson, 1980). Shleifer and Vishny (1997) show that, when arbitrageurs' access to capital covaries with their immediate past performance on a mark-to-market basis, arbitrageurs lose the capacity to exploit arbitrage opportunities as their expected returns increase. In addition, as the counter-cyclicality between arbitrageurs' access to capital and expected returns increases, the persistence of mispricing increases. Abreu and Brunnermeier (2002) show that in these circumstances arbitrageurs would delay attempting to exploit a mispricing until they believe that a critical mass of other arbitrageurs have become aware of the mispricing. The authors label this coordination problem as "synchronization risk." Abreu and Brunnermeier (2003) show that rational arbitrageurs might even trade in the same direction as, rather than against, the mispricing until they believe that enough other arbitrageurs have become aware of the mispricing and gathered to exploit it.

2.1.4. Complications in identifying non-Bayesian investor behavior

Theoretical models of non-Bayesian weighting of information signals often yield the same predictions regarding observable trading activity as theoretical models of information asymmetry or trading costs yield. The similarity of these comparative statics has impeded identifying non-Bayesian investor behavior empirically. Fischer and Verrecchia (1999) recognize this challenge:

> Our comparative static results provide explicit predictions regarding the extent of heuristic behavior. Direct tests of these predictions, however, are likely to be difficult because doing so would require a good proxy for heuristic trade. We are reluctant to suggest such a proxy. (p. 104)[3]

Nevertheless, some authors have suggested empirical proxies for non-Bayesian investor behavior. For example, Gervais and Odean (2001) argue that investors are prone to overestimate their information processing ability due to self-attribution bias. They predict that, following positive portfolio returns,

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[3]Similarly, Kim and Verrecchia (1997) explain the challenge in separating information precision differences from differences of opinion, as follows:

> As a practical matter, there is no way to distinguish whether differential interpretations of an announcement result explicitly from event-period information or different likelihood functions arising from other sources. We assume that differential interpretations arise from event-period information (and a common likelihood function) in an attempt to draw a distinction between effects on price change and volume that arise from pre-announcement phenomena versus event-period phenomena. (p. 399)

investors behave like their information precision is greater and trade more aggressively. As evidence of this prediction, Statman, Thorley, and Vorkink (2006) and Griffin, Nardari, and Stulz (2007) find that trading volume in individual stocks increases after positive market returns. Trading volume also could have increased, however, due to a change in the heterogeneity in investors' information precision (Kim and Verrecchia, 1997). Consistent with an information asymmetry explanation, Griffin, Nardari, and Stulz (2007) find that this increase in trading volume is greater in countries with greater corruption, short sale constraints, and market volatility. Similarly, Huddart, Lang, and Yetman (2009) find that trading volume is higher after a stock crosses through its 52-week high or 52-week low. This increase in trading volume around highs and lows appears stronger when information asymmetry is likely to be higher – for small, young, and volatile firms and when institutional investor holdings are low. In these settings, separating exaggerated information precision from genuinely superior information precision is particularly difficult because, in equilibrium, more investors would choose to exaggerate their information precision when information quality is lower (Fischer and Verrecchia, 1999).

Similarly, recent empirical literature questions whether "home bias" actually reflects an information advantage. French and Poterba (1991) first documented that U.S. investors hold excessively large portfolio allocations in U.S. assets relative to an efficient frontier portfolio that includes international assets. Coval and Moskowitz (1999) document that mutual fund managers tend to hold large positions in firms whose headquarters are closer geographically. More recently authors have questioned whether this seeming under-diversification puzzle reflects an information advantage. Coval and Moskowitz (2001) and Baik, Kang, and Kim (2010) argue that investors exhibit an advantage in gathering and processing information on geographically close firms, and document that institutional investors in the U.S. appear to earn excess profits on their holdings in local firms. Internationally, evidence is mixed. For example, Choe et al. (2001) using Korean data, Hau (2001) using German data, Dvořák (2005) using Indonesian data, and Choi et al. (2017) using a cross section of 72 countries find that investors who hold larger concentrations of their portfolios in domestic firms earn higher risk-adjusted returns. In contrast, Grinblatt and Keloharju (2000) using Finnish data and Froot and Ramadorai (2008) using a cross section of 25 countries find that foreigners outperform local investors. Kang and Stulz (1997) using Japanese data find no difference in the performance of domestic and foreign investors. Further, Graham, Harvey, and Huang (2009) document that investors who feel more competent tend to allocate their investments more internationally. This finding suggests, counterintuitively, that investors tend to under-diversify due to risk aversion. Finally, Giannetti

and Laeven (2012) document a "flight home bias" in which syndicated lenders exhibit a tendency to concentrate their lending to local firms when market-wide costs of capital increase. In sum, extant research has not been able to identify definitively whether investors' portfolio concentration in geographically local firms reflects an information advantage or a bias in risk preferences.

Market-making activities and other market microstructure institutions also confound empirical identification of whether investors process information efficiently. Amihud and Mendelson (1980) study how a market maker's inventory carrying costs – such as capital requirements, the opportunity cost of capital, and the actual costs of trading – affect the bid-ask spread. They find that, in the presence of inventory carrying costs, a market maker will lean the bid price and ask price toward lessening the inventory; i.e., the market maker will lower the bid and ask prices if the market maker has positive inventory or increase the bid and ask prices if the market maker has negative inventory. In addition, as a market maker takes on a larger position (positive or negative), the market maker widens the bid-ask spread. This simultaneous leaning and widening of the bid-ask spread ensures that transaction prices are efficient, in the sense that an investor with only public information cannot trade against the market maker profitably.

Ho and Stoll (1981) show that, if trading costs are positive and the distribution of investors' demand for shares is symmetric (e.g., given an initial bid-ask spread, the probability of a buy order for a certain number of shares equals the probability of a sell order for that number of shares), price changes will exhibit negative serial covariance. Roll (1984) provides a simple example to illustrate this result. Suppose that the expected terminal value of a risky asset, v_t, follows a random walk over three rounds of trade, $t = 1, 2, 3$. A competitive market maker in the risky asset faces a transaction cost, w, and passes this cost through to investors by increasing the market-clearing price if net order flow is to buy or lowering the market-clearing price if net order flow is to sell. That is, in each round the market maker sets the bid price to $p_{B,t} = v_t - w$ and the ask price to $p_{A,t} = v_t + w$. Roll labels this adjustment to the market-clearing price as the effective bid-ask spread. Suppose the probability of a buy order, event b, or sell order, event s, for one share in each period is equal to $\frac{1}{2}$, and orders are independent over time. The serial covariance in price changes over the three rounds of trade is $\text{Cov}(p_3 - p_2, p_2 - p_1) = -w^2$, as illustrated in Table 1. In sum, transaction costs give rise to short-term mean reversion in prices.

Table 1: Roll (1984) derivation of negative serial covariance in price changes

Suppose the probability of a buy order, b, or sell order, s, is $\Pr(b) = \Pr(s) = \frac{1}{2}$; bid prices are $p_{B,t} = v_t - w$; and, ask prices are $p_{A,t} = v_t + w$. The mean price change is zero. The serial covariance in price changes, $\text{Cov}(p_3 - p_2, p_2 - p_1) = -w^2$, can be calculated by considering the eight possible combinations of buy and sell orders over the three rounds of trade and their corresponding probabilities:

Combination of buy and sell orders	Probability	Price change from $t=1$ to $t=2$	Price change from $t=2$ to $t=3$
b, b, b	1/8	0	0
b, b, s	1/8	0	$-2w$
b, s, b	1/8	$-2w$	$2w$
b, s, s	1/8	$-2w$	0
s, b, b	1/8	$2w$	0
s, b, s	1/8	$2w$	$-2w$
s, s, b	1/8	0	$2w$
s, s, s	1/8	0	0

Stoll (1989) extends this illustrative example to allow for inventory holding costs and information-driven trading. He shows that in the presence of inventory holding costs not only do transaction price changes exhibit negative serial correlation, but also bid price changes and ask price changes exhibit negative serial correlation as well.

Overall, these papers demonstrate that securities could exhibit predictable returns in an efficient market. As a result, evidence of predictable returns is not sufficient to demonstrate that investors do not use all publicly available information or misweight public and private information.

2.2. Analytical model

The analytical model in the main analysis extends the theoretical model in Kyle (1985) to allow for transaction costs – as in Roll (1984) – and the possibility that investors misuse their private information signals. The private information signal and misweighting structure extends those postulated in Kyle and Wang (1997) and Fischer and Verrecchia (1999). The analytical model also allows for serial correlation in liquidity trader demand, as conjectured in Dontoh, Ronen, and Sarath (2003). The combination of transaction costs, investors' misuse of their private signal, and serial correlation in liquidity trader demand in a Kyle (1985) environment yields a structural estimation specification

with identified parameters for these constructs.

Kyle (1985) presents a theoretical model of how informed trading affects asset prices. In this model, a single risk-neutral informed investor and noise traders trade a single risky asset in an auction market with competitive risk-neutral market makers. The informed investor knows the value of the risky asset and anticipates the price impact of his demand for shares. Orders from the informed investor and noise traders arrive as an aggregate to the market makers, such that the noise traders' random demand partially camouflages the information content of the informed investor's order. The market maker sets price efficiently by assessing the information content of the net order flow. The key result is that the price impact of the net order flow is proportional to the information asymmetry between the informed investor and the market maker, as measured by the ratio of the variance of the value of the risky asset to the variance of noise trader demand. The coefficient that relates net demand for shares to its price impact reflects this information asymmetry and has become known as Kyle's lambda.

Kyle and Wang (1997) and Fischer and Verrecchia (1999) present theoretical models in which informed investors could exaggerate the precision of their private information. Extending the Kyle (1985) framework, the authors assume that two or more informed investors observe noisy, independent, private signals about the value of a risky asset. These informed investors may behave as if the precision of the signal is greater or less than it truly is. The authors show that, given the choice, exaggerating one's precision could be an informed investor's optimal strategy. Informed investors who exaggerate their information precision ("heuristic investors") essentially are committed to trading aggressively, which leads investors who weight their private information fairly ("Bayesian investors") to trade less aggressively. As a result, heuristic investors could earn higher expected profits than Bayesian investors would earn. Fischer and Verrecchia (1999) show that, if few heuristic investors are present, an informed investor might choose to behave as if his private signal has greater precision than the signal really has. Further, Kyle and Wang (1997) show that, if two investment funds must decide whether to hire a heuristic investor or a Bayesian investor as portfolio manager, these funds face a prisoner's dilemma in which hiring a heuristic investor is the Nash dominant strategy, even though each fund would earn higher expected profits if both hired Bayesian portfolio managers. In the analytical model below, however, informed investors' expected profits are strictly decreasing in their misweighting of information.

Dontoh, Ronen, and Sarath (2003) demonstrate that post-earnings announcement drift and other predictable patterns in securities returns could result from serial correlation in liquidity trader demand for a risky asset. Risk-averse informed investors do not arbitrage away this predictable liquidity trader demand and delay acting on their private information. Risk aversion serves as a friction to arbitrage, such that serial correlation in non-information-based demand and the stymied flow of private information leads to predictable patterns in price changes.

2.3. Structural estimation

Like Beaver (1968), I infer the flow of information from capital markets outcomes. Following Kyle (1985), I assume that unanticipated price changes reflect the price impact of informed investors' trading on private information. Predictable price changes do not contain new information. Building on these assumptions, the analytical model in Chapter 3 predicts that price changes follow a moving average process with a state variable. This section provides an overview of the estimation of this time series process.

Durbin and Koopman (2012) define a state space model as the relation between a series of observations $y_1, \ldots, y_n$ and an unobserved series of state vectors $\alpha_1, \ldots, \alpha_n$. The basic model for representing a time series is the additive model

$$y_t = Z\alpha_t + \epsilon_t, \quad t = 1, \ldots, n \tag{2.3.1}$$

where y_t is a vector of observations called the observation vector, α_t is an unobserved vector called the state vector, the matrix Z relates the state space vector to the observation vector, and ϵ_t is a disturbance term. The state vector is assumed to follow a linear process of the form

$$\alpha_{t+1} = T\alpha_t + R\eta_t \tag{2.3.2}$$

where the matrices T and R describe the transition process for the state vector and η_t is a disturbance term.

The analytical model derived in Chapter 3 predicts that price changes, ΔP_t, follow the time series process

$$\Delta P_t = k_1 \nu_{t-1} - k_1 \nu_{t-2} + k_2 \eta_{t-1} + k_3 \eta_{t-2} + \eta_t \tag{2.3.3}$$

in which the state variable ν_{t-1} follows the process

$$\nu_{t-1} = k_4\nu_{t-2} + k_5\eta_{t-1} \tag{2.3.4}$$

and $k_1, \ldots, k_5$ are constants that will be derived in Chapter 3.

This model can be written as a state space model. The state vector is

$$\alpha_t = \begin{bmatrix} \nu_{t-1} & \nu_{t-2} & \eta_{t-1} & \eta_{t-2} \end{bmatrix}' \tag{2.3.5}$$

The disturbance term in the observation equation is the same as the disturbance term in the state equation; i.e., $\epsilon_t = \eta_t$. The matrix relating the state space vector to the observation vector is

$$Z = \begin{bmatrix} k_1 & -k_1 & k_2 & k_3 \end{bmatrix} \tag{2.3.6}$$

The state vector follows the linear process

$$\alpha_{t+1} = \begin{bmatrix} \nu_t \\ \nu_{t-1} \\ \eta_t \\ \eta_{t-1} \end{bmatrix} = \begin{bmatrix} k_4 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \nu_{t-1} \\ \nu_{t-2} \\ \eta_{t-1} \\ \eta_{t-2} \end{bmatrix} + \begin{bmatrix} k_5 \\ 0 \\ 1 \\ 0 \end{bmatrix} \eta_t \tag{2.3.7}$$

where the matrices describing the transition process for the state vector are

$$T = \begin{bmatrix} k_4 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{2.3.8}$$

and

$$R = \begin{bmatrix} k_5 & 0 & 1 & 0 \end{bmatrix}' \tag{2.3.9}$$

The analytical model allows for the possibility that the variance of unexpected returns varies over

time. For simplicity, I assume that the variance of returns follows a generalized auto-regressive conditional heteroskedastic (GARCH) process. Bollerslev (1986) extends the auto-regressive conditional heteroskedastic process from Engle (1982) to allow past conditional variances to be predictive of the current conditional variance. This GARCH process allows a random variable, ε_t, to exhibit time-varying variance of the following form:

$$\varepsilon_t \sim \mathcal{N}(0, h_t) \tag{2.3.10}$$

$$h_t = \alpha_0 + \sum_{s=1}^{q} \alpha_s \varepsilon_{t-s}^2 + \sum_{s=1}^{p} \beta_s h_{t-s} \tag{2.3.11}$$

where $p \geq 0$, $q > 0$, $\alpha_0 > 0$, $\alpha_s \geq 0$, $\beta_s \geq 0$, and $\text{Cov}(\varepsilon_t, \varepsilon_s) \, \forall s \neq t$. To ensure stationarity, one could assume that $\alpha_1 + \beta_1 < 1$. The notation GARCH(p, q) denotes the assumed number of lag terms.

I assume that the error terms, η_t, follow a GARCH$(1, 1)$ model of the process $\eta_t \sim \mathcal{N}(0, h_t)$. Following Bollerslev (1986) and Durbin and Koopman (2012), the log-likelihood function for this model with a sample of N observations is

$$
\begin{aligned}
L\left(\theta | \eta_1, \ldots, \eta_T\right) &= \sum_{t=1}^{N} \ln \left(\frac{1}{\sqrt{2\pi h_t}} \exp \left(-\frac{\eta_t^2}{2h_t} \right) \right) \\
&= -\frac{N}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{N} \left[\ln(h_t) + \frac{\eta_t^2}{h_t} \right]
\end{aligned}
\tag{2.3.12}
$$

where θ is the parameter set.

Obtaining maximum likelihood estimates of the parameter set θ calls for an iterative optimization procedure. In general, iterative optimization procedures update estimates of the parameters according to a function of the log-likelihood value (or gradient of the log-likelihood function) and a step length (e.g., Newton's method and quasi-Newton's methods). If the step length is too small or large in any iteration step, an iterative procedure is vulnerable to identifying a locally optimal parameter set as the globally optimal parameter set. Numerous optimization algorithms and software packages, which trade-off vulnerability to selecting locally optimal parameter sets and speed of convergence, have been developed (see Nash, 2014 for a review).

In the estimations below, I use multiple optimization algorithms through a software package in R (Nash and Varadhan, 2011). Specifically, I use the Barzilai-Borwein spectral projected gradient

method, bound optimization by quadratic approximation, the Nelder-Mead optimization method, and the Broyden–Fletcher–Goldfarb–Shanno algorithm. I run each optimization method on nine sets of random starting values for each parameter. From the 36 sets of optimized parameters, I select the set of parameters with the highest log-likelihood value.

3.1. Analytical model

3.1.1. Setup

The following model extends Kyle (1985) to allow for the possibility that informed investors mis-weight redundant information. Informed investors, liquidity traders, a market maker, and rational arbitrageurs trade a single, risky asset and a numeraire asset. The risky asset has terminal value $\tilde{V} = \sum_{t=1}^{T} \tilde{v}_t$, where $\tilde{v}_t$ are independently distributed on $\mathcal{N}\left(0, \sigma_{v,t}^2\right)$.[1] At the end of period T, V reveals publicly. One informed investor, one liquidity trader, and $M \geq 0$ rational arbitrageurs arrive in each in period, $t = 1, \ldots, T$, to trade the risky asset with the market maker.

The market maker clears the market by taking the order imbalance, D_t, into his inventory. The market maker cannot distinguish the trading of the informed investors or rational arbitrageurs from the trading of liquidity traders; that is, the market maker observes the order imbalance as an aggregate. The market maker sets price, P_t, according to the expected value of the risky asset conditional on the order imbalance, the set of public information, denoted H_{t-1}, and a private transaction cost, $\rho \left|D_t\right|$, where $\rho \geq 0$. The parameter ρ conflates the market maker's operating costs (such as interest on margin debt and capital requirements), quasi-rents for supplying liquidity, and risk aversion. The market maker passes this transaction cost through to investors by increasing the trade price by ρD_t if the net demand is positive or lowering the trade price by $-\rho D_t$ if the net demand is negative. This transaction cost ensures that demand pressures, even if known to arise from uninformed traders, can affect prices.

Formally, the market maker sets price by

$$P_t = \mathrm{E}\left[\tilde{V} | D_t, H_{t-1}\right] + \rho D_t \tag{3.1.1}$$

where $\mathrm{E}\left[\tilde{V} | D_t, H_{t-1}\right] = \mathrm{E}\left[\tilde{V} | H_t\right]$ denotes the expected value of the risky asset given all available public information at the end of period t. Within the context of the model, the public information set at the end of period t comprises the history of order flow: $H_t = \{D_1, \ldots, D_t\}$.

---

[1]Tilde accent marks distinguish random variables from their realizations.

In an informationally efficient market, investors gather and process information signals to gain an information advantage over other investors (e.g., Verrecchia, 1982). These information signals could include mandatory and voluntary disclosures, reports from analysts and the mass media, public information from regulators, etc. Since these information signals are public, some of their information content would be impounded into prices immediately. To obtain private information from these public signals and gain an information advantage, an investor must separate these public signals into that which is already priced and that which has not been priced. I examine an environment in which some informed investors might behave like information that is already priced is novel and exclusive insight into the value of a firm. I label information that already is priced as "redundant information" and novel, exclusive insight as "private information."

All informed investors are risk neutral.[2] The informed investor in period t may trade in period t only. The informed investor in period t observes the public information set, H_{t-1}, and infers the expected value of the risky asset given public information, $\mathrm{E}\left[\tilde{V}|H_{t-1}\right]$.

The informed investor in period t also observes a private signal. The private signal comprises incremental private information and redundant information,

$$s_t = v_t + \alpha u_{t-1} \tag{3.1.2}$$

where $u_{t-1} = \mathrm{E}\left[\tilde{v}_{t-1}|H_{t-1}\right]$ denotes the information about v_{t-1} that was priced in period $t-1$ and α is an exogenous scalar. The information u_{t-1} is redundant because it is already known publicly and is impounded into price. Although u_{t-1} is endogenous to the model, this assumption offers a straightforward way to describe information that already is public and priced.

Since v_t is independent of all prior signals, the Bayesian updating process is simply additive. If the informed investor in period t updated his beliefs according to Bayes's rule, he would calculate the expected value of the risky asset by

$$\mathrm{E}\left[\tilde{V}|s_t, H_{t-1}\right] = (s_t - \alpha u_{t-1}) + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] = v_t + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] \tag{3.1.3}$$

---

[2]In the present model, the risky asset has a known liquidation date. As the liquidation date approaches, the remaining risk decreases. If informed investors were risk averse, the risk premium they would demand would decrease as the liquidation date approaches. As a result, prices could exhibit positive returns drift due to risk aversion, but not negative returns drift. Prior empirical literature, however, documents that securities exhibit positive and negative returns drift (See Section 2.1.2). The present model can predict momentum in positive returns and negative returns.

Instead, the informed investor acts as if the private signal comprises only private information; that is, as if αu_{t-1} was private information. In neglecting to back out the redundant information from the private signal, the informed investor in effect chooses how much to trade using the belief

$$v_t + \alpha u_{t-1} + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] \tag{3.1.4}$$

The parameter α represents the extent to which informed investors misweight the redundant information content in their private signals. If informed investors backed out redundant information perfectly, $\alpha = 0$. If informed investors behave like their private signals have more private information and less redundant information than the signals truly have, $\alpha > 0$. If informed investors understate the novelty of their private signals and overstate the extent to which their private signals already have been priced, $\alpha < 0$. Using this miscalibrated belief, the informed investor in t submits a market order, x_t, to maximize his perceived expected profit.[34]

Liquidity traders demand a random number of shares for reasons unrelated to the value of the risky asset. Black (1986) describes liquidity traders as investors who receive a signal that is "noise" relative to the value of a risky asset – i.e., independent of the value of a risky asset. Similarly, Grossman (1995) states:

> Reasons for these noninformational trades include cross-sectional changes in wealth, risk
> preferences, liquidity needs, unanticipated investment opportunities, and all factors that
> do not directly relate to the payoffs on the securities being traded. (p. 775)

Many theoretical models of the price impact of information asymmetry assume that liquidity trader demand arrives randomly and independently over time (e.g., Kyle, 1985; Glosten and Milgrom, 1985). Dontoh, Ronen, and Sarath (2003) consider a rational expectations equilibrium setting in which the supply of the risky asset – which functions as noise trader demand – exhibits serial correlation over time. In practice, liquidity trader demand could be correlated across investors due investors' year-end tax-loss selling, mutual fund managers' quarterly window dressing, or hedge funds' restricted windows on redemptions and new investments (e.g., He, Ng, and Wang, 2004, Ng

---

[3]Although I construct this theoretical model using a single informed investor, an alternative would be to introduce multiple informed investors with heterogenous misweightings of redundant information. Since the market maker observes net demand as an aggregate, only the average level of informed investors' misweighting would affect prices. In my empirical estimation, the estimated α parameters represent the average misweighting of redundant information within each estimation.

[4]While I do not specify the utility function of the informed investor, one could be constructed such that the informed investor faces a private cost to minimizing $|\alpha|$ or receives private, non-monetary utility from having $\alpha \neq 0$. Chapter 4 considers this distinction.

and Wang, 2004, Sadka, 2010). These examples suggest that non-informational trading may have a tendency to cluster in time. Formally, I allow liquidity trader demand to be serially correlated by assuming that the liquidity trader in period t submits a random market order,

$$\tilde{z}_t = \phi z_{t-1} + \tilde{\zeta}_t \tag{3.1.5}$$

where $\tilde{\zeta}_t \sim \mathcal{N}\left(0, \sigma_{\zeta,t}^2\right)$, $\tilde{\zeta}_t$ are serially independent and independent of $\tilde{v}_t$, and ϕ is an exogenous scalar. Since unexpected liquidity trader demand is independent of fundamental information flows, the assumption that liquidity trader demand is serially correlated does not affect the precision of public information.

The combination of the market maker's transaction cost and either predictable informed investor demand or predictable liquidity trader demand could induce a situation in which a rational investor could earn positive expected profits by trading only on public information. The possibility of arbitrage in this manner suggests that rational arbitrageurs could be present in this market. I assume that M rational arbitrageurs participate in this market to exploit the arbitrage opportunity. Each risk-neutral rational arbitrageur is identical, has no private information, holds his trades until the terminal date, and submits a market order, y_t. Each arbitrageur knows that the informed investor is misweighting information, the time series properties of liquidity trader demand, and the market maker's transaction cost parameter. Meanwhile, the informed investor anticipates the arbitrageurs' demand in choosing his own demand. Since the informed investor behaves as if his private signal is correct, he treats the rational arbitrageurs' demand as additional liquidity.

To allow for heteroscedasticity in stock price returns, I assume that the variance of liquidity trade and the variance of private information vary over time. Extensive finance literature documents that securities returns do not exhibit constant volatility over time (See Engle, 2001 for a review). In the present model, the volatility of returns comprises a weighted average of the variance of liquidity trade and the variance of private information flows. Nevertheless, to make information asymmetry constant over time, I assume that the ratio of the variance of private information to the variance of liquidity trade is constant over time. If liquidity traders have partial discretion over the timing over their trades, they would choose to trade when many other liquidity traders also are trading. Informed investors also want to trade when liquidity is the greatest (Admati and Pfleiderer, 1988). As a result, information asymmetry is likely to be constant over short time horizons. If information asymmetry varied over short time horizons, an informed investor or a liquidity trader with discretion could

reduce the price impact of his trades by choosing to trade during a period with lower information asymmetry. Formally, I assume that

$$\frac{\sigma_{v,t}^2}{\sigma_{\zeta,t}^2} \equiv \bar{\sigma} \tag{3.1.6}$$

is constant over time.

3.1.2. Equilibrium characterization

I focus on recursive equilibria, which are equilibria in which price and informed demand are of the following linear forms. As in a standard Kyle (1985) framework, I restrict attention to linear demand and pricing functions. Price satisfies

$$P_t = (\lambda_d + \rho) D_t + \lambda_u u_{t-1} + \lambda_\phi \mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] + \lambda_E \mathrm{E}\left[\tilde{V}|H_{t-1}\right] \tag{3.1.7}$$

Informed demand satisfies

$$x_t = \kappa_d v_t + \kappa_u u_{t-1} + \kappa_\phi \mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] + \kappa_E \mathrm{E}\left[\tilde{V}|H_{t-1}\right] \tag{3.1.8}$$

Each rational arbitrageur's demand satisfies

$$y_t = \gamma_u u_{t-1} + \gamma_\phi \mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] + \gamma_E \mathrm{E}\left[\tilde{V}|H_{t-1}\right] \tag{3.1.9}$$

3.1.2.1. Informed demand

In any recursive equilibrium, the informed investor in period t chooses his demand, x_t, to maximize his perceived expected profit, which is:

$$\max_{x_t}\left\{x_t\left(s_t + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] - \mathrm{E}\left[\tilde{P}_t|x_t, H_{t-1}\right]\right)\right\}$$

$$
\begin{aligned}
= \max_{x_t}\Big\{ &x_t\Big(v_t + \alpha u_{t-1} + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] \\
&- (\lambda_d + \rho)\Big(x_t + M\left(\gamma_u u_{t-1} + \gamma_\phi \mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] + \gamma_E \mathrm{E}\left[\tilde{V}|H_{t-1}\right]\right) + \phi \mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right]\Big) \\
&- \Big(\lambda_u u_{t-1} + \lambda_\phi \mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] + \lambda_E \mathrm{E}\left[\tilde{V}|H_{t-1}\right]\Big)\Big)\Big\}
\end{aligned}
\tag{3.1.10}
$$

Maximization of this objective function yields demand of the form:

$$x_t = \frac{1}{2(\lambda_d + \rho)} v_t + \frac{\alpha - (\lambda_d + \rho) M \gamma_u - \lambda_u}{2(\lambda_d + \rho)} u_{t-1}$$

$$+ \frac{-(\lambda_d + \rho)(M \gamma_\phi + \phi) - \lambda_\phi}{2(\lambda_d + \rho)} \mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] + \frac{1 - (\lambda_d + \rho) M \gamma_E - \lambda_E}{2(\lambda_d + \rho)} \mathrm{E}\left[\tilde{V}|H_{t-1}\right] \quad (3.1.11)$$

It follows that, in any recursive equilibrium, the coefficients of the informed demand function must satisfy:

$$\kappa_d = \frac{1}{2(\lambda_d + \rho)} \quad (3.1.12)$$

$$\kappa_u = \frac{\alpha - (\lambda_d + \rho) M \gamma_u - \lambda_u}{2(\lambda_d + \rho)} \quad (3.1.13)$$

$$\kappa_\phi = \frac{-(\lambda_d + \rho)(M \gamma_\phi + \phi) - \lambda_\phi}{2(\lambda_d + \rho)} \quad (3.1.14)$$

$$\kappa_E = \frac{1 - (\lambda_d + \rho) M \gamma_E - \lambda_E}{2(\lambda_d + \rho)} \quad (3.1.15)$$

Since $\tilde{v}_t$ has a mean of zero, κ_d is the response coefficient of unexpected demand to informed investor t's observation of v_t. The coefficient κ_d is the standard demand response for a Kyle (1985) model with transaction costs. The coefficient κ_u is informed investor t's response to misweighted redundant information. The coefficient κ_ϕ is informed investor t's response to expected liquidity trade. The coefficient κ_E is informed investor t's response to the mean of $\tilde{V}$ conditional on public information.

3.1.2.2. Rational arbitrage demand

In any recursive equilibrium, each rational arbitrageur, j, in period t chooses his demand $y_{j,t}$ to maximize his perceived expected profit, which is:

$$\max_{y_{j,t}} \left\{ y_{j,t} \left(\mathrm{E}\left[\tilde{V} - \tilde{P}_t|y_{j,t}, H_{t-1}\right] \right) \right\} \quad (3.1.16)$$

$$= \max_{y_{j,t}} \left\{ y_{j,t} \left(\mathrm{E} \left[\tilde{V} | H_{t-1} \right] \right. \right.$$

$$- (\lambda_d + \rho) \left(\kappa_u u_{t-1} + (\kappa_\phi + \phi) \, \mathrm{E} \left[\tilde{z}_{t-1} | H_{t-1} \right] + \kappa_E \mathrm{E} \left[\tilde{V} | H_{t-1} \right] + y_{j,t} + (M-1) \, y_{-j,t} \right)$$

$$\left. \left. - \lambda_u u_{t-1} - \lambda_\phi \mathrm{E} \left[\tilde{z}_{t-1} | H_{t-1} \right] - \lambda_E \mathrm{E} \left[\tilde{V} | H_{t-1} \right] \right) \right\} \tag{3.1.17}$$

where $y_{-j,t}$ denotes the demand from each of the remaining $M-1$ identical rational arbitrageurs.

Maximization of this objective function yields demand of the form:

$$y_t = - \frac{(\lambda_d + \rho) \, \kappa_u + \lambda_u}{2 \, (\lambda_d + \rho)} u_{t-1} - \frac{(\lambda_d + \rho) \, (\kappa_\phi + \phi) + \lambda_\phi}{2 \, (\lambda_d + \rho)} \mathrm{E} \left[\tilde{z}_{t-1} | H_{t-1} \right]$$

$$+ \frac{1 - (\lambda_d + \rho) \, \kappa_E - \lambda_E}{2 \, (\lambda_d + \rho)} \mathrm{E} \left[\tilde{V} | H_{t-1} \right] - \frac{1}{2} \, (M-1) \, y_{-j,t} \tag{3.1.18}$$

Since all rational arbitrageurs are identical, each chooses demand of the form

$$y_t = - \frac{(\lambda_d + \rho) \, \kappa_u + \lambda_u}{(M+1) \, (\lambda_d + \rho)} u_{t-1} - \frac{(\lambda_d + \rho) \, (\kappa_\phi + \phi) + \lambda_\phi}{(M+1) \, (\lambda_d + \rho)} \mathrm{E} \left[\tilde{z}_{t-1} | H_{t-1} \right]$$

$$+ \frac{1 - (\lambda_d + \rho) \, \kappa_E - \lambda_E}{(M+1) \, (\lambda_d + \rho)} \mathrm{E} \left[\tilde{V} | H_{t-1} \right] \tag{3.1.19}$$

It follows that, in any recursive equilibrium, the coefficients of the rational arbitrage demand function must satisfy:

$$\gamma_u = - \frac{(\lambda_d + \rho) \, \kappa_u + \lambda_u}{(M+1) \, (\lambda_d + \rho)} \tag{3.1.20}$$

$$\gamma_\phi = - \frac{(\lambda_d + \rho) \, (\kappa_\phi + \phi) + \lambda_\phi}{(M+1) \, (\lambda_d + \rho)} \tag{3.1.21}$$

$$\gamma_E = \frac{1 - (\lambda_d + \rho) \, \kappa_E - \lambda_E}{(M+1) \, (\lambda_d + \rho)} \tag{3.1.22}$$

The coefficient γ_u is each rational arbitrageur's response to the informed investor's demand due to the misweighting of redundant information. The coefficient γ_ϕ is each rational arbitrageur's response to expected liquidity trade. The coefficient γ_E is each rational arbitrageur's response to the mean of $\tilde{V}$ conditional on public information.

3.1.2.3. Market maker's pricing

The market maker sets the market-clearing price to satisfy

$$P_t = \mathrm{E}\left[\tilde{V}|D_t, H_{t-1}\right] + \rho D_t$$

Since v_t is independent of all prior signals, the Bayesian updating process of $\mathrm{E}\left[\tilde{V}|D_t, H_{t-1}\right]$ is simply additive:

$$\mathrm{E}\left[\tilde{V}|D_t, H_{t-1}\right] = \mathrm{E}\left[\tilde{v}_t|D_t, H_{t-1}\right] + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] \tag{3.1.23}$$

The market maker sets price

$$P_t = \mathrm{E}\left[\tilde{v}_t|D_t, H_{t-1}\right] + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] + \rho D_t \tag{3.1.24}$$

where

$$
\begin{aligned}
\mathrm{E}\left[\tilde{v}_t|D_t, H_{t-1}\right] &= \mathrm{E}\left[\tilde{v}_t|H_{t-1}\right] + \frac{\mathrm{Cov}\left(\tilde{v}_t, \tilde{D}_t\right)}{\mathrm{Var}\left(\tilde{D}_t\right)}\left(D_t - \mathrm{E}\left[\tilde{D}_t|H_{t-1}\right]\right) \\
&= \frac{(\kappa_d)\,\sigma_{v,t}^2}{(\kappa_d)^2\,\sigma_{v,t}^2 + \sigma_{\zeta,t}^2}\left(D_t - \mathrm{E}\left[\tilde{D}_t|H_{t-1}\right]\right)
\end{aligned} \tag{3.1.25}
$$

and

$$\mathrm{E}\left[\tilde{D}_t|H_{t-1}\right] = (\kappa_u + M\gamma_u)\,u_{t-1} + (\kappa_\phi + \phi + M\gamma_\phi)\,\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] + (\kappa_E + M\gamma_E)\,\mathrm{E}\left[\tilde{V}|H_{t-1}\right] \tag{3.1.26}$$

Given informed investor's and the rational arbitrageur's linear demand functions, the coefficients of the market maker's pricing function satisfy:

$$\lambda_d = \frac{(\kappa_d)\,\sigma_{v,t}^2}{(\kappa_d)^2\,\sigma_{v,t}^2 + \sigma_{\zeta,t}^2} \tag{3.1.27}$$

$$\lambda_u = -\lambda_d\,(\kappa_u + M\gamma_u) \tag{3.1.28}$$

$$\lambda_\phi = -\lambda_d \left(\kappa_\phi + \phi + M\gamma_\phi \right) \tag{3.1.29}$$

$$\lambda_E = 1 - \lambda_d \left(\kappa_E + M\gamma_E \right) \tag{3.1.30}$$

The coefficient λ_d is the standard single-period Kyle's lambda. The coefficient λ_u is the market maker's adjustment to net demand related to informed investor t's misweighting of redundant information. The coefficient λ_ϕ is the market maker's adjustment to net demand related to expected liquidity trade. The coefficient λ_E is the market maker's response to the mean of $\tilde{V}$ conditional on public information.

3.1.3. Equilibrium

Characterizing a recursive equilibrium entails identifying the set

$$\{\lambda_d, \lambda_u, \lambda_\phi, \lambda_E, \kappa_d, \kappa_u, \kappa_\phi, \kappa_E, \gamma_u, \gamma_\phi, \gamma_E\}$$

that satisfy Equations (3.1.12), (3.1.13), (3.1.14), (3.1.15), (3.1.20), (3.1.21), (3.1.22), (3.1.27), (3.1.28), (3.1.29), and (3.1.30), and a specification of the conditional expectation of $\tilde{V}$ as a function of past demands. Observation 1, which is proven in Section 3.5.1, characterizes the recursive equilibrium.

Observation 1: In every period, there exists a unique equilibrium in which:

1. λ_d is the unique solution of $\lambda_d^3 + 2\rho\lambda_d^2 + \left(\rho^2 - \frac{1}{4}\bar{\sigma} \right)\lambda_d - \frac{1}{2}\bar{\sigma}\rho = 0$ in which $\lambda_d > -\rho$;
2. $\lambda_u = \frac{-\alpha\lambda_d}{\lambda_d + (M+2)\rho}$;
3. $\lambda_\phi = \frac{-\lambda_d(\lambda_d+\rho)\phi}{\lambda_d + (M+2)\rho}$; and,
4. $\lambda_E = 1$.

In summary, the market maker sets price using the strategy

$$P_t = \lambda_d \left(D_t - \frac{\alpha}{\lambda_d + (M+2)\,\rho} u_{t-1} - \frac{(\lambda_d + \rho)\,\phi}{\lambda_d + (M+2)\,\rho} \mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] \right) + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] + \rho D_t \tag{3.1.31}$$

where λ_d is the unique real root of

$$\lambda_d^3 + 2\rho\lambda_d^2 + \left(\rho^2 - \frac{1}{4}\bar{\sigma}\right)\lambda_d - \frac{1}{2}\bar{\sigma}\rho = 0 \tag{3.1.32}$$

in which $\lambda_d > 0 \geq -\rho$.

