Shorting Opaque Signals

by

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Submitted to the Sloan School of Management
in partial fulfillment of the requirements for the degree of

Master of Science in Management Research

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2016

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Abstract

This study uses short interest data to show that quantitative equity investors devote more capital to firm-specific arbitrage strategies in stocks with more opaque earnings. There are also higher strategy returns in stocks with opaque earnings. Together, these results suggest that quantitative investors exploit their sophistication by trading when the firm's earnings make it more costly for other market participants to understand the future implications of a signal. The result is stronger for fundamental-based strategies such as post-earnings-announcement drift than for market-based strategies such as return momentum, suggesting that arbitrageurs shift capital from market strategies to fundamental strategies when earnings are opaque. Overall, the paper highlights the role of sophisticated quantitative investors in impounding signals that are difficult to understand into prices and suggests that the opacity of a firm's fundamentals is a key determinant of sophisticated investors' trading strategies.

Thesis Supervisor: John E. Core
Title: Professor

Acknowledgments

I thank Eric So for advice and encouragement during many discussions about the project, John Core and seminar participants at MIT for helpful comments, and Ben Yost for help obtaining data. Most importantly, I thank my wife Jenessa for making this degree and thesis possible. All errors are my own.

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1. Introduction

Many equity investors compete for trading profits using publicly available signals of firm value. Hundreds of papers in finance and accounting find that numerous firm-specific signals continue to predict returns in the months after they are made public [27, 2]. However, we know very little about how investors choose what signals to rely on as they develop their strategies. One approach to understanding how investors choose strategies is to group signals into categories based on shared characteristics that could determine the strategy's profitability. In this study, I assign several of the most common equity signals to two groups, fundamental signals that rely on periodic releases of accounting data and market signals that inherit information content primarily from cross-sectional variation in market prices. This study furthers our understanding of return predictability by documenting that quantitative equity investors devote more capital to signals in stocks with more opaque earnings. This result is especially strong for fundamental signals that are closely linked to earnings opacity, implying that sophisticated investors shift capital from market strategies to fundamental strategies because of earnings opacity.

Throughout the paper, I use the term "opaque earnings" to refer to earnings properties that make it more difficult for investors to extract value-relevant signals from accounting data. Earnings might fail to be informative about firm value if they are excessively volatile, if the accruals component does not reliably map into cash flows, or if they reflect economic events differently than earnings of related firms. To the extent these earnings characteristics create opacity, understanding the future implications of the financial statements can be more costly. However, the impact of opacity on the allocation of arbitrage capital is unclear ex ante. On the one hand, opaque earnings likely increase the propensity for some market participants to misprice signals, creating an advantage for sophisticated investors who can gather and trade on signals at a lower cost. On the other hand, sophisticated investors might be less likely to devote trading resources to signals when opacity makes them less informative indicators of firm value. This study examines this tension by exploring whether earnings opacity affects the signals the arbitrageurs choose to pursue and the intensity of their trading when pursuing them.

In this study, I focus on the earnings quality dimension of firm-level opacity because of the close theoretical link between the mapping from earnings to cash flows and fundamental trading strategies such as the post-earnings-announcement drift and the accruals anomaly that rely on periodic earnings data. However, previous accounting research has identified multiple dimensions of a firm's information environment that influence the ease with which investors extract value-relevant signals from accounting and market data. These dimensions include information intermediaries (e.g., analysts, auditors, and media), voluntary disclosures [34, 37], financial statement complexity [31, 8], comparability [15], and accruals quality [17, 16]. [4] and [25] are representative of researchers' recent efforts to understand to what extent these sources of information are substitutes or complements. These studies provide evidence that managers increase voluntary disclosure to substitute for decreased analyst coverage and complex financial statements.

Collectively, the evidence in this study builds on prior research about firm-level opacity by pointing to a distinct role for earnings opacity in determining short-sellers firm-level and strategy-level trading choices. This evidence relates to the finding in [32] that stock holdings of international mutual funds predict returns better in firms and countries with more opaque financial reporting. A key distinction of this study is that, while [32] shows that opacity determines which stocks investors trade in, I show that opacity determines which signals investors trade on. Additionally, this paper highlights a role for the earnings dimension of opacity that is distinct from the general opacity of the firm's information environment, such as analyst coverage and auditor quality that are the focus of [32]. This distinction is important because the hypothesis is less clear-cut in this study than in [32] due to the potential for earnings opacity to actually make the informed investor's earnings-based strategy less useful for predicting future outcomes. Finally, [32] studies changes in the holdings of mutual funds, but this study is able to provide evidence on specific signals that sophisticated investors have been found to trade on.

I apply the methodology developed in [26] that uses short interest data to infer the amount of capital allocated to quantitative equity strategies. Because equity short sellers are mostly sophisticated investors such as hedge funds [23], short positions likely reflect sophisticated efforts to actively trade on signals of expected returns and are not contaminated by passive institutional trading or less-sophisticated active investing that often results in liquidity trading [14]. The key premise underlying the measure of arbitrage capital is that cross-sectional variation in short interest reveals the intensity with which arbitrageurs are trading on a given firm-specific characteristic. That is, short interest should be high for stocks that a signal recommends shorting when sophisticated investors are trading heavily on that signal. I apply the [26] methodology to both fundamental and market signals. Regressions of short interest on firm-specific signals produce coefficients that can be used as proxies for the amount of capital devoted to a given strategy. Consistent with [26], I find that quantitative investors devote significant amounts of capital to several of the quantitative strategies examined in this study.

My first tests show that sophisticated investors allocate more capital to trading on several well-known signals such as earnings surprise and book-to-market among firms with more opaque earnings. In particular, earnings opacity is positively associated with the ability of the signals to explain the cross-section of short interest. Earnings opacity is measured using the standard deviation of residuals from accruals regressions [17, 22] and the (lack of) comparability of the firm's earnings to the earnings of other firms in the industry [15]. I choose these measures because prior research documents that these earnings properties influence the ability of some market participants to understand the implications of firm characteristics for future performance, which could impact the success with which sophisticated investors exploit their information advantage.

The next test establishes that returns to both fundamental- and market-based arbitrage strategies are higher in the most opaque firms. This result suggests that arbitrageurs receive compensation for devoting more trading resources to opaque firms, an apparent necessary condition for this arbitrage behavior to be sustainable [24, 29]. However, while arbitrage activity reduces future strategy returns by definition, the result also implies that increased arbitrage capital does not fully eliminate return predictability [26, 10, 1]. This paper also complements prior accounting research on the relationship between disclosure quality and stock returns [e.g., 22] by directly measuring how short-sellers' choice of trading strategy and the subsequent performance of the strategy vary with earnings quality.

Much of the discussion to this point emphasizes the impact earnings opacity can have on the set of stocks investors choose to trade. Once investors have chosen which stocks to trade, earnings opacity could also determine which signals investors choose to trade on. Specifically, the signals that are commonly used by finance practitioners and academics to predict returns vary in the extent to which they are based on earnings and other accounting data. I create two groups of signals, fundamental-based signals such as earnings surprise and the fundamental score from [33] that rely on periodic releases of accounting data such as quarterly earnings announcements and market-based signals such as book-to-market and return momentum that inherit information content primarily from cross-sectional variation in market prices. Of these two types of strategies, prior accounting literature suggests the ability of the fundamental-based signals to predict future returns is most likely to be connected to the properties of earnings. For example, [35] posits that the accrual anomaly arises because investors fixate on earnings and overestimate the persistence of accruals. Consistent with this reasoning, I show that opaque earnings lead quantitative investors to shift capital from market to fundamental strategies. In particular, the impact of earnings opacity on the amount of capital devoted to a strategy is greater for earnings surprise and a composite "fundamental" strategy than for return momentum and a composite "market" strategy.

The distinct nature of fundamental and market strategies presents a powerful falsification test, specifically, that earnings opacity should not have as strong of an effect on the amount of capital allocated to strategies that are not based on accounting data (e.g., return momentum). As explained above, my tests reject the falsification hypothesis, providing clear evidence of a link between earnings opacity and strategies that rely on accounting earnings. A key takeaway from this analysis is that earnings opacity not only shifts arbitrage capital towards opaque stocks but also shifts capital towards accounting signals because they are more likely to be sensitive to the properties of earnings.