Each informed investor chooses his demand according to:

$$x_t = \frac{1}{2\left(\lambda_d + \rho\right)}v_t + \frac{\alpha\left(\lambda_d + \left(M+1\right)\rho\right)}{\left(\lambda_d + \rho\right)\left(\lambda_d + \left(M+2\right)\rho\right)}u_{t-1} - \frac{\phi\rho}{\lambda_d + \left(M+2\right)\rho}\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] \tag{3.1.33}$$

Each rational arbitrageur each chooses his demand according to:

$$y_t = -\frac{\alpha\rho}{\left(\lambda_d + \rho\right)\left(\lambda_d + \left(M+2\right)\rho\right)}u_{t-1} - \frac{\phi\rho}{\lambda_d + \left(M+2\right)\rho}\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] \tag{3.1.34}$$

Expected net demand is

$$\begin{aligned}
\mathrm{E}\left[\tilde{D}_t|H_{t-1}\right] &= \mathrm{E}\left[\tilde{x}_t + M\tilde{y}_t + \tilde{z}_t|H_{t-1}\right] \\
&= \frac{\alpha}{\lambda_d + \left(M+2\right)\rho}u_{t-1} + \frac{\left(\lambda_d + \rho\right)\phi}{\lambda_d + \left(M+2\right)\rho}\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] \tag{3.1.35}
\end{aligned}$$

As seen in Equation (3.1.31), price in period t comprises the impact of unexpected demand on the expected value of asset, the expected value of the asset given all previously available information, and the transaction cost. As seen in Equation (3.1.32) and depicted in Figure 1, the model predicts that the sensitivity of the expected value of the risky asset to net demand (i.e., Kyle's lambda) steepens as information asymmetry increases and flattens as transaction costs increase. That is, $\frac{\partial\lambda_d}{\partial\bar{\sigma}} > 0$ and $\frac{\partial\lambda_d}{\partial\rho} < 0$. Kyle's lambda is decreasing in transaction costs because the market maker recognizes that informed investors choose to trade less when facing passed-through transaction costs. If transaction costs were zero, informed investors weighted redundant information fairly, and liquidity traders' demand was independent of past demand – i.e., if $\rho = 0$, $\alpha = 0$, and $\phi = 0$ – this equilibrium would match the classic Kyle (1985) single-period model.

Trading on redundant information leads to predictable net demand, as seen in Equation (3.1.35). When $\alpha > 0$, expected informed demand follows in the same direction as the prior net demand. When $\alpha < 0$, expected informed demand partially reverses prior net demand. The market maker recognizes

informed investors' misweighting of redundant information. Using the parameter $\lambda_u = -\frac{\alpha \lambda_d}{\lambda_d + (M+2)\rho}$, the market maker backs out the expected portion of demand due to trading on redundant information. Trading on redundant information does not affect the market maker's expectation of the value of the risky asset because the market maker knows the redundant information already. The misweighting of redundant information also does not affect information asymmetry, i.e., $\frac{\partial \lambda_d}{\partial \alpha} = 0$.

Nevertheless, trading on redundant information affects prices because the market maker passes through the trading costs of this order flow. Specifically, the market maker adjusts the market-clearing price by $\rho \frac{\alpha}{\lambda_d + (M+2)\rho} u_{t-1}$. If transaction costs were zero, i.e., $\rho = 0$, trading on redundant information would affect net demand, but would not affect prices. The price impact of trading on redundant information increases in magnitude as transaction costs increase and as information asymmetry decreases.

Similarly, predictable liquidity trader demand also leads to predictable net order flow, as seen in Equation (3.1.35). When $\phi > 0$, expected liquidity trade follows in the same direction as the prior liquidity trader demand; when $\phi < 0$, expected liquidity trade partially reverses prior liquidity trader demand. The market maker backs out the expected portion of net order flow due to expected liquidity trade using the parameter $\lambda_\phi = -\frac{\phi \lambda_d (\lambda_d + \rho)}{\lambda_d + (M+2)\rho}$. Expected liquidity trade does not affect the market maker's expectation of the value of the risky asset and does not affect information asymmetry. Nevertheless, expected liquidity trade affects prices because the market maker passes through the trading costs of this order flow. Specifically, the market maker adjusts the market-clearing price by $\rho \frac{(\lambda_d + \rho)\phi}{\lambda_d + (M+2)\rho} \mathrm{E}\left[\tilde{z}_{t-1} | H_{t-1}\right]$. The price impact of expected liquidity trade increases in magnitude as transaction costs or information asymmetry increases.

The rational arbitrageurs reduce, but do not eliminate, the price impact of trading on redundant information and expected liquidity demand. If M is finite, the rational arbitrageurs act like Cournot oligopolists, and would not completely overwhelm expected demand from informed investors and liquidity traders. As $M \to \infty$, the rational arbitrageurs' demand negates expected net demand from informed investors and liquidity traders. The time series of price changes would approach the pattern with $\rho > 0$, $\alpha = 0$, and $\phi = 0$.

3.1.4. Time series properties of price changes

To estimate informed investors' misweighting of redundant information, the α parameter, I study the time series of price changes. Let η_t denote the price impact of unexpected demand, where

$$\eta_t \equiv (\lambda_d + \rho)\left(D_t - \mathrm{E}\left[\tilde{D}_t|H_{t-1}\right]\right) = \frac{1}{2}v_t + (\lambda_d + \rho)\,\zeta_t \tag{3.1.36}$$

By assumption, η_t are independent and normally distributed random variables with means equal to zero and variances equal to $\frac{1}{4}\sigma^2_{v,t} + (\lambda_d + \rho)^2\,\sigma^2_{\zeta,t}$.

The change in the expected value of the risky asset equals what market makers learn from unexpected demand, as follows:

$$u_t = \mathrm{E}\left[\tilde{V}|H_t\right] - \mathrm{E}\left[\tilde{V}|H_{t-1}\right] = \frac{\lambda_d}{\lambda_d + \rho}\eta_t \tag{3.1.37}$$

The price change in period t reflects the information content of the net demand in t and the transaction costs of net demand in t and $t-1$, as follows:

$$
\begin{aligned}
P_t - P_{t-1} &= \left(\lambda_d\left(D_t - \mathrm{E}\left[\tilde{D}_t|H_{t-1}\right]\right) + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] + \rho D_t\right) - \left(\mathrm{E}\left[\tilde{V}|H_{t-1}\right] + \rho D_{t-1}\right) \\
&= \eta_t + \rho\mathrm{E}\left[\tilde{D}_t|H_{t-1}\right] - \rho D_{t-1} \\
&= \eta_t + \rho\left(\frac{\alpha}{\lambda_d + (M+2)\rho}u_{t-1} + \frac{(\lambda_d + \rho)\phi}{\lambda_d + (M+2)\rho}\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right]\right) \\
&\quad - \rho\left(\frac{1}{\lambda_d + \rho}\eta_{t-1} + \frac{\alpha}{\lambda_d + (M+2)\rho}u_{t-2} + \frac{(\lambda_d + \rho)\phi}{\lambda_d + (M+2)\rho}\mathrm{E}\left[\tilde{z}_{t-2}|H_{t-2}\right]\right) \\
&= \eta_t + \rho\left(\frac{\alpha}{\lambda_d + (M+2)\rho}\left(\frac{\lambda_d}{\lambda_d + \rho}\eta_{t-1}\right) + \frac{(\lambda_d + \rho)\phi}{\lambda_d + (M+2)\rho}\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right]\right) \\
&\quad - \rho\left(\frac{1}{\lambda_d + \rho}\eta_{t-1} + \frac{\alpha}{\lambda_d + (M+2)\rho}\left(\frac{\lambda_d}{\lambda_d + \rho}\eta_{t-2}\right) + \frac{(\lambda_d + \rho)\phi}{\lambda_d + (M+2)\rho}\mathrm{E}\left[\tilde{z}_{t-2}|H_{t-2}\right]\right) \\
&= \eta_t + \frac{\rho\phi}{\lambda_d + (M+2)\rho}(\lambda_d + \rho)\left(\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] - \mathrm{E}\left[\tilde{z}_{t-2}|H_{t-2}\right]\right) \\
&\quad + \frac{\rho}{\lambda_d + \rho}\left(\frac{\alpha\lambda_d}{\lambda_d + (M+2)\rho} - 1\right)\eta_{t-1} - \frac{\rho}{\lambda_d + \rho}\left(\frac{\alpha\lambda_d}{\lambda_d + (M+2)\rho}\right)\eta_{t-2} \tag{3.1.38}
\end{aligned}
$$

Having observed the history of order flow, H_{t-1}, market participants believe that liquidity demand

in the prior period was

$$
\begin{aligned}
\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right] =& \mathrm{E}\left[\tilde{z}_{t-1}|H_{t-2}\right] + \frac{\sigma_{\zeta,t}^2}{\frac{1}{4(\lambda_d+\rho)^2}\sigma_{v,t}^2 + \sigma_{\zeta,t}^2}\left(D_{t-1} - \mathrm{E}\left[\tilde{D}_{t-1}|H_{t-2}\right]\right) \\
=& \phi\mathrm{E}\left[\tilde{z}_{t-2}|H_{t-2}\right] + \left(1 - \frac{\lambda_d}{2\left(\lambda_d+\rho\right)}\right)\left(\frac{1}{\lambda_d+\rho}\eta_{t-1}\right) \\
=& \phi\mathrm{E}\left[\tilde{z}_{t-2}|H_{t-2}\right] + \frac{1}{\lambda_d+\rho}\left(\frac{\lambda_d+2\rho}{2\left(\lambda_d+\rho\right)}\right)\eta_{t-1} \quad\quad (3.1.39)
\end{aligned}
$$

Let

$$
\nu_t \equiv \left(\lambda_d + \rho\right)\mathrm{E}\left[\tilde{z}_t|H_t\right] \quad\quad (3.1.40)
$$

and

$$
\psi \equiv \rho/\lambda_d \quad\quad (3.1.41)
$$

Multiplying Equation (3.1.39) by $\lambda_d + \rho$, market participants' belief about the price impact of liquidity demand in the prior period can be written as

$$
\nu_{t-1} = \phi\nu_{t-2} + \frac{1+2\psi}{2\left(1+\psi\right)}\eta_{t-1} \qu\quad (3.1.42)
$$

Combining Equations (3.1.38), (3.1.41), and (3.1.42), price change in period t can be written as

$$
\begin{aligned}
\Delta P_t =& \eta_t + \frac{\phi\psi}{1+\left(M+2\right)\psi}\left(\Delta\nu_{t-1}\right) \\
&+ \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+\left(M+2\right)\psi} - 1\right)\eta_{t-1} - \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+\left(M+2\right)\psi}\right)\eta_{t-2} \quad\quad (3.1.43)
\end{aligned}
$$

where $\Delta\nu_{t-1} = \nu_{t-1} - \nu_{t-2}$.

Equation (3.1.43) shows that price changes exhibit an moving average process that depends on a state variable, $\Delta\nu_{t-1}$. If the market maker has zero transaction costs, price would equal the expected value of the risky asset in every round of trade, and price changes would follow a random walk; that is, if $\rho = 0$, $P_t = \mathrm{E}\left[\tilde{V}|H_t\right] \forall t$, and $\Delta P_t = \eta_t$. If the market maker has positive transaction costs but all informed investors weight redundant information perfectly and liquidity trade demand is independent of prior demand, prices would be mean reverting, as in Roll (1984). In other words, if $\rho > 0$, $\alpha = 0$, and $\phi = 0$, the transaction cost portion of price changes, $\frac{\psi}{1+\psi}\eta_t$, would unwind exactly in the subsequent period.

If transaction costs are positive, $\rho > 0$, price changes could exhibit momentum or mean reversion, depending on informed investors' misweighting of redundant information and the parameters of liquidity trader demand. Substituting for the first and second lagged ν_{t-1} terms, the time series of price changes can be written as

$$\Delta P_t = \eta_t + \frac{\left(\alpha + \phi\left(\frac{1}{2} + \psi\right) - (1 + (M+2)\psi)\right)\psi}{(1+\psi)(1+(M+2)\psi)}\eta_{t-1}$$
$$+ \frac{\left(-\alpha + \phi(\phi-1)\left(\frac{1}{2} + \psi\right)\right)\psi}{(1+\psi)(1+(M+2)\psi)}\eta_{t-2} + \frac{\phi^2(\phi-1)\psi}{1+(M+2)\psi}\nu_{t-3} \tag{3.1.44}$$

Equation (3.1.44) shows that the current period price change can exhibit a positive association with the prior period unexpected price change if transaction costs are positive and informed investors' misweighting of redundant information is sufficiently positive. That is, $\mathrm{Cov}\left(\Delta P_t, \eta_{t-1}|H_{t-2}\right) > 0$ if $\psi > 0$ and $\alpha + \phi\left(\frac{1}{2} + \psi\right) > 1 + (M+2)\psi$. If $\alpha = 0$, $\mathrm{Cov}\left(\Delta P_t, \eta_{t-1}|H_{t-2}\right) > 0$ if $\phi > \frac{1+(M+2)\psi}{\frac{1}{2}+\psi}$. This inequality cannot hold, however, because $\psi \geq 0$, $M \geq 0$, and $|\phi| \leq 1$ so that liquidity trader demand cannot grow unboundedly. Thus, only the overweighting of redundant information by informed investors can give rise to momentum in returns in this analytical model.

Equation (3.1.44) further shows that the current period price change exhibits a positive association with the unexpected price change two periods prior if transaction costs are positive and $\phi(\phi-1)\left(\frac{1}{2} + \psi\right) > \alpha$. For example, $\mathrm{Cov}\left(\Delta P_t, \eta_{t-2}|H_{t-3}\right) > 0$ if $\alpha < 0$ and $\phi < 0$. The current period price change exhibits a negative association with the unexpected price change two periods prior if transaction costs are positive and $\phi(\phi-1)\left(\frac{1}{2} + \psi\right) < \alpha$. For example, $\mathrm{Cov}\left(\Delta P_t, \eta_{t-2}|H_{t-3}\right) < 0$ if $\alpha > 0$ and $\phi > 0$. This result comports with empirical evidence in Tetlock (2011) that firms with more stale news stories in one week exhibit reversion in returns in the subsequent week.

For a given level of α and ϕ, the magnitudes of momentum and mean reversion in price changes are increasing in the ratio of transaction costs to information asymmetry, ψ. This result comports with extensive evidence that momentum in stock price changes appears greater when transaction costs are higher (e.g., Korajczyk and Sadka, 2004).

Finally, the influence of earlier price changes declines over time, assuming $|\phi| \leq 1$, because $\frac{\psi}{1+(M+2)\psi} < 1$.

3.2. Structural estimation and results

3.2.1. Estimation procedure

The analytical model predicts that price changes exhibit the following state space process:

$$\Delta P_t = \eta_t + \frac{\phi\psi}{1 + (M+2)\,\psi}\,(\Delta\nu_{t-1})$$
$$+ \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+(M+2)\,\psi} - 1\right)\eta_{t-1} - \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+(M+2)\,\psi}\right)\eta_{t-2} \qquad (3.2.1)$$

where ΔP_t is the price change from period $t-1$ to period t, η_t is the stock price impact of unexpected order flow in period t, $\psi \equiv \rho/\lambda_d$ is the ratio of transaction costs to information asymmetry, ϕ is the autoregressive parameter of liquidity trader demand, $\Delta\nu_{t-1}$ is the change in the market participants' belief about the price impact of expected liquidity demand from time $t-2$ to $t-1$, and α is the parameter for the extent to which informed investors misweight information that is already priced ("redundant information"). I substitute $\psi = \rho/\lambda_d$ because ρ and λ_d are not identifiable separately. Market participants' belief about the price impact of expected liquidity demand can be written as

$$\nu_{t-1} = \phi\nu_{t-2} + \frac{1+2\psi}{2\,(1+\psi)}\eta_{t-1} \qquad (3.2.2)$$

The parameter M is not identifiable distinctly. For the purposes of the empirical estimation, I assume $M = 1$. Assuming $M = 1$ implies that the rational arbitrageur is a monopolist in exploiting predictable order flow. Since M appears in the denominator of the coefficients, if I assumed $M > 1$, estimates of α, ϕ, or ψ would likely be higher. Even though rational arbitrageurs earn positive expected profits when $\rho > 0$, I cannot observe arbitrageurs' cost of capital, risk aversion, or other fixed costs, and thus I cannot comment on the likely degree of competition among the arbitrageurs.

The parameter of interest is α. If α is estimated to be greater than zero, that would suggest on average informed investors act like redundant information is novel private information. If α is estimated to be less than zero, that would suggest some informed investors back out redundant information from their private signals excessively.

The analytical model assumes that informed investors' private signals and unexpected net demand are independent and normally distributed. For consistency, I assume that the price impact of unexpected order flows, η_t, are independent and normally distributed with means equal to zero.

Since η_t and ν_{t-1} are not observable directly, I cannot estimate Equation (3.2.1) by least squares estimation. Rather, I estimate Equation (3.2.1) by maximum likelihood estimation. The estimation procedure attempts to identify the parameters α, ϕ, and ψ that maximize the likelihood that observed price changes came from the estimated distribution of η_t, where price changes are normally distributed with conditional expectation equal to $\mathrm{E}\left[\Delta P_t|\eta_0,\ldots,\eta_{t-1}\right]$ (Wooldridge, 2010).[5]

The analytical model above allows the variance of η_t to exhibit heteroscedasticity over time, without specifying a particular form for this heteroscedasticity. The market participants in the analytical model know the variance of η_t at all points in time. As an empirical researcher, however, I must estimate the variance of η_t. For simplicity, I assume that the variance of η_t follows a generalized auto-regressive conditional heteroscedasticity (GARCH) process (See Engle, 2001 for a review). In a GARCH process, the variance of a time series variable is conditional on the magnitude of recent past realizations of that variable. I assume that the variance of η_t, denoted $\sigma_{\eta,t}^2$, evolves according to a GARCH(1,1) process with normal shocks:

$$\sigma_{\eta,t}^2 = \beta_0 + \beta_1\eta_{t-1}^2 + \beta_2\sigma_{\eta,t-1}^2 \tag{3.2.3}$$

Following Bollerslev (1986) and Durbin and Koopman (2012), the log-likelihood function for this state space model is:

$$L = \sum_{t=3}^{N}\ln\left(\frac{1}{\sqrt{2\pi\sigma_{\eta,t}^2}}\exp\left(-\frac{\eta_t^2}{2\sigma_{\eta,t}^2}\right)\right) = -\frac{N}{2}\ln\left(2\pi\right) - \frac{1}{2}\sum_{t=3}^{N}\left[\ln\left(\sigma_{\eta,t}^2\right) + \frac{\eta_t^2}{\sigma_{\eta,t}^2}\right] \tag{3.2.4}$$

where N is the number of observations. I constrain the estimate of ψ to be greater than zero and $\phi \in (-1,1)$. I also constrain the estimates of β_1 to be between zero and one and $\beta_2 \in (0, 1-\beta_1)$ so that the variance of returns cannot increase without limit. Following Durbin and Koopman (2012), I impose constraints on the parameter estimation by transforming the parameters and maximizing the log-likelihood function with respect to the transformed parameters. Since ψ and β_0 must be greater than zero, I use the transformation $\psi = \exp\left(\chi_\psi\right)$ and $\beta_0 = \exp\left(\chi_{\beta_0}\right)$ and estimate χ_ψ and χ_{β_0}. Since $\phi \in (-1,1)$, $\beta_1 \in (0,1)$, and $\beta_2 \in (0, 1-\beta_1)$, I use the transformations $\phi = \chi_\phi/\sqrt{1+\chi_\phi^2}$,

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[5]One could estimate Equation (3.2.1) by method of moments. The main advantage of maximum likelihood estimation as compared to method of moments is that maximum likelihood estimation is the most efficient estimation procedure asymptotically. The main drawback is that maximum likelihood estimation relies on assumptions about the conditional distribution of the dependent variable. In effect, if the theoretical model is misspecified or relies on incorrect distributional assumptions, the estimated parameters would be inconsistent. As discussed below, to examine whether this model is properly specified, I conduct Box-Ljung tests on each firm-quarter estimation.

$\beta_1 = \frac{1}{2} + \frac{1}{2}\left(\chi_{\beta_1}/\sqrt{1+\chi_{\beta_1}^2}\right)$, and $\beta_2 = (1-\beta_1)\left(\frac{1}{2} + \frac{1}{2}\left(\chi_{\beta_2}/\sqrt{1+\chi_{\beta_2}^2}\right)\right)$ and estimate χ_ϕ, χ_{β_1}, and χ_{β_2}. To initialize the estimation, I set $\eta_1 = \eta_2 = \nu_1 = \nu_2 = 0$ and $\sigma_{\eta,3}^2$ equal to the variance of price changes over the sample period.

Maximization of this log-likelihood function involves a non-linear optimization that is vulnerable to identifying local maxima as optimal parameters. To address this weakness, I use four non-linear optimization methods and nine sets of random starting values for each parameter. I sample the starting values, $\alpha_{(0)}, \chi_\phi, \chi_\psi, \chi_{\beta_0(0)}, \chi_{\beta_1(0)}, \chi_{\beta_2(0)}$, independently from a standard normal distribution. From these starting values, I use four optimization methods from a non-linear optimization package in R: the spectral projected gradient method, bound optimization by quadratic approximation, the Nelder-Mead optimization method, and the Broyden–Fletcher–Goldfarb–Shanno algorithm (Nash and Varadhan, 2011). From the 36 sets of optimized parameters, I select the set of parameters with the highest log-likelihood value.

3.2.2. Sample selection and variable measurement

To hold information asymmetry and transaction costs constant within an estimation, I estimate Equation (3.2.1) by firm-quarter. Within a firm-quarter, firm characteristics and secular factors that would affect information asymmetry and transaction costs, such as firm size or market volatility, are likely to vary little. Variation in the parameters across firm characteristics and secular factors will be examined in Chapter 4.

To carry out the structural estimation, my sample comprises stock price changes during stock exchange hours only. In the analytical model, public information arrives only through the price impact of trades, rather than through public announcements. Public announcements generally occur while U.S. stock exchanges are closed because U.S. stock exchange rules discourage companies from releasing material information during stock exchange hours. Further, little trading takes place while U.S. stock exchanges are closed; Barclay and Hendershott (2003) find that 4 percent of the average daily trading volume occurs after-hours for the 250 highest volume firms on the Nasdaq Stock Exchange. The lack of liquidity while stock exchanges are closed suggests that overnight price changes primarily reflect shocks to public information. The analytical model abstracts from shocks to public information because all investors can observe this information and should incorporate it into their beliefs unbiasedly. Price changes that occur while stock exchanges are open represent the net information

content of order flow (French and Roll, 1986).[6]

I draw price data for every firm-trading day from 2003 through 2014 from the WRDS TAQ dataset, which contains intraday trade and quote data for all securities listed on the New York Stock Exchange, American Stock Exchange, Nasdaq National Market System, and Nasdaq Small Cap issues. For a trading day to be included in the sample, I require that the firm appears in the CRSP daily stock price table on that date.

Since the Kyle model posits that order flow from informed and uninformed investors arrives as an aggregated batch, I group stock prices into five-minute intervals and thirty-minute intervals. Grouping prices into time intervals also reduces the market microstructure effects of high frequency trading. In high frequency markets, informed investors often split large orders into small ones and mimic the quoting behavior of market makers in attempt to disguise the information content of their trades (Easley, Lopez de Prado, and O'Hara, 2012; Cready, Kumas, and Subasi, 2014). Easley, Lopez de Prado, and O'Hara (2016) find that aggregating trades into intervals of between one minute and 60 minutes reduces the vast majority of the noise due to microstructure effects, saves on computing time, and captures the information content of trades at least as well as traditional tick tests do (e.g., Lee and Ready, 1991). In their study of Chicago Mercantile Exchange S&P 500 futures contracts, the authors show that using five-minute bars eliminates 88 percent of the market microstructure noise and reduces computational demands by 95 percent.

For each time interval, I measure the trade price as the volume-weighted average price. For example, if the only two trades within an interval were $10.00 for 9900 shares and $10.10 for 100 shares, I use $10.001 as the volume-weighted average price for that interval. I calculate price changes as the change in the natural logarithm of the volume-weighted average prices, consistent with Hasbrouck (2009).

The analytical model assumes that private information signals and unexpected liquidity trader demand arrive in fixed time intervals. To be consistent with this assumption, I restrict the sample to actively traded firms. For a trading day to be included in the sample, I require that it not have a gap between trades of longer than one time interval. For example, when estimating the model using five-minute intervals, I remove any trading day that has two consecutive five-minute intervals without a trade. For a firm-quarter to be included in the sample, I require that it have at least 20

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[6]The analytical model could be extended to allow for overnight price changes by modifying the market maker's pricing strategy. See Section 4.6. Estimation of this model is presented in Section 4.1.

trading days that satisfy this criterion. A more generalized analytical model might allow for an endogenous schedule of sequential, market-clearing auctions. Classic analytical models of how private information affects prices typically assume a fixed schedule of sequential auctions (e.g., Kyle, 1985; Glosten and Milgrom, 1985). I follow this convention. Empirically, these sample selection criteria imply that firms with sporadic liquidity trader demand have been excluded.

Using five-minute returns, the estimates were conducted for approximately 107,300 firm-quarters (on average, 2,235 firms per quarter). These firm-quarter estimations used a mean and median of 4,247 and 4,711 price changes over consecutive five-minute intervals. U.S. stock exchanges have on average 63 trading days per quarter. Each trading day lasts six-and-a-half hours, or 78 five-minute intervals. At the mean (median) number of observations per firm-quarter, the estimations used approximately 54 (60) days per firm-quarter or 67 (74) observations per trading day. Figure 5 plots the time-series of the number of unique firms and median and mean number of observations per firm by calendar quarter.

Using 30-minute returns, the estimates were conducted for approximately 159,800 firm-quarters (on average, 3,329 firms per quarter). These firm-quarter estimations used a mean and median of 729 and 767 price changes over consecutive 30-minute intervals. On U.S. stock exchanges, each trading day lasts thirteen 30-minute intervals. At the mean (median) number of observations per firm-quarter, the estimations used approximately 56 (59) days per firm-quarter or 11.6 (12) observations per trading day. Figure 6 plots the time-series of the number of unique firms and median and mean number of observations per firm by calendar quarter.

3.2.3. Results

Tables 2 and 3 show the distributions of parameter estimates – investors' misweighting of redundant information, α, the autoregressive parameter of liquidity trader demand, ϕ, the ratio of transaction costs to the information asymmetry of order flow, ψ, and, the coefficients of the variance of the time series – using five-minute returns and 30-minute returns, respectively. Figures 7 to 12 show histograms of the estimated α, ϕ, and ψ parameters, estimated using five-minute and 30-minute returns. Figures 13 to 18 plot the time series of the estimated α, ϕ, and ψ parameters, estimated using five-minute and 30-minute returns.

Estimated α parameters greater than zero suggest that investors behave as if their private signals have less redundant information than the signals truly have, and estimated α parameters less than

zero suggest that investors behave as if their private signals have more redundant information than the signals truly have. Using five-minute returns, I find that the mean (median) estimated α parameter is approximately 1.8 (1.7). Using 30-minute returns, I find that the mean (median) estimated α parameter is approximately 1.7 (1.7). At these levels of α, informed investors on average treat the redundant information that was revealed in the prior time intervals as if it was private information. Using five-minute returns, approximately 83 percent of the estimated α parameters are greater than zero; 75 percent of the estimated α parameters are greater than zero at the 10 percent statistical significance level; 74 percent of the estimated α parameters are greater than zero at the 5 percent statistical significance level; and 72 percent of the estimated α are greater than zero at the 1 percent statistical significance level. Approximately 12 percent of the estimated α parameters are less than zero at the 10 percent statistical significance level and 11 percent of the estimated α parameters are less than zero at the 1 percent statistical significance level. Using 30-minute returns, approximately 82 percent of the estimated α parameters are greater than zero; 62 percent of the estimated α parameters are greater than zero at the 10 percent statistical significance level; 59 percent of the estimated α parameters are greater than zero at the 5 percent statistical significance level; and 52 percent of the estimated α are greater than zero at the 1 percent statistical significance level. Approximately 7 percent of the estimated α parameters are less than zero at the 10 percent statistical significance level and 5 percent of the estimated α parameters are less than zero at the 1 percent statistical significance level. These results suggest that, for the vast majority of firm-quarters, investors overweight redundant information.

The estimates of the parameter representing the autocorrelation of liquidity trader demand, ϕ, exhibit U-shaped distributions (Figues 9 and 12). Using five-minute returns, the estimated ϕ parameters have a mean and median of 0.37 and 0.72. Approximately 72 percent of the estimated ϕ parameters are greater than zero; 61 percent of the estimated ϕ parameters are greater than zero at the 10 percent statistical significance level; 59 percent of the estimated ϕ parameters are greater than zero at the 5 percent statistical significance level; and 55 percent of the estimated ϕ are greater than zero at the 1 percent statistical significance level. Approximately 23 percent of the estimated ϕ parameters are less than zero at the 10 percent statistical significance level and 21 percent of the estimated ϕ parameters are less than zero at the 1 percent statistical significance level. Using 30-minute returns, the estimated ϕ parameters have a mean and median of 0.31 and 0.65. Approximately 68 percent of the estimated ϕ parameters are greater than zero; 23 percent of the estimated ϕ parameters are greater than zero at the 10 percent statistical significance level; 20 percent of the

estimated ϕ parameters are greater than zero at the 5 percent statistical significance level; and 15 percent of the estimated ϕ are greater than zero at the 1 percent statistical significance level. Approximately 20 percent of the estimated ϕ parameters are less than zero at the 10 percent statistical significance level and 18 percent of the estimated ϕ parameters are less than zero at the 1 percent statistical significance level. These results suggest that liquidity trader demand often exhibits either positive or negative serial correlation. The tendency for liquidity trader demand to exhibit positive autocorrelation is consistent with the theoretical model in Dontoh, Ronen, and Sarath (2003).

The estimates of the parameter representing the ratio of transaction costs to Kyle's lambda, ψ, have a mean and median of 0.12 and 0.04 using five-minute returns and 0.45 and 0.05 using 30-minute returns. At these levels, approximately 3 to 31 percent of the price impact of trades is temporary and lacks information content. As benchmarks, since the price impact of a trade is the sum of transaction costs and Kyle's lambda, $\psi = 0.11$ ($\psi = 0.25$) implies that approximately 10 percent (20 percent) of the price impact of trades is due to transaction costs and 90 percent (80 percent) of the price impact of trades is due to information asymmetry. Using five-minute returns, approximately 72 percent of the estimated ψ parameters are less than 0.11 and 85 percent of the estimated ψ parameters are less than 0.25. Using 30-minute returns, approximately 67 percent of the estimated ψ parameters are less than 0.11 and 78 percent of the estimated ψ parameters are less than 0.25. These results suggest that, in general, the price impact of trades largely is permanent and reflects information asymmetry.

These estimates of the ratio of the temporary portion to the permanent portion of the price impact of trades are consistent with prior research. Using proprietary data from Alliance-Bernstein from January 2009 to June 2011, Bershova and Rakhlin (2013) find that the price impact of trades reverts by 5 to 10 percent in the first five minutes, approximately 10 to 20 percent in the first 10 minutes, and approximately one-third in the first hour following the completion of a large order. Using proprietary data from a large investment manager from 1998 to 2011, Frazzini, Israel, and Moskowitz (2012) find that approximately 30 percent of the price impact of trades reverts within 24 hours. The vast majority of the reversion in price impact appears to occur through overnight price changes. Out of the average price impact per trade of approximately 9 basis points, less than one-half basis point of the reversion appears to occur during trading hours.

At these levels of α and ψ, stock price changes tend to exhibit momentum and mean reversion equally often. Using five-minute returns, the estimated first-lag moving average coefficient exhibits a mean

and median of -0.023 and 0.015. That is, if unexpected order flow affected price by 1 percent, one would expected a mean 2.3 basis point reversion (median 1.5 basis point continuation) in returns in the subsequent five-minute interval. If α and ϕ were zero and ψ equaled its mean (median), these coefficients would be -0.110 (-0.035). The estimated second-lag moving average coefficient exhibits a mean and median of -0.054 and -0.067. That is, if unexpected order flow affected price by 1 percent, one would expected a mean 5.4 (median 6.7) basis point reversion in stock price two five-minute intervals later. If α and ϕ were zero, these coefficients would equal zero. Using 30-minute returns, the estimated first-lag moving average coefficient exhibits a mean and median of -0.071 and 0.010. That is, if unexpected order flow affected price by 1 percent, one would expected a mean 7.1 basis point reversion (median 1.0 basis point continuation) in returns in the subsequent 30-minute interval. If α and ϕ were zero and ψ equaled its mean (median), these coefficients would be -0.31 (-0.051). The estimated second-lag moving average coefficient exhibits a mean and median of -0.064 and -0.077. That is, if unexpected order flow affected price by 1 percent, one would expected a mean 6.4 (median 7.7) basis point reversion in stock price two 30-minute intervals later. Histograms of these estimated coefficients appears in Figures 19 and 20.

The estimated coefficients of the variance updating process show that the variance of price change fluctuates over time, as well as mean-reverts. Using five-minute returns, the auto-regressive term in the GARCH structure, β_1, exhibits a mean of 0.40 and median of 0.44, which suggests that a one-standard deviation stock price change is associated with a 63 to 66 percent increase in the variance of returns in the subsequent period. The moving average term in the GARCH structure, β_2, exhibits a mean of 0.37 and median of 0.37, which suggests that changes in variance mean-revert. At the mean and median levels of β_1 and β_2, changes in variance have a half-life of approximately 2.7 to 3.2 periods.[7] At the mean and median levels of the intercept term, β_0, annualized stock price volatility is approximately 38 percent and 27 percent per year. In comparison, for the same sample of firms over 2003 to 2014, the volatility of returns from the opening price to closing price exhibited a mean and median of 51 percent and 42 percent per year. Using 30-minute returns, the auto-regressive term in the GARCH structure, β_1, exhibits a mean of 0.37 and median of 0.25, which suggests that a one-standard deviation stock price change is associated with a 50 to 61 percent increase in the variance of returns in the subsequent period. The moving average term in the GARCH structure, β_2, exhibits a mean of 0.48 and median of 0.47, which suggests that changes in variance mean-revert. At the mean and median levels of β_1 and β_2, changes in variance have a half-life of approximately

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[7]The half life of changes in variance is $\ln(0.5) / \ln(\beta_1 + \beta_2)$ in this GARCH specification.

2.1 to 4.2 periods. At the mean and median levels of the intercept term, β_0, annualized stock price volatility is approximately 41 percent and 21 percent per year.

To assess goodness of fit, I consider the likelihood ratio statistic of these estimations. The likelihood ratio statistic jointly tests the statistical significance of the estimated parameters against the parameters under the null hypothesis. This statistic is distributed chi-squared with degrees of freedom equal to the number of restricted parameters. Using five-minute returns, as compared to the null hypothesis that $\alpha = 0$, $\phi = 0$, $\psi = 0$, and the variance of unexpected returns is homoscedastic, I find that approximately 99 percent of the estimations have likelihood ratio statistics that are statistically significant at the 1 percent level. As compared to the null hypothesis that $\alpha = 0$, $\phi = 0$, $\psi = 0$, and the variance of unexpected returns is time-varying, I find that approximately 51 percent of the estimations have likelihood ratio statistics that are statistically significant at the 10 percent level and approximately 46 percent of the estimations have likelihood ratio statistics that are statistically significant at the 1 percent level. Using 30-minute returns, as compared to the null hypothesis that $\alpha = 0$, $\phi = 0$, $\psi = 0$, and the variance of unexpected returns is homoscedastic, I find that approximately 99 percent of the estimations have likelihood ratio statistics that are statistically significant at the 1 percent level. As compared to the null hypothesis that $\alpha = 0$, $\phi = 0$, $\psi = 0$, and the variance of unexpected returns is time-varying, approximately 26 percent of the estimations have likelihood ratio statistics that are statistically significant at the 10 percent level and approximately 13 percent of the estimations have likelihood ratio statistics that are statistically significant at the 1 percent level. These result suggests that, for a minority of the five-minute and 30-minute return estimations, the structural model captures the time-series properties of returns better than a random walk model does.

As another measure of goodness of fit, I examine whether this estimation specification fully captures the autocorrelation structure of the time series of stock price changes by calculating Ljung-Box statistics for each firm-quarter estimation. The Ljung-Box statistic tests whether the residuals from a time series model exhibit auto-correlation. For each estimation, I examine the auto-correlation among the estimated residuals with one and two lags. Using five-minute returns and one lagged residual terms, approximately 90 percent of the estimations exhibit Ljung-Box statistics with p-values less than 5 percent. Using five-minute returns and two lagged residual terms, approximately 94 percent of the estimations exhibit Ljung-Box statistics with p-values less than 5 percent. Using 30-minute returns and one lagged residual term, approximately 76 percent of the estimations exhibit Ljung-Box statistics with p-values less than 5 percent. Using 30-minute returns and two lagged

residual terms, approximately 79 percent of the estimations exhibit Ljung-Box statistics with p-values less than 5 percent. This result suggests that, for the majority of the estimations, the residuals exhibit statistically significant auto-correlation and the model specification does not fully describe the auto-correlation among stock price changes.