Despite conceptual differences in the dimensions of opacity and evidence that some dimensions are negatively correlated, the measures are often positively correlated in the cross-section. This correlation complicates efforts to attribute causality to one dimension of opacity or another, but holding constant other dimensions of opacity as much as possible can help isolate the impact of the dimension of interest. The final tests of this paper attempt to distinguish earnings opacity from other dimensions of opacity by repeating the main analyses in the subset of firms without any analyst earnings forecasts or management earnings guidance. As before, short-sellers devote more capital to trading on arbitrage strategies in firms with more opaque earnings. In fact, for return momentum the result is much stronger than before. One rationale for this result is that analysts' and managers' sluggish responses to past news bring about momentum returns [7], suggesting that earnings opacity is actually a second-order determinant of momentum returns that only becomes apparent in the absence of analyst coverage and management guidance.

Even though recent research highlights the proliferation of return predictive signals [20, 27, 30], we still know relatively little about how investors choose from this large set of signals. This study alleviates this problem by documenting the impact of opacity in the accounting system on the intensity with which arbitrageurs rely on the many distinct types of information available to them as they develop their trading models. This study also improves our understanding of the incentives to engage in active investment strategies. Prior evidence about both the intensity with which investors attempt to eliminate mispricing and the extent to which they profit from these attempts is mixed. While some evidence suggests that increases in arbitrage capital reduce mispricing [26, 1], other studies provide evidence that sophisticated investors may not always stabilize prices by trading against mispricing, such as when hedge funds invested heavily in technology stocks during the tech bubble [6]. Whether investors are trying to trade against or with mispricing, there is little evidence of consistent returns to active investing by institutional investors such as mutual funds [21]. The evidence in this paper suggests that researchers' attempts to identify the returns to active management could be more fruitful if they focus on (1) strategy types instead of investor types and (2) settings that create information advantages for certain investors or strategies.

The rest of this paper is organized as follows. Section 2 describes the research design and data. Section 3 contains empirical results on the relationship between earnings opacity and the amount of capital devoted to quantitative equity strategies. Section 4 concludes.

2. Research Design

2.1 Measuring Strategy-Level Capital

[26] develop a methodology to measure the amount of capital quantitative equity arbitrageurs devote to different equity strategies. Assuming that short interest reflects the positions of sophisticated arbitrageurs, the measure exploits the premise that short interest should be high for stocks that a quantitative equity strategy recommends shorting. As a result, regressions of short interest on strategy signals are informative about the amount of capital devoted to the strategies. The coefficients $\boldsymbol{\kappa}^{SIGNAL}$ from the following panel regression provide estimates of the amount of capital allocated to a given strategy:

$$SR_{it} = \boldsymbol{\kappa}^{SIGNAL} \cdot \mathbf{1}_{it}^{SIGNAL} + \boldsymbol{\beta}'\mathbf{x}_{it} + \textstyle\sum_f \alpha_f + \varepsilon_{it}, \qquad (1)$$

where SR_{it} is stock i's short interest ratio (short interest divided by total shares outstanding) during month-year t, $\mathbf{1}_{it}{}^{SIGNAL}$ is a full set of decile dummies created by sorting on a strategy variable $SIGNAL_{it}$ (omitting the dummy for decile 5), and $\mathbf{x}_{it}$ is a vector of controls that previous research has shown to be important determinants of short interest, including decile ranks of size (R_SIZE_{it}), institutional ownership ($R\_INSTOWN_{it}$), three-month turnover (R_TURN_{it}), and trailing twelve-month return volatility (R_RETVOL_{it}), and an indicator for whether the firm has convertible securities outstanding ($CONSEC_{it}$). The regression includes a full set of fixed effects $\sum_f \alpha_f$ for stock α_i, year α_y, month α_m, and exchange α_e.[1]

[1]Although the unit of observation of the short interest data is stock-month, [26] estimate stacked annual

The first type of strategy variables I investigate in this study includes past twelve-month return (MOM_{it}) and book-to-market (BTM_{it}). I label these strategies finance- or market-based signals because their content comes primarily from cross-sectional variation in market prices. I include these strategies because they are the most popular firm-specific equity strategies and are the focus of a large empirical asset pricing literature, especially since [28] and [19]. More importantly, these signals' reliance on market prices means they should not be affected by earnings opacity as much as accounting signals, providing a convenient falsification hypothesis that I can test to strengthen the main hypothesis. Thus, I also consider a set of popular accounting- or fundamental-based signals. Because these fundamental-based signals rely on periodic releases of accounting data such as quarterly earnings announcements and 10-K filings I expect them to be closely linked to the opacity of the firm's earnings. The fundamental-based signals are earnings surprise [SUE_{it}; 7], accruals [$TACC_{it}$; 35], fundamental score [FSC_{it}; 33], and external financing [FIN_{it}; 5]. I multiply $TACC_{it}$ and FIN_{it} by negative one so that lower values of all six strategy variables can be interpreted as a sell signal.

Following recent research that aggregates multiple signals into an expected return model [e.g., 30], in some of the tests I consider strategies based on the first principal component of all six signals ($SIGNAL_{it}$), of the market-based signals ($SIGNALMKT_{it}$), and of the fundamental-based signals ($SIGNALFUN_{it}$).[2] While quantitative investors certainly use more sophisticated models than the principal component technique I employ, this approach should provide a rough approximation to the aggregate portfolios generated by practitioners' state-of-the-art investing methodologies.

(and quarterly) panel regressions with month fixed effects to reduce measurement error and identify lower-frequency variation in strategy capital. To mirror their methodology as closely as possible, I include analogous year and month fixed effects in my panel regressions that use data over the entire sample period.

[2]Each of these components has an eigenvalue greater than one and captures much of the variation underlying the signals. $SIGNAL_{it}$ ($SIGNALMKT_{it}$) [$SIGNALFUN_{it}$] captures 26% (64%) [34%] of the total variation.

2.2 Conditioning on Earnings Opacity

According to the definition in [16], high quality earnings "provide more information about the features of a firm's financial performance that are relevant to a specific decision made by a specific decision-maker." While high quality fundamental information likely helps many investors to understand the future implications of the firm's earnings, quantitative equity investors who employ strategies that attempt to profit from mispricing may actually benefit when opaque earnings prevent other investors from fully impounding fundamental information into price. Thus, high quality information environments in general, and high quality earnings in particular, may be good for one group of decision-makers and bad for another [32]. Instead of discussing earnings quality, throughout the paper I emphasize that earnings *opacity* benefits short-sellers' quantitative equity arbitrage strategies that are the focus of this study.

I use two measures of earnings opacity that I expect to be related to the extent to which short-sellers use fundamental-based signals to decide which firms to short. First, [17] develop a measure called accruals quality that is meant to capture the ability of accruals to shift the recognition of cash flows over time so that earnings better reflect a firm's economic performance. $ACCRUALQ_{it}$ is the standard deviation of residuals from accruals regressions calculated following [22], who augment the [17] model with the fundamental variables from the modified Jones model. Second, [15] develop a measure called earnings comparability that is meant to capture the extent to which a firm's mapping from economic events to earnings is similar to the mapping of other firms in the industry. $COMPARE_{it}$ is the firm-specific measure of comparability $CompAcct4_{it}$ in [15], multiplied by negative one so that higher $COMPARE_{it}$ is interpreted as more opaque earnings. For parsimony, my reported tests use the first principal component of these two proxies ($OPAQUE_{it}$).[3] All of the results in the study hold if I use either of the earnings opacity proxies alone.

[3] $OPAQUE_{it}$ has an eigenvalue greater than one and captures 56% of the variation underlying the earnings opacity proxies.

In equation (1), the coefficient on the dummy for the lowest $SIGNAL_{it}$ decile, $\kappa^{SIGNAL1}$, reflects the difference in short interest for extreme losers relative to the omitted decile 5. While [26] use $\kappa^{SIGNAL1}$ as the main proxy for arbitrage capital devoted to a given strategy, they show that measuring arbitrage capital with the coefficient κ^{SIGNAL} from a regression using the raw strategy decile rank R_SIGNAL_{it} captures similar information as the less parametric specification in equation (1) using a full set of strategy dummies $\mathbf{1}_{it}^{SIGNAL}$. For parsimony, in most of the tests I use the decile rank approach because it delivers a single coefficient that summarizes arbitrage capital. Inferences and economic magnitudes are similar if I use the more flexible approach. Hence, in order to understand the relationship between strategy-level capital and firm-level earnings opacity I estimate the following panel regression separately for the high and low terciles of $OPAQUE_{it}$:

$$SR_{it} = \kappa^{SIGNAL} \cdot R\_SIGNAL_{it} + \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\delta}'(\mathbf{x}_{it} \cdot R\_SIGNAL_{it}) + \textstyle\sum_f \alpha_f + \varepsilon_{it}. \tag{2}$$

I test the hypothesis that earnings opacity influences the allocation of capital across strategies by comparing t-statistics on the coefficients κ^{SIGNAL} from the high and low terciles and by testing the equality of these coefficients.[4] I also test whether returns to signals vary with earnings opacity by estimating equation (2) with RET_{it} as the dependent variable, where RET_{it} is stock i's return during month-year t.