Both histograms of the estimated α parameters (Figures 7 and 10) exhibit two modes. The α parameters estimated on five-minute returns exhibit modes near 0.5 (28th percentile) and 3.6 (86th percentile). The α parameters estimated on 30-minute returns exhibit modes near 0.5 (30th percentile) and 3.3 (83rd percentile). To explore the properties of these bimodal distributions, I present correlation matrices of the estimated α, ϕ, ψ, and $\sigma_{\eta,t}^2$ parameters (Table 4), where $\sigma_{\eta,t}^2 = \beta_0 / (1 - \beta_1 - \beta_2)$ is the overall variance of unexpected returns. I also split the estimated α parameters at the median and present correlation matrices of the four parameters when the estimated α parameter is below its median and above its median. Using the whole sample of estimated parameters, α exhibits a negative correlation with ψ, positive correlation with ϕ, and negative correlation with $\sigma_{\eta,t}^2$. These correlations are consistent using Pearson and Spearman (rank) correlations and parameters estimated on five-minute returns and 30-minute returns. The correlations among the estimated α, ϕ, ψ, and $\sigma_{\eta,t}^2$ parameters are substantially weaker when the sample of parameters is split according to whether the estimated α is high or low. When $\alpha_{j,q}$ is below its median, using the parameters estimated on five-minute returns, α exhibits positive Pearson and Spearman (rank) correlations with ψ, ϕ, and $\sigma_{\eta,t}^2$. Using the parameters estimated on 30-minute returns, α exhibits negative Pearson and Spearman correlations with ψ, positive Pearson and Spearman correlations with ϕ, and negative Pearson and Spearman correlations with $\sigma_{\eta,t}^2$. When $\alpha_{j,q}$ is above its median, using the parameters estimated on five-minute returns, α exhibits negative Pearson and Spearman correlations with ψ, positive Pearson and Spearman correlations with ϕ, and negative Pearson and Spearman correlations with $\sigma_{\eta,t}^2$. Using the parameters estimated on 30-minute returns, α exhibits negative Pearson correlation with ψ, positive Spearman correlation with ψ, zero Pearson correlation with ϕ, positive Spearman correlations with ϕ, and negative Pearson and Spearman correlations with $\sigma_{\eta,t}^2$. Overall, the estimated α parameters generally exhibit negative correlation with the estimated variance of unexpected returns, negative correlation with the estimated ψ parameters, and positive correlation with the estimated ϕ parameters. Although the signs of the correlations exhibit similar patterns to those using the whole sample of estimated parameters, the magnitudes of the correlations are substantially attenuated. The analytical model here assumes that these parameters are exogenous and does not suggest underlying determinants of the correlations between these parameters.

3.3. Construct validity tests

I offer three tests to support my claim that the estimated α parameters measure investors' mis-weighting of redundant information and the estimated ϕ parameters measure autocorrelation in liquidity trader demand.

3.3.1. The viability of trading on redundant information

In the analytical model, informed investors' expected profits decrease as α diverges from zero (See Section 3.5.2). Trading on redundant information does not, however, completely wipe out informed investors' expected profits as long as $|\alpha|$ is not too large. I solve the analytical model numerically for the α parameter at which informed investors would break even, inclusive of trading costs, information asymmetry, serially correlated liquidity trader demand, and rational arbitrageur demand. In Figure 2, I plot the (positive root of) α at which informed investors would break even with $M = 0$ and $\phi = 0$. For any $\bar{\sigma} \in (0, 2]$ and $\rho \in (0, 2]$, informed investors' expected profits are still positive as long as $|\alpha| < 2.00$. As depicted, this break-even level of α is increasing in ρ, increasing in $\bar{\sigma}$ if ρ is sufficiently low, and decreasing in $\bar{\sigma}$ if ρ is sufficiently high. In Figure 3, I plot the minimum break-even level of the redundant information parameter, α, for any $\bar{\sigma} \in (0, 2]$ and $\rho \in (0, 2]$ as a function of expected liquidity trader demand and the number of arbitrageurs (i.e., the minimum point one would observe on Figure 2 for various levels of ϕ and M). The lowest break-even level of α is 1.77, when $M = 0$ and $\phi = 1$. The minimum break-even level of α is increasing in M because rational arbitrageurs mitigate the price impact of trading on redundant information. The minimum break-even level of α is decreasing in ϕ because serially correlated liquidity trader demand exacerbates the price impact of trading on redundant information.

I use the results of the empirical estimations to study whether informed investors still earn positive expected profits on their trades, despite their misweighting of redundant information. Table 5 shows the fraction of estimations in which the absolute value of the estimated α parameter is below the minimum break-even level of α for any $\bar{\sigma} \in (0, 2]$ and $\rho \in (0, 2]$. Specifically, the table shows the deciles of the estimated ϕ parameters, the theoretical minimum break-even level of $|\alpha|$ at upper bound of the ϕ decile, and the percent of estimations with $|\alpha|$ below the minimum break-even level of $|\alpha|$ at upper bound of the ϕ decile. Based on the parameters estimated using five-minute returns, I find that 54 percent of the absolute value of the estimated α parameters are below the minimum break-even level of $|\alpha|$ at upper bound of the ϕ decile. Based on the parameters estimated using

30-minute returns, I find that 55 percent of the absolute value of the estimated α parameters are below the minimum break-even level of $|\alpha|$ at upper bound of the ϕ decile. Using five-minute returns, I find that the majority of estimated α parameters are below the minimum break-even level of $|\alpha|$ in six deciles. Using 30-minute returns, I find that the majority of estimated α parameters are below the minimum break-even level of $|\alpha|$ in five deciles. In sum, in at least half of the estimations the α parameter is below the minimum level at which an informed investor would break even. These results suggest that informed investors earn positive expected profits despite misweighting redundant information in the majority of cases.

3.3.2. Mean reversion in investors' misweighting of redundant information

Investors' misweighting of redundant information is likely to be mean-reverting. The analytical model shows that rational arbitrageurs who trade against predictable order flow earn positive expected profits that are increasing in α^2, ϕ^2, and $\alpha\phi$. These rational arbitrageurs might delay taking advantage, however, until the misweighting reaches extreme levels and enough time passes for rational arbitrageurs to recognize the opportunity (Abreu and Brunnermeier, 2002). This argument suggests that extreme levels of information misweighting and serial correlation in liquidity trader demand are likely to be fleeting. Empirically, α and ϕ are likely to exhibit mean reversion over time.

To test these predictions, I study the time series of changes in the estimated α and ϕ parameters using an autoregressive model with two lags. Table 6 shows the results. Based on the parameters estimated using five-minute returns, changes in α appear to revert by 62 percent in the subsequent quarter and by an additional 30 percent two quarters later. Changes in ϕ appear to revert by 66 percent in the subsequent quarter and by an additional 33 percent two quarters later. Based on the parameters estimated using 30-minute returns, changes in α appear to revert by 64 percent in the subsequent quarter and by an additional 32 percent two quarters later. Changes in ϕ appear to revert by 65 percent in the subsequent quarter and by an additional 33 percent two quarters later. These results are materially unchanged after allowing for calendar quarter fixed effects. Overall, investors' misweighting of redundant information and the autocorrelation in liquidity trader demand appear to mean revert substantially over time.

3.3.3. Trading volume

In Section 3.5.4, I derive expressions for expected trading volume from informed investors who misweight redundant information, liquidity traders whose demand is serially correlated, and rational

arbitrageurs who trade to take advantage of other investors' mistakes. Expected trading volume from informed investors who misweight redundant information, $\mathrm{E}\left[|x_t|\right]$, can be written as

$$\mathrm{E}\left[|x_t|\right] \propto b_{0,t}^x + \left(b_1^x \alpha^2 - b_2^x \alpha\phi + b_3^x \phi^2\right) \sigma_{\eta,t}^2 + b_4^x \phi^4 \sigma_{\nu,t}^2 \tag{3.3.1}$$

where $\sigma_{\eta,t}^2$ is the variance of unexpected price changes, $\sigma_{\nu,t}^2$ is the variance of the price impact of expected liquidity trader demand, $b_{0,t}^x$ is proportional to the variance of private information flows, and b_1^x, b_2^x, b_3^x, and b_4^x are time-invariant constants. The coefficient on $\alpha\phi\sigma_{\eta,t}^2$ is negative because an informed investor who misweights redundant information trades as if serially correlated liquidity trader demand is a competitor in demand.

Expected trading volume from liquidity traders whose demand is serially correlated, $\mathrm{E}\left[|z_t|\right]$, can be written as

$$\mathrm{E}\left[|z_t|\right] \propto b_{0,t}^z + b_3^z \phi^2 \sigma_{\eta,t}^2 - b_{5,t}^z \phi^2 \tag{3.3.2}$$

where b_3^z is a time-invariant constant and $b_{5,t}^z$ is proportional to the variance of private information flows. The coefficient $b_{0,t}$ is greater than zero because the variance of unexpected liquidity trader demand is assumed to be correlated with the variance of private information flows.

Expected trading volume from rational arbitrageurs who take advantage of other investors' mistakes, $\mathrm{E}\left[|y_t|\right]$, can be written as

$$\mathrm{E}\left[|y_t|\right] \propto \left(b_1^y \alpha^2 + b_2^y \alpha\phi + b_3^y \phi^2\right) \sigma_{\eta,t}^2 + b_4^y \phi^4 \sigma_{\nu,t}^2 \tag{3.3.3}$$

These three expressions can be consolidated as

$$\begin{aligned}
\mathrm{E}\left[|x_t| + M\,|y_t| + |z_t|\right] \propto{} & b_{0,t} + b_1\left[\alpha^2 \sigma_{\eta,t}^2\right] + b_2\left[\alpha\phi\sigma_{\eta,t}^2\right] + b_3\left[\phi^2 \sigma_{\eta,t}^2\right] \\
& + b_4\left[\phi^4 \sigma_{\nu,t}^2\right] + b_{5,t}\left[\phi^2\right]
\end{aligned} \tag{3.3.4}$$

where $\mathrm{E}\left[|x_t| + M\,|y_t| + |z_t|\right]$ denotes expected trading volume.

To test this predicted relationship between trading volume and the estimated parameters, I estimate

the following regression:

$$
\begin{aligned}
\ln\left(Turn_{j,q}\right) = & \, b_1 \left[\alpha^2 \sigma^2_{\eta,t}\right]_{j,q} + b_2 \left[\alpha\phi\sigma^2_{\eta,t}\right]_{j,q} + b_3 \left[\phi^2 \sigma^2_{\eta,t}\right]_{j,q} \\
& + b_4 \left[\phi^4 \sigma^2_{\nu,t}\right]_{j,q} + b_5 \left[\phi^2\right]_{j,q} + \sum_j b_j + \sum_q b_q + \epsilon_{j,q}
\end{aligned}
\tag{3.3.5}
$$

where the dependent variable is the natural log of quarterly share turnover, total volume divided by average shares outstanding, and $\epsilon_{j,q}$ is an error term. The regressions include firm and calendar quarter fixed effects, denoted $\sum_j b_j$ and $\sum_q b_q$, because the variance of the fundamental value of a firm and the variance of unexpected liquidity trader demand are assumed to vary across firms and over time. If the estimated α parameters measure investors' misweighting of redundant information and the estimated ϕ parameters measure autocorrelation in liquidity trader demand, the analytical model predicts that $b_1 > 0$, $b_3 > 0$, $b_4 > 0$, and $b_5 < 0$.

Table 7 shows the results. In the estimation of Equation (3.3.5) using the parameters estimated using five-minute returns, I find b_1 is statistically indistinguishable from zero, $b_3 > 0$ at the one percent statistical significance level, b_4 is statistically indistinguishable from zero, and $b_5 < 0$ at the 0.1 percent statistical significance level. Using the parameters estimated using 30-minute returns, I find $b_1 > 0$ at the 0.1 percent statistical significance level, b_3 is statistically indistinguishable from zero, $b_4 > 0$ at the 0.1 percent statistical significance level, and b_5 is statistically indistinguishable from zero. These coefficients weakly align with those predicted from the analytical model, and support my claim that the estimated α parameters measure investors' misweighting of redundant information and the estimated ϕ parameters measure autocorrelation in liquidity trader demand.

3.4. Exhibits

Table 2: Estimated parameters of the structural model

The following tables show descriptive statistics for the estimated parameters of the structural model. α measures the extent to which informed investors misweight information that is already priced ("redundant information"). The overarching null hypothesis is $\alpha = 0$. ϕ is the estimated autoregressive parameter of liquidity trader demand. ψ is the estimated ratio of trading costs to information asymmetry. The variance of unexpected price changes is assumed to follow a GARCH(1,1) process with parameters β_0, β_1, and β_2. I impose constraints on the parameter estimates – $\psi > 0$, $\phi \in (-1, 1)$, $\beta_0 > 0$, $\beta_1 \in (0, 1)$, and $\beta_2 \in (0, 1 - \beta_1)$ – by transforming the parameters, following Durbin and Koopman (2012). I estimate the parameter set $\{\alpha, \phi, \psi, \beta_0, \beta_1, \beta_2\}$ by maximizing the log-likelihood function in Equation (3.2.4) with respect to the transformed parameters.

Parameters are estimated by firm-quarter from 2003 through 2014. Thorough descriptions of the sample and variable construction appear in Section 3.2.2.

This table shows the parameters estimated using five-minute returns and assuming that there is one rational arbitrageur who trades against investors' predictable order flow.

	Mean	St.Dev.	Percentiles			Num.Obs.
			5th	Median	95th	
Investors' misweighting of redundant information, α	1.756	1.597	-0.861	1.682	4.161	107,296
t-statistic ($H_0 : \alpha = 0$)	15.5	19.8	-17.4	12.5	68.4	107,296
Autoregressive parameter of liquidity trader demand, ϕ	0.369	0.621	-0.809	0.722	0.919	107,296
t-statistic ($H_0 : \phi = 0$)	4.7	29.4	-59.7	3.6	88.3	107,296
Ratio of transaction costs to Kyle's lambda, ψ	0.124	0.175	0.011	0.036	0.665	107,296
t-statistic ($H_0 : \psi = 0$)	126.4	134.2	3.7	83.9	519.5	107,296
GARCH intercept parameter, β_0 (annualized)	0.029	0.032	0.002	0.016	0.122	107,296
t-statistic ($H_0 : \beta_0 = 0$)	14.3	4.5	6.3	14.4	25.0	107,296
GARCH autoregressive parameter, β_1	0.441	0.163	0.216	0.400	0.644	107,296
t-statistic ($H_0 : \beta_1 = 0$)	5.1	1.4	2.2	5.3	7.1	107,296
GARCH moving average parameter, β_2	0.365	0.049	0.253	0.374	0.441	107,296
t-statistic ($H_0 : \beta_2 = 0$)	13.5	4.4	5.5	13.7	21.2	107,296

Table 3: Estimated parameters of the structural model, continued

The following table shows descriptive statistics for the parameters of the structural model, $\{\alpha, \phi, \psi, \beta_0, \beta_1, \beta_2\}$, estimated using 30-minute returns and assuming that there is one rational arbitrageur who trades against investors' predictable order flow.

			Percentiles			
	Mean	St.Dev.	5th	Median	95th	Num.Obs.
Investors' misweighting of redundant information, α	1.657	1.533	-0.939	1.680	4.025	159,792
t-statistic $(H_0 : \alpha = 0)$	3.6	4.1	-2.20	2.6	13.6	159,792
Autoregressive parameter of liquidity trader demand, ϕ	0.306	0.643	-0.859	0.651	0.918	159,792
t-statistic $(H_0 : \phi = 0)$	0.5	7.5	-16.4	0.5	22.6	159,792
Ratio of transaction costs to Kyle's lambda, ψ	0.45	1.071	0.015	0.054	4.461	159,792
t-statistic $(H_0 : \psi = 0)$	23.4	23.8	0.6	15.9	91.7	159,792
GARCH intercept parameter, β_0 (annualized)	0.026	0.033	0.001	0.012	0.129	159,792
t-statistic $(H_0 : \beta_0 = 0)$	13.9	14.7	3.8	7.6	61.6	159,792
GARCH autoregressive parameter, β_1	0.371	0.254	0.062	0.253	0.697	159,792
t-statistic $(H_0 : \beta_1 = 0)$	1.7	0.5	0.6	1.8	2.5	159,792
GARCH moving average parameter, β_2	0.479	0.146	0.302	0.471	0.75	159,792
t-statistic $(H_0 : \beta_2 = 0)$	6.1	1.3	2.9	6.5	7.9	159,792

Table 4: Correlation among estimated parameters

The following correlation matrices describe the relationships among the estimated α, ϕ, ψ, and $\sigma_{\eta,t}^2 \equiv \beta_0/(1 - \beta_1 - \beta_2)$ parameters. The variables – $\alpha_{j,q}$, $\phi_{j,q}$, $\psi_{j,q}$, and $\left[\sigma_{\eta,t}^2\right]_{j,q}$ – are the firm-quarter estimates of the corresponding parameters. Panel A shows the Pearson (lower-triangle) and Spearman rank (upper-triangle) correlations among the estimated parameters, estimated on five-minute returns and 30-minute returns. In Panels B and C, I split the sample of estimated parameters according to the level of $\alpha_{j,q}$. Panel B shows the Pearson (lower-triangle) and Spearman rank (upper-triangle) correlations among the estimated parameters when $\alpha_{j,q}$ is below the median $\alpha_{j,q}$; Panel C shows the correlations among the parameters when $\alpha_{j,q}$ is above the median $\alpha_{j,q}$.

Panel A: Whole sample of estimated parameters

	Estimated on five-minute returns				Estimated on 30-minute returns			
	$\alpha_{j,q}$	$\psi_{j,q}$	$\phi_{j,q}$	$\left[\sigma_{\eta,t}^2\right]_{j,q}$	$\alpha_{j,q}$	$\psi_{j,q}$	$\phi_{j,q}$	$\left[\sigma_{\eta,t}^2\right]_{j,q}$
$\alpha_{j,q}$	1	-0.456	0.434	-0.233	1	-0.416	0.367	-0.286
$\psi_{j,q}$	-0.464	1	-0.228	0.161	-0.434	1	-0.226	0.270
$\phi_{j,q}$	0.375	-0.182	1	-0.140	0.286	-0.164	1	-0.201
$\left[\sigma_{\eta,t}^2\right]_{j,q}$	-0.241	0.196	-0.130	1	-0.293	0.336	-0.180	1

Panel B: Estimated parameters when $\alpha_{j,q}$ is below its median

	Estimated on five-minute returns				Estimated on 30-minute returns			
	$\alpha_{j,q}$	$\psi_{j,q}$	$\phi_{j,q}$	$\left[\sigma_{\eta,t}^2\right]_{j,q}$	$\alpha_{j,q}$	$\psi_{j,q}$	$\phi_{j,q}$	$\left[\sigma_{\eta,t}^2\right]_{j,q}$
$\alpha_{j,q}$	1	0.037	0.025	0.014	1	-0.054	0.018	-0.044
$\psi_{j,q}$	0.022	1	0.124	0.097	-0.086	1	0.074	0.264
$\phi_{j,q}$	0.033	0.111	1	0.036	0.019	0.053	1	-0.069
$\left[\sigma_{\eta,t}^2\right]_{j,q}$	0.016	0.104	0.037	1	-0.050	0.283	-0.069	1

Panel C: Estimated parameters when $\alpha_{j,q}$ is above its median

	Estimated on five-minute returns				Estimated on 30-minute returns			
	$\alpha_{j,q}$	$\psi_{j,q}$	$\phi_{j,q}$	$\left[\sigma_{\eta,t}^2\right]_{j,q}$	$\alpha_{j,q}$	$\psi_{j,q}$	$\phi_{j,q}$	$\left[\sigma_{\eta,t}^2\right]_{j,q}$
$\alpha_{j,q}$	1	-0.045	0.238	-0.127	1	-0.005	0.143	-0.100
$\psi_{j,q}$	-0.231	1	-0.014	-0.021	-0.190	1	-0.128	0.031
$\phi_{j,q}$	0.093	-0.158	1	-0.095	0.000	-0.177	1	-0.116
$\left[\sigma_{\eta,t}^2\right]_{j,q}$	-0.138	0.052	-0.111	1	-0.110	0.150	-0.122	1

Table 5: The viability of trading on redundant information

This table describes the fraction of estimations in which the absolute value of the estimated α parameter is below the minimum break-even level of α for any $\bar{\sigma} \in (0, 2]$ and $\rho \in (0, 2]$. Panel A tabulates the α and ϕ parameters estimated using five-minute returns; Panel B tabulates the α and ϕ parameters estimated using 30-minute returns. Each panel tabulates deciles of the estimated ϕ parameters, the theoretical minimum break-even level of $|\alpha|$ at upper bound of the ϕ decile, and the percent of estimations with $|\alpha|$ below the minimum break-even level of $|\alpha|$.

Panel A: Parameters estimated using five-minute returns

Decile of estimated ϕ	Range of estimated ϕ	Theoretical minimum break-even level of $|\alpha|$ at upper bound of ϕ decile	Percent of estimations with $|\alpha|$ below minimum break-even level of $|\alpha|$
1	$(-1, -0.721]$	2.46	56%
2	$(-0.721, -0.416]$	2.32	83
3	$(-0.416, 0.091]$	2.13	94
4	$(0.091, 0.500]$	2.00	94
5	$(0.500, 0.722]$	1.94	84
6	$(0.722, 0.813]$	1.92	56
7	$(0.813, 0.857]$	1.91	22
8	$(0.857, 0.882]$	1.90	17
9	$(0.882, 0.903]$	1.90	16
10	$(0.903, 0.982]$	1.88	18
Total			54%

Panel B: Parameters estimated using 30-minute returns

Decile of estimated ϕ	Range of estimated ϕ	Theoretical minimum break-even level of $|\alpha|$ at upper bound of ϕ decile	Percent of estimations with $|\alpha|$ below minimum break-even level of $|\alpha|$
1	$(-1, -0.776]$	2.48	47%
2	$(-0.776, -0.499]$	2.36	80
3	$(-0.499, -0.045]$	2.18	93
4	$(-0.045, 0.349]$	2.05	93
5	$(0.349, 0.651]$	1.96	88
6	$(0.651, 0.780]$	1.93	65
7	$(0.780, 0.835]$	1.91	41
8	$(0.835, 0.870]$	1.91	21
9	$(0.870, 0.899]$	1.90	14
10	$(0.899, 0.984]$	1.88	11
Total			55%

Table 6: Mean reversion in investors' misweighting of redundant information

This table describes the time series properties of the estimated parameters for investors' misweighting of redundant information, α, and the autocorrelation of liquidity trader demand, ϕ. In Panel A, the dependent variables is the change in the estimated α parameter for a firm, $\Delta\alpha_{j,q} = \alpha_{j,q} - \alpha_{j,q-1}$. The explanatory variables are one-quarter and two-quarter lagged changes in estimated α parameters, $\Delta\alpha_{j,q-1}$ and $\Delta\alpha_{j,q-2}$. In Panel B, the dependent variables is the change in the estimated ϕ parameter for a firm, $\Delta\phi_{j,q}$. The explanatory variables are one-quarter and two-quarter lagged changes in estimated ϕ parameters, $\Delta\phi_{j,q-1}$ and $\Delta\phi_{j,q-2}$. In each panel, the regressions in columns (II) and (IV) include calendar quarter fixed effects.

Standard errors are clustered by firm and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Panel A: Time series properties of estimated α parameters

Dependent variable = $\Delta\alpha_{j,q}$	Estimated on five-minute returns		Estimated on 30-minute returns	
	(I)	(II)	(III)	(IV)
$\Delta\alpha_{j,q-1}$	-0.618***	-0.636***	-0.641***	-0.651***
	(0.017)	(0.008)	(0.013)	(0.005)
$\Delta\alpha_{j,q-2}$	-0.298***	-0.312***	-0.321***	-0.322***
	(0.017)	(0.008)	(0.012)	(0.004)
Intercept	-0.007		-0.024	
	(0.101)		(0.059)	
Calendar quarter fixed effects	No	Yes	No	Yes
R^2 (full)	0.294	0.383	0.313	0.349
R^2 (within)		0.310		0.321
Num. obs.	93,428	93,428	140,910	140,910

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Panel B: Time series properties of estimated ϕ parameters

Dependent variable = $\Delta\phi_{j,q}$	Estimated on five-minute returns		Estimated on 30-minute returns	
	(I)	(II)	(III)	(IV)
$\Delta\phi_{j,q-1}$	-0.659***	-0.663***	-0.655***	-0.659***
	(0.005)	(0.004)	(0.004)	(0.004)
$\Delta\phi_{j,q-2}$	-0.325***	-0.328***	-0.330***	-0.331***
	(0.004)	(0.003)	(0.004)	(0.004)
Intercept	0.003		-0.002	
	(0.018)		(0.012)	
Calendar quarter fixed effects	No	Yes	No	Yes
R^2 (full)	0.328	0.347	0.326	0.333
R^2 (within)		0.332		0.328
Num. obs.	93,428	93,428	140,910	140,910

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 7: Investors' misweighting of redundant information and trading volume

This table describes the association between investors' misweighting of redundant information and trading volume. Based on the expression for expected trading volume derived in Section 3.5.4, I estimate the following regression:

$$\ln\left(Turn_{j,q}\right) = b_1\left[\alpha^2\sigma_{\eta,t}^2\right]_{j,q} + b_2\left[\alpha\phi\sigma_{\eta,t}^2\right]_{j,q} + b_3\left[\phi^2\sigma_{\eta,t}^2\right]_{j,q}$$
$$+ b_4\left[\phi^4\sigma_{\nu,t}^2\right]_{j,q} + b_5\left[\phi^2\right]_{j,q} + \sum_j b_j + \sum_q b_q + \epsilon_{j,q}$$

where the dependent variable is the natural log of quarterly share turnover, total volume divided by average shares outstanding, and $\epsilon_{j,q}$ is the error term. The explanatory variables were estimated by firm-quarter and are normalized to have means equal to zero and variances equal to one. The regressions include firm and calendar quarter fixed effects because the variance of the fundamental value of a firm and the variance of unexpected liquidity trader demand – which drive trading volume in the absense of predictable demand – are assumed to vary across firms and over time. The analytical model predicts that $b_1 > 0$, $b_3 > 0$, $b_4 > 0$, and $b_5 < 0$.
Standard errors are clustered by firm and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Dependent variable = $\ln\left(Turn_{j,q}\right)$	Estimated on five-minute returns	Estimated on 30-minute returns
$\alpha^2\sigma_{\eta,t}^2$	0.059	0.073***
	(0.031)	(0.010)
$\alpha\phi\sigma_{\eta,t}^2$	0.009	0.020***
	(0.013)	(0.004)
$\phi^2\sigma_{\eta,t}^2$	0.148**	-0.009
	(0.054)	(0.008)
$\phi^4\sigma_{\nu,t}^2$	-0.002	0.018***
	(0.009)	(0.004)
ϕ^2	-0.032***	-0.010
	(0.005)	(0.005)
Firm fixed effects	Yes	Yes
Calendar quarter fixed effects	Yes	Yes
R^2 (full)	0.645	0.619
R^2 (within)	0.012	0.025
Num. obs.	107,167	159,486

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Figure 1: Kyle's lambda as a function of information asymmetry and transaction costs

Kyle's lambda measures the sensitivity of the expected value of the risky asset to unexpected order flow.

Kyle's lambda
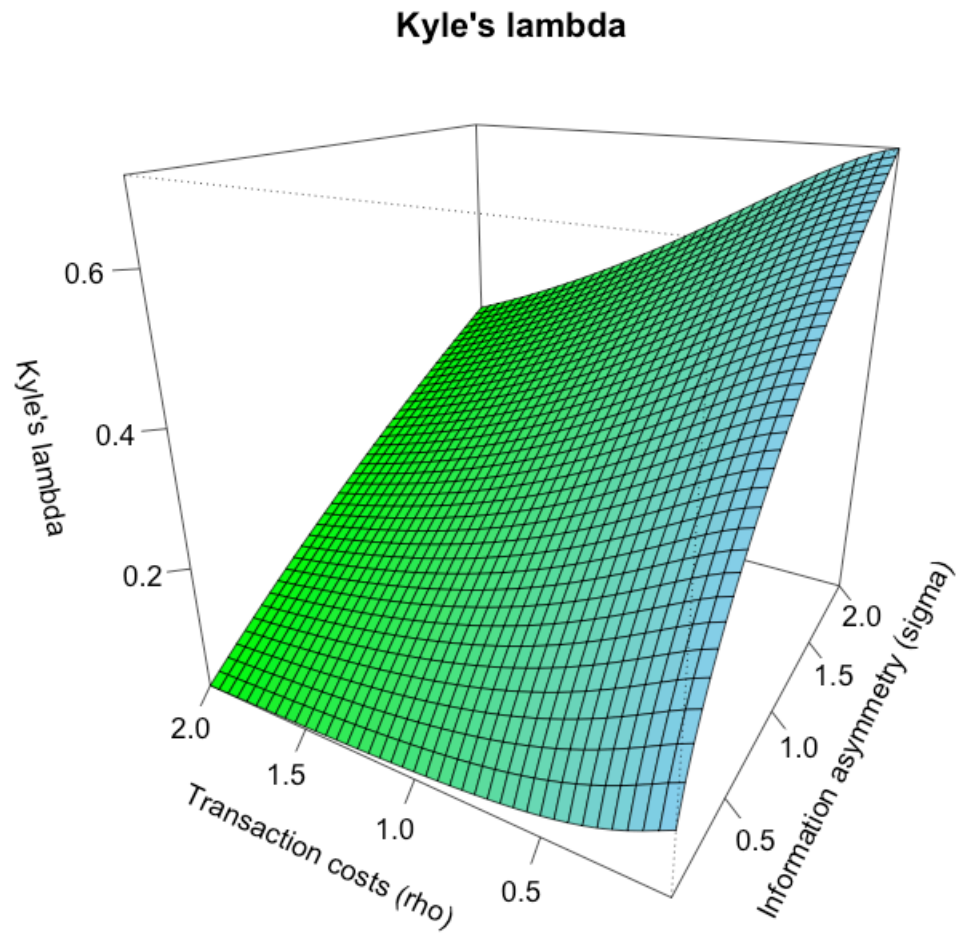
Figure 2: The break-even level of the redundant information parameter, α, as a function of information asymmetry and transaction costs with $\phi = 0$ and $M = 0$

Break-even misweighting of redundant information
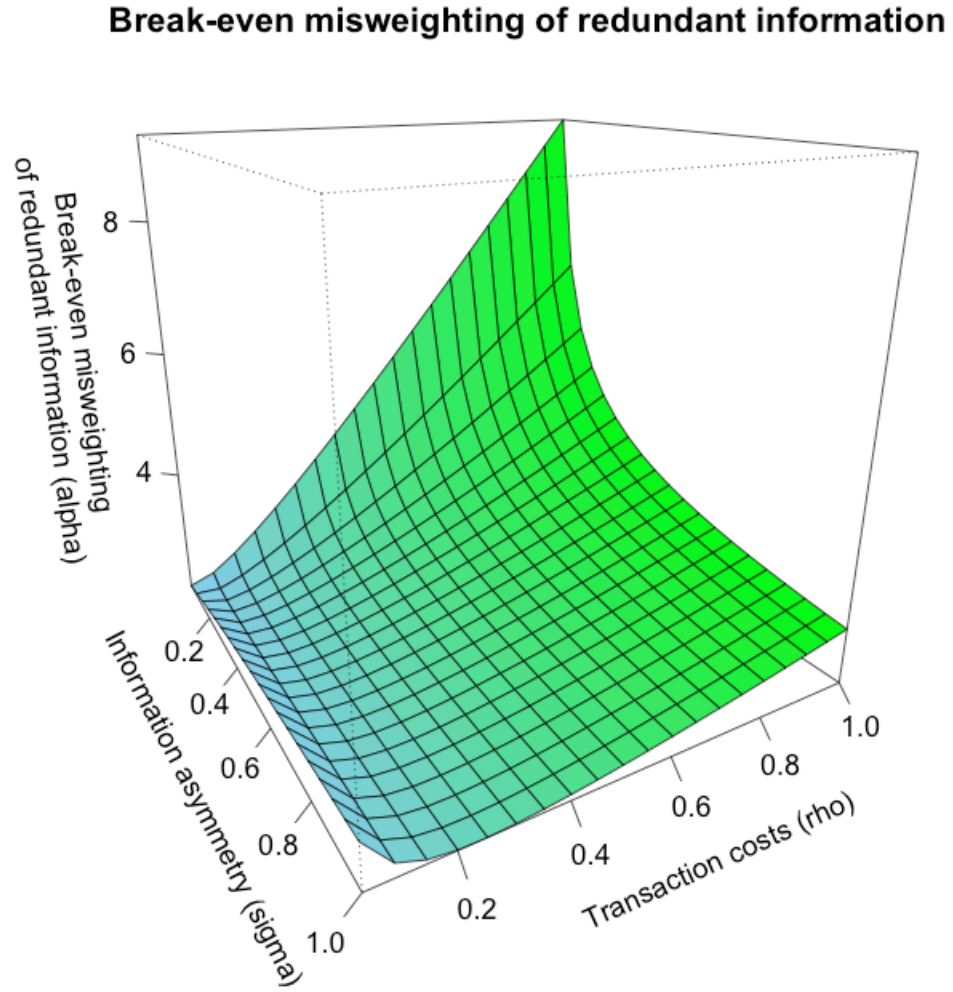
Figure 3: The break-even level of the redundant information parameter, α, as a function of expected liquidity trader demand and the number of arbitrageurs

Break-even misweighting of redundant information
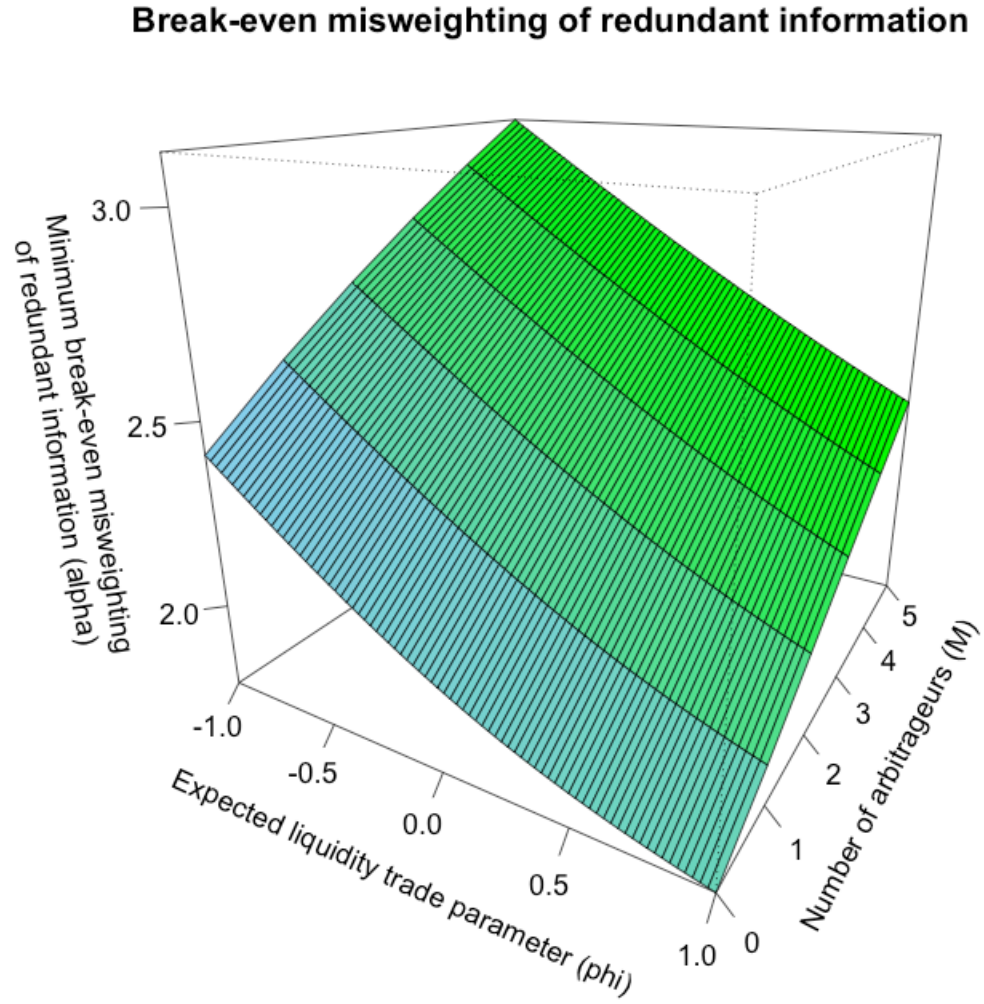
Figure 4: Rational arbitrageurs' expected profit

The following charts show a rational arbitrageur's expected profits as a function of information asymmetry (sigma) and transaction costs (rho).
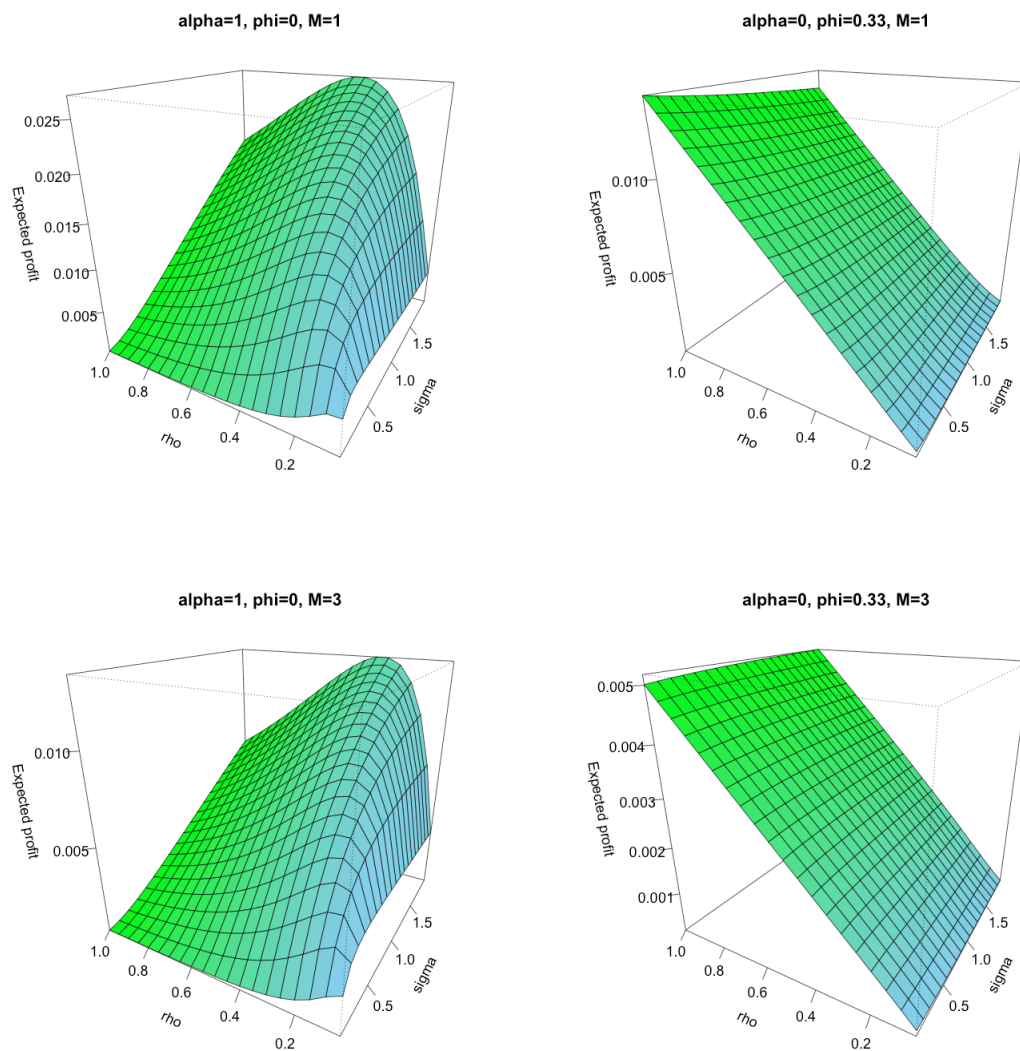
Figure 5: Sample size by calendar quarter, estimations using five-minute returns