2.3 Data

The analysis in this paper uses monthly short interest data available from Compustat from June 1988 through December 2012. Short interest data for NYSE and AMEX stocks is available for the entire sample period, and data for NASDAQ stocks is available beginning in

[4] I test the equality of coefficients across groups following [12]. In untabulated analyses, I also estimate equation (2) on the entire sample and include the main effect of the decile rank of $OPAQUE_{it}$ (i.e., R_OPAQUE_{it}) and its interaction with R_SIGNAL_{it} (i.e., R_OPAQUE_{it}*R_SIGNAL_{it}) among the regressors. Inferences from this latter specification are qualitatively similar to the specification that estimates separate regressions for the high and low terciles of $OPAQUE_{it}$. However, I tabulate results from the tercile specification in attempts to offer the clearest exposition possible.

July 2003. Short interest is measured as of the last trading-day on or before the 15th of each month. Market data is from CRSP and accounting data is from Compustat. I also collect institutional ownership data from Thomson Reuters Institutional (13f) Holdings database, analyst coverage data from IBES, and earnings guidance data from Thomson First Call's Company Issued Guidance database. Requiring non-missing data to calculate the variables used in the tests produces a final sample of 295,019 stock-month observations.[5]

All independent variables are measured with a lag, that is, using data that is known at the end of the month prior to each observation of SR_{it} and RET_{it}. I assume market data are known immediately and accounting data are known four months after the end of the fiscal period. Continuous independent variables, except returns, are winsorized at the 1st and 99th percentiles within each year to reduce the effects of outliers. Decile ranks are determined by sorting variables each year. All decile ranks are scaled to vary between zero and one so that, for example, $R\_SIGNAL_{it} = 0$ means that a firm is in decile 1 and should be shorted and $R\_SIGNAL_{it} = 1$ means that a firm is in decile 10 and should be bought. As a result, the regression coefficients can be interpreted as the difference in the average short interest ratio of decile 1 and decile 10 of a given variable. Standard errors in all regressions are adjusted for correlation across firms and across time by clustering by both stock and year following the procedure developed by [36]. For parsimony, I omit the variables' stock i and month-year t subscripts from the rest of the discussion and tables.

2.4 Descriptive Statistics

Table 1 presents descriptive statistics of the variables used in this paper. Panel A presents distributional statistics. The mean firm-month has a short ratio of 2.94 percent of shares outstanding, monthly stock return of 1.50 percent, a 0.20 standard deviation earnings surprise, a negative one percent accrual, fundamental score of 5.05, a one percent increase in

[5]Following [11], who argue that the First Call data is unreliable before 1998, the sample for one test (Table 6, Panel B) that relies on two years of past First Call data includes 202,256 observations from 2000 to 2012.

external financing, a 15 percent stock return over the prior year, a book-to-market ratio of 0.59, standard deviation of accruals residuals of six percent of assets, and a one percent of assets difference between the firm's predicted earnings and the predicted earnings of similar firms in the industry. Also, for the mean firm-month market capitalization is $561 million, 55 percent of shares outstanding are held by 13f institutions, 13 percent of the stock's shares are traded each month, and the annual standard deviation of returns is 41 percent. Twenty percent of the sample has convertible securities outstanding, 57 percent are NYSE stocks, 30 percent have no analyst coverage, and 52 percent of firms after January 2000 do not issue earnings guidance.

Panel B shows linear (Pearson) and rank (Spearman) correlation coefficients. Short ratios and returns are slightly negatively correlated, consistent with short sales providing a negative signal about the firm's future prospects [3, 13]. Many of the signal variables are positively correlated, but the correlations are all far from one and there are even a few negative correlations, suggesting that the signals have different implications for future performance that investors need to consider as they decide which stocks to trade. For example, although the momentum (or underreaction) strategies *SUE* and *MOM* are positively correlated ($\hat{\rho} = 0.20$), the correlation is not close to one, consistent with prior evidence that each provides distinct information and predicts large drifts in returns even after controlling for the other [7]. Because they are related strategies yet differ in their reliance on accounting data, I use *SUE* and *MOM* to represent their respective strategy types (fundamental vis-á-vis market) in several of the tests. The two earnings opacity proxies, *ACCRUALQ* and *COMPARE*, and their first principal component (*OPAQUE*) are all positively correlated, with higher values reflecting more opaque earnings. Also, note that the earnings opacity proxies have positive correlations with the indicators for no analyst coverage and no earnings guidance (*NOANALYST* and *NOGUIDANCE*) that range between 0.11 and 0.24, consistent with there being multiple related yet distinct dimensions of firm-level opacity [25].

3. Empirical Results

3.1 Estimating Strategy-Level Capital

Before testing the main hypotheses, I establish that arbitrageurs devoted substantial amounts of capital to market- and fundamental-based strategies during the sample period considered in the paper. Table 2 presents estimates of equation (1) that measure the average amount of capital devoted to each strategy during the sample period. The coefficient $\kappa^{SIGNAL1}$ on the first signal decile dummy *SIGNAL1* is interpreted as the intensity with which arbitrageurs trade on a particular strategy because this coefficient reflects the spread in short interest between extreme losers in decile 1 and central firms in the omitted decile 5. Short-sellers seem to allocate statistically and economically significant amounts of capital to *SUE*, *FSC*, *MOM*, *BTM*, and the composite *SIGNAL* strategy. As expected, more capital is devoted to the market-based strategies *MOM* and *BTM* than to fundamental-based strategies. *TACC* does not seem to be a significant strategy among short-sellers. Even considering the statistically significant coefficient on the second decile dummy *SIGNAL2*, 13 basis points (bps) is economically small relative to the arbitrage capital estimates for other strategies and relative to the mean short interest ratio of 294 bps.[6] Although the 21 bps estimate for the *FIN* strategy is only statistically significant using a one-tailed test (t-statistic = 1.56), I infer that *FIN* is a statistically significant strategy when using the alternative short-long

[6] When I estimate the regression for *TACC* during the period after the publication of [35], the coefficient on *SIGNAL1* is unchanged and the coefficient on *SIGNAL2* increases to 16 bps.

and decile rank measures of arbitrage capital considered by [26].[7]

3.2 Earnings Opacity and Strategy-Level Capital

The first main result of the paper is that short-sellers devote more capital to trading on firm-specific signals in firms with more opaque fundamentals. Table 3 shows estimates of equation (2) for the high and low terciles of *OPAQUE*. While a large positive coefficient on the decile 1 dummy in equation (1) implies high strategy-level capital, a large *negative* coefficient on *R_SIGNAL* in equation (2) implies high strategy-level capital. That is, values of *R_SIGNAL* near zero are sell signals and values near one are buy signals, meaning that short interest should be decreasing in *R_SIGNAL* when short-sellers trade heavily on a signal. The estimate of the amount of arbitrage capital devoted to the composite *SIGNAL* strategy is more than five-times larger among the high *OPAQUE* firms (91 bps) than among the low *OPAQUE* firms (17 bps). This finding suggests that short-sellers believe arbitrage strategies will be more profitable in firms with opaque earnings, perhaps because understanding and/or trading on the future implications of these firms' fundamental and market data is more costly for other market participants. In the next section, I consider whether short-sellers' beliefs about the relationship between earnings opacity and the returns to arbitrage strategies are correct.

3.3 Earnings Opacity and Strategy Returns

[24] and [29] argue that sustained arbitrage depends on the continued existence of exploitable opportunities, so that investors are compensated for their efforts to become informed. In this section, I present evidence that short-sellers are compensated for devoting more trading resources to opaque firms. Table 4 shows estimates of equation (2) with

[7]Specifically, for *FIN* the short-long measure, $\kappa^{SIGNAL1} - \kappa^{SIGNAL10}$, is 42 bps (t-statistic = 2.53) and the decile rank measure, the coefficient κ^{SIGNAL} on *R_SIGNAL*, is −30 bps (t-statistic = −2.92).