Sample size by calendar year

——Number of firms ——Median observations per firm ·······Mean observations per firm
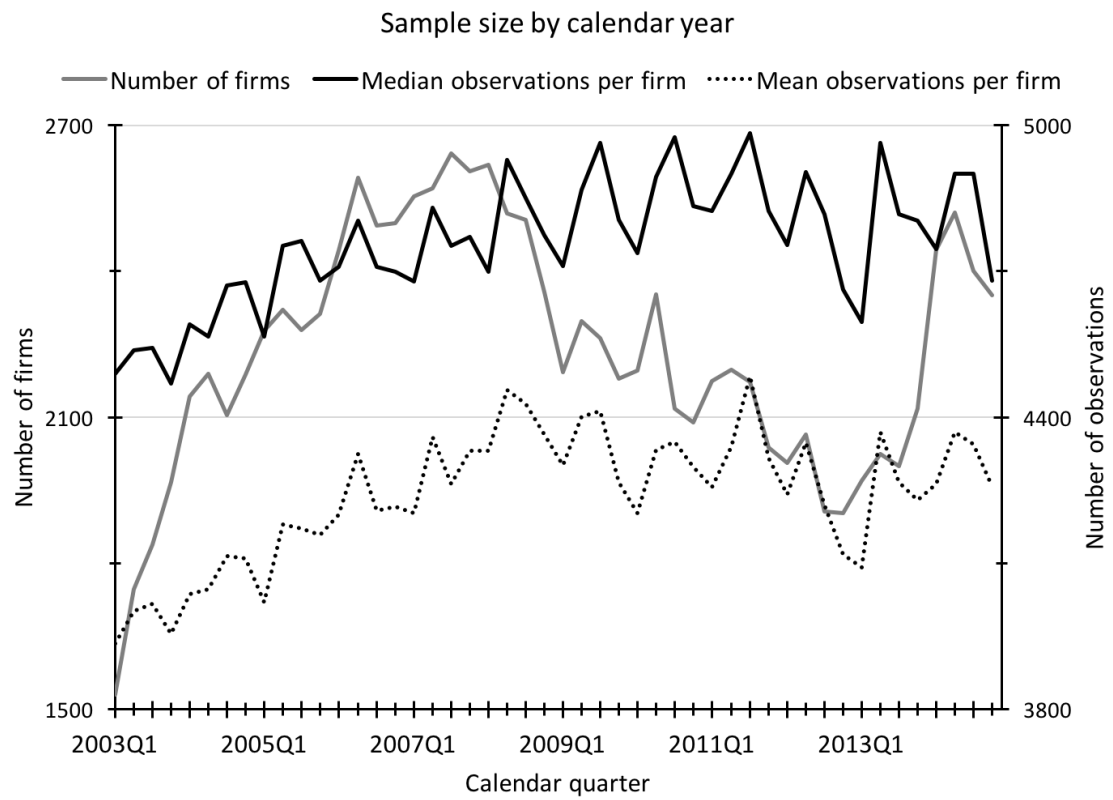
Figure 6: Sample size by calendar quarter, estimations using 30-minute returns

Sample size by calendar year

— Number of firms ⸻ Median observations per firm ⋯⋯ Mean observations per firm
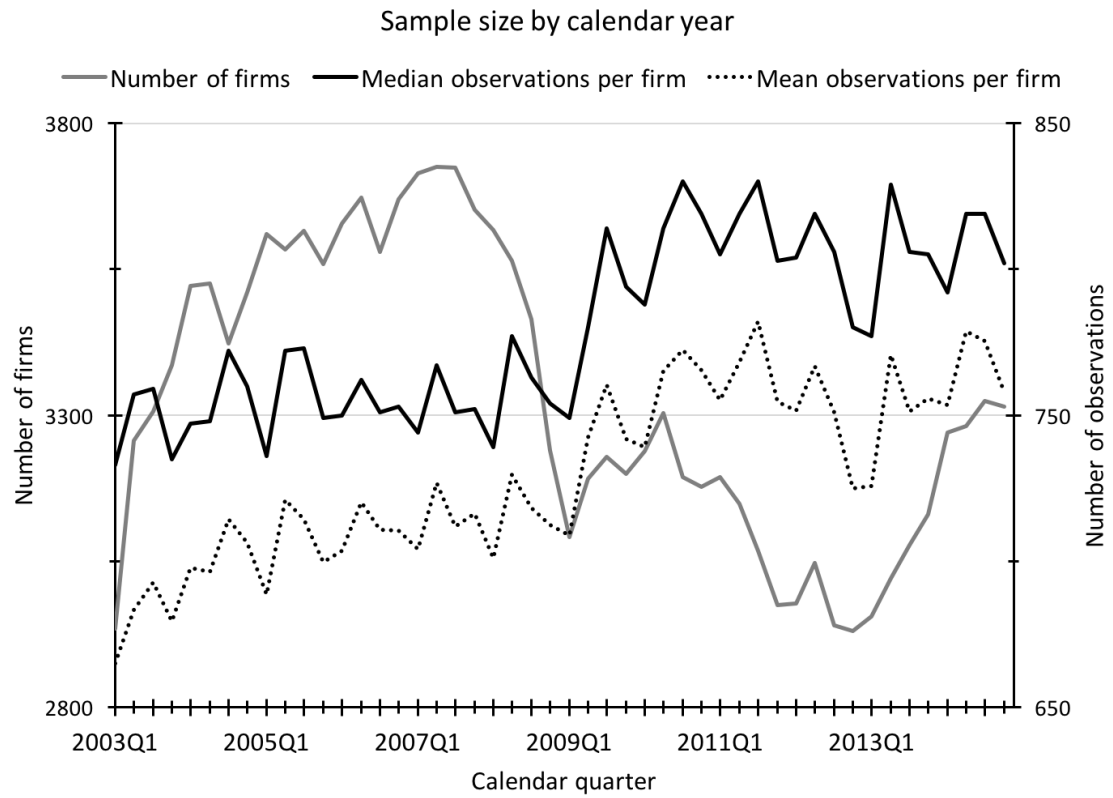
Figure 7: Histogram of estimated α parameters, investors' misweighting of redundant information, estimations using five-minute returns

Histogram of estimated alpha parameters, investors' misweighting of redundant information
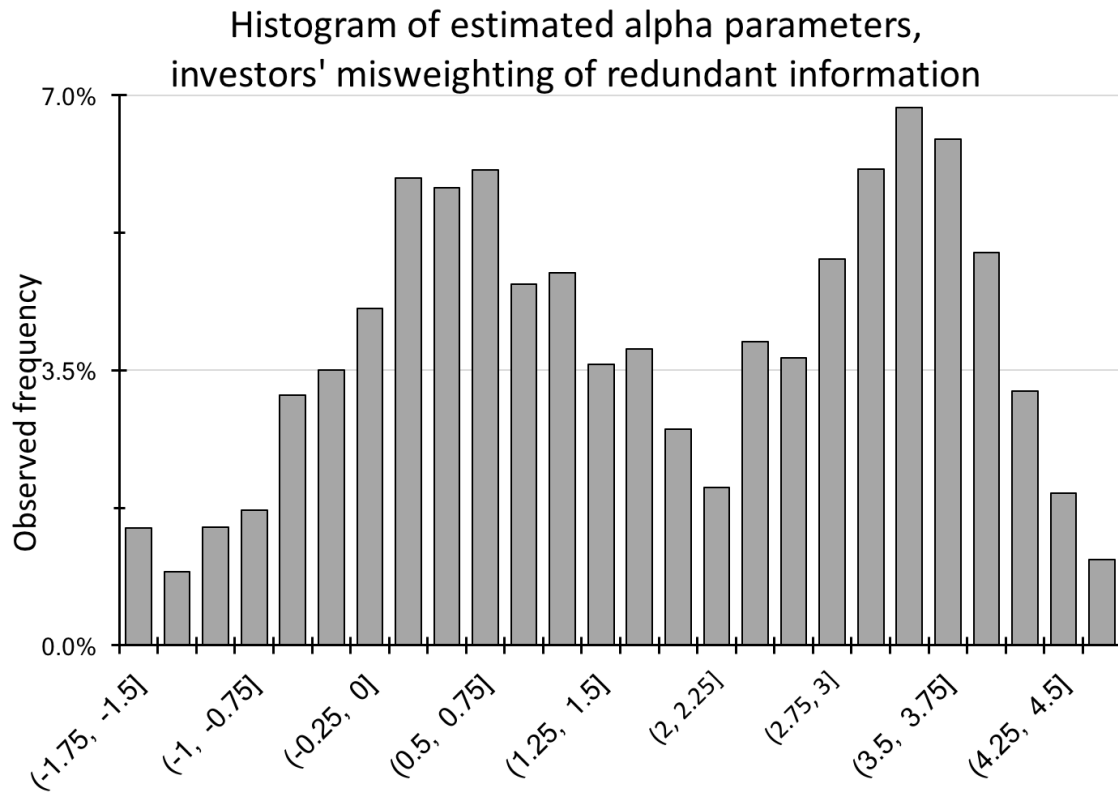
Figure 8: Histogram of estimated ϕ parameters, the autoregressive parameter of liquidity trader demand, estimations using five-minute returns

Histogram of estimated phi parameters,
autoregressive parameter of liquidity trade
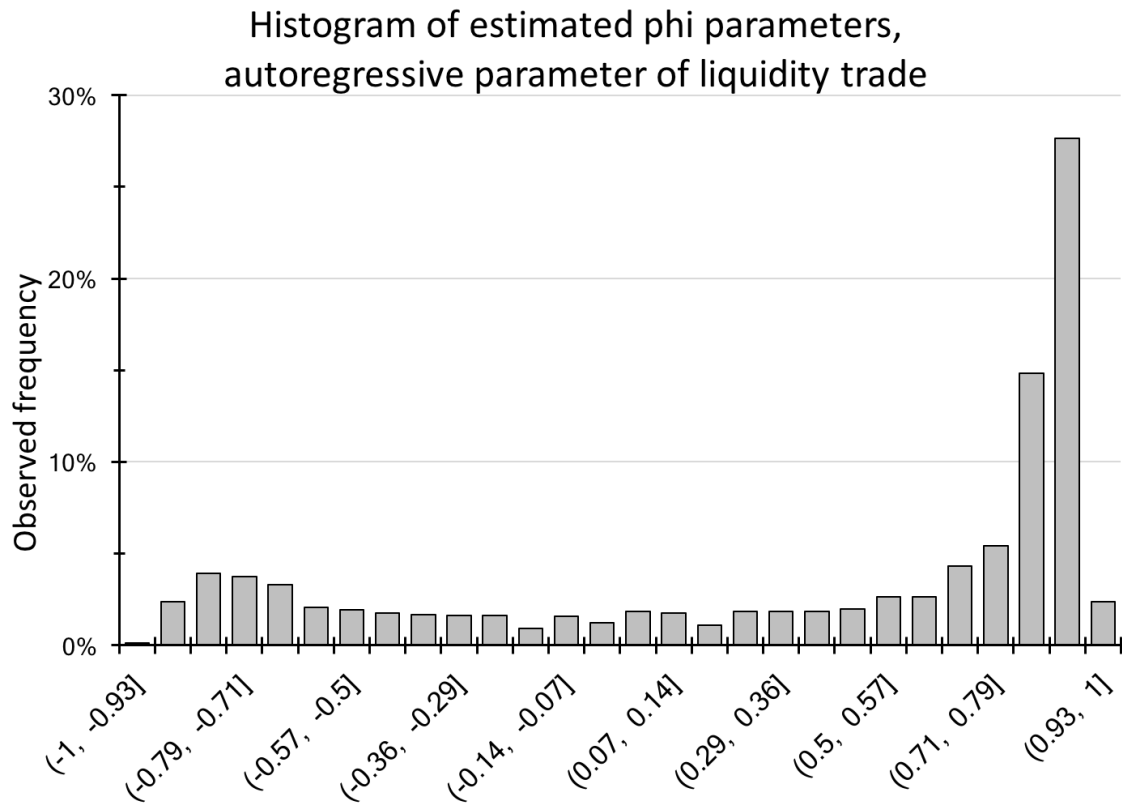
Figure 9: Histogram of estimated ψ parameters, the ratio of transaction costs to the Kyle's lambda, estimations using five-minute returns

Histogram of the ratio of transaction costs to Kyle's lambda
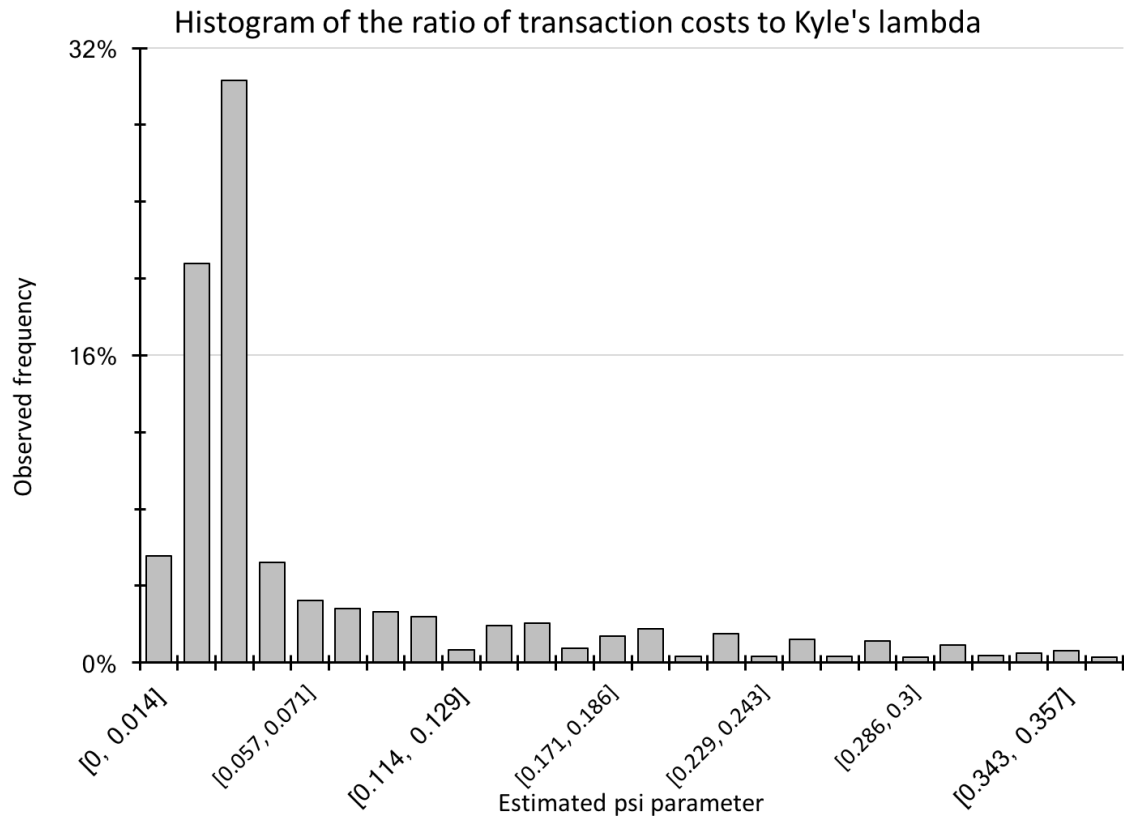
Figure 10: Histogram of estimated α parameters, investors' misweighting of redundant information, estimations using 30-minute returns

Histogram of estimated alpha parameters,
investors' misweighting of redundant information
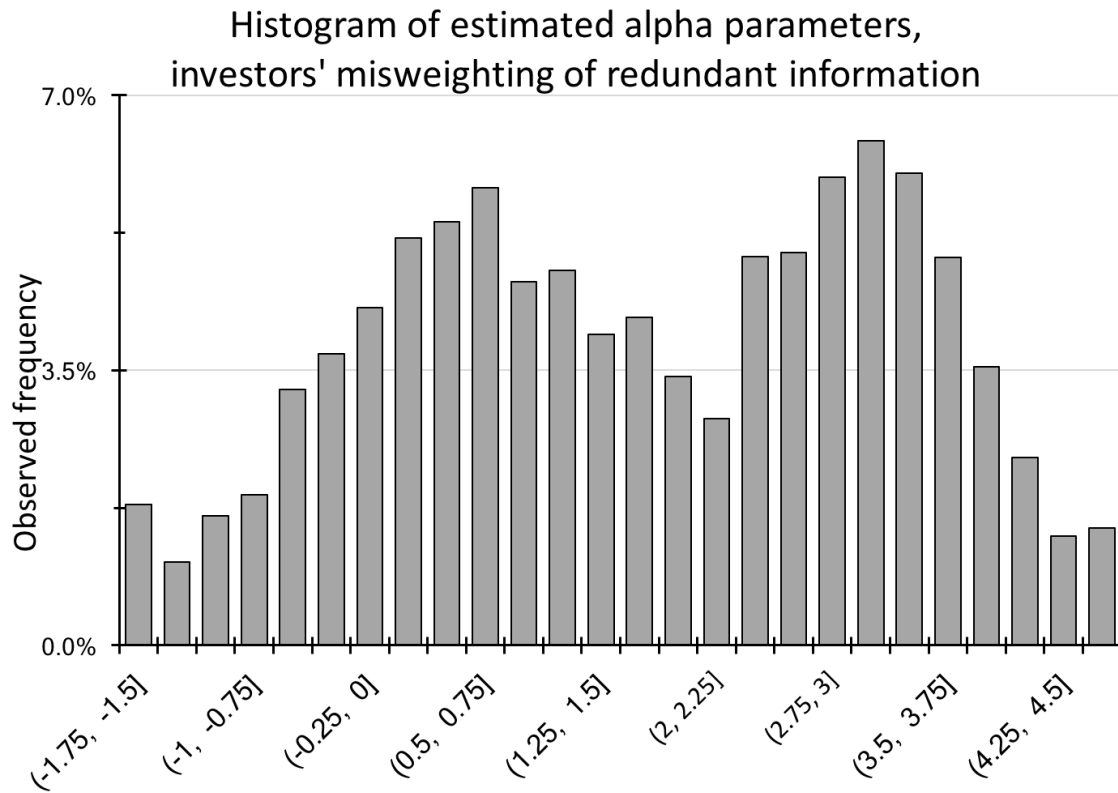
Figure 11: Histogram of estimated ϕ parameters, the autoregressive parameter of liquidity trader demand, estimations using 30-minute returns
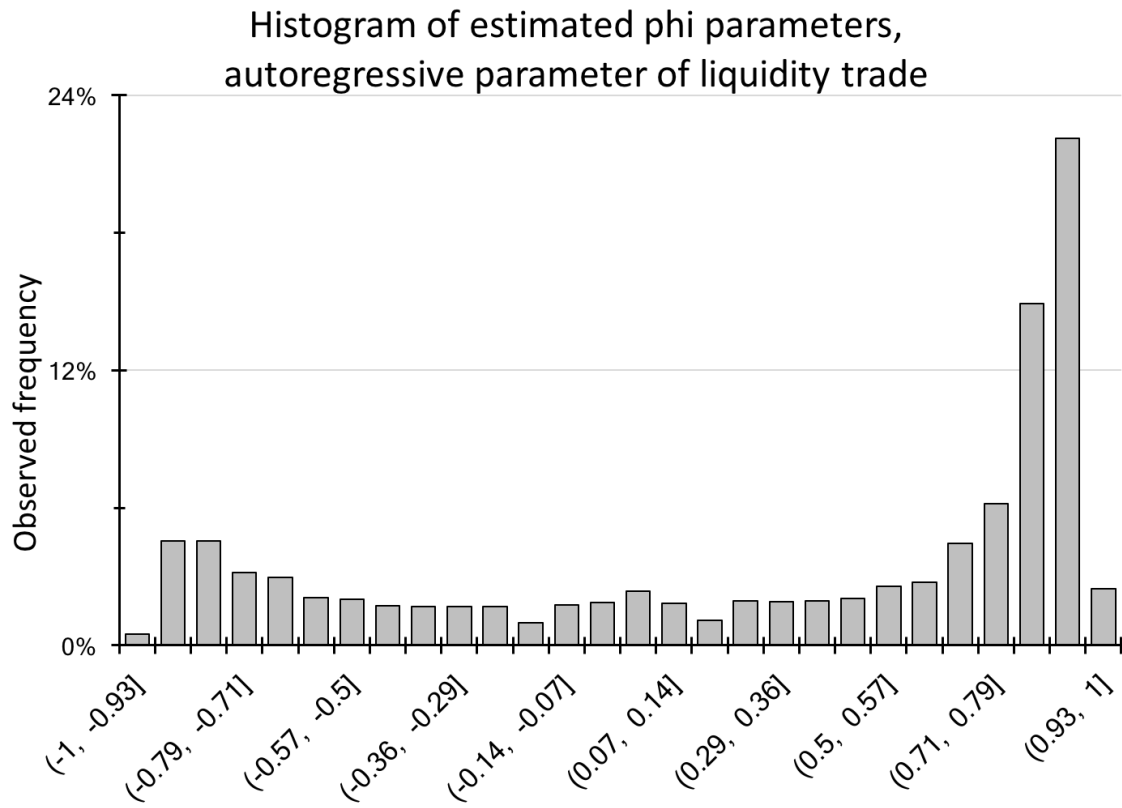
Figure 12: Histogram of estimated ψ parameters, the ratio of transaction costs to the Kyle's lambda, estimations using 30-minute returns
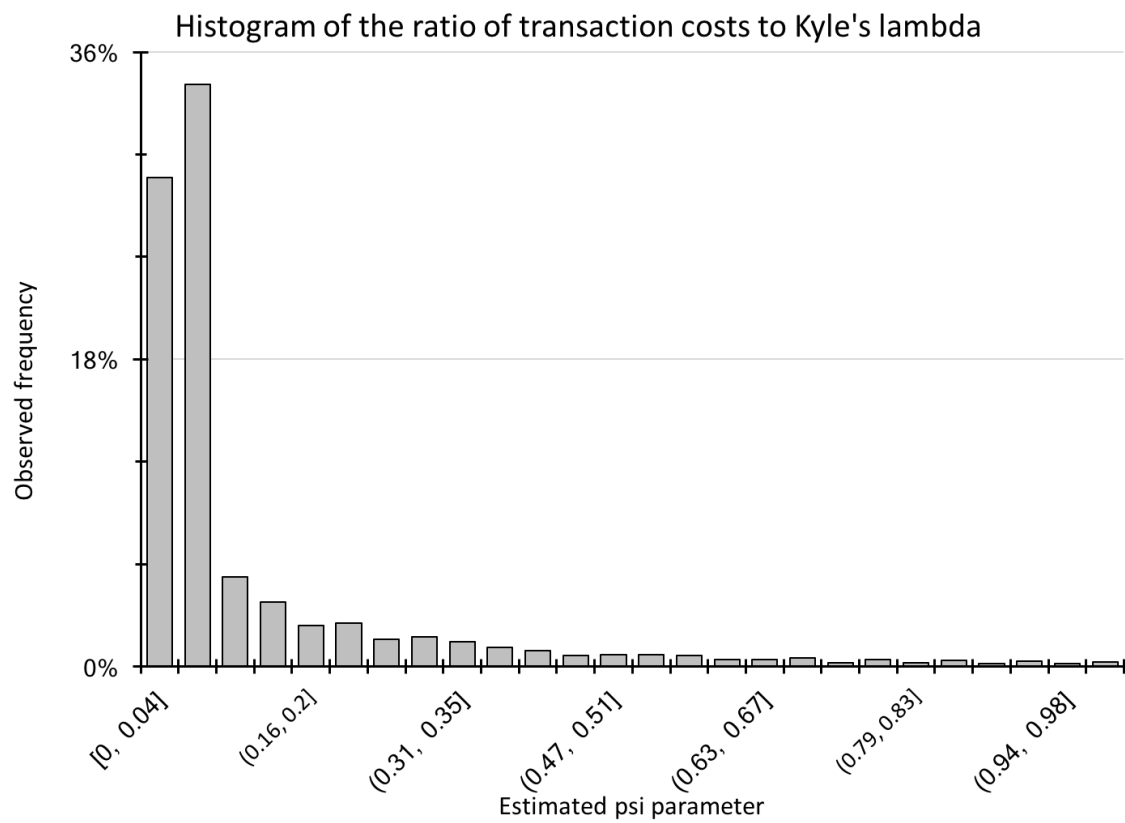
Figure 13: Time series of estimated α parameters, investors' misweighting of redundant information, estimations using five-minute returns

Time series of estimated alpha parameters

—Median alpha —Mean alpha ······Value-weighted average alpha

Calendar quarter
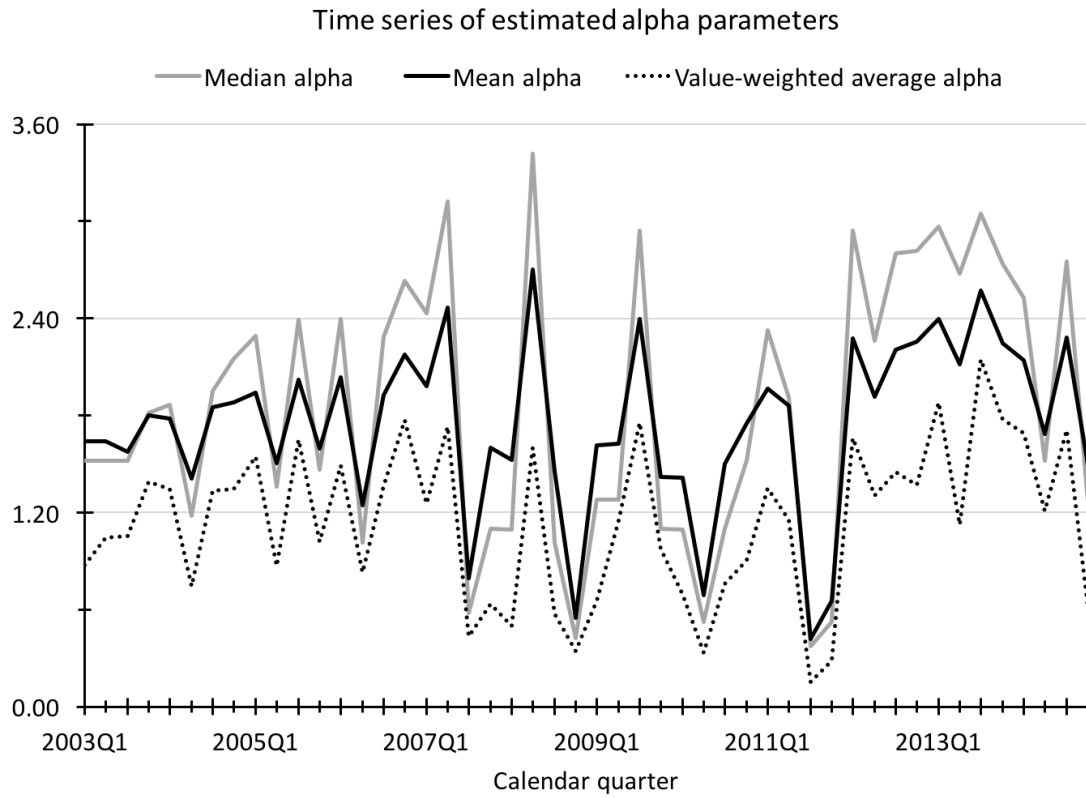
Figure 14: Time series of estimated estimated ϕ parameters, the autoregressive parameter of liquidity trader demand, estimations using five-minute returns

Time series of estimated phi parameters
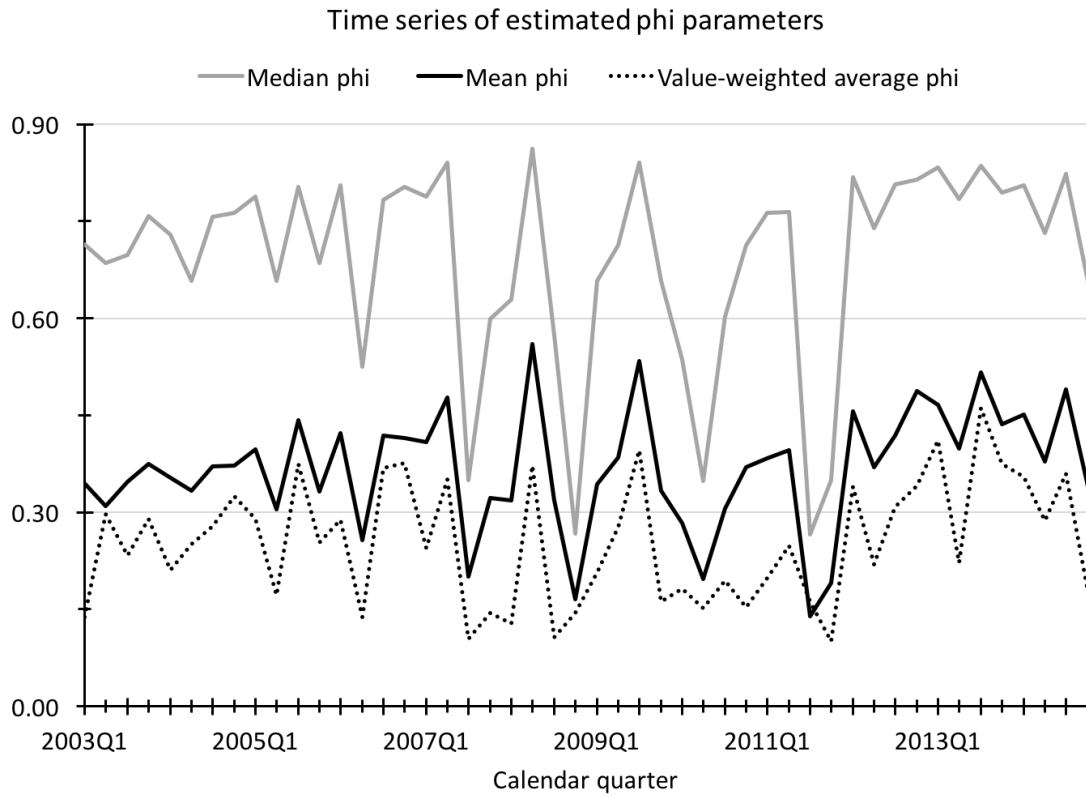
Figure 15: Time series of estimated ψ parameters, the ratio of transaction costs to the Kyle's lambda, estimations using five-minute returns
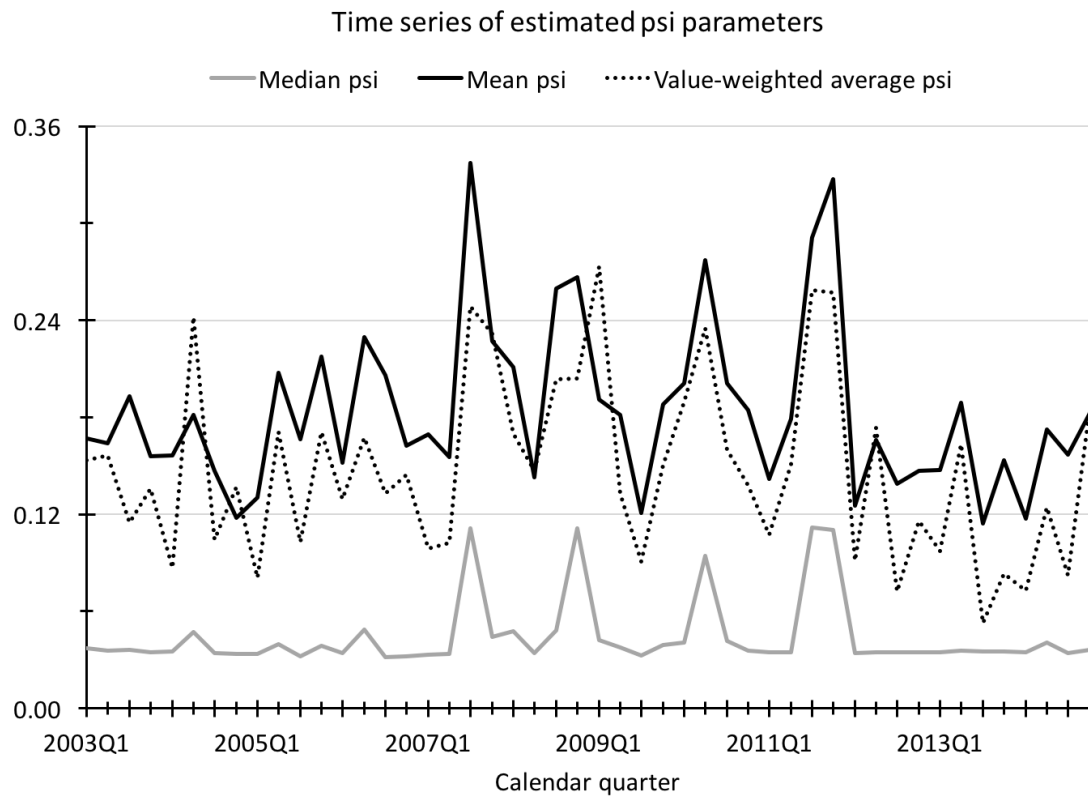
Figure 16: Time series of estimated α parameters, investors' misweighting of redundant information, estimations using 30-minute returns

Time series of estimated alpha parameters
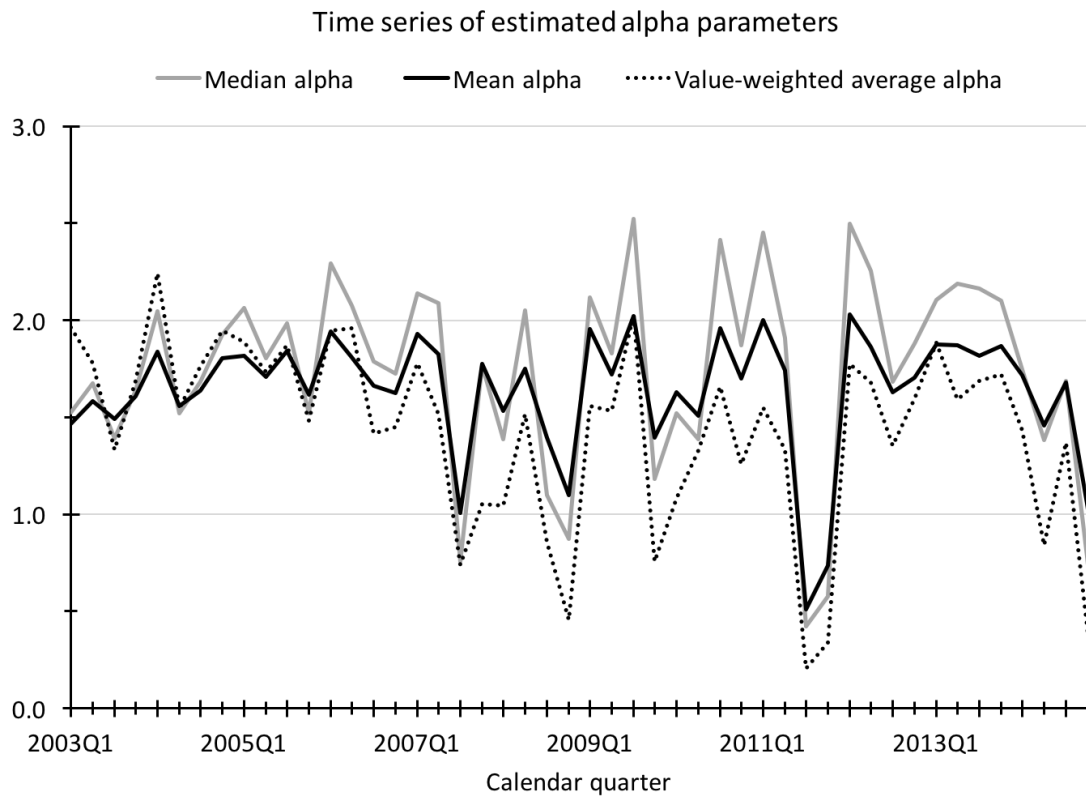
Figure 17: Time series of estimated estimated ϕ parameters, the autoregressive parameter of liquidity trader demand, estimations using 30-minute returns

Time series of estimated phi parameters
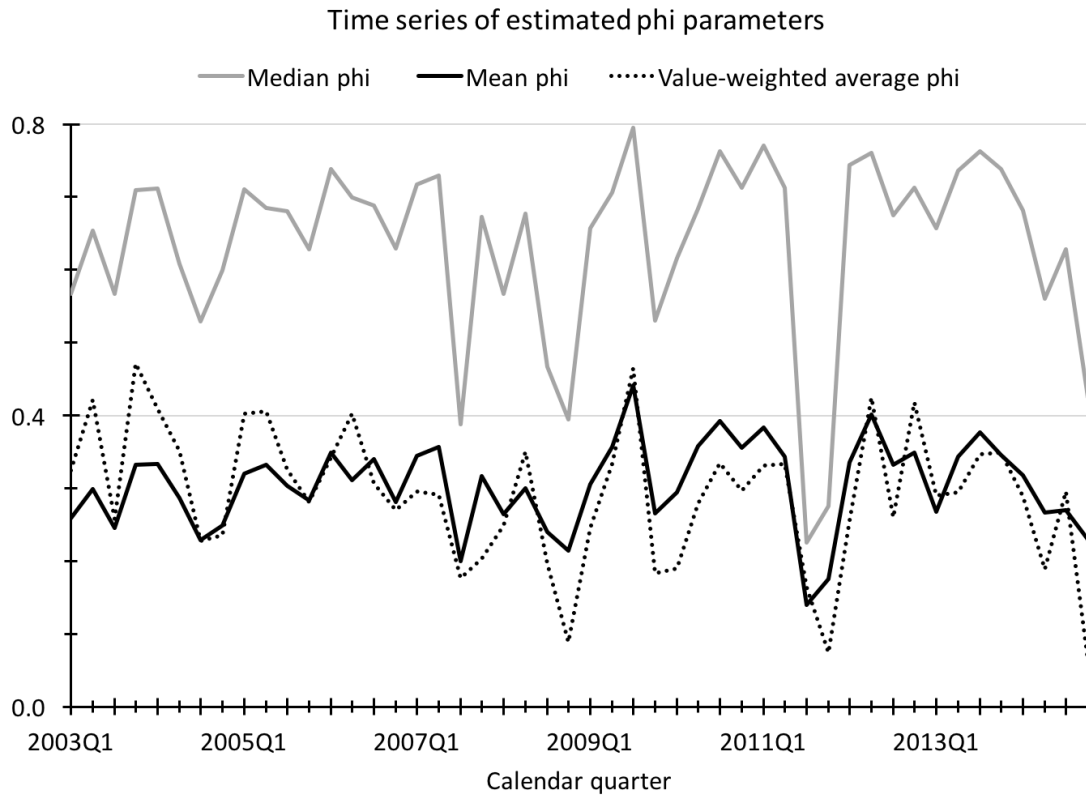
Figure 18: Time series of estimated ψ parameters, the ratio of transaction costs to the Kyle's lambda, estimations using 30-minute returns

Time series of estimated psi parameters

— Median psi — Mean psi ······ Value-weighted average psi
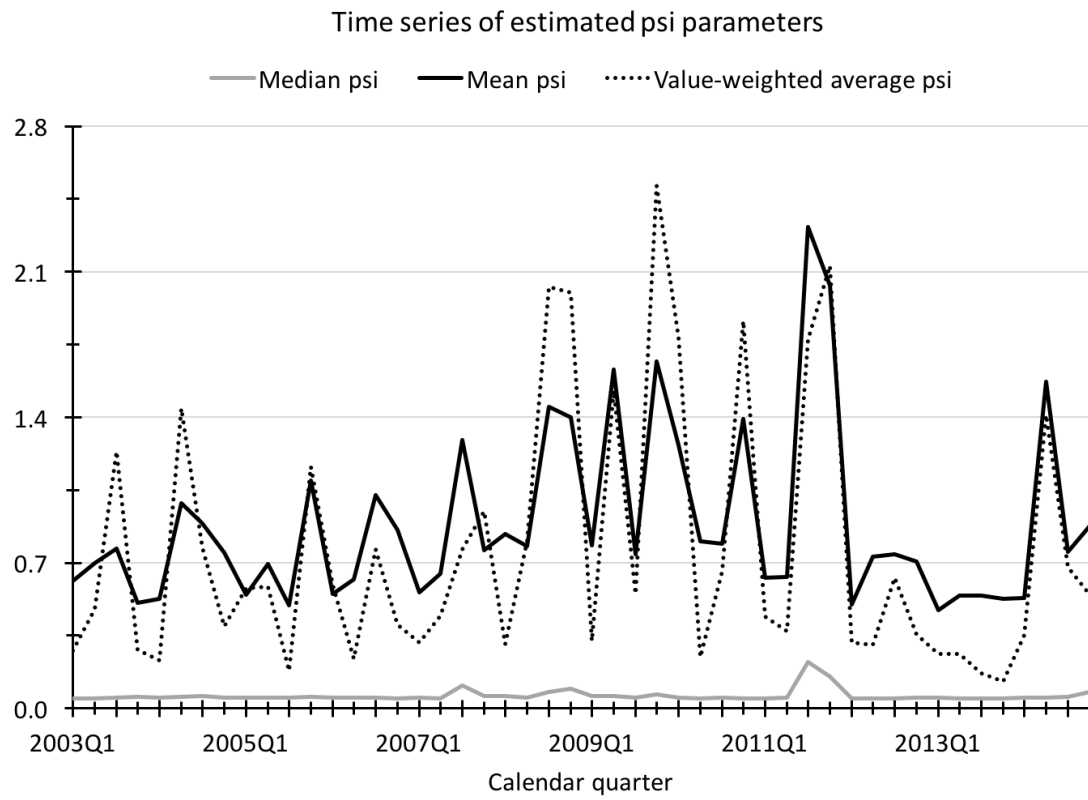
Figure 19: Histogram of estimated moving average coefficients, estimations using five-minute returns

Histogram of estimated moving average coefficients
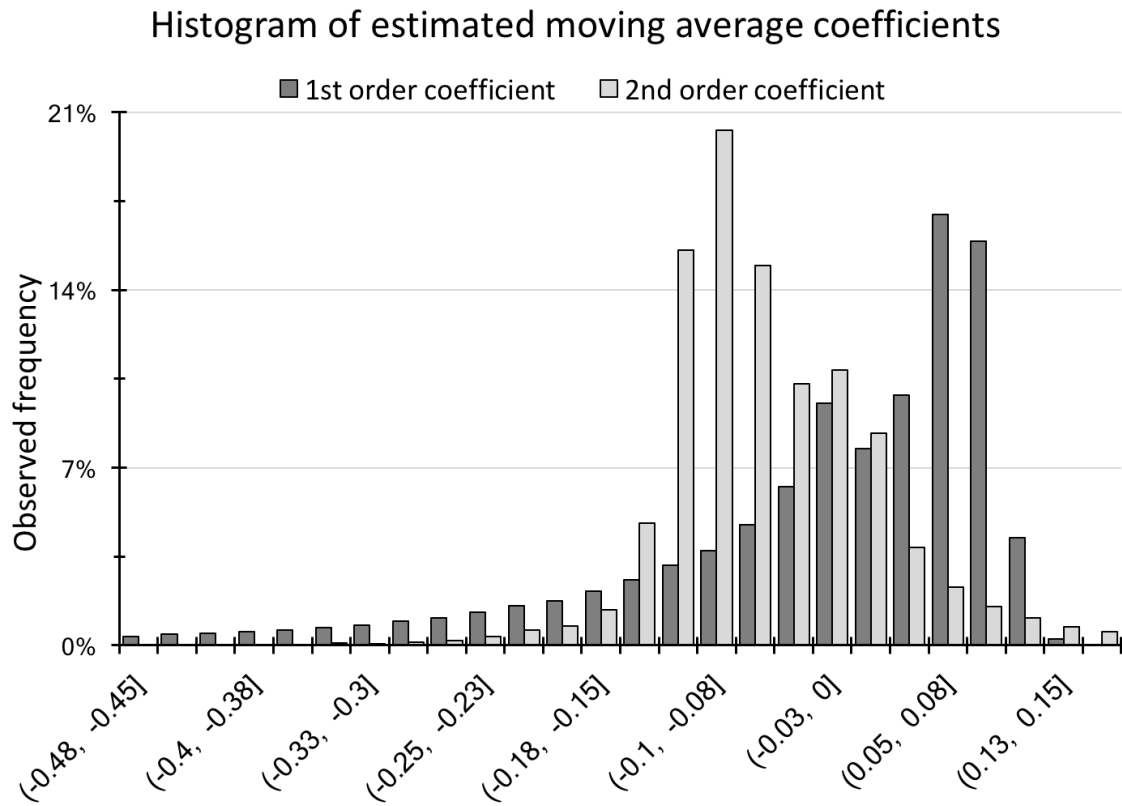
Figure 20: Histogram of estimated moving average coefficients, estimations using 30-minute returns

Histogram of estimated moving average coefficients
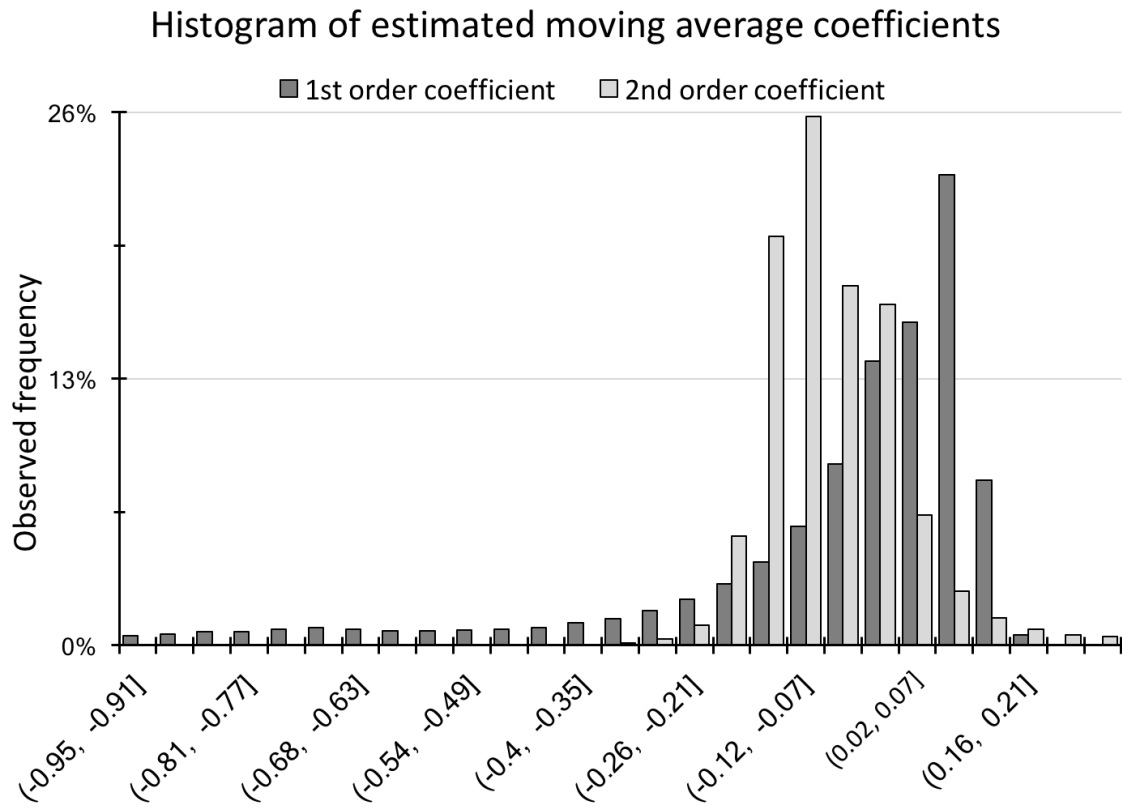
3.5. Additional properties of the analytical model

3.5.1. Equilibrium characterization

The unique equilibrium satisfies:

$$\lambda_d = \frac{\left(\frac{1}{2(\lambda_d+\rho)}\right)\sigma_{v,t}^2}{\left(\frac{1}{2(\lambda_d+\rho)}\right)^2 \sigma_{v,t}^2 + \sigma_{\zeta,t}^2} \tag{3.5.1}$$

$$\Rightarrow 4\lambda_d\left(\lambda_d+\rho\right)^2 + \bar{\sigma}\lambda_d - 2\left(\lambda_d+\rho\right)\bar{\sigma} = 0 \tag{3.5.2}$$

$$\Rightarrow \lambda_d^3 + 2\rho\lambda_d^2 + \left(\rho^2 - \frac{1}{4}\bar{\sigma}\right)\lambda_d - \frac{1}{2}\bar{\sigma}\rho = 0 \tag{3.5.3}$$

Since $\lambda_d + \rho$ must be positive to satisfy the informed investor's profit maximization problem, λ_d must be positive to satisfy Equation (3.5.2). Also, the left hand side expression of Equation (3.5.3) is increasing in λ_d. Thus, this polynomial has one real root for λ_d in which $\lambda_d \geq -\rho$ and $\lambda_d > 0$. By assumption, $\frac{\sigma_{v,t}^2}{\sigma_{\zeta,t}^2} = \bar{\sigma}$ and ρ are constant over time, so λ_d is constant over time.

To satisfy the remaining parameters in the market maker's pricing function,

$$\kappa_u = \frac{\alpha - (\lambda_d+\rho)M\gamma_u - \lambda_u}{2(\lambda_d+\rho)} = \frac{\alpha - (\lambda_d+\rho)M\left(-\frac{(\lambda_d+\rho)\kappa_u+\lambda_u}{(M+1)(\lambda_d+\rho)}\right) - \lambda_u}{2(\lambda_d+\rho)}$$

$$\Rightarrow \kappa_u = \frac{(M+1)\alpha - \lambda_u}{(M+2)(\lambda_d+\rho)} \tag{3.5.4}$$

$$\gamma_u = -\frac{(\lambda_d+\rho)\kappa_u + \lambda_u}{(M+1)(\lambda_d+\rho)} = -\frac{(\lambda_d+\rho)\frac{\alpha-(\lambda_d+\rho)M\gamma_u-\lambda_u}{2(\lambda_d+\rho)} + \lambda_u}{(M+1)(\lambda_d+\rho)}$$

$$\Rightarrow \gamma_u = \frac{-\alpha - \lambda_u}{(M+2)(\lambda_d+\rho)} \tag{3.5.5}$$

$$\lambda_u = -\lambda_d\left(\kappa_u + M\gamma_u\right) = -\lambda_d\left(\frac{(M+1)\alpha - \lambda_u}{(M+2)(\lambda_d+\rho)} + M\left(\frac{-\alpha - \lambda_u}{(M+2)(\lambda_d+\rho)}\right)\right)$$

$$\Rightarrow \lambda_u = \frac{-\lambda_d\alpha}{\lambda_d + (M+2)\rho} \tag{3.5.6}$$

$$\kappa_\phi = \frac{-\left(\lambda_d + \rho\right)\left(M\gamma_\phi + \phi\right) - \lambda_\phi}{2\left(\lambda_d + \rho\right)} = -\frac{\left(\lambda_d + \rho\right)\left(M\left(-\frac{\left(\lambda_d + \rho\right)\left(\kappa_\phi + \phi\right) + \lambda_\phi}{\left(M+1\right)\left(\lambda_d + \rho\right)}\right) + \phi\right) + \lambda_\phi}{2\left(\lambda_d + \rho\right)}$$

$$\Rightarrow \kappa_\phi = -\frac{\left(\lambda_d + \rho\right)\phi + \lambda_\phi}{\left(M+2\right)\left(\lambda_d + \rho\right)} \tag{3.5.7}$$

$$\gamma_\phi = -\frac{\left(\lambda_d + \rho\right)\left(\kappa_\phi + \phi\right) + \lambda_\phi}{\left(M+1\right)\left(\lambda_d + \rho\right)} = -\frac{\left(\lambda_d + \rho\right)\left(\frac{-\left(\lambda_d + \rho\right)\left(M\gamma_\phi + \phi\right) - \lambda_\phi}{2\left(\lambda_d + \rho\right)} + \phi\right) + \lambda_\phi}{\left(M+1\right)\left(\lambda_d + \rho\right)}$$

$$\gamma_\phi = -\frac{\left(\lambda_d + \rho\right)\phi + \lambda_\phi}{\left(M+2\right)\left(\lambda_d + \rho\right)} \tag{3.5.8}$$

$$\lambda_\phi = -\lambda_d\left(\kappa_\phi + \phi + M\gamma_\phi\right) = -\lambda_d\left(\phi - \left(M+1\right)\frac{\left(\lambda_d + \rho\right)\phi + \lambda_\phi}{\left(M+2\right)\left(\lambda_d + \rho\right)}\right)$$

$$\Rightarrow \lambda_\phi = \frac{-\lambda_d\left(\lambda_d + \rho\right)\phi}{\lambda_d + \left(M+2\right)\rho} \tag{3.5.9}$$

$$\kappa_E = \frac{1 - \left(\lambda_d + \rho\right)M\gamma_E - \lambda_E}{2\left(\lambda_d + \rho\right)} = \frac{1 - \left(\lambda_d + \rho\right)M\frac{1 - \left(\lambda_d + \rho\right)\kappa_E - \lambda_E}{\left(M+1\right)\left(\lambda_d + \rho\right)} - \lambda_E}{2\left(\lambda_d + \rho\right)}$$

$$\Rightarrow \kappa_E = \frac{1 - \lambda_E}{\left(M+2\right)\left(\lambda_d + \rho\right)} \tag{3.5.10}$$

$$\gamma_E = \frac{1 - \left(\lambda_d + \rho\right)\kappa_E - \lambda_E}{\left(M+1\right)\left(\lambda_d + \rho\right)} = \frac{1 - \left(\lambda_d + \rho\right)\frac{1 - \left(\lambda_d + \rho\right)M\gamma_E - \lambda_E}{2\left(\lambda_d + \rho\right)} - \lambda_E}{\left(M+1\right)\left(\lambda_d + \rho\right)}$$

$$\Rightarrow \gamma_E = \frac{1 - \lambda_E}{\left(M+2\right)\left(\lambda_d + \rho\right)} \tag{3.5.11}$$

$$\Rightarrow \lambda_E = 1 - \lambda_d\left(\kappa_E + M\gamma_E\right) = 1 - \lambda_d\left(M+1\right)\frac{1 - \lambda_E}{\left(M+2\right)\left(\lambda_d + \rho\right)}$$

$$\Rightarrow \lambda_E = 1 \tag{3.5.12}$$

Returning to the informed investor's demand function,

$$\kappa_u = \frac{\left(M+1\right)\alpha - \lambda_u}{\left(M+2\right)\left(\lambda_d + \rho\right)} = \frac{\alpha\left(\lambda_d + \left(M+1\right)\rho\right)}{\left(\lambda_d + \rho\right)\left(\lambda_d + \left(M+2\right)\rho\right)} \tag{3.5.13}$$

$$\kappa_\phi = -\frac{(\lambda_d + \rho)\phi + \lambda_\phi}{(M+2)(\lambda_d + \rho)} = -\frac{\phi\rho}{\lambda_d + (M+2)\rho} \tag{3.5.14}$$

$$\kappa_E = \frac{1 - \lambda_E}{3(\lambda_d + \rho)} = 0 \tag{3.5.15}$$

Returning to the rational arbitrageur's demand function,

$$\gamma_u = \frac{-\alpha - \lambda_u}{(M+2)(\lambda_d + \rho)} = \frac{-\alpha\rho}{(\lambda_d + \rho)(\lambda_d + (M+2)\rho)} \tag{3.5.16}$$

$$\gamma_\phi = -\frac{(\lambda_d + \rho)\phi + \lambda_\phi}{(M+2)(\lambda_d + \rho)} = -\frac{\phi\rho}{\lambda_d + (M+2)\rho} \tag{3.5.17}$$

$$\gamma_E = \frac{1 - \lambda_E}{(M+2)(\lambda_d + \rho)} = 0 \tag{3.5.18}$$

3.5.2. Informed investors' viability of trading on redundant information

Can informed investors who trade on redundant information traders survive in equilibrium? The informed investor in period t trades based on the biased posterior belief $v_t + \alpha u_{t-1} + \mathrm{E}\left[\tilde{V}|H_{t-1}\right]$, but his expected profits are

$$\mathrm{E}\left[\left(v_t + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] - \mathrm{E}\left[\tilde{P}_t|s_t\right]\right)x_t\right]$$

$$\begin{aligned}
&= \mathrm{E}\Bigg[\left(v_t + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] - \mathrm{E}\left[\left(\lambda_d\left(D_t - \mathrm{E}\left[\tilde{D}_t|H_{t-1}\right]\right) + \mathrm{E}\left[\tilde{V}|H_{t-1}\right] + \rho D_t\right)|s_t\right]\right) \\
&\qquad \times \left(\frac{1}{2(\lambda_d + \rho)}v_t + \frac{\alpha(\lambda_d + (M+1)\rho)}{(\lambda_d + \rho)(\lambda_d + (M+2)\rho)}u_{t-1} - \frac{\phi\rho}{\lambda_d + (M+2)\rho}\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right]\right)\Bigg] \\
&= \frac{1}{4(\lambda_d + \rho)}\sigma_{v,t}^2 - \frac{\rho}{(\lambda_d + (M+2)\rho)^2(\lambda_d + \rho)}F(\alpha,\phi) \tag{3.5.19}
\end{aligned}$$

where

$$
\begin{aligned}
F\left(\alpha, \phi\right) =&\operatorname{E}\left[\left(\alpha u_{t-1} + \phi \nu_{t-1}\right)\left(\alpha \left(\lambda_d + (M+1)\rho\right) u_{t-1} - \phi \rho \nu_{t-1}\right)\right] \\
=&\alpha^2 \left(\lambda_d + (M+1)\rho\right)\operatorname{E}\left[u_{t-1}^2\right] + \alpha\phi\left(\lambda_d + M\rho\right)\operatorname{E}\left[u_{t-1}\nu_{t-1}\right] - \phi^2\rho\operatorname{E}\left[\nu_{t-1}^2\right]
\end{aligned}
\tag{3.5.20}
$$

$$
\operatorname{E}\left[u_{t-1}^2\right] = \frac{\lambda_d^2}{\left(\lambda_d + \rho\right)^2}\operatorname{E}\left[\eta_{t-1}^2\right]
\tag{3.5.21}
$$

$$
\operatorname{E}\left[u_{t-1}\nu_{t-1}\right] = \frac{\lambda_d\left(\lambda_d + 2\rho\right)}{2\left(\lambda_d + \rho\right)^2}\operatorname{E}\left[\eta_{t-1}^2\right]
\tag{3.5.22}
$$

$$
\operatorname{E}\left[\nu_{t-1}^2\right] = \phi^2\operatorname{E}\left[\nu_{t-2}^2\right] + \frac{\left(\lambda_d + 2\rho\right)^2}{4\left(\lambda_d + \rho\right)^2}\operatorname{E}\left[\eta_{t-1}^2\right]
\tag{3.5.23}
$$

and

$$
\operatorname{E}\left[\eta_{t-1}^2\right] = \frac{1}{4}\sigma_{v,t-1}^2 + \left(\lambda_d + \rho\right)^2 \sigma_{\zeta,t-1}^2
\tag{3.5.24}
$$

Thus, an informed investor's expected profits increase as α^2 decreases, $\alpha\phi$ decreases, and ϕ^2 increases. In addition, as M increases, the effect of $\alpha \neq 0$ and $\phi \neq 0$ on an informed investor's expected profits attenuates because rational arbitrageurs lessen the price impact of trading on redundant information.

Although trading on redundant information detracts from an informed investor's expected profits, his expected profits are not necessarily negative. Rather, his expected profits are positive if

$$
0 < \operatorname{E}\left[\left(v_t + \operatorname{E}\left[V|H_{t-1}\right] - \operatorname{E}\left[\tilde{P}_t|s_t\right]\right)x_t\right]
\tag{3.5.25}
$$

I set Equation (3.5.25) as an equality, and solve it numerically for the break-even level of α over various values of ρ, $\bar{\sigma}$, ϕ, and M. Since an informed investor's expected profits are increasing in ϕ^2, I solve for the minimum break-even level of α by assuming $\operatorname{E}\left[\nu_{t-2}^2\right] = 0$. Assuming $\sigma_{v,t}^2 = \sigma_{v,t-1}^2$, the informed investor has zero expected profits if

$$
\begin{aligned}
\frac{\left(\lambda_d + \rho\right)^2 \left(\lambda_d + (M+2)\rho\right)^2 \bar{\sigma}}{\rho\left(\frac{1}{4}\bar{\sigma} + \left(\lambda_d + \rho\right)^2\right)} =&4\alpha^2\lambda_d^2\left(\lambda_d + (M+1)\rho\right) \\
&+ 2\alpha\phi\lambda_d\left(\lambda_d + M\rho\right)\left(\lambda_d + 2\rho\right) - \phi^2\rho\left(\lambda_d + 2\rho\right)^2
\end{aligned}
\tag{3.5.26}
$$

If $\phi = 0$ and $M = 0$, and for any $\bar{\sigma} \in [0.01, 3]$ and $\rho \in (0, 3]$, an informed investor earns positive expected profits if $|\alpha| < 2.00$. I plot the (positive) break-even level of α as a function of $\bar{\sigma}$ and ρ with $\phi = 0$ and $M = 0$ in Figure 2. As depicted, this break-even level of α is non-monotonic in ρ and λ_d; the breakeven α is decreasing in ρ when ρ is sufficiently low, increasing in ρ when ρ is sufficiently high, increasing in $\bar{\sigma}$ when ρ is sufficiently low, and decreasing in $\bar{\sigma}$ if ρ is sufficiently high.

As ϕ increases or M decreases, the minimum break-even $|\alpha|$ decreases. In Figure 3, I plot the lowest positive break-even α as a function of ϕ and M for any $\bar{\sigma} \in [0.01, 3]$ and $\rho \in (0, 3]$ (i.e., the minimum point of Figure 2 as a function of ϕ and M). The minimum point on this chart appears when $\phi = 1$ and $M = 0$. When $\phi = 1$ and $M = 0$, an informed investor earns positive expected profits as long as $|\alpha| < 1.77$.

In summary, although an informed investor might misweight information, he still would earn positive expected profits as long as his non-Bayesian behavior is not too severe.

3.5.3. Rational arbitrageurs' expected profits

A rational arbitrageur earns expected profits

$$\mathrm{E}\left[y_t \left(\mathrm{E}\left[\tilde{V} - \tilde{P}_t | y_t, H_{t-1}\right]\right)\right] \tag{3.5.27}$$

Each rational arbitrageur chooses his demand according to

$$y_t = -\frac{\alpha\rho}{(\lambda_d + \rho)(\lambda_d + (M+2)\rho)}u_{t-1} - \frac{\phi\rho}{\lambda_d + (M+2)\rho}\mathrm{E}\left[\tilde{z}_{t-1} | H_{t-1}\right] \tag{3.5.28}$$

and

$$\mathrm{E}\left[\tilde{V} - \tilde{P}_t | y_t, H_{t-1}\right] = -\rho\mathrm{E}\left[\tilde{D}_t | y_t, H_{t-1}\right] \tag{3.5.29}$$

$$= -\rho\left(\frac{\alpha}{\lambda_d + (M+2)\rho}u_{t-1} + \frac{(\lambda_d + \rho)\phi}{\lambda_d + (M+2)\rho}\mathrm{E}\left[\tilde{z}_{t-1} | H_{t-1}\right]\right) \tag{3.5.30}$$

Combining these equations implies that the rational arbitrageur earns expected profits:

$$\mathrm{E}\left[y_t \left(\mathrm{E}\left[\tilde{V} - \tilde{P}_t | y_t, H_{t-1}\right]\right)\right] = \frac{\rho^2}{(\lambda_d + (M+2)\rho)^2 (\lambda_d + \rho)}\mathrm{E}\left[(\alpha u_{t-1} + \phi\nu_{t-1})^2\right] \tag{3.5.31}$$

where

$$E\left[\left(\alpha u_{t-1} + \phi \nu_{t-1}\right)^2\right] = \left(\frac{\alpha \lambda_d + \phi\left(\frac{1}{2}\lambda_d + \rho\right)}{\lambda_d + \rho}\right)^2 E\left[\eta_{t-1}^2\right] + \phi^4 E\left[\nu_{t-2}^2\right] \qquad (3.5.32)$$

and $E\left[\eta_{t-1}^2\right] = \frac{1}{4}\sigma_{v,t-1}^2 + \left(\lambda_d + \rho\right)^2 \sigma_{\zeta,t-1}^2$.

A rational arbitrageur earns positive expected profits if $\rho \neq 0$ and either $\alpha \neq 0$, $\phi \neq 0$, or both. His expected profits increase as α^2 increases, ϕ^2 increases, and $\alpha\phi$ increases. As shown in Figure 4, a rational arbitrageur's expected profits are non-monotonic in information asymmetry, $\bar{\sigma}$, and transaction costs, ρ. Over most levels of transaction costs, a rational arbitrageur's expected profits increase as information asymmetry increases. At low levels of transaction costs and high levels of information asymmetry, a rational arbitrageur's expected profits decrease as information asymmetry increases. When $\alpha = 0$, a rational arbitrageur's expected profits increase as transaction costs increase. When $\alpha > 0$, a rational arbitrageur's expected profits increase as transaction costs increase when transaction costs are low, and a rational arbitrageur's expected profits decrease as transaction costs increase when transaction costs are high. Expected profits for a single rational arbitrageur are decreasing in M, but total expected profits for all rational arbitrageurs are increasing in M.

3.5.4. Sensitivity of trading volume to the misweighting of redundant information and expected liquidity trade

Expected trading volume is

$$E\left[|x_t| + M|y_t| + |z_t|\right] \propto \mathrm{Var}\left(x_t\right) + M\mathrm{Var}\left(y_t\right) + \mathrm{Var}\left(z_t\right) \qquad (3.5.33)$$

The variance of informed demand is

$$
\begin{aligned}
\mathrm{Var}\left(x_t\right) =& \mathrm{Var}\left(\frac{1}{2\left(\lambda_d + \rho\right)}v_t + \frac{\alpha\left(\lambda_d + (M+1)\rho\right)}{\left(\lambda_d + \rho\right)\left(\lambda_d + (M+2)\rho\right)}u_{t-1} - \frac{\phi\rho}{\lambda_d + (M+2)\rho}E\left[\tilde{z}_{t-1}|H_{t-1}\right]\right) \\
=& \frac{1}{4\left(\lambda_d + \rho\right)^2}\mathrm{Var}\left(v_t\right) + \frac{\left(\alpha\lambda_d\left(\lambda_d + (M+1)\rho\right) - \phi\rho\left(\frac{1}{2}\lambda_d + \rho\right)\right)^2}{\left(\lambda_d + \rho\right)^4\left(\lambda_d + (M+2)\rho\right)^2}E\left[\eta_{t-1}^2\right] \\
&+ \frac{\phi^4\rho^2}{\left(\lambda_d + (M+2)\rho\right)^2\left(\lambda_d + \rho\right)^2}E\left[\nu_{t-2}^2\right] \qquad (3.5.34)
\end{aligned}
$$

Equation (3.5.34) shows that the variance of informed trade is increasing α^2, increasing in ϕ^2, and

decreasing in $\alpha\phi$.

The variance of rational arbitrage demand is

$$
\begin{aligned}
\mathrm{Var}\left(y_t\right) =&\mathrm{Var}\left(-\frac{\alpha\rho}{\left(\lambda_d + \rho\right)\left(\lambda_d + \left(M+2\right)\rho\right)}u_{t-1} - \frac{\phi\rho}{\lambda_d + \left(M+2\right)\rho}\mathrm{E}\left[\tilde{z}_{t-1}|H_{t-1}\right]\right) \\
=&\frac{\rho^2\left(\alpha\lambda_d + \phi\left(\lambda_d + \rho\right)\right)^2}{\left(\lambda_d + \rho\right)^4\left(\lambda_d + \left(M+2\right)\rho\right)^2}\mathrm{E}\left[\eta_{t-1}^2\right] + \frac{\phi^4\rho^2}{\left(\lambda_d + \left(M+2\right)\rho\right)^2\left(\lambda_d + \rho\right)^2}\mathrm{E}\left[\nu_{t-2}^2\right] \quad (3.5.35)
\end{aligned}
$$

Equation (3.5.35) shows that the variance of rational arbitrage demand is increasing in α^2, ϕ^2, and $\alpha\phi$.

If $\sigma_{\zeta,t}^2$ is constant over time, the variance of liquidity trade is

$$
\mathrm{Var}\left(z_t\right) =\frac{\sigma_{\zeta,t}^2}{1 - \phi^2} \tag{3.5.36}
$$

Equation (3.5.36) shows that the variance of liquidity trade is increasing in ϕ^2.

Since the informed investor and the rational arbitrageurs trade against each other more as α^2 increases, and the informed investor and the rational arbitrageurs trade against the liquidity trader more as ϕ^2 increases, total trading volume is increasing in α^2, ϕ^2, and $\alpha\phi$. In summary, trading volume is increasing in α^2, ϕ^2, and $\alpha\phi$.

3.6. Predictability of returns in a sequential Kyle (1985) model with transaction costs

3.6.1. Setup

The following model extends the sequential auction model in Kyle (1985) to allow for transaction costs. The objective of this section is to demonstrate that a Kyle (1985) model with long-lived information and transaction costs cannot give rise to momentum in returns.

I assume that the risky asset has terminal value $\tilde{V} \sim \mathcal{N}\left(0, \sigma_0^2\right)$. Trading occurs in rounds $t = 1, 2$. At the end of $t = 2$, the risky asset liquidates. The liquidity trader in each period t submits a random market order $\tilde{z}_t \sim \mathcal{N}\left(0, \sigma_z^2\right)$ where z_1 and z_2 are independently distributed. The informed investor knows V, and demands x_t shares in round $t = 1, 2$ to maximize expected profits over the

remaining rounds of trade.

The market maker sets price in $t = 1, 2$ by

$$P_1 = \mathrm{E}\left[\tilde{V}|D_1\right] + \rho D_1 \tag{3.6.1}$$

$$P_2 = \mathrm{E}\left[\tilde{V}|D_1, D_2\right] + \rho D_2 \tag{3.6.2}$$

where $D_t = x_t + z_t$ and $\rho \geq 0$. Within the context of the present model, the set of public information comprises the history of order flow.

3.6.2. Equilibrium characterization

I focus on recursive equilibria, which are equilibria in which price and informed demand are of the following linear forms. Price satisfies

$$P_1 = \lambda_{0,1} + \lambda_{d,1} D_1 + \rho D_1 \tag{3.6.3}$$

$$P_2 = \lambda_{0,2}\mathrm{E}\left[\tilde{V}|D_1\right] + \lambda_{d,2} D_2 + \rho D_2 \tag{3.6.4}$$

Informed demand satisfies

$$x_1 = \kappa_{0,1} + \kappa_{V,1} V \tag{3.6.5}$$

$$x_2 = \kappa_{0,2}\mathrm{E}\left[\tilde{V}|D_1\right] + \kappa_{V,2} V \tag{3.6.6}$$

In $t = 2$, the informed investor chooses x_2 by

$$\max_{x_2} \left\{ \mathrm{E}\left[x_2\left(V - \mathrm{E}\left[\tilde{P}_2|D_1, x_2\right]\right)\right] \right\} \tag{3.6.7}$$

$$= \max_{x_2} \left\{ x_2\left(V - \left(\left(\lambda_{d,2} + \rho\right) x_2 + \lambda_{0,2}\mathrm{E}\left[\tilde{V}|D_1\right]\right)\right) \right\}$$

$$\Rightarrow 0 = V - \left(2\left(\lambda_{d,2} + \rho\right) x_2 + \lambda_{0,2}\mathrm{E}\left[\tilde{V}|D_1\right]\right)$$

$$\Rightarrow x_2 = \frac{1}{2\left(\lambda_{d,2} + \rho\right)}\left(V - \lambda_{0,2}\mathrm{E}\left[\tilde{V}|D_1\right]\right) \tag{3.6.8}$$

Anticipating his demand in $t = 2$, the informed investor chooses x_1 by

$$\max_{x_1} \left\{ x_1 \left(V - \mathrm{E}\left[\tilde{P}_1 | x_1 \right] \right) + \mathrm{E}\left[x_2 \left(V - \tilde{P}_2 \right) | x_1 \right] \right\} \qquad (3.6.9)$$

$$= \max_{x_1} \Bigg\{ x_1 \left(V - \lambda_{0,1} - \left(\lambda_{d,1} + \rho \right) x_1 \right)$$

$$+ \frac{1}{4 \left(\lambda_{d,2} + \rho \right)} \left(V - \lambda_{0,2} \left(\lambda_{0,1} + \lambda_{d,1} x_1 \right) \right)^2 \Bigg\}$$

$$\Rightarrow 0 = V - \lambda_{0,1} - 2 \left(\lambda_{d,1} + \rho \right) x_1 + \frac{-\lambda_{0,2} \lambda_{d,1}}{2 \left(\lambda_{d,2} + \rho \right)} \left(V - \lambda_{0,2} \left(\lambda_{0,1} + \lambda_{d,1} x_1 \right) \right)$$

$$\Rightarrow x_1 = - \frac{2 \left(\lambda_{d,2} + \rho \right) - \lambda_{0,2}^2 \lambda_{d,1}}{4 \left(\lambda_{d,2} + \rho \right) \left(\lambda_{d,1} + \rho \right) - \lambda_{0,2}^2 \lambda_{d,1}^2} \lambda_{0,1} + \frac{2 \left(\lambda_{d,2} + \rho \right) - \lambda_{0,2} \lambda_{d,1}}{4 \left(\lambda_{d,2} + \rho \right) \left(\lambda_{d,1} + \rho \right) - \lambda_{0,2}^2 \lambda_{d,1}^2} V \qquad (3.6.10)$$

It follows that, in any recursive equilibrium, the coefficients of the informed demand functions must satisfy:

$$\kappa_{0,2} = \kappa_{V,2} = \frac{1}{2 \left(\lambda_{d,2} + \rho \right)} \qquad (3.6.11)$$

$$\kappa_{V,1} = \frac{2 \left(\lambda_{d,2} + \rho \right) - \lambda_{0,2} \lambda_{d,1}}{4 \left(\lambda_{d,2} + \rho \right) \left(\lambda_{d,1} + \rho \right) - \lambda_{0,2}^2 \lambda_{d,1}^2} \qquad (3.6.12)$$

$$\kappa_{0,1} = - \frac{2 \left(\lambda_{d,2} + \rho \right) - \lambda_{0,2}^2 \lambda_{d,1}}{4 \left(\lambda_{d,2} + \rho \right) \left(\lambda_{d,1} + \rho \right) - \lambda_{0,2}^2 \lambda_{d,1}^2} \lambda_{0,1} \qquad (3.6.13)$$

Let $\sigma_1^2 \equiv \mathrm{Var}\left(\tilde{V} - \mathrm{E}\left[\tilde{V} | D_1 \right] \right)$.