RET(%) as the dependent variable. A positive coefficient on *R_SIGNAL* is evidence of returns to the signal strategy that shorts decile 1 firms and buys decile 10 firms. This coefficient is more than twice as large in the high *OPAQUE* tercile than in the low *OPAQUE* tercile, suggesting that there is more mispricing for sophisticated investors to exploit among opaque firms and that the increased arbitrage activity in these stocks documented in the previous section only partially impounds strategy signals into price. In addition, the finding of significant mispricing in both the high and low *OPAQUE* terciles is consistent with the evidence in [26] that more arbitrage capital does not completely eliminate returns to equity strategies.

This differential predictability across *OPAQUE* terciles also complements the result in [18] that stock prices better reflect the persistence of accruals and cash flows in firms with high analyst ratings of disclosure quality (i.e., AIMR disclosure scores), and the result in [9] that returns of good accruals quality (AQ) firms predict future returns of bad AQ firms in the same industry. However, unlike this paper, neither of these prior studies shows which investor groups amplify and mitigate predictability or addresses heterogeneous effects of accounting quality on different types of strategies.

3.4 Shifting Capital Across Strategy Types

Having established that short-sellers devote more capital to quantitative strategies in firms with opaque earnings, the next tests consider whether this result is concentrated in fundamental strategies that should be more sensitive to the properties of earnings than market strategies. Table 5 compares estimates of equation (2) for fundamental-based strategies and market-based strategies. This analysis is similar to Table 3 but replaces the strategy that aggregates all fundamental and market signals (*SIGNAL*) with proxies for each type of strategy.

Panel A compares *SUE* and *MOM*, which epitomize fundamental and market strategies, respectively, as argued in section 2.4 above. While considerable capital (60 bps) is devoted to SUE in the high $OPAQUE$ tercile, I find evidence that arbitrageurs do not trade on SUE at all in firms that have high quality earnings. There is also more capital devoted to MOM in more opaque firms (96 bps) than in less opaque firms (49 bps), but I emphasize that short-sellers still devote a significant amount of capital to MOM in less opaque firms. This result suggests that opaque earnings is a necessary ingredient to induce arbitrageurs to trade on fundamental signals. Stated differently, even though opaque earnings induce short-sellers to trade on both strategy types more intensely, the relative importance of fundamental strategies shifts significantly when moving from transparent to opaque firms. To be precise, none of the aggregate capital devoted to underreaction strategies (SUE and MOM) in the low $OPAQUE$ tercile is devoted to SUE, but SUE makes up about 40 percent (i.e., $\frac{60}{60+96} \approx 0.40$) of the capital devoted to underreaction strategies in the high $OPAQUE$ tercile. This result becomes slightly stronger in untabulated tests that include R_SUE and R_MOM in the same regressions to account for the significant correlation between the two strategies. Panel B compares the strategy types by using the first principal components $SIGNALFUN$ and $SIGNALMKT$ to aggregate the information contained in all strategies of each type. The inferences from the Panel B regressions are qualitatively similar to inferences made about Panel A, strengthening the conclusion that opaque earnings lead short-sellers to shift weight from market to fundamental strategies in their trading models.

Figure 1 provides a visual summary of the main results to this point. Each graph in the figure plots coefficients from equation (2) using a full set of strategy dummies $\mathbf{1}^{SIGNAL}$ in order to better understand the full mapping from firm-characteristics (i.e., strategy signals) to short interest. Consistent with Table 3, the slope coefficients in the left side of Panel A shows that the relationship between the $SIGNAL$ deciles and short interest is much more pronounced in the high $OPAQUE$ tercile, suggesting that more arbitrage capital is dedicated to stocks with opaque earnings. As shown in Table 4, the right side of Panel A shows that the composite signal better predicts returns in the opaque subsample, consistent with short-sellers receiving compensation for trading more intensely on signals when earnings are more opaque. The left side of Panels B and C illustrate the Table 5 result. Panel B shows that

SUE is much more important for explaining short interest among opaque stocks, but, in contrast, Panel C shows that the slopes on *MOM* are similar in the high and low *OPAQUE* terciles. In fact, the coefficient on the *MOM* decile 1 dummy is much larger in the *low OPAQUE* tercile, providing even stronger evidence than Table 5 that earnings opacity is a significant determinant of the weight that short-sellers place on fundamental- and market-based strategies. Finally, the right side of Panels B and C provide additional evidence that there is more mispricing for short-sellers to exploit in stocks with opaque earnings.