The market maker sets the market clearing price in $t = 2$ to satisfy

$$P_2 = \mathrm{E}\left[\tilde{V} | D_2, D_1 \right] + \rho D_2$$

$$= \frac{\kappa_{V,2} \sigma_1^2}{\kappa_{V,2}^2 \sigma_1^2 + \sigma_z^2} \left(D_2 - \mathrm{E}\left[\tilde{D}_2 | D_1 \right] \right) + \mathrm{E}\left[\tilde{V} | D_1 \right] + \rho D_2 \qquad (3.6.14)$$

The market maker sets the market clearing price in $t = 1$ to satisfy

$$P_1 = \mathrm{E}\left[\tilde{V} | D_1 \right] + \rho D_2$$

$$= \frac{\kappa_{V,1} \sigma_0^2}{\kappa_{V,1}^2 \sigma_0^2 + \sigma_z^2} D_1 + \rho D_1 \qquad (3.6.15)$$

It follows that, in any recursive equilibrium, the coefficients of the market maker's pricing functions must satisfy:

$$\lambda_{d,2} = \frac{\kappa_{V,2}\sigma_1^2}{\kappa_{V,2}^2\sigma_1^2 + \sigma_z^2} \tag{3.6.16}$$

$$\lambda_{0,2} = 1 \tag{3.6.17}$$

$$\lambda_{d,1} = \frac{\kappa_{V,1}\sigma_0^2}{\kappa_{V,1}^2\sigma_0^2 + \sigma_z^2} \tag{3.6.18}$$

$$\lambda_{0,1} = 0 \tag{3.6.19}$$

The unique equilibrium satisfies:

$$\lambda_{d,2} = \frac{\left(\frac{1}{2(\lambda_{d,2}+\rho)}\right)\sigma_1^2}{\left(\frac{1}{2(\lambda_{d,2}+\rho)}\right)^2\sigma_1^2 + \sigma_z^2}$$

$$\Rightarrow 0 = \lambda_{d,2}^3 + 2\rho\lambda_{d,2}^2 + \left(\rho^2 - \frac{\sigma_1^2}{4\sigma_z^2}\right)\lambda_{d,2} - \frac{\sigma_1^2}{2\sigma_z^2}\rho \tag{3.6.20}$$

As before, this polynomial has one real root for $\lambda_{d,2}$ in which $\lambda_{d,2} \geq -\rho$ and $\lambda_{d,2} > 0$.

$$\lambda_{d,1} = \frac{\left(\frac{2(\lambda_{d,2}+\rho)-\lambda_{0,2}\lambda_{d,1}}{4(\lambda_{d,2}+\rho)(\lambda_{d,1}+\rho)-\lambda_{0,2}^2\lambda_{d,1}^2}\right)\sigma_0^2}{\left(\frac{2(\lambda_{d,2}+\rho)-\lambda_{0,2}\lambda_{d,1}}{4(\lambda_{d,2}+\rho)(\lambda_{d,1}+\rho)-\lambda_{0,2}^2\lambda_{d,1}^2}\right)^2\sigma_0^2 + \sigma_z^2}$$

$$= \frac{\left(\frac{1}{2(\lambda_{d,1}+\rho)}\right)\sigma_0^2}{\left(\frac{1}{2(\lambda_{d,1}+\rho)}\right)^2\sigma_0^2 + \sigma_z^2} \tag{3.6.21}$$

$$0 = \lambda_{d,1}^3 + 2\rho\lambda_{d,1}^2 + \left(\rho^2 - \frac{\sigma_0^2}{4\sigma_z^2}\right)\lambda_{d,1} - \frac{\sigma_0^2}{2\sigma_z^2}\rho \tag{3.6.22}$$

The right hand side of this polynomial is increasing in $\lambda_{d,1}$. Also, $\lambda_{d,1} > 0$ to satisfy this equation. Thus, this polynomial has one real root for $\lambda_{d,1}$ in which $\lambda_{d,1} \geq -\rho$ and $\lambda_{d,1} > 0$.

Given this strategy, informed demand in $t = 1$ and $t = 2$ is

$$x_1 = \frac{1}{2(\lambda_{d,1}+\rho)}V \tag{3.6.23}$$

and

$$x_2 = \frac{1}{2(\lambda_{d,2}+\rho)}\left(V - \mathrm{E}\left[\tilde{V}|D_1\right]\right) \tag{3.6.24}$$

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The variance of the value of the risky asset, conditional on demand in the first period is

$$
\begin{aligned}
\sigma_1^2 &= \mathrm{Var}\left(\tilde{V} - \mathrm{E}\left[\tilde{V}|D_1\right]\right) \\
&= \frac{(\lambda_{d,1} + 2\rho)^2}{4\left(\lambda_{d,1} + \rho\right)^2}\sigma_0^2 + \lambda_{d,1}^2\sigma_z^2
\end{aligned}
\tag{3.6.25}
$$

3.6.3. Equilibrium summary

The market maker sets price using the strategy

$$
P_1 = \left(\lambda_{d,1} + \rho\right)D_1
\tag{3.6.26}
$$

$$
P_2 = \left(\lambda_{d,2} + \rho\right)D_2 + \mathrm{E}\left[\tilde{V}|D_1\right] = \left(\lambda_{d,2} + \rho\right)D_2 + \lambda_{d,1}D_1
\tag{3.6.27}
$$

where $\lambda_{d,1}$ and $\lambda_{d,2}$ satisfy Equations (3.6.20) and (3.6.22).

The informed investor chooses his demand according to:

$$
x_1 = \frac{2\left(\lambda_{d,2} + \rho\right) - \lambda_{d,1}}{4\left(\lambda_{d,2} + \rho\right)\left(\lambda_{d,1} + \rho\right) - \lambda_{d,1}^2}V
\tag{3.6.28}
$$

$$
x_2 = \frac{1}{2\left(\lambda_{d,2} + \rho\right)}\left(V - \mathrm{E}\left[\tilde{V}|D_1\right]\right)
\tag{3.6.29}
$$

3.6.4. Properties of price changes

I demonstrate that $\mathrm{E}\left[P_2 - P_1|P_1\right] \propto -P_1$ when $\rho > 0$ and $\frac{\partial}{\partial\rho}\mathrm{E}\left[P_2 - P_1|P_1\right] \propto -P_1$. Since the informed investor is assumed to be Bayesian, his demand in each round of trade reflects the remaining information asymmetry between him and the market maker. The informed investor's linear demand functions can be summarized as:

$$
x_1 = \kappa_{V,1}V
\tag{3.6.30}
$$

$$
x_2 = \kappa_{V,2}\left(V - \mathrm{E}\left[\tilde{V}|D_1\right]\right)
\tag{3.6.31}
$$

From the market maker's perspective $\mathrm{E}\left[\tilde{x}_2|D_1\right] = \mathrm{E}\left[\kappa_{V,2}\left(\tilde{V} - \mathrm{E}\left[\tilde{V}|D_1\right]\right)|D_1\right] = 0$, and $\mathrm{E}\left[\tilde{z}_2\right] = 0$,

so $\mathrm{E}\left[\tilde{D}_2 | D_1\right] = 0$. Given the market maker's pricing functions,

$$P_2 - P_1 = -\rho D_1 + (\lambda_{d,2} + \rho) D_2 \qquad (3.6.32)$$

$$\Rightarrow \mathrm{E}\left[P_2 - P_1 | P_1\right] = \mathrm{E}\left[-\rho D_1 + (\lambda_{d,2} + \rho) D_2 | P_1\right] = -\frac{\rho}{\lambda_{d,1} + \rho} P_1 \qquad (3.6.33)$$

and

$$\frac{\partial}{\partial \rho} \mathrm{E}\left[P_2 - P_1 | P_1\right] = -\frac{\lambda_{d,1}}{(\lambda_{d,1} + \rho)^2} P_1 \qquad (3.6.34)$$

Thus, a sequential auction Kyle (1985) model with transaction costs predicts mean reversion in returns and cannot give rise to momentum.

CHAPTER 4 : Cross-sectional studies

The prior chapter presents a firm-quarter measure of investors' misweighting of redundant information, α, that is estimable distinctly from information asymmetry and transaction costs. While I do not specify the utility function of the informed investor, one could be constructed such that the informed investor faces private information processing frictions to minimizing $|\alpha|$ or receives private, non-monetary utility from having $\alpha \neq 0$. In this chapter, I explore whether investors' misweighting of redundant information is associated with information processing frictions or behavioral biases (i.e., private, non-monetary benefit from having $\alpha \neq 0$).

The misweighting of information might reflect an information processing friction in which the investor does not know the distribution from which his private signals are drawn or does not know his own information processing ability. This meta-level of information friction has been described as "structural uncertainty" by Brav and Heaton (2002), "parameter uncertainy" by Pastor and Veronesi (2009), and "endogenous learning" by Xiong (2013). The two-armed bandit theory in Rothschild (1974) illustrates the friction to information processing. A gambler can play two slot machines and does not know the probability of a payout on either machine. The gambler will experiment by playing the two machines until he assesses that the probability of a payout on one machine exceeds that of the other. At this point, the gambler ceases playing the other slot machine forever and never will learn the true probability of payout of that machine. That is, the gambler learns precise knowledge of the distribution parameters for a subset of available gambles and only imprecise knowledge of the distribution parameters for the remaining ones. In the present context, an investor might not know precisely which components of his private signals are redundant information and which are genuinely novel and exclusive information. Making this distinction might require additional time, effort, or other costs. If distinguishing the redundant information component from the private information component is sufficiently costly, an informed investor's optimal strategy might be to act on a private signal as if the entire signal had more private information content than the signal truly had.

On the other hand, investors might learn about structural parameters or their information processing ability in a biased way if doing so provided some incremental, non-monetary utility. Gervais and Odean (2001) consider an environment in which an investor does not know his information processing ability initially. Rather, he infers his information processing ability from his accuracy in forecasting a firm's dividends. The investor exhibits self-attribution by attributing accurate forecasts to his own

ability and inaccurate forecasts to bad luck. Over time, the investor develops an exaggerated belief of his information precision. In the present context, an investor vulnerable to self-attribution bias might learn about the novelty and exclusivity of his private signals in an upwardly biased manner.

Structural uncertainty and behavioral biases are not mutually exclusive explanations for investors' misprocessing of information. Brav and Heaton (2002) argue that if behavioral biases initially induce predictable returns, structural uncertainty about the magnitude of these biases is likely to impede rational arbitrageurs' exploitation of any mispricing. Arbitrageurs' uncertainty over the extent of other investors' behavioral biases acts as a friction to arbitrage unto itself. Consequently, structural uncertainty can facilitate the survival of behavioral biases.

To assess the association between investors' misweighting of redundant information, information processing frictions, and behavioral biases, I examine cross-sectional variation in the estimated parameters for informed investors' misweighting of redundant information. I explore the covariation between investors' misweighting of redundant information and the following investor and information environment characteristics:

First, I re-estimate the measure of investors' misweighting of redundant information when investors have more time to process information. In particular, I modify the analytical model from Chapter 3 to allow for price changes when stock exchanges are closed (i.e., overnight price changes). Using this structural model, I estimate the extent to which investors misweight information revealed during the prior trading day. If investors' misweighting of redundant information is associated with information processing frictions, investors should misweight redundant information less when they have more time to process information. If investors' misweighting of redundant information is associated with behavioral biases, investors should misweight redundant information similarly regardless of how much time they have to process information.

Second, I consider how investors' misweighting of redundant information varies with price informativeness. If investors' misweighting of redundant information is associated with information processing frictions, this misweighting should be lower when prices are more informative. If investors' misweighting of redundant information is associated with behavioral biases, this misweighting should not vary with price informativeness. Diamond and Verrecchia (1987) show that stock prices are less informative when short sales are restricted. As a proxy for exogenous variation in stock price informativeness, I use the Regulation SHO uptick exemption pilot study.

Third, I consider whether investors' misweighting of redundant information is consistent with self-attribution bias. Gervais and Odean (2001) argue that investors overestimate their information processing ability more after experiencing positive portfolio returns. If investors' misweighting of redundant information is associated with self-attribution bias, this misweighting should be greater after investors experience positive portfolio returns. If investors' misweighting of redundant information is associated with information processing frictions, this misweighting should not be correlated with the direction of past portfolio returns. I present two studies. First, since most investors have positive exposure to the market portfolio, I assess the correlation between past stock price returns and changes in the estimated misweighting of redundant information. A positive association would be consistent with self-attribution bias. Second, I assess the correlation between institutional investors' past portfolio returns and changes in the average misweighting of redundant information in their portfolios. Again, a positive association would be consistent with self-attribution bias.

Fourth, I study how investors' misweighting of redundant information varies with institutional investors' information gathering and processing capacities. I study the association between the average misweighting of redundant information in institutional investors' portfolios and these investors' subsequent returns. Investors who gather and process information more should earn above average returns (Grossman and Stiglitz, 1980). If investors' misweighting of redundant information is associated with information processing frictions, institutional investors should earn greater returns on holding investments in firms with greater misweighting of redundant information. If investors' misweighting of redundant information is associated with behavioral biases, institutional investors should not earn greater returns on holding investments in firms with greater misweighting of redundant information. Further, I identify institutional investors with greater information processing ability, following Bushee and Goodman (2007). If investors' misweighting of redundant information is associated with information processing frictions, institutional investors with greater information processing ability should earn above average returns on holding investments in firms with greater misweighting of redundant information. If investors' misweighting of redundant information is associated with behavioral biases, institutional investors with greater information processing ability should not earn above average returns on holding investments in firms with greater misweighting of redundant information.

Fifth, I consider how investors' misweighting of redundant information varies with the cost of gathering information. When investors' cost of obtaining information from an information intermediary is below their private cost of acquiring this information, many investors will gather this informa-

tion (Veldkamp, 2006). How many investors will gather this information, and how quickly, is likely to be uncertain. When investors can be more certain that other investors have not acquired the same private signals, they are less likely to overestimate the novelty and exclusivity of the signals. If investors' misweighting of redundant information is associated with information processing frictions, this misweighting is likely to be higher when investors' cost of obtaining information from an information intermediary is below their private cost of acquiring this information. If investors' misweighting of redundant information is associated with behavioral biases, this misweighting would not vary with the cost of acquiring the information. Veldkamp (2006) shows that competitive information intermediaries sell industry-wide information to investors at a low price because they have synergies in gathering industry-wide information and selling this information to a wide audience of investors. To examine how investors' misweighting of redundant information varies with the cost of gathering information, I study whether the estimated misweighting of redundant information varies at an industry-wide level, with the similarity of firms within an industry, and with the level of competition among analysts.

Evidence from these tests suggests that the misweighting of redundant information reflects an information processing friction. When investors can process information overnight, the mean and median estimated parameter for the misweighting of redundant information are approximately zero. When short sale constraints are lessened and stock prices are more informative, the estimated parameter for the misweighting of redundant information appears lower. Investors' misweighting of redundant information is not consistently higher after a stock experiences positive returns and institutional investors do not appear to acquire positions in firms with greater misweighting of redundant information after experiencing positive portfolio returns. Rather, institutional investors appear to earn higher returns as their exposure to the misweighting of redundant information increases. Sophisticated institutional investors – large institutions, blockholders, and transient investors – outperform other institutional investors increasingly with their exposure to the misweighting of redundant information increases. The misweighting of redundant information covaries at an industry-wide level and increasingly so with the similarity of firms within an industry and the level of competition among analysts. These associations are consistent with an information processing friction explanation.

These findings complement prior accounting and finance literature on whether predictable patterns in stock prices and excessive (i.e., unprofitable) investor trading are associated with behavioral biases or information processing frictions. Chan, Frankel, and Kothari (2004) examine whether investors exhibit "representativeness" and "conservatism" biases. The authors find that seasonally-differenced

growth in sales, operating income, and net income are predictive of three-month to six-month returns, but these returns do not mean revert subsequently. The authors conclude that this evidence is not consistent with representativeness and conservatism biases because those biases would predict mean reversion in returns when the events about which investors' beliefs were miscalibrated realize. Statman, Thorley, and Vorkink (2006) and Griffin, Nardari, and Stulz (2007) find that trading volume in individual stocks increases after positive market returns, consistent with the predictions in Gervais and Odean (2001). Other studies have used proprietary data on investor attributes to identify proxies for cross-sectional variation in investors' misperception of their own information processing ability. Based on monthly statements for 78,000 households from a retail brokerage firm, Barber and Odean (2001) find that men trade more frequently than women do and earn lower profits by the differential in their total transaction costs due to this additional trading. Grinblatt and Keloharju (2009) combine Finnish records of individuals' equities trades, driving records, and the Finnish military's mandatory psychological tests and find that individuals who received more speeding tickets traded more frequently. Døskeland and Hvide (2011) study whether individual investors in Norway earn greater profits when investing in firms in the industry in which they work. The authors find that these investors do not earn excess profits from holdings in professionally close firms, but do trade in these firms' shares more often, which suggests an overestimation of the precision of their information. Overall, empirical evidence is mixed on whether predictable patterns in stock prices and excessive investor trading are associated behavioral biases.

An association between predictable in stock price returns and information processing frictions is documented in empirical tests of the functional fixation hypothesis — that investors with limited attention exaggerate the precision of easily accessible information in forming their beliefs about the value of risky assets (Watts and Zimmerman, 1986). Hand (1990) studies investors' response to firms' reporting of debt-equity swaps. He finds positive stock price responses to both the immediate announcement of the gain on the debt-equity swap and the repetition of this announcement in the subsequent earnings report, consistent with investors fixating on earnings announcements. Sloan (1996) finds abnormal returns associated with the reversal of abnormal accruals, and argues that investors fixate on earnings and underweight operating cash flows in forecasting future earnings. Green, Hand, and Zhang (2013) provide a meta-analysis of 330 publicly available accounting-based (e.g., abnormal accruals), finance-based (e.g., return momentum), and other (e.g., a stock's ticker symbol) signals. They document that the mean annualized return and Sharpe ratio of these signals were 12.1 percent and 1.04, whereas the CRSP U.S. equal-weighted (value-weighted) market

portfolio annualized return and Sharpe ratio were 9.5 percent and 0.50 (6.6 percent and 0.44) over the same time period. Further, the authors find that portfolios formed on these signals exhibit an average cross-correlation of 0.05, suggesting that an investor can reduce his portfolio volatility by combining these signals. Functional fixation studies often show that investors correct their information processing error at some future event, such as an earnings announcement, and predictable price changes appear as jumps around the event date. If price corrections occur gradually over time, price changes could exhibit momentum or mean reversion. In all, this empirical work suggests that predictable returns are related to information processing frictions. This chapter reinforces these findings.

4.1. Overnight price changes

4.1.1. Estimation

I modify the main analytical model to allow for stock price changes that occur when stock exchanges are closed (See Section 4.6). I refer to stock price changes when stock exchanges are closed as "overnight" price changes and stock price changes due to trading activity as "intraday" price changes. To simplify the analysis, I assume that liquidity trader demand does not exhibit serial correlation and there are zero rational arbitrageurs (i.e., $\phi = 0$ and $M = 0$). This version of the analytical model assumes that informed investors receive a private signal that contains information revealed during the prior trading day and investors might misweight this portion of the private signal.

This analytical model predicts that price changes exhibit the following moving average process. The random variable η_t denotes the price impact of unexpected demand in period t and w_t denotes overnight shocks to the value of the risky asset in period t. The parameter ψ denotes the ratio of transaction costs to information asymmetry and α denotes the extent of investors' misweighting of redundant information. Overnight price changes – labeled $P_t^O - P_{t-1}^C$ to indicate changes from the closing price on day $t-1$ to the opening price on day t – are predicted to follow the process:

$$P_t^O - P_{t-1}^C = -\frac{\psi}{1+\psi}\eta_{t-1} - \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+2\psi}\right)\eta_{t-2} + w_t \qquad (4.1.1)$$

Intraday price changes – labeled $P_t^C - P_t^O$ to indicate changes from the opening price to the closing

price on day t – follow the process:

$$P_t^C - P_t^O = \frac{\psi}{1 + \psi} \left(\frac{\alpha}{1 + 2\psi} \right) \eta_{t-1} + \eta_t \qquad (4.1.2)$$

I jointly estimate Equations (4.1.1) and (4.1.2) by maximum likelihood estimation. I assume that the error terms, $\epsilon_t \equiv \begin{bmatrix} w_t & \eta_t \end{bmatrix}'$, have the following joint distribution:

$$\epsilon_t \sim N \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, Q_t \right) \qquad (4.1.3)$$

where $Q_t = \begin{bmatrix} g_t & 0 \\ 0 & h_t \end{bmatrix}$,

$$g_t = \gamma_0 + \gamma_1 w_{t-1}^2 + \gamma_2 g_{t-1}^2 + \gamma_3 \eta_{t-1}^2 \qquad (4.1.4)$$

and

$$h_t = \beta_0 + \beta_1 \eta_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 w_t^2 \qquad (4.1.5)$$

Following Engle and Kroner (1995), the log-likelihood function for this ARMA-GARCH process is $L(\theta) = \sum_{t=3}^{N} L_t$, where

$$-2L_t = N \ln(2\pi) + \ln(\det(Q_t)) + \epsilon_t' Q_t^{-1} \epsilon_t \qquad (4.1.6)$$

and $\theta = \{\alpha, \psi, \beta_0, \beta_1, \beta_2, \beta_3, \gamma_0, \gamma_1, \gamma_2, \gamma_3\}$ and N is the number of observations. I constrain the estimate of ψ to be greater than zero. I also constrain the estimates of $\beta_1 + \beta_2$ and $\gamma_1 + \gamma_2$ to be less than or equal to one. To initialize the estimation, I set $\epsilon_1 = \epsilon_2 = 0$ and Q_3 equal to the variance of price changes over the sample period. I use non-linear optimization software to estimate the parameters (Nash, 2014). I choose 15 random starting values for each parameter, and from the 15 sets of optimized parameters I select the set of parameters with the highest log-likelihood value.

To carry out the structural estimation, I estimate the models above by firm-year. My sample comprises close-to-open and open-to-close stock price returns from the CRSP database from 2003 to 2014. I limit the sample to common shares (share codes 10 and 11). I further require that a firm-year has at least 120 trading days of data – approximately one half of a year – to be included in the sample.

The estimates were conducted for 51,533 firm-years. These firm-years estimations used a mean and median of 242 and 252 trading days. U.S. stock exchanges have approximately 252 trading days per year. Figure 21 plots the number of estimations and mean and median number of trading days used per estimation by calendar year.

4.1.2. Results

Table 8 shows the distribution of parameter estimates across the 51,533 estimated models: investors' misweighting of redundant information, α; the ratio of transaction costs to the information asymmetry of order flow, ψ; and, the coefficients of the variance processes. Figures 22 and 23 show histograms of the estimated α and ψ parameters. Figures 24 and 25 plot the time series of the estimated α and ψ parameters.

Estimated α parameters greater than zero suggest that investors treat redundant information as if it were private information, and estimated α parameters less than zero suggest that investors behave as if their private signals have more redundant information than the signals truly have. I find that the mean and median estimated α parameters are approximately 0.033 and 0.037. At these levels of α, informed investors on average correctly process the information that was revealed through trading during the prior day. Nevertheless, a substantial number of estimated α parameters differ from zero. At the 10 percent statistical significance level 12 percent of the estimated α parameters are less than zero and 16 percent of the estimated α parameters are greater than zero; at the 5 percent statistical significance level 8 percent of the estimated α parameters are less than zero and 11 percent of the estimated α parameters are greater than zero; and, at the 1 percent statistical significance level 4 percent of the estimated α are less than zero and 5 percent of the estimated α parameters are greater than zero. The 1st percentile of the estimated α parameters is -2.51 and the 99th percentile of the estimated α parameters is 2.52. These results also suggest that investors overweight redundant information from the prior trading day as often and as much as they underweight redundant information from the prior trading day.

The estimates of the parameter representing the ratio of transaction costs to Kyle's lambda, ψ, have a mean and median of 0.16 and 0.13. At these levels, approximately 12 to 14 percent of the price impact of trades is temporary and lacks information content. Approximately 81 percent of the estimated ψ parameters are less than 0.25, suggesting that, in general, less than one-fifth of the price impact of trades is temporary. As compared to the null hypothesis that $\psi = 0$, approximately 54

percent of the estimated ψ parameters are greater than zero at the 10 percent statistical significance level, 41 percent of the estimated ψ parameters are greater than zero at the 5 percent statistical significance level, and 18 percent of the estimated ψ parameters are greater than zero at the 1 percent statistical significance level. These estimates of the ratio of the temporary portion to the permanent portion of the price impact of trades are consistent with Frazzini, Israel, and Moskowitz (2012). They find that approximately 30 percent of the price impact of trades reverts within 24 hours and the majority of the reversion in price impact appears to occur through overnight price changes.

At these levels of α and ψ, stock price changes tend to exhibit mean reversion in overnight returns. Since the mean and median estimated α parameters are close to zero, the first order moving average term in the model for overnight returns, $-\psi/(1+\psi)$, tends to be greater in magnitude than the second order moving average term in the model for overnight returns, $-\alpha\psi/((1+\psi)(1+2\psi))$. The 5th percentile of the moving average term in the model for intraday returns (the negative of the second order moving average term in the model for overnight returns) is -0.116 and the 95th percentile of this estimated coefficient is 0.105. These results suggest that a 1 percent stock price change in an intraday period is associated with a -11.6 basis point return to 10.5 basis point return in the subsequent intraday period 90 percent of the time.

The estimated coefficients of the variance updating process show that the variance of returns fluctuates over time, as well as mean-reverts. The auto-regressive term in the intraday GARCH structure, β_1, exhibits a mean of 0.163 and median of 0.135, which suggests that a one-standard deviation stock price change is associated with a 37 to 40 percent increase in the variance of returns in the subsequent intraday period. The term β_3 measures how changes in the variance of returns in the intraday period are associated with prior overnight price changes. This parameter exhibits a mean of 0.168 and median of 0.136, which suggests that a one-standard deviation stock price change overnight is associated with a 37 to 41 percent increase in the variance of returns in the subsequent intraday period. The moving average term in the intraday returns GARCH structure, β_2, exhibits a mean of 0.119 and median of 0.103, which suggests that changes in the variance of intraday returns mean-revert. At the mean estimates of β_1, β_2, and β_3 changes in variance of intraday returns have a half-life of approximately 0.9 intraday periods.[1] At the mean and median levels of β_0, the annualized stock price volatility of intraday returns is approximately 45 percent and 16 percent per year.

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[1] The half life of changes in the variance of intraday returns is $\ln(0.5)/\ln(\beta_1+\beta_2+\beta_3)$ and the half life of changes in the variance of overnight returns is $\ln(0.5)/\ln(\gamma_1+\gamma_2+\gamma_3)$ in this GARCH specification.

The auto-regressive term in the overnight GARCH structure, γ_1, exhibits a mean of 0.167 and median of 0.136, which suggests that a one-standard deviation stock price change overnight is associated with a 37 to 41 percent increase in the variance of returns in the subsequent night. The term γ_3 measures how changes in the variance of returns in the overnight period are associated with prior intraday price changes. This parameter exhibits a mean of 0.207 and median of 0.186, which suggests that a one-standard deviation stock price change overnight is associated with a 43 to 45 percent increase in the variance of returns in the subsequent intraday period. The moving average term in the intraday returns GARCH structure, γ_2, exhibits a mean of 0.119 and median of 0.099, which suggests that changes in the variance of overnight returns mean-revert. At the mean estimates of γ_1, γ_2, and γ_3 changes in variance have a half-life of approximately 1.0 overnight periods. At the mean and median levels of γ_0, the annualized stock price volatility of overnight returns is approximately 60 percent and 30 percent per year.

To assess goodness of fit, I consider the likelihood ratio statistic of these estimations. The likelihood ratio statistic jointly tests the statistical significance of the estimated parameters against the parameters under the null hypothesis. As the null hypothesis parameters, I restrict $\alpha = 0$, $\psi = 0$, and the variance of stock price changes to be homoscedastic. I find that approximately 79 percent of the estimations have likelihood ratio statistics that are statistically significant at the 1 percent level and 82 percent of the estimations have likelihood ratio statistics that are statistically significant at the 10 percent level.

4.1.3. Discussion

On average informed investors appear to correctly process the redundant information that was revealed during the prior trading day. Nevertheless, informed investors appear to misweight redundant information a substantial fraction of the time.

As compared to the parameters for investors' misweighting of redundant information estimated on intraday returns only, informed investors appear to overweight redundant information in sequential days' returns substantially less. This result suggests that, when given more time to process information, informed investors on average can distinguish what information has already been reflected in stock prices from what information is genuinely exclusive and novel. In all, these results suggest that informed investors' misuse of the redundant information in intraday returns reflects an information processing friction, rather than a behavioral bias.

Table 8: Estimated parameters of overnight structural model

The following table shows descriptive statistics for the estimated parameters of the following structural model. Overnight price changes are predicted to follow the process

$$P_t^O - P_{t-1}^C = -\frac{\psi}{1+\psi}\eta_{t-1} - \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+2\psi}\right)\eta_{t-2} + w_t$$

and intraday price changes are predicted to follow the process

$$P_t^C - P_t^O = \eta_t + \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+2\psi}\right)\eta_{t-1}$$

where $P_t^O - P_{t-1}^C$ is the price change from the closing price on day $t-1$ to the opening price on day t, $P_t^C - P_t^O$ is the price change from the opening price to the closing price on day t, ψ is the ratio of trading costs to information asymmetry, and α is the extent to which informed investors misweight information that is already priced ("redundant information"). The variances of error terms w_t and η_t are assumed to follow the joint GARCH processes $g_t = \gamma_0 + \gamma_1 w_{t-1}^2 + \gamma_2 g_{t-1}^2 + \gamma_3 \eta_{t-1}^2$ and $h_t = \beta_0 + \beta_1 \eta_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 w_t^2$. I estimate the parameter set $\theta = \{\alpha, \psi, \beta_0, \beta_1, \beta_2, \beta_3, \gamma_0, \gamma_1, \gamma_2, \gamma_3\}$ by maximum likelihood. Parameters are estimated by firm-year from 2003 through 2014. The overarching null hypothesis is $\alpha = 0$.

			Percentiles			
	Mean	St.Dev.	1st	Median	99th	Num.Obs.
Investors' misweighting of redundant information, α	0.033	0.620	-2.511	0.037	2.518	51,533
t-statistic ($H_0 : \alpha = 0$)	0.1	1.5	-4.9	0.0	4.7	51,533
Ratio of transaction costs to Kyle's lambda, ψ	0.163	0.111	0.028	0.129	0.569	51,533
t-statistic ($H_0 : \psi = 0$)	1.7	1.3	0.0	1.5	8.5	51,533
Estimated β_0	0.011	0.073	0.000	0.000	0.503	51,533
t-statistic ($H_0 : \beta_0 = 0$)	6.3	6.8	0.0	3.9	24.5	51,533
Estimated β_1	0.163	0.109	0.024	0.135	0.561	51,533
t-statistic ($H_0 : \beta_1 = 0$)	1.4	1.3	0.0	1.0	7.8	51,533
Estimated β_2	0.119	0.085	0.015	0.103	0.555	51,533
t-statistic ($H_0 : \beta_2 = 0$)	1.5	1.9	0.0	0.9	11.4	51,533
Estimated β_3	0.168	0.117	0.024	0.136	0.58	51,533
t-statistic ($H_0 : \beta_3 = 0$)	2.7	2.5	0.0	2.0	14.7	51,533
Estimated γ_0	0.012	0.078	0.000	0.000	0.551	51,533
t-statistic ($H_0 : \gamma_0 = 0$)	3.9	3.9	0.0	2.9	27.1	51,533
Estimated γ_1	0.167	0.112	0.025	0.136	0.562	51,533
t-statistic ($H_0 : \gamma_1 = 0$)	1.6	1.2	0.0	1.3	7.4	51,533
Estimated γ_2	0.119	0.086	0.015	0.099	0.552	51,533
t-statistic ($H_0 : \gamma_2 = 0$)	0.8	1.0	0.0	0.5	5.4	51,533
Estimated γ_3	0.207	0.124	0.029	0.186	0.602	51,533
t-statistic ($H_0 : \gamma_3 = 0$)	1.5	1.2	0.0	1.2	6.3	51,533

Figure 21: Sample size by calendar year
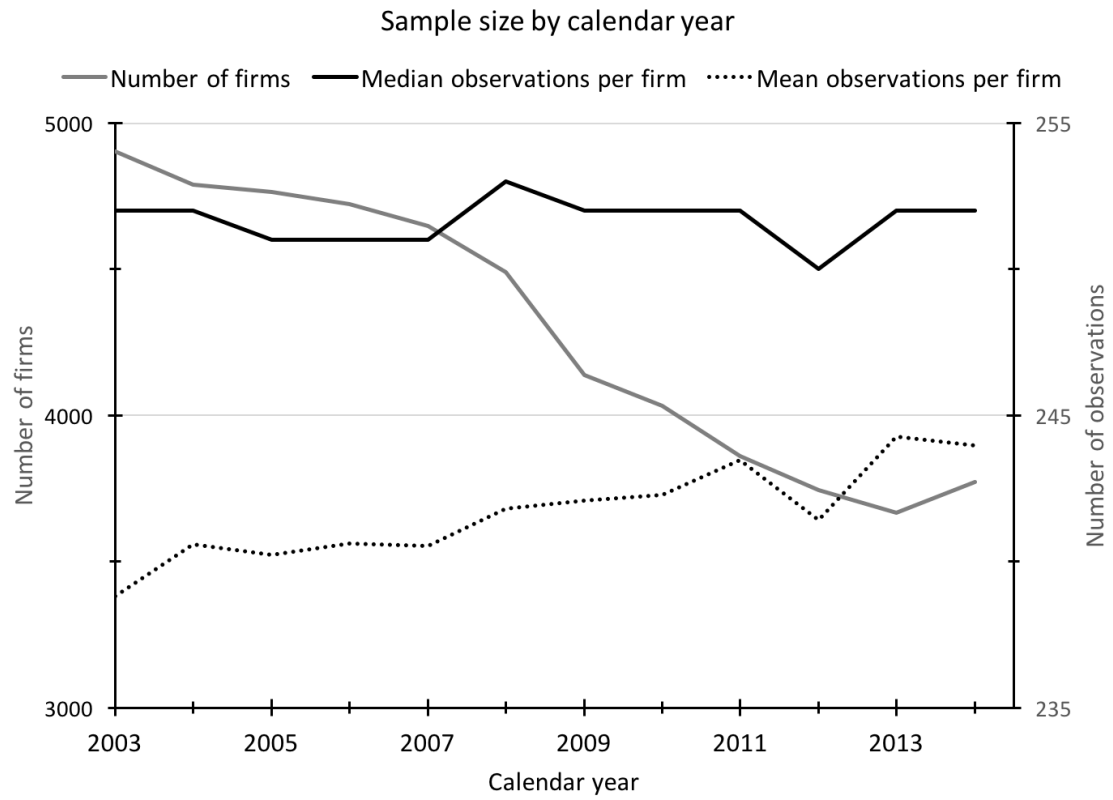
Figure 22: Histogram of estimated α parameters, investors' misweighting of redundant information

Histogram of estimated alpha parameters, investors' misweighting of redundant information
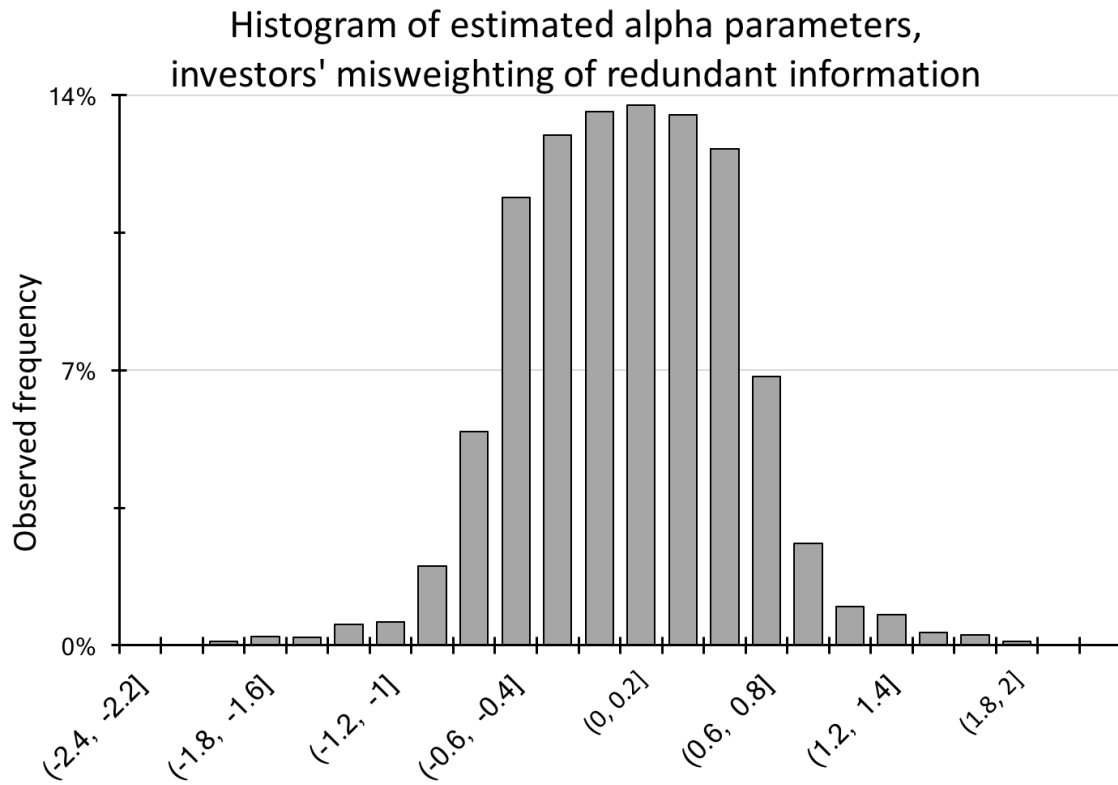
Figure 23: Histogram of estimated ψ parameters, the ratio of transaction costs to the Kyle's lambda

Figure 24: Times series of estimated α parameters, investors' misweighting of redundant information
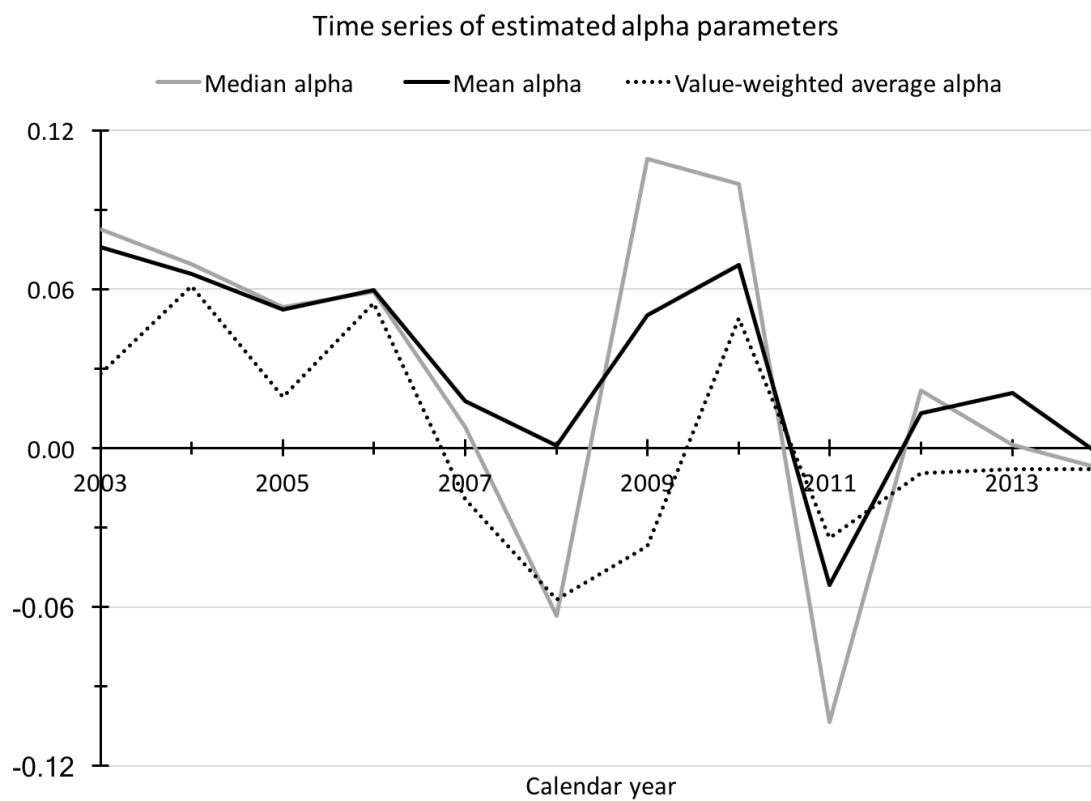
Figure 25: Time series of estimated ψ parameters, the ratio of transaction costs to the Kyle's lambda

Time series of estimated psi parameters

─── Median psi ━━━ Mean psi ⋯⋯ Value-weighted average psi
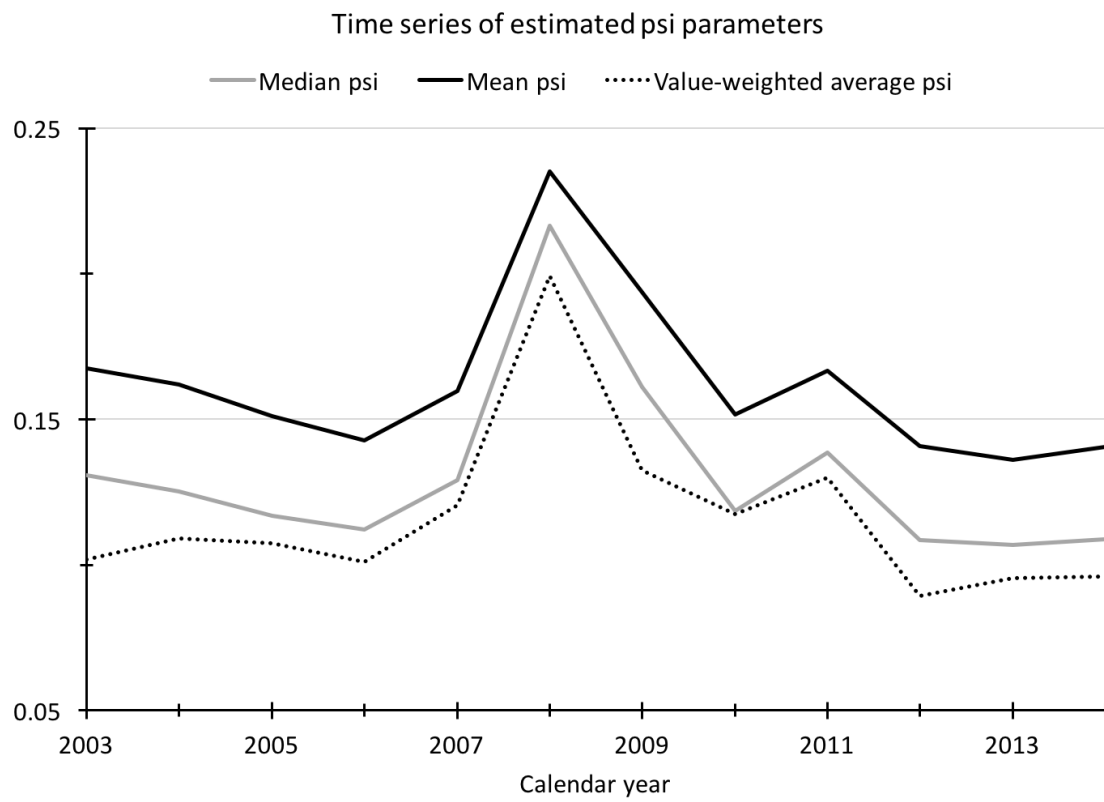
4.2. Price informativeness

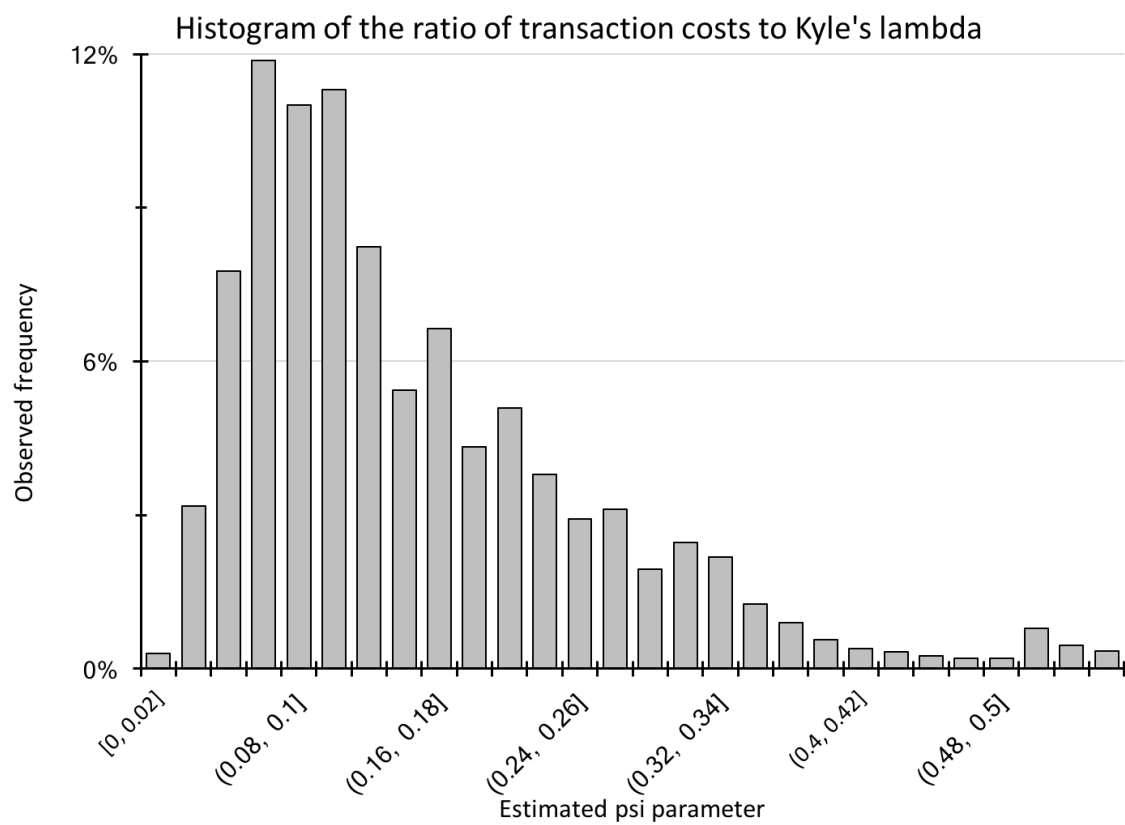If investors' misweighting of redundant information is associated with information processing frictions, rather than behavioral biases, this misweighting should be lower when investors can be more certain about how much information stock prices already contain. Investors might misinterpret or underestimate how much information stock prices already contain because making this assessment is a costly process. In other words, if investors' misweighting of redundant information is associated with information processing frictions, this misweighting should be lower when stock prices are more informative.

4.2.1. Research design

Under rational expectations, investors are aware that other investors have private information and might or might not have traded on this information. Investors who have private information might not trade on it immediately if frictions to arbitrage reduce their expected returns. As a result, frictions to arbitrage are likely to impede investors' ability to asses how much information stock prices already contain. Diamond and Verrecchia (1987) show that short sale restrictions are one friction to arbitrage that impedes stock price informativeness.

To examine the association between stock price informativeness and the estimated α parameters, I use the Regulation SHO uptick exemption pilot. Under the Securities Exchange Act of 1934 and until 2007, an investor could short sell a stock on a U.S. stock exchange only if the previous price change was positive, i.e., after an "uptick." Regulation SHO ordered a pilot study that suspended the uptick rule for a set of randomly chosen stocks from September 1, 2005 to June 30, 2007. This pilot study provides a natural experiment to examine the relationship between short sale constraints and the estimated α parameters. Following the argument in Diamond and Verrecchia (1987), I use the suspension of the uptick rule as a proxy for exogenous variation in stock price informativeness.

I use a difference-in-difference regression to assess whether the estimated α parameters were lower for firms subject to the uptick exemption pilot. Specifically, I estimate the following regression:

$$\alpha_{j,q} = b_0 + b_1 \left[Pilot_j \times PilotPeriod_q \right] + b_2 \left[Pilot_j \times Post_q \right] + \sum_j b_j + \sum_q b_q + \epsilon_{j,q}$$

$Pilot_j$ is an indicator variable that equals one if the firm was in the Regulation SHO uptick exemption pilot and zero otherwise. $PilotPeriod_q$ is an indicator variable that equals one if the estimation

period was between the third quarter of 2005 and second quarter of 2007 – during the Regulation SHO uptick exemption pilot period – and zero otherwise. $Post_q$ is an indicator variable that equals one if the estimation period was between the third quarter of 2007 and second quarter of 2008. I end the sample period at the second quarter of 2008 because the U.S. Securities and Exchange Commission banned short selling in 797 financial sector firms traded on major U.S. stock exchanges from September 19, 2008 to October 8, 2008.[2] The regressions include firm and calendar quarter fixed effects, denoted $\sum_j b_j$ and $\sum_q b_q$, respectively.

If $b_1 < 0$, that would suggest that investors' misweighting of redundant information is lower for firms subject to the uptick exemption pilot during the pilot period as compared to other firms during the same period and the same firms before the pilot period. If b_2 is indistinguishable from zero, that would suggest that investors' misweighting of redundant information is similar for firms subject to the uptick exemption pilot after the pilot period as compared to other firms during the same period and the same firms before the pilot period. In all, if $b_1 < 0$ and b_2 is indistinguishable from zero, that would suggest that investors' misweighting of redundant information is lower when stock prices are more informative.

4.2.2. Results

Table 9 shows the results. Using the α parameters estimated using five-minute returns, firms in the uptick exemption pilot exhibit 0.20 lower estimated α parameters during the pilot study period firms in the uptick exemption pilot as compared to the control group firms and the same firms in the before pilot period. After the pilot study ended, the difference in estimated α parameters appears to be negligible. Using the α parameters estimated using 30-minute returns, firms in the uptick exemption pilot exhibit 0.08 lower estimated α parameters during the pilot study period firms in the uptick exemption pilot as compared to the control group firms and the same firms in the before pilot period. Again, after the pilot study ended, the difference in estimated α parameters appears to be negligible. These results suggest that investors' misweighting of redundant information is lower when short sale constraints are lessened and stock prices are more informative.

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[2]The Regulation SHO uptick exemption pilot is a valid natural experiment because the firms subject to the pilot study were chosen randomly. The 2008 short sale ban is not a valid natural experiment because the firms subject to the ban were chosen according to characteristics that could also affect stock price informativeness.

4.2.3. Exhibits

Table 9: Stock price informativeness

This table describes the the association between investors' misweighting of redundant information, α, and stock price informativeness. $Pilot_j$ is an indicator variable that equals one if the firm was in the Regulation SHO uptick exemption pilot and zero otherwise. $PilotPeriod_q$ is an indicator variable that equals one if the estimation period was between the third quarter of 2005 and second quarter of 2007 – during the Regulation SHO uptick exemption pilot period – and zero otherwise. $Post_q$ is an indicator variable that equals one if the estimation period was between the third quarter of 2007 and second quarter of 2008. I end the sample period at the second quarter of 2008 to eliminate the short sale restrictions that occurred during 2008 financial crisis. Firm and calendar quarter fixed effects are included.
The data comprises firm-quarters from the first quarter of 2003 to the second quarter of 2008. Standard errors are clustered by firm and calendar quarter, and appear in parentheses beneath the estimated coefficients.

	Estimated on five-minute returns	Estimated on 30-minute returns
Dependent variable = $\alpha_{j,q}$	(I)	(II)
$Pilot_j \times PilotPeriod_q$	-0.204***	-0.082*
	(0.045)	(0.040)
$Pilot_j \times Post_q$	0.035	0.023
	(0.071)	(0.047)
Firm fixed effects	Yes	Yes
Calendar quarter fixed effects	Yes	Yes
R^2 (full)	0.185	0.140
R^2 (within)	0.001	0.000
Num. obs.	43,186	55,373

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

4.3. Self-attribution bias

Behavioral finance literature suggests that investors overweight private information signals because they overestimate their own information processing ability (See Daniel and Hirshleifer, 2015 for a review). Gervais and Odean (2001) present a model in which informed investors increasingly overestimate their own information processing ability over time because these investors learn about their ability in a biased manner. In updating their beliefs about their information processing ability, these investors update their beliefs excessively following accurate forecasts of a firm's dividends and dismiss their inaccurate forecasts as bad luck. As a result, they obtain updated beliefs about their ability that are upwardly biased. Gervais and Odean (2001) label this biased learning process as "self-serving attribution bias." Regarding empirical predictions, investors are most likely to exhibit this upwardly biased learning after experiencing positive positive portfolio returns. Since investors generally forecast positive returns and hold positive beta portfolios, investors are most likely to exhibit this upwardly biased learning after positive returns on a broad market index, industry, or firm.

Biased learning about one's information processing ability could lead investors to overestimate the novelty and exclusivity of their private signals and underestimate the extent to which the information in their private signals already has been priced. If investors' misweighting of redundant information is associated with self-attribution bias, this misweighting should be greater after investors experience positive portfolio returns. If investors' misweighting of redundant information is associated with information processing frictions, this misweighting should not be correlated with the direction of investors' past returns.

4.3.1. Research design

I use two approaches to examine the association between investors' misweighting of redundant information and lagged returns. First, on a firm-quarter level, I examine how changes in investors' misweighting of redundant information vary with contemporaneous and lagged quarterly returns on S&P 500 index, the outperformance of an industry as compared to the S&P 500 index, and the outperformance of a firm as compared to its industry. To measure industry returns, I use the Fama and French (1997) 30-industry classification. I estimate the following regression:

$$\Delta\alpha_{j,q} = b_0 + b_1 R_q^{S\&P} + b_2 R_{q-1}^{S\&P} + b_3 R_q^{Ind} + b_4 R_{q-1}^{Ind} + b_5 R_q^{Firm} + b_6 R_{q-1}^{Firm} + \epsilon_{j,q} \qquad (4.3.1)$$

where $\Delta\alpha_{j,q} = \alpha_{j,q} - \alpha_{j,q-1}$ is the change the estimated misweighting parameter for firm j from quarter $q - 1$ to q; $R_q^{S\&P}$ is the total return on the the the S&P 500 index in quarter q; R_q^{Ind} is the outperformance of a firm's industry as compared to the total return on the S&P 500 index in quarter q; and, R_q^{Firm} is the outperformance of a firm's stock price as compared to its industry in quarter q. If $b_2 > 0$, $b_4 > 0$, or $b_6 > 0$, that would be consistent with investors' misweighting of redundant information reflecting self-attribution bias.

Second, I examine how the average misweighting of redundant information among the holdings in institutional investors' portfolios covaries with these investors' past portfolio returns. If the portfolio manager of an investment fund is subject to self-attribution bias, he is likely to overestimate his information processing ability following positive portfolio returns. If so, institutional investors should exhibit changes in the average misweighting of redundant information among their holdings that covary positively with lagged portfolio returns.

Using Thomson-Reuters 13-F filings data and CRSP stock and index price data, I decompose changes in the net asset value of an institutional investor's portfolio into changes in the market value of its initial holdings and net inflows from investors. I further break down the changes in the market value of its initial holdings into market-wide returns, industry outperformance, and firm outperformance components.

I also measure changes in the average misweighting of redundant information among the holdings in an institutional investor's portfolio. That is, if firm j in quarter q exhibits misweighting of redundant information $\alpha_{j,q}$, I measure institutional investor i's average holdings in the misweighting of redundant information as $\bar{\alpha}_{i,q} = \sum_j w_{i,j,q}\alpha_{j,q}$, where $w_{i,j,q}$ is the weight of firm j in investor i's portfolio as of the end of quarter q.[3] I separate changes in the average misweighting of redundant information among an institutional investor's holdings into changes in the misweighting of redundant information among its existing holdings, labeled $\Delta\bar{\alpha}_{i,q}^{Organic}$, and changes in the investor's holdings,

---

[3] I calculate these weights among a fund's holdings for which the α parameters were estimated. In effect, I assume that the average misweighting of redundant information among the holdings in an institutional investor's portfolio for holdings for which the α parameters were not estimated equals that for holdings for which the α parameter were estimated.

labeled $\Delta\bar{\alpha}_{i,q}^{Trading}$.[4]

I estimate the following regressions:

$$
\begin{aligned}
\Delta\bar{\alpha}_{i,q}^{Trading} =& b_0 + b_1 R_q^{S\&P} + b_2 R_{q-1}^{S\&P} + b_3 R_{i,q}^{Ind} + b_4 R_{i,q-1}^{Ind} + b_5 R_{i,q}^{Firm} + b_6 R_{i,q-1}^{Firm} \\
& + b_5 NetInflow_{i,q} + b_6 NetInflow_{i,q-1}
\end{aligned}
\tag{4.3.2}
$$

$$
\begin{aligned}
\Delta\bar{\alpha}_{i,q}^{Organic} =& b_0 + b_1 R_q^{S\&P} + b_2 R_{q-1}^{S\&P} + b_3 R_{i,q}^{Ind} + b_4 R_{i,q-1}^{Ind} + b_5 R_{i,q}^{Firm} + b_6 R_{i,q-1}^{Firm} \\
& + b_5 NetInflow_{i,q} + b_6 NetInflow_{i,q-1}
\end{aligned}
\tag{4.3.3}
$$

where $\Delta\bar{\alpha}_{i,q}^{Trading}$ denotes changes in the average misweighting of redundant information in institutional investor i's portfolio due to changes in its holdings from quarter $q-1$ to q; $\Delta\bar{\alpha}_{i,q}^{Organic}$ denotes changes in the average misweighting of redundant information in institutional investor i's portfolio due to changes in α from quarter $q-1$ to q among its initial holdings; $R_q^{S\&P}$ is the total return on the the S&P 500 index in quarter q; $R_{i,q}^{Ind}$ is the return on institutional investor i's portfolio in quarter q due to the outperformance of the fund's industry exposure as compared to the return on the S&P 500 index; $R_{i,q}^{Firm}$ is the the return on institutional investor i's portfolio in quarter q due to firm-specific outperformance as compared to a firm's industry; and, $NetInflow_{i,q}$ is institutional investor i's net inflows from outside investors in quarter q. I normalize these variables to have means equal to zero and standard deviations equal to one.

If $b_2 > 0$, $b_4 > 0$, or $b_6 > 0$ in Equation (4.3.2), that would be consistent with investors' misweighting of redundant information reflecting self-attribution bias among institutional investors. If $b_2 > 0$, $b_4 > 0$, or $b_6 > 0$ in Equation (4.3.3), that would be consistent with investors' misweighting of redundant information reflecting self-attribution bias among non-institutional investors.

---

[4]That is,

$$
\begin{aligned}
\Delta\bar{\alpha}_{i,q} = \bar{\alpha}_{i,q} - \bar{\alpha}_{i,q-1} &= \sum_j w_{i,j,q}\alpha_{j,q} - \sum_j w_{i,j,q-1}\alpha_{j,q-1} \\
&= \sum_j w_{i,j,q}\alpha_{j,q} - \sum_j w_{i,j,q-1}\alpha_{j,q} + \sum_j w_{i,j,q-1}\alpha_{j,q} - \sum_j w_{i,j,q-1}\alpha_{j,q-1} \\
&= \sum_j \left(w_{i,j,q} - w_{i,j,q-1}\right)\alpha_{j,q} + \sum_j w_{i,j,q-1}\left(\alpha_{j,q} - \alpha_{j,q-1}\right)
\end{aligned}
$$

I define $\Delta\bar{\alpha}_{i,q}^{Organic} \equiv \sum_j w_{i,j,q-1}\left(\alpha_{j,q} - \alpha_{j,q-1}\right)$ and $\Delta\bar{\alpha}_{i,q}^{Trading} \equiv \sum_j \left(w_{i,j,q} - w_{i,j,q-1}\right)\alpha_{j,q}$.

4.3.2. Results

Table 10 shows the estimation of Equation (4.3.1). Using the α parameters estimated on five-minute returns, a one standard deviation return on the S&P 500 index is associated with a 0.29 standard deviation increase in firm-quarter α parameters contemporaneously. Using the α parameters estimated on 30-minute returns, a one standard deviation outperformance of a firm's industry as compared to the S&P 500 index is associated with a 0.06 standard deviation increase in firm-quarter α parameters contemporaneously. A one standard deviation outperformance of a firm as compared its industry is associated with a 0.04 standard deviation increase in firm-quarter α parameters contemporaneously and a 0.04 standard deviation increase in firm-quarter α parameters in the subsequent quarter. This relationship between between changes in the α parameters and lagged returns is consistent with the α parameters reflecting self-attribution bias. These results do not change materially after controlling for calendar quarter fixed effects.

Table 11 show descriptive statistics for the measures of institutional investors' portfolio returns and changes in the average misweighting of redundant information among the holdings in institutional investors' portfolios. The mean and median change in the average misweighting of redundant information in institutional investors' portfolios are close to zero, based on the parameters estimated using five-minute returns and those estimated using 30-minute returns. Changes in the average misweighting of redundant information in institutional investors' portfolios due to changes in holdings and those due to changes in α also exhibit means and medians close to zero. Changes in the average misweighting of redundant information in institutional investors' portfolios due to changes in holdings exhibit lower variation than those due to changes in α. This result might suggest that variation in the average misweighting of redundant information in institutional investors' portfolios is largely attributable to misweighting by non-institutional investors.

Table 12 shows the estimation of Equation (4.3.2). Using the α parameters estimated on five-minute returns, a one standard deviation return on the S&P 500 index is associated with a 0.32 standard deviation increase in the average misweighting of redundant information in an institutional investor's portfolio due to changes in its holdings contemporaneously. Using the α parameters estimated on 30-minute returns, a one standard deviation industry outperformance is associated with a 0.12 standard deviation increase in the average misweighting of redundant information in an institutional investor's portfolio due to changes in its holdings contemporaneously. These associations are not statistically significant after controlling for calendar quarter fixed effects. These contemporaneous relationships

between returns and an institutional investor's changes in the average misweighting of redundant information in its portfolio are not consistent with the α parameters reflecting self-attribution bias.

Table 13 shows the estimation of Equation (4.3.3). Using the α parameters estimated on five-minute returns, a one standard deviation return on an institutional investor's portfolio due to industry outperformance is associated with a 0.02 standard deviation decrease in the average misweighting of redundant information in an institutional investor's portfolio in the subsequent quarter. A one standard deviation return on an institutional investor's portfolio due to firm-specific outperformance is associated with a 0.03 standard deviation increase in the average misweighting of redundant information in an institutional investor's portfolio contemporaneously. Similar results appear after controlling for calendar quarter fixed effects and using the α parameters estimated on 30-minute returns. These relationships between returns and changes in the average misweighting of redundant information in an institutional investor's portfolio are not consistent with the α parameters reflecting self-attribution bias.

Overall, this evidence is not consistent with the estimated α parameters reflecting self-attribution bias. In only one regression specification do the estimated α parameters increase with lagged returns. Further, in one regression specification, the estimated α parameters decrease with lagged returns. This mixed evidence is not consistent with investors increasingly overestimating the novelty and exclusivity of their private signals after experiencing positive portfolio returns.

Table 10: Self-attribution bias in individual stocks

This table assesses the association between investors' misweighting of redundant information and lagged stock price returns. Gervais and Odean (2001) posit that investors are vulnerable to self-attribution bias and overestimate the precision of their private signals more after experiencing positive market returns, industry outperformance, and firm outperformance.

The dependent variable is the change in the estimated parameter for investors' misweighting of redundant information for firm j from quarter $q-1$ to q, $\Delta\alpha_{j,q} = \alpha_{j,q} - \alpha_{j,q-1}$. $R_q^{S\&P}$ and $R_{q-1}^{S\&P}$ are the contemporaneous and lagged quarterly return on the S&P 500 index. R_q^{Ind} and R_{q-1}^{Ind} are the contemporaneous and lagged outperformance of a firm's industry as compared to the S&P 500 index. R_q^{Firm} and R_{q-1}^{Firm} are the contemporaneous and lagged outperformance of a firm as compared to its industry.

The data comprises firm-quarters from 2003 to 2014. Standard errors are clustered by firm and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Dependent variable = $\Delta\alpha_{j,q}$	Predicted signs under self-attribution bias	Parameters estimated using five-minute returns		Parameters estimated using 30-minute returns	
		(I)	(II)	(III)	(IV)
$R_q^{S\&P}$		0.287***		0.110	
		(0.087)		(0.064)	
$R_{q-1}^{S\&P}$	+	-0.161		-0.053	
		(0.104)		(0.071)	
R_q^{Ind}		0.021	-0.006	0.058***	0.032***
		(0.023)	(0.012)	(0.016)	(0.009)
R_{q-1}^{Ind}	+	-0.037	-0.017	-0.018	-0.010
		(0.024)	(0.013)	(0.014)	(0.010)
R_q^{Firm}		0.014	0.015	0.041***	0.031***
		(0.020)	(0.009)	(0.010)	(0.007)
R_{q-1}^{Firm}	+	-0.010	-0.009	0.044***	0.044***
		(0.020)	(0.014)	(0.013)	(0.010)
Intercept		-0.010		-0.014	
		(0.092)		(0.057)	
Quarter fixed effects		No	Yes	No	Yes
R^2 (full)		0.019	0.094	0.005	0.040
R^2 (within)			0.000		0.001
Num. obs.		102,369	102,369	153,194	153,194

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 11: Descriptive statistics for changes in institutional investors' holdings in firms with misweighting of redundant information

This table provides descriptive statistics for the measures of institutional investors' changes in the average misweighting of redundant information among the holdings in institutional investors' portfolios. $\bar{\alpha}_{i,q}$ denotes the average misweighting of redundant information in institutional investor i's portfolio at the end of quarter q. $\Delta\bar{\alpha}_{i,q}$ denotes the change in the average misweighting of redundant information in institutional investor i's portfolio from quarter $q-1$ to q. $\Delta\bar{\alpha}_{i,q}^{Trading}$ denotes changes in the average misweighting of redundant information in institutional investor i's portfolio due to changes in its holdings from quarter $q-1$ to q. $\Delta\bar{\alpha}_{i,q}^{Organic}$ denotes changes in the average misweighting of redundant information in institutional investor i's portfolio due to changes in α among its initial holdings from quarter $q-1$ to q. $R_{i,q}^{Ind}$ is the return on institutional investor i's portfolio in quarter q due to the outperformance of the fund's industry exposure as compared to the return on the S&P 500 index. $R_{i,q}^{Firm}$ is the the return on institutional investor i's portfolio in quarter q due firm-specific outperformance as compared to the firm's industry. $NetInflow_{i,q}$ is the percent change in the net asset value of institutional investor i's portfolio in quarter q due to inflows or outflows from outside investors.

| | Variable | Mean | St.Dev | Percentiles | | |
				1st	Median	99th
Parameters estimated using five-minute returns	$\bar{\alpha}_{i,q}$	1.14	0.78	-0.16	1.08	3.23
	$\Delta\bar{\alpha}_{i,q}$	-0.02	0.79	-1.98	0.00	2.01
	$\Delta\bar{\alpha}_{i,q}^{Trading}$	-0.01	0.77	-2.14	0.00	2.19
	$\Delta\bar{\alpha}_{i,q}^{Organic}$	-0.01	0.25	-1.06	-0.00	1.00
Parameters estimated using 30-minute returns	$\bar{\alpha}_{i,q}$	1.38	0.76	-0.11	1.47	3.19
	$\Delta\bar{\alpha}_{i,q}$	-0.03	0.74	-1.98	-0.01	2.01
	$\Delta\bar{\alpha}_{i,q}^{Trading}$	-0.03	0.71	-2.10	-0.01	2.16
	$\Delta\bar{\alpha}_{i,q}^{Organic}$	-0.00	0.25	-1.06	0.00	1.00
	$R_{i,q}^{S\&P}$	0.0130	0.0602	-0.1771	0.0127	0.1434
	$R_{i,q}^{Ind}$	0.0056	0.0157	-0.0407	0.0041	0.0616
	$R_{i,q}^{Firm}$	0.0016	0.0343	-0.1167	0.0000	0.1435
	$NetInflow_{i,q}$	0.0009	0.1753	-0.5217	-0.0056	0.9934

Table 12: Self-attribution bias in institutional investor portfolios

This table describes the association between investors' misweighting of redundant information and institutional investors' lagged returns. Gervais and Odean (2001) posit that investors are vulnerable to self-attribution bias and overestimate the precision of their private signals more after experiencing positive portfolio returns.

The dependent variable, $\Delta\bar{\alpha}_{i,q}^{Trading}$, is the change in the average misweighting of redundant information in institutional investor i's portfolio due to changes in its holdings from quarter $q-1$ to q. The explanatory variables are as follows: $R_q^{S\&P}$ is the total return on the the S&P 500 index in quarter q; $R_{i,q}^{Ind}$ is the return on institutional investor i's portfolio in quarter q due to the outperformance of the fund's industry exposure as compared to the return on the S&P 500 index; $R_{i,q}^{Firm}$ is the the return on institutional investor i's portfolio in quarter q due outperformance of a firm's stock price as compared to its industry; and, $NetInflow_{i,q}$ is institutional investor i's net inflows from outside investors in quarter q. These variables are normalized to have means equal to zero and standard deviations equal to one.

The data comprises institutional investor-quarters from 2003 to 2014. Standard errors are clustered by firm and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Dependent variable $= \Delta\bar{\alpha}_{i,q}^{Trading}$	Predicted signs under self-attribution bias	Parameters estimated using five-minute returns		Parameters estimated using 30-minute returns	
		(I)	(II)	(IIII)	(IV)
$R_q^{S\&P}$		0.320***		0.087	
		(0.083)		(0.099)	
$R_{q-1}^{S\&P}$	+	-0.157		-0.080	
		(0.089)		(0.114)	
$R_{i,q}^{Ind}$		0.075	0.005	0.115*	0.035
		(0.040)	(0.017)	(0.046)	(0.018)
$R_{i,q-1}^{Ind}$	+	-0.043	-0.016	-0.021	-0.014
		(0.049)	(0.016)	(0.043)	(0.013)
$R_{i,q}^{Firm}$		-0.041	-0.017	-0.010	-0.002
		(0.023)	(0.014)	(0.013)	(0.007)
$R_{i,q-1}^{Firm}$	+	0.013	-0.008	0.011	0.005
		(0.020)	(0.011)	(0.019)	(0.011)
$NetInflow_{i,q}$		0.020	0.004	0.010	-0.007
		(0.015)	(0.009)	(0.009)	(0.008)
$NetInflow_{i,q-1}$		-0.017	-0.001	-0.009	0.002
		(0.011)	(0.008)	(0.008)	(0.005)
Intercept		0.013		-0.017	
		(0.102)		(0.097)	
Quarter fixed effects		No	Yes	No	Yes
R^2 (full)		0.124	0.506	0.037	0.441
R^2 (within)			0.001		0.003
Num. obs.		80,298	80,298	86,662	86,662

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 13: Self-attribution bias in non-institutional investor portfolios

This table describes the association between investors' misweighting of redundant information and non-institutional investors' lagged returns.

The dependent variable, $\Delta\bar{\alpha}_{i,q}^{Organic}$, is the change in the average misweighting of redundant information in institutional investor i's portfolio due to changes in its holdings from quarter $q-1$ to q. The explanatory variables are as the same as those in Table 12. These variables are normalized to have means equal to zero and standard deviations equal to one.

The data comprises institutional investor-quarters from 2003 to 2014. Standard errors are clustered by firm and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Dependent variable $= \Delta\bar{\alpha}_{i,q}^{Organic}$	Predicted signs under self-attribution bias	Parameters estimated using five-minute returns		Parameters estimated using 30-minute returns	
		(I)	(II)	(IIII)	(IV)
$R_{i,q}^{S\&P}$		0.015		0.024*	
		(0.011)		(0.010)	
$R_{i,q-1}^{S\&P}$	+	0.003		0.006	
		(0.012)		(0.017)	
$R_{i,q}^{Ind}$		0.008	-0.001	0.009	-0.006
		(0.010)	(0.009)	(0.008)	(0.010)
$R_{i,q-1}^{Ind}$	+	-0.019*	-0.016*	-0.025*	-0.023**
		(0.010)	(0.008)	(0.010)	(0.008)
$R_{i,q}^{Firm}$		0.032***	0.036***	0.022*	0.025**
		(0.009)	(0.010)	(0.010)	(0.009)
$R_{i,q-1}^{Firm}$	+	-0.006	-0.009	-0.011	-0.011
		(0.008)	(0.009)	(0.007)	(0.008)
$NetInflow_{i,q}$		-0.032	-0.034	-0.037	-0.039
		(0.027)	(0.026)	(0.022)	(0.021)
$NetInflow_{i,q-1}$		0.015	0.014	0.017	0.016
		(0.015)	(0.013)	(0.012)	(0.012)
Intercept		-0.008		0.001	
		(0.018)		(0.018)	
Quarter fixed effects		No	Yes	No	Yes
R^2 (full)		0.003	0.020	0.004	0.020
R^2 (within)			0.003		0.003
Num. obs.		80,298	80,298	86,662	86,662

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

4.4. Institutional investors' information gathering and processing ability

In expectation, investors who gather and process information more earn above average expected returns. These expected returns are increasing in the degree of information processing frictions (Grossman and Stiglitz, 1980). If investors' misweighting of redundant information is associated with information processing frictions, investors should earn greater returns on holding investments in firms with greater misweighting of redundant information. Further, if investors' misweighting of redundant information is associated with information processing frictions, investors with greater information processing ability who hold investments in firms with greater misweighting of redundant information are likely to outperform other investors.

On the other hand, if investors' misweighting of redundant information reflects that investors earn non-monetary utility from misweighting information (i.e., behavioral biases), one would not expect these investors to earn above average returns on holding investments in firms with greater misweighting of redundant information. Rather, the analytical model in Chapter 3 predicts that investors' expected returns are lower if they misweight redundant information or do not take into account that other investors misweight redundant information. Thus, if investors' misweighting of redundant information is associated with behavioral biases, investors should not earn greater returns on holding investments in firms with greater misweighting of redundant information. Further, investors with greater information processing ability would not outperform other investors by holding investments in firms with greater misweighting of redundant information.

4.4.1. Research design

Bushee and Goodman (2007) propose a framework to examine whether institutional investors have private information and exploit an information advantage. If institutional investors have private information about the value of a firm, they exploit this information advantage by accumulating a position in the firm before that private information becomes public and exiting the position after that private information becomes public. This trading on private information should appear largest for institutional investors with the greatest incentive and ability to gain an information advantage. In particular, large institutional investors (in terms of fund size) are likely to have more access to corporate managers and more in-house analysts. Transient institutional investors are likely to act quickly on advantageous information and then immediately exit positions once their information advantage declines. Institutional investors that hold large and concentrated positions take on

greater risk than diversified investors do, and thus have greater incentive to obtain precise private information. Bushee and Goodman (2007) present evidence that large, transient, and concentrated institutional investors accumulate positions prior to positive 12-month buy-and-hold returns and positive returns around earnings announcements. These findings suggest that large, transient, and concentrated institutional investors are likely to have the greatest ability to gather and process private signals.

As in Section 4.3, using Thomson-Reuters 13-F filings data and CRSP stock and index price data, I decompose changes in the net asset value of an institutional investor's portfolio into returns on its initial holdings due to market-wide returns, returns on its initial holdings due to industry outperformance, returns on its initial holdings due to firm outperformance, and net inflows from investors. I also separate changes in the average misweighting of redundant information among the holdings in an institutional investor's portfolio into changes in the misweighting of redundant information among its existing holdings and changes in the investor's holdings.

To assess whether institutional investors earn above average profits on holding investments in firms with greater misweighting of redundant information, I estimate the following regressions:

$$R_{i,q}^{Ind} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.1)$$

$$R_{i,q}^{Firm} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.2)$$

where $R_{i,q}^{Ind}$ is the return on institutional investor i's portfolio in quarter q due to the outperformance of the fund's industry-specific exposure; $R_{i,q}^{Firm}$ is the the return on institutional investor i's portfolio in quarter q due firm-specific outperformance; $\Delta \bar{\alpha}_{i,q}^{Trading}$ denotes changes in the average misweighting of redundant information in institutional investor i's portfolio due to changes in its holdings from quarter $q-1$ to q; and, $\Delta \bar{\alpha}_{i,q}^{Organic}$ denotes changes in the average misweighting of redundant information in institutional investor i's portfolio due to changes in α from quarter $q-1$ to q among its initial holdings. I normalize these variables to have means equal to zero and standard deviations equal to one. I also include calendar quarter fixed effects, labeled $\sum_q b_q$, to control for secular changes in α over time and isolate cross-sectional variation.