3.5 Holding Constant Other Sources of Earnings Information

This paper highlights the link between earnings opacity and the ability of sophisticated investors to generate returns using earnings-related trading strategies. However, I acknowledge that prior research, especially [32], also addresses the question of whether informed investors are able to exploit opaque information environments. Also, I showed in section 2.4 that the earnings quality proxies used in this study are correlated with proxies for the quality of the information environment, such as analyst coverage, that are the focus of [32], complicating efforts to distinguish different dimensions of firm-level opacity conceptually and empirically. In this section, I attempt to distinguish earnings opacity from alternative information sources by holding constant the level of earnings information provided by analysts and managers and then examining whether the main results of the study change.

Despite the above caveat, I emphasize several key differences between the contributions made by this paper and [32] before presenting the empirical evidence. First, while [32] shows that informed investors' aggregate strategy better predicts returns in opaque firms, this paper documents the tendency of some informed investors to shift capital from one type of strategy (market) to another (fundamental) due to firm-level opacity. Second, this paper links a specific dimension of firm-level opacity, earnings quality, to a popular set of signals that are likely affected by this type of opacity to varying degrees. Third, while [32] makes the intuitive argument that opacity increases the returns to identifying signals and becoming informed, this paper addresses a tension that is specific to earnings opacity. That is, the same earnings opacity that makes it difficult for other market participants to understand the future implications of a signal may also limit the predictive usefulness of the signal for short-sellers. If this were the case then instead of observing more informed trade in opaque firms, we would observe less informed trade by quantitative traders who would understand that the signal is less useful for predicting future returns. Fourth, this paper considers quantitative hedge funds' strategies and [32] considers mutual funds' holdings, two characteristics of trading with varied capacity to capture investors' efforts to exploit firm-level opacity. For example, unlike hedge funds, mutual funds are often prohibited from short-selling and taking on other types of leverage, are usually required to track some kind of benchmark, and are often given little time to meet investor redemptions.

To address these issues empirically, Table 6 compares the amount of capital dedicated to *SUE* and *MOM* strategies among the subsamples of firms that do not have any analyst earnings forecasts (Panel A) or issue any earnings guidance (Panel B) during the prior two years. Among firms with little available earnings information outside the financial statements, I continue to find that short-sellers devote more capital to trading on firm-specific signals when earnings are more opaque. Curiously, this result is much stronger for *MOM* than it was in the full sample. One potential explanation for this finding is that analysts' forecasts and managers' guidance generate momentum returns by responding sluggishly to past news [7]. If this is true, then the collective evidence in Tables 5 and 6 indicates that (1) analysts' and managers' stale forecasts are a more important source of *MOM* returns (and investing) than earnings opacity in the full sample of stocks, but (2) earnings opacity is a second-order determinant of *MOM* investing that becomes apparent in the absence of analyst coverage and management guidance.

4. Conclusion

We know that significant amounts of equity investors' capital is invested based on firm-specific signals that are easily calculated from publicly available accounting and market data. Sophisticated investors expect these strategies to generate returns [2]. But we know very little about how investors choose what signals to rely on. Using observed returns to infer the determinants of investor expectations about the returns to a trading strategy is imperfect. This study attempts to overcome these challenges using cross-sectional variation in short interest [26]. I find quantitative equity investors devote more capital to firm-level arbitrage strategies in stocks with more opaque earnings. More than a firm's general opacity, earnings opacity is closely linked to the performance of earnings-based trading strategies such as earnings surprise.

Strategy returns are also higher in stocks with opaque earnings. Thus, quantitative investors seemingly exploit their sophistication by trading when the firm's earnings make it more costly for other market participants to understand the future implications of a signal. The result is stronger for earnings- or fundamental-based strategies such as post-earnings-announcement drift than for market-based strategies such as return momentum, implying that arbitrageurs shift capital from market strategies to fundamental strategies when earnings are opaque. Overall, the paper gives insight into the efforts of sophisticated quantitative investors to profit by impounding signals that are difficult to understand into prices and suggests that the opacity of a firm's fundamentals is a key determinant of sophisticated investors' strategy choices.

Appendix A

Tables

Table 1. Descriptive statistics

Panel A reports distributional statistics. Panel B reports linear (Pearson) and rank (Spearman) correlations. For