If $b_1 > 0$ or $b_2 > 0$ in the estimations of Equations (4.4.1) or (4.4.2), that would be consistent with institutional investors earning above average profits by increasing their holdings in firms with greater misweighting of redundant information. If $b_3 > 0$ or $b_4 > 0$ in the estimations of Equations

(4.4.1) or (4.4.2), that would be consistent with institutional investors earning above average profits on their holdings in firms in which non-institutional investors increasingly misweighted redundant information. In all, if $b_1 > 0$, $b_2 > 0$, $b_3 > 0$, or $b_4 > 0$ in the estimations of Equations (4.4.1) or (4.4.2), that would suggest that institutional investors earn above average profits on increasing their exposure to the misweighting of redundant information.

In addition, I designate an institutional investor as having superior information processing ability by four proxies, building on Bushee and Goodman (2007). I label an institutional investor as large by the indicator variable $Large_{i,q}$ if the market value of its equity portfolio is in the top quintile for that quarter. I label an institutional investor as transient by the indicator variable $Transient_{i,q}$ based on the Bushee (1998) classification. To designate an institutional investor as having concentrated positions, the variable $Block_{i,q} \in [0, 1]$ is the fraction of institutional investor i's portfolio in quarter q in which investor i is a blockholder – its ownership of a firm's shares is in the top quintile of institutional owners. I also create an aggregate measure of an institutional investor having superior information processing ability, $Informed_{i,q}$, by averaging $Large_{i,q}$, $Transient_{i,q}$, and $Block_{i,q}$.

To assess whether institutional investors with superior information processing ability earn above average profits on holding investments in firms with greater misweighting of redundant information, I estimate the following regressions:

$$R_{i,q}^{Ind} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.3)$$

$$R_{i,q}^{Firm} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.4)$$

where $\theta_{i,q} \in \{Large_{i,q}, Transient_{i,q}, Block_{i,q}, Informed_{i,q}\}$ and the remaining variables are the same as those in Equations (4.4.1) and (4.4.2).

If $b_6 > 0$ or $b_7 > 0$ in the estimations of Equations (4.4.3) or (4.4.4), that would be consistent with institutional investors with superior information processing ability earning above average profits by increasing their holdings in firms with greater misweighting of redundant information. If $b_8 > 0$ or $b_9 > 0$ in the estimations of Equations (4.4.3) or (4.4.4), that would be consistent with institutional investors with superior information processing ability earning above average profits on their holdings

in firms in which other institutional investors increasingly misweighted redundant information. In all, if $b_7 > 0$, $b_8 > 0$, or $b_9 > 0$ in the estimations of Equations (4.4.3) or (4.4.4), that would suggest that institutional investors with superior information processing ability earn above average profits on holding positions in firms with greater misweighting of redundant information.

4.4.2. Results

Table 14 shows the estimation of Equations (4.4.1) and (4.4.2). Based on the standard deviations of industry-specific and firm-specific returns in Table 11 and the α parameters estimated using five-minute returns, a one standard deviation increase in the average misweighting of redundant information in an institutional investor's portfolios due to changes in holdings is associated with a 2 basis point increase in the return on an institutional investor's portfolio in the subsequent quarter due to the outperformance of the funds' industry exposure as compared to the return on the S&P 500 index. A one standard deviation increase in the average misweighting of redundant information in an institutional investor's portfolios due to changes in holdings is associated with an 11 basis point increase in the return on an institutional investor's portfolio in the same quarter due to firm-specific outperformance. Based on the α parameters estimated using 30-minute returns, a one standard deviation increase in the average misweighting of redundant information in an institutional investor's portfolios due to changes in α is associated with a 12 basis point increase in the return on an institutional investor's portfolio in the same quarter due to industry outperformance. A one standard deviation increase in the average misweighting of redundant information in an institutional investor's portfolios due to changes in holdings is associated with an 8 basis point increase in the return on an institutional investor's portfolio in the same quarter due to firm-specific outperformance. This evidence suggests that institutional investors earn higher expected profits when their portfolio has greater exposure to investors' misweighting of redundant information. These results are weakly consistent with investors' misweighting of redundant information reflecting an information processing friction.

Tables 15 to 18 show the estimation of Equations (4.4.1) and (4.4.2). Large institutional investors on average earn 18 to 20 basis points per quarter more than smaller institutional investors due to industry-specific outperformance and 25 to 27 basis points per quarter more than smaller institutional investors due to firm-specific outperformance. Based on the α parameters estimated using five-minute returns, a one standard deviation increase in the average misweighting of redundant information in a large investor's portfolio due to changes in α is associated with a 13 basis point

increase in returns in the subsequent quarter due to industry-specific outperformance. Based on the α parameters estimated using 30-minute returns, a one standard deviation increase in the average misweighting of redundant information in a large investor's portfolio due to changes in its holdings is associated with a 8 basis point increase in returns in the subsequent quarter due to industry-specific outperformance. These results are consistent with large institutional investors earning above average returns due to their exposure to investors' misweighting of redundant information.

Transient institutional investors on average earn 20 to 21 basis points per quarter more than other institutional investors due to industry-specific outperformance and 70 to 73 basis points per quarter more than other institutional investors due to firm-specific outperformance. A one standard deviation increase in the average misweighting of redundant information in a transient investor's portfolio due to changes in α is associated with a 18 to 20 basis point increase in returns in the same quarter due to industry-specific outperformance and 50 to 52 basis points in returns in the same quarter due to firm-specific outperformance. These results are consistent with transient institutional investors earning above average returns due to other investors' misweighting of redundant information.

Blockholder institutional investors outperform other institutional investors due to the outperformance of their industry exposure and firm-specific outperformance. An institutional investor that held only block positions on average outperformed an institutional investor that held no block positions by 27 to 32 basis points due industry-specific outperformance. A one standard deviation increase in the average misweighting of redundant information in a blockholder investor's portfolio due to changes in α is associated with a 47 to 65 basis point increase in returns in the same quarter due to firm-specific outperformance. Based on the α parameters estimated using five-minute returns, a one standard deviation increase in the average misweighting of redundant information in a blockholder investor's portfolio due to changes in α is associated with a 36 basis point increase in returns in the subsequent quarter due to firm-specific outperformance. Based on the α parameters estimated using 30-minute returns, a one standard deviation increase in the average misweighting of redundant information in a blockholder investor's portfolio due to changes in α is associated with a 11 basis point decrease in returns in the subsequent quarter due to industry-specific outperformance. These results are consistent with blockholder institutional investors earning above average returns due to other investors' misweighting of redundant information.

Finally, institutional investors with superior information processing ability – as measured by the average of the large investor indicator variable, the transient investor indicator variable, and the

fraction of an institutional investor's portfolio in block positions – outperform institutional investors without such ability. On average, a large, transient institutional investor that held only block positions outperformed a small, non-transient institutional investor that held no block positions by 50 to 52 basis points per quarter due to industry-specific outperformance and 110 to 111 basis points per quarter due to firm-specific outperformance. A one standard deviation increase in the average misweighting of redundant information due to changes in α in the portfolio of an institutional investor with superior information processing ability is associated with a 27 basis point increase in returns in the same quarter and a 25 basis point increase in returns in the subsequent quarter due industry-specific outperformance. A one standard deviation increase in the average misweighting of redundant information due to changes in α in the portfolio of an institutional investor with superior information processing ability is associated with a 91 to 112 basis point increase in returns in the same quarter due to firm-specific outperformance. These results are consistent with institutional investors with superior information processing ability earning above average returns due to other investors' misweighting of redundant information.

In all, institutional investors with superior information processing ability appear to outperform other investors increasingly when the average misweighting of redundant information increases. Some evidence suggests that institutional investors generally earn higher returns by increasing positions held in firms with greater misweighting of redundant information. Institutional investors with superior information processing ability outperform other institutional investors not because they increase their positions in firms with greater misweighting of redundant information but rather because the level of misweighting of redundant information in their existing holdings increased. This result suggests that other investors' trading activity increased the misweighting of redundant information in the firms held by institutional investors with superior information processing ability. This evidence that institutional investors with superior information processing ability earn above average returns when other investors misweight redundant information suggests that investors' misweighting of redundant information reflects an information friction, rather than a behavioral bias.

4.4.3. Exhibits

Table 14: Institutional investors' returns on holding investments in firms with mis-weighting of redundant information

This table examines whether institutional investors earn above average profits on holding investments in firms with greater misweighting of redundant information. I estimate the regressions:

$$R_{i,q}^{Ind} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.5)$$

$$R_{i,q}^{Firm} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.6)$$

The variables $R_{i,q}^{Ind}$, $R_{i,q}^{Firm}$, $\Delta \bar{\alpha}_{i,q}^{Trading}$, and $\Delta \bar{\alpha}_{i,q}^{Organic}$ – defined in Table 11 – are normalized to have means equal to zero and standard deviations equal to one. $\sum_q b_q$ denotes calendar quarter fixed effects. The data comprises institutional investor-quarters from 2003 to 2014. Standard errors are clustered by institutional investor and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Dependent variable	Parameters estimated using five-minute returns		Parameters estimated using 30-minute returns	
	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$
$\Delta \bar{\alpha}_{i,q}^{Trading}$	0.004	0.032**	0.008	0.022*
	(0.009)	(0.011)	(0.009)	(0.010)
$\Delta \bar{\alpha}_{i,q-1}^{Trading}$	0.014*	0.008	0.007	-0.014
	(0.006)	(0.009)	(0.009)	(0.012)
$\Delta \bar{\alpha}_{i,q}^{Organic}$	0.012	-0.016	0.077*	-0.002
	(0.030)	(0.028)	(0.035)	(0.025)
$\Delta \bar{\alpha}_{i,q-1}^{Organic}$	0.028	0.012	0.030	-0.029
	(0.023)	(0.023)	(0.017)	(0.030)
Quarter fixed effects	Yes	Yes	Yes	Yes
R^2 (full)	0.167	0.016	0.178	0.016
R^2 (within)	0.000	0.001	0.003	0.001
Num. obs.	62,882	62,882	69,127	69,127

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 15: Large institutional investors' returns on holding investments in firms with misweighting of redundant information

This table examines whether large institutional investors earn above average profits on holding investments in firms with greater misweighting of redundant information. I estimate the regressions:

$$R_{i,q}^{Ind} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \quad (4.4.7)$$

$$R_{i,q}^{Firm} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \quad (4.4.8)$$

$\theta_{i,q} \equiv Large_{i,q}$ is an indicator variable equal to one if the market value of institutional investor i's equity portfolio is in the top quintile in quarter q and zero otherwise. The variables $R_{i,q}^{Ind}$, $R_{i,q}^{Firm}$, $\Delta \bar{\alpha}_{i,q}^{Trading}$, and $\Delta \bar{\alpha}_{i,q}^{Organic}$ – defined in Table 11 – are normalized to have means equal to zero and standard deviations equal to one. $\sum_q b_q$ denotes calendar quarter fixed effects. In the table below, the estimates of $b_1, \dots, b_4$ are omitted for brevity.

The data comprises institutional investor-quarters from 2003 to 2014. Standard errors are clustered by institutional investor and calendar quarter, and appear in parentheses beneath the estimated coefficients.

	Parameters estimated using five-minute returns		Parameters estimated using 30-minute returns	
Dependent variable	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$
$\theta_{i,q}$	0.126***	0.080***	0.113***	0.072***
	(0.033)	(0.022)	(0.029)	(0.021)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$	0.025	-0.046	-0.010	-0.055
	(0.033)	(0.027)	(0.044)	(0.032)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading}$	0.005	-0.006	-0.007	-0.026
	(0.030)	(0.036)	(0.026)	(0.033)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic}$	0.060	-0.004	0.017	-0.013
	(0.031)	(0.024)	(0.023)	(0.021)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic}$	0.082***	-0.015	0.052*	-0.014
	(0.020)	(0.022)	(0.025)	(0.013)
Main effects included	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
R^2 (full)	0.169	0.017	0.179	0.016
R^2 (within)	0.002	0.002	0.004	0.001
Num. obs.	62,882	62,882	69,127	69,127

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 16: Transient institutional investors' returns on holding investments in firms with misweighting of redundant information

This table examines whether transient institutional investors earn above average profits on holding investments in firms with greater misweighting of redundant information. I estimate the regressions:

$$R_{i,q}^{Ind} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.9)$$

$$R_{i,q}^{Firm} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.10)$$

$\theta_{i,q} \equiv Transient_{i,q}$ is an indicator variable for transient institutional investors, based on the Bushee (1998) classification. The variables $R_{i,q}^{Ind}$, $R_{i,q}^{Firm}$, $\Delta \bar{\alpha}_{i,q}^{Trading}$, and $\Delta \bar{\alpha}_{i,q}^{Organic}$ – defined in Table 11 – are normalized to have means equal to zero and standard deviations equal to one. $\sum_q b_q$ denotes calendar quarter fixed effects. In the table below, the estimates of $b_1, \ldots, b_4$ are omitted for brevity. The data comprises institutional investor-quarters from 2003 to 2014. Standard errors are clustered by institutional investor and calendar quarter, and appear in parentheses beneath the estimated coefficients.

	Parameters estimated using five-minute returns		Parameters estimated using 30-minute returns	
Dependent variable	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$
$\theta_{i,q}$	0.134**	0.203***	0.129**	0.213***
	(0.048)	(0.042)	(0.045)	(0.042)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$	-0.021	-0.039	-0.010	0.022
	(0.020)	(0.020)	(0.021)	(0.020)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading}$	0.013	-0.022	0.022	0.001
	(0.025)	(0.022)	(0.014)	(0.016)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic}$	0.126***	0.151***	0.113**	0.147***
	(0.036)	(0.038)	(0.038)	(0.036)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic}$	0.074	0.017	0.064	0.043
	(0.041)	(0.031)	(0.050)	(0.043)
Main effects included	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
R^2 (full)	0.171	0.023	0.181	0.022
R^2 (within)	0.005	0.008	0.006	0.007
Num. obs.	62,882	62,882	69,127	69,127

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 17: Blockholder institutional investors' returns on holding investments in firms with misweighting of redundant information

This table examines whether blockholder institutional investors earn above average profits on holding investments in firms with greater misweighting of redundant information. I estimate the regressions:

$$R_{i,q}^{Ind} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.11)$$

$$R_{i,q}^{Firm} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.12)$$

$\theta_{i,q} \equiv Block_{i,q}$ is the fraction of institutional investor i's portfolio in quarter q in which investor i is a blockholder – its ownership of a firm's shares is in the top quintile of institutional owners. The variables $R_{i,q}^{Ind}$, $R_{i,q}^{Firm}$, $\Delta \bar{\alpha}_{i,q}^{Trading}$, and $\Delta \bar{\alpha}_{i,q}^{Organic}$ – defined in Table 11 – are normalized to have means equal to zero and standard deviations equal to one. $\sum_q b_q$ denotes calendar quarter fixed effects. In the table below, the estimates of $b_1, \ldots, b_4$ are omitted for brevity.

The data comprises institutional investor-quarters from 2003 to 2014. Standard errors are clustered by institutional investor and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Dependent variable	Parameters estimated using five-minute returns		Parameters estimated using 30-minute returns	
	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$
$\theta_{i,q}$	0.182**	0.139*	0.174**	0.120
	(0.060)	(0.059)	(0.059)	(0.071)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$	0.004	-0.011	-0.016	-0.020
	(0.024)	(0.028)	(0.021)	(0.021)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading}$	-0.021	0.006	-0.006	-0.024
	(0.021)	(0.020)	(0.021)	(0.027)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic}$	0.024	0.190***	0.063	0.138**
	(0.043)	(0.040)	(0.047)	(0.048)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic}$	0.038	0.105*	0.072*	0.079
	(0.030)	(0.041)	(0.035)	(0.064)
Main effects included	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
R^2 (full)	0.171	0.023	0.182	0.020
R^2 (within)	0.005	0.008	0.007	0.005
Num. obs.	62,882	62,882	69,127	69,127

$^{***}p < 0.001$, $^{**}p < 0.01$, $^*p < 0.05$

Table 18: Informed institutional investors' returns on holding investments in firms with misweighting of redundant information

This table examines whether institutional investors with superior information processing ability earn above average profits on holding investments in firms with greater misweighting of redundant information. I estimate the regressions:

$$R_{i,q}^{Ind} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.13)$$

$$R_{i,q}^{Firm} = b_1 \Delta \bar{\alpha}_{i,q}^{Trading} + b_2 \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_3 \Delta \bar{\alpha}_{i,q}^{Organic} + b_4 \Delta \bar{\alpha}_{i,q-1}^{Organic} + b_5 \theta_{i,q} + b_6 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$$
$$+ b_7 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading} + b_8 \theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic} + b_9 \theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic} + \sum_q b_q + \epsilon_{i,q} \qquad (4.4.14)$$

$\theta_{i,q} \equiv Informed_{i,q}$ is the average of $Large_{i,q}$, $Transient_{i,q}$, and $Block_{i,q}$. The variables $R_{i,q}^{Ind}$, $R_{i,q}^{Firm}$, $\Delta \bar{\alpha}_{i,q}^{Trading}$, and $\Delta \bar{\alpha}_{i,q}^{Organic}$ – defined in Table 11 – are normalized to have means equal to zero and standard deviations equal to one. $\sum_q b_q$ denotes calendar quarter fixed effects. In the table below, the estimates of $b_1, \dots, b_4$ are omitted for brevity.

The data comprises institutional investor-quarters from 2003 to 2014. Standard errors are clustered by institutional investor and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Dependent variable	Parameters estimated using five-minute returns		Parameters estimated using 30-minute returns	
	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$	$R_{i,q}^{Ind}$	$R_{i,q}^{Firm}$
$\theta_{i,q}$	0.331***	0.325***	0.319***	0.321***
	(0.092)	(0.080)	(0.087)	(0.087)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Trading}$	-0.026	-0.092	-0.038	-0.016
	(0.038)	(0.049)	(0.037)	(0.039)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Trading}$	-0.009	-0.029	0.011	-0.037
	(0.034)	(0.039)	(0.031)	(0.034)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q}^{Organic}$	0.168**	0.326***	0.174**	0.266***
	(0.062)	(0.067)	(0.064)	(0.070)
$\theta_{i,q} \Delta \bar{\alpha}_{i,q-1}^{Organic}$	0.153*	0.120	0.159*	0.111
	(0.060)	(0.062)	(0.080)	(0.089)
Main effects included	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
R^2 (full)	0.173	0.025	0.183	0.022
R^2 (within)	0.007	0.010	0.009	0.007
Num. obs.	62,882	62,882	69,127	69,127

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

4.5. The cost of information gathering

Veldkamp (2006) shows that, when information gathering entails high fixed costs yet low variable costs, competitive information intermediaries can sell information only at a low price.[5] Information intermediaries would take advantage of economies of scale by gathering information about a related group of firms with widespread investor following or the common risk factors of such firms, rather than about individual firms with narrow investor following or their idiosyncratic risk factors. Many investors would purchase this information because the price is low relative to their private cost of acquiring this information.

How many investors will gather this information, and how quickly, is likely to be uncertain. When investors can be more certain that other investors have not acquired the same private signals, they are less likely to overestimate the novelty and exclusivity of the signals. If investors' misweighting of redundant information is associated with information processing frictions, this misweighting is likely to be higher when investors' cost of obtaining information from an information intermediary is low. If investors' misweighting of redundant information is associated with behavioral biases, this misweighting would not vary with the cost of acquiring the information.

4.5.1. Research design

To examine how investors' misweighting of redundant information varies with the cost of gathering information, I study whether the estimated misweighting of redundant information varies at an industry-wide level, with the similarity of firms within an industry, and with competition among sell-side analysts. Following the arguments in Veldkamp (2006), I assume that investors' cost of gathering industry-wide information from sell-side analysts is lower than than investors' private cost of gathering this information. This cost of gathering industry-wide information from sell-side analysts is likely to be decreasing in the similarity of firms within an industry and competition among sell-side analysts.

I study how the firm-quarter measure of investors' misweighting of redundant information, $\alpha_{j,q}$, varies with the industry average of this misweighting, α_q^{Ind}. I measure the industry average on equal-weighted and market capitalization-weighted bases, denoted $\alpha_{j,q}^{Ind,EW}$ and $\alpha_{j,q}^{Ind,VW}$, using the

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[5]This assumption is consistent with institutional practice. Sell-side brokerage firms typically do not charge for research reports directly. Rather, buy-side clients typically compensate sell-side analysts for high-quality reports ex-post by directing trading commissions to the brokerage firm (Brown et al., 2015).

Fama and French (1997) 30-industry classification.[6]

I use two proxies for the similarity of firms within an industry. I measure the average exposure of firms in an industry to industry-specific factors by the average stock price beta of firms in a Fama and French (1997) industry to the industry returns over the prior four quarters. I correct these estimated beta coefficients for infrequent trading following Minton and Schrand (2016). I label this variable β_q^{Ind}.

As a second proxy for the similarity between a firm and its industry peers, I measure the "uniqueness" of a firm following Litov, Moreton, and Zenger (2012). I calculate this variable, $Uniq_{j,q}$, by the Euclidean distance between the distribution of a firm's segment sales as a percent of the firm's total sales, and the distribution of the industry aggregate segment sales as a percent of total sales. This measure is decreasing in the similarity of a firm to its industry. For example, if an industry's aggregate segment sales are split evenly between two segments (classified by four-digit SIC codes), I measure a firm as more unique if its sales are heavily concentrated in one segment. I measure a firm as more similar to its industry peers if its sales mix across segments resembles the industry average.

As proxy for the level of competition among sell-side analysts, I use the natural log of one plus the number of earnings per share forecasts for that firm-quarter, based on I/B/E/S data and denoted $NumEst_{j,q}$ (Lys and Soo, 1995).

I estimate the following regression specifications:

$$\alpha_{j,q} = \gamma_0 + \gamma_1 \left\{ \alpha_q^{Ind} \right\} + \gamma_2 \left\{ \beta_q^{Ind} \right\} + \gamma_3 \left\{ NumEst_{j,q} \right\}$$
$$+ \gamma_4 \left\{ \beta_q^{Ind} \times \alpha_q^{Ind} \right\} + \gamma_5 \left\{ NumEst_{j,q} \times \alpha_q^{Ind} \right\} + \epsilon_{j,q} \tag{4.5.1}$$

$$\alpha_{j,q} = \gamma_0 + \gamma_1 \left\{ \alpha_q^{Ind} \right\} + \gamma_2 \left\{ Uniq_{j,q} \right\} + \gamma_3 \left\{ NumEst_{j,q} \right\}$$
$$+ \gamma_4 \left\{ Uniq_{j,q} \times \alpha_q^{Ind} \right\} + \gamma_4 \left\{ NumEst_{j,q} \times \alpha_q^{Ind} \right\} + \epsilon_{j,q} \tag{4.5.2}$$

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[6]I exclude the firm referenced in the dependent variable from the average. For example, for firm j in an industry of N firms, I calculate $\alpha_{j,q}^{Ind,EW}$ by

$$\alpha_{j,q}^{Ind,EW} = \frac{1}{N-1} \sum_{k \neq j} \alpha_{k,q}$$

4.5.2. Results

Table 19 presents descriptive statistics for the explanatory variables in Equations (4.5.1) and (4.5.2). The value-weighted average α parameters exhibit higher means, medians, and variation than do the equal-weighted average α parameters. This result suggests that the misweighting of redundant information is on average greater and more volatile for large firms than for small firms. The distributions of the industry average α parameters are similar when estimated on five-minute returns and 30-minute returns.

Table 20 presents the results of estimating Equation (4.5.1). An individual firm's parameter for investors' misweighting of redundant information appears to covary positively with the industry average. Based on the α parameters estimated on five-minute returns, a one standard deviation increase in the equal-weighted average α is associated with an 0.09 standard deviation increase in an individual firm's α parameter; a one standard deviation increase in the market capitalization-weighted average α is associated with an 0.05 standard deviation increase in an individual firm's α parameter. Based on the α parameters estimated on 30-minute returns, a one standard deviation increase in the equal-weighted average α is associated with an 0.06 standard deviation increase in an individual firm's α parameter; a one standard deviation increase in the market capitalization-weighted average α is associated with an 0.04 standard deviation increase in an individual firm's α parameter. When a firm has greater exposure to its industry, the covariation between an individual firm's α and its industry α is greater. Based on the α parameters estimated on five-minute returns, a one standard deviation increase in a firm's exposure to its industry, β_q^{Ind}, is associated with a 0.04 greater response of a firm's α to its industry's equal-weighted average α and a 0.01 greater response of a firm's α to its industry's value-weighted average α. Based on the α parameters estimated on 30-minute returns, a one standard deviation increase in a firm's exposure to its industry, β_q^{Ind}, is associated with a 0.02 greater response of a firm's α to its industry's equal-weighted average α. A firm's α also appears larger when analyst competition is greater. Based on the α parameters estimated on five-minute returns, a one standard deviation increase in the natural log of the number of analysts that issued EPS forecasts for the firm is associated with a 0.12 standard deviation increase in a firm's α. In addition, a one standard deviation increase in the natural log of the number of analysts that issued EPS forecasts for the firm is associated with a 0.02 greater response of a firm's α to its industry's equal-weighted and value-weighted average α. Based on the α parameters estimated on 30-minute returns, a one standard deviation increase in the natural log of the number of analysts

that issued EPS forecasts for the firm is associated with a 0.22 standard deviation increase in a firm's α. In addition, a one standard deviation increase in the natural log of the number of analysts that issued EPS forecasts for the firm is associated with a 0.01 greater response of a firm's α to its industry's equal-weighted average α and a 0.02 greater response of a firm's α to its industry's value-weighted average α.

Table 21 presents the results of estimating Equation (4.5.2). Based on the α parameters estimated on five-minute returns, a one standard deviation increase in $Uniq_{j,q}$ is association with a 0.01 decrease in a firm's α, a 0.02 lower response of a firm's α to its industry's equal-weighted and value-weighted industry average α, and a 0.01 lower response of a firm's α to its industry's value-weighted and value-weighted industry average α. Based on the α parameters estimated on 30-minute returns, $Uniq_{j,q}$ does not exhibit a statistically significant relationship with a firm's α.

In all, these results suggest that, when investors' cost of acquiring information industry-wide information from sell-side analysts is low as compared their private cost of acquiring this information, investors are more likely to overweight the redundant information content in their private signals.

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4.5.3. Exhibits

Table 19: Descriptive statistics for the cost of information gathering

This table provides descriptive statistics for the measures of industry average misweighting of redundant information, the similarity of firms within an industry, and the level of competition among sell-side analysts. $\alpha_q^{Ind,EW}$ and $\alpha_q^{Ind,VW}$ are the industry equal-weighted and market capitalization-weighted average $\alpha_{j,q}$ by calendar quarter. β_q^{Ind} is average stock price beta of firms in a Fama and French (1997) industry over the prior four quarters, corrected for infrequent trading following Minton and Schrand (2016). $Uniq_{j,q}$ is the Euclidean distance between the distribution of a firm's segment sales as a percent of the firm's total sales, and the distribution of the industry aggregate segment sales as a percent of total sales (Litov, Moreton, and Zenger, 2012). $NumEst_{j,q}$ is the natural log of one plus the number of earnings per share forecasts for that firm-quarter, based on I/B/E/S data.

					Percentiles	
	Variable	Mean	St.Dev	1st	Median	99th
Parameters estimated using five-minute returns	$\alpha_q^{Ind,EW}$	1.69	0.44	0.37	1.77	2.47
	$\alpha_q^{Ind,VW}$	1.73	0.70	0.07	1.80	3.11
Parameters estimated using 30-minute returns	$\alpha_q^{Ind,EW}$	1.69	0.43	0.38	1.76	2.46
	$\alpha_q^{Ind,VW}$	1.73	0.69	0.07	1.80	3.11
	$\beta_q^{j,Ind}$	0.99	0.99	-1.36	0.89	4.29
	$Uniq_{j,q}$	0.23	0.37	0.00	0.06	1.69
	$NumEst_{j,q}$	2.09	0.74	0.00	2.14	3.42

Table 20: Investors' misweighting of redundant information and the cost of information gathering

This table describes the association between investors' misweighting of redundant information and the cost of information gathering. The dependent variable is the firm-quarter estimated parameter for investors' misweighting of redundant information, $\alpha_{j,q}$. $\alpha_q^{Ind,EW}$ and $\alpha_q^{Ind,VW}$ are the industry equal-weighted and market capitalization-weighted average $\alpha_{j,q}$ by calendar quarter. β_q^{Ind} is average stock price beta of firms in a Fama and French (1997) industry over the prior four quarters, corrected for infrequent trading following Minton and Schrand (2016). $NumEst_{j,q}$ is the natural log of one plus the number of earnings per share forecasts for that firm-quarter, based on I/B/E/S data. I normalize these variables to have means equal to zero and variances equal to one by calendar quarter. The data comprises firm-quarters from 2003 to 2014. Standard errors are clustered by firm and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Dependent variable = $\alpha_{j,q}$	Estimated on five-minute returns		Estimated on 30-minute returns	
	(I)	(II)	(III)	(IV)
$\alpha_q^{Ind,EW}$	0.088***		0.061***	
	(0.007)		(0.006)	
$\alpha_q^{Ind,VW}$		0.042***		0.037***
		(0.006)		(0.004)
$\beta_q^{j,Ind}$	0.002	-0.000	0.007	0.003
	(0.005)	(0.006)	(0.004)	(0.004)
$NumEst_{j,q}$	0.115***	0.122***	0.215***	0.219***
	(0.018)	(0.018)	(0.016)	(0.016)
$\alpha_q^{Ind,EW} \times \beta_q^{j,Ind}$	0.042***		0.019***	
	(0.007)		(0.004)	
$\alpha_q^{Ind,VW} \times \beta_q^{j,Ind}$		0.014*		0.006
		(0.006)		(0.004)
$\alpha_q^{Ind,EW} \times NumEst_{j,q}$	0.022***		0.009*	
	(0.006)		(0.005)	
$\alpha_q^{Ind,VW} \times NumEst_{j,q}$		0.020***		0.019***
		(0.006)		(0.004)
Calendar quarter fixed effects	Yes	Yes	Yes	Yes
R^2 (full)	0.040	0.032	0.064	0.062
R^2 (within)	0.021	0.013	0.056	0.054
Num. obs.	95,605	95,605	140,755	140,755

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 21: Investors' misweighting of redundant information and the cost of information gathering (alternative proxy)

This table describes the association between investors' misweighting of redundant information and the cost of information gathering, using an alternative proxy for the similarity of a firm to its industry peers. Here, I measure the similarity between a firm and its industry peers by the Euclidean distance between the distribution of a firm's segment sales as a percent of the firm's total sales, and the distribution of the industry aggregate segment sales as a percent of total sales, following Litov, Moreton, and Zenger (2012). This measure, $Uniq_{j,q}$, is decreasing in the similarity of a firm to its industry peers.

As in the prior table, the dependent variable is the estimated parameter for investors' misweighting of redundant information, $\alpha_{j,q}$. $\alpha_q^{Ind,EW}$ and $\alpha_q^{Ind,VW}$ are the industry equal-weighted and market capitalization-weighted average $\alpha_{j,q}$ by calendar quarter. $NumEst_{j,q}$ is the natural log of one plus the number of earnings per share forecasts for that firm-quarter, based on I/B/E/S data. I normalize all of these variables to have means equal to zero and variances equal to one by calendar quarter. The data comprises firm-quarters from 2003 to 2014. Standard errors are clustered by firm and calendar quarter, and appear in parentheses beneath the estimated coefficients.

Dependent variable = $\alpha_{j,q}$	Estimated on five-minute returns		Estimated on 30-minute returns	
	(I)	(II)	(III)	(IV)
$\alpha_q^{Ind,EW}$	0.089***		0.051***	
	(0.007)		(0.006)	
$\alpha_q^{Ind,VW}$		0.038***		0.027***
		(0.007)		(0.004)
$Uniq_{j,q}$	-0.012*	-0.011	0.004	0.004
	(0.006)	(0.006)	(0.004)	(0.004)
$NumEst_{j,q}$	0.116***	0.123***	0.222***	0.226***
	(0.018)	(0.018)	(0.016)	(0.016)
$\alpha_q^{Ind,EW} \times Uniq_{j,q}$	-0.015**		-0.005	
	(0.005)		(0.004)	
$\alpha_q^{Ind,VW} \times Uniq_{j,q}$		-0.010*		-0.001
		(0.005)		(0.003)
$\alpha_q^{Ind,EW} \times NumEst_{j,q}$	0.010		0.008	
	(0.007)		(0.005)	
$\alpha_q^{Ind,VW} \times NumEst_{j,q}$		0.009		0.016***
		(0.007)		(0.004)
Calendar quarter fixed effects	Yes	Yes	Yes	Yes
R^2 (full)	0.038	0.031	0.067	0.065
R^2 (within)	0.020	0.013	0.058	0.057
Num. obs.	72,799	72,799	106,766	106,766

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

4.6. Extension of the analytical model to allow for overnight price changes

In this section, I extend the analytical model from Chapter 3 to allow for stock price changes that occur due to announcements of public information. I assume that all investors observe these announcements of public information immediately and simultaneously, and agree on their valuation implications. I refer to these valuation revisions as "overnight" price changes and valuation revisions due to trading activity as "intraday" price changes.

4.6.1. Setup

The risky asset has terminal value $\tilde{V} = \sum_{t=1}^{T} (\tilde{v}_t + \tilde{w}_t)$, where $\tilde{v}_t$ are independently distributed on $\mathcal{N}\left(0, \sigma_{v,t}^2\right)$, $\tilde{w}_t$ are independently distributed on $\mathcal{N}\left(0, \sigma_{w,t}^2\right)$, and $\tilde{v}_t$ and $\tilde{w}_t$ are independent. Each day, t, comprises a sub-period in which trading does not occur ("overnight"), followed by sub-period in which trading occurs ("intraday"). During the overnight sub-period, the random variable $\tilde{w}_t$ realizes publicly. All market participants observe w_t immediately and simultaneously, and agree on its valuation impact. At the end of each overnight sub-period, the market maker sets price by

$$P_t^O = \mathrm{E}\left[\tilde{V}|H_{t-1}\right] + w_t \tag{4.6.1}$$

At the end of each intraday sub-period, the market maker sets price as in Section 3.1.1 by

$$P_t^C = \mathrm{E}\left[\tilde{v}_t|D_t, H_{t-1}\right] + P_t^O + \rho D_t \tag{4.6.2}$$

where D_t denotes the net order imbalance and $\mathrm{E}\left[\tilde{v}_t|D_t, H_{t-1}\right] + P_t^O = \mathrm{E}\left[\tilde{V}|H_t\right]$ denotes the expected value of the risky asset given all available public information at the end of the intraday sub-period. Within the context of this model, the public information set at the end of period t comprises the history of order flow and the history of price changes due to public information announcements:

$$H_t = \{D_1, \ldots, D_t, w_1, \ldots, w_t\}$$

I assume that informed investors behave as specified in Section 3.1.1, that there are no arbitrageurs in this market (i.e., $M = 0$), and that liquidity trader demand is not serially correlated (i.e., $\phi = 0$).

4.6.2. Equilibrium

Because trading does not occur during the overnight sub-period, the informed investors choose their demand as in the analytical model in Section 3.1. That is, the informed investors choose their demand according to

$$x_t = \frac{1}{2(\lambda_d + \rho)} v_t + \frac{\alpha}{\lambda_d + 2\rho} u_{t-1} \tag{4.6.3}$$

where expected demand is

$$\mathrm{E}\left[\tilde{D}_t | H_{t-1}\right] = \frac{\alpha}{\lambda_d + 2\rho} u_{t-1} \tag{4.6.4}$$

The market maker sets price using the strategy

$$P_t^O = \mathrm{E}\left[\tilde{V} | H_{t-1}\right] + w_t \tag{4.6.5}$$

$$P_t^C = \lambda_d \left(D_t - \mathrm{E}\left[\tilde{D}_t | H_{t-1}\right]\right) + P_t^O + \rho D_t \tag{4.6.6}$$

where λ_d is the unique real root of

$$\lambda_d^3 + 2\rho\lambda_d^2 + \left(\rho^2 - \frac{1}{4}\bar{\sigma}\right)\lambda_d - \frac{1}{2}\bar{\sigma}\rho = 0 \tag{4.6.7}$$

in which $\lambda_d > 0 \geq -\rho$.

4.6.3. Properties of price changes

Overnight price changes follow the process:

$$P_t^O - P_{t-1}^C = -\rho D_{t-1} + w_t \tag{4.6.8}$$

Intraday price changes follow the process:

$$P_t^C - P_t^O = (\lambda_d + \rho)\left(D_t - \mathrm{E}\left[\tilde{D}_t | H_{t-1}\right]\right) + \rho \mathrm{E}\left[\tilde{D}_t | H_{t-1}\right] \tag{4.6.9}$$

As in Section 3.1, let $\eta_t \equiv (\lambda_d + \rho)\left(D_t - \mathrm{E}\left[\tilde{D}_t | H_{t-1}\right]\right)$ denote the price impact of unexpected demand and $\psi \equiv \rho/\lambda_d$ denote the ratio of transaction costs to information asymmetry. Also, recall

that $u_{t-1} = \frac{1}{1+\psi}\eta_{t-1}$.

Overnight price changes follow the process:

$$P_t^O - P_{t-1}^C = -\frac{\psi}{1+\psi}\eta_{t-1} - \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+2\psi}\right)\eta_{t-2} + w_t \qquad (4.6.10)$$

At the beginning of the overnight sub-period,

$$E\left[P_t^O - P_{t-1}^C|H_{t-1}\right] = -\frac{\psi}{1+\psi}\eta_t - \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+2\psi}\right)\eta_{t-1} \qquad (4.6.11)$$

Intraday price changes follow the process:

$$P_t^C - P_t^O = \eta_t + \frac{\psi}{1+\psi}\left(\frac{\alpha}{1+2\psi}\right)\eta_{t-1} \qquad (4.6.12)$$

At the beginning of the intraday sub-period,

$$E\left[P_t^C - P_t^O|H_{t-1}\right] = \psi\left(\frac{\alpha}{1+2\psi}\right)\left(\frac{1}{1+\psi}\right)\eta_{t-1} \qquad (4.6.13)$$

Again, the parameters ψ and α are identifiable empirically.

I estimate this model empirically in Section 4.1.

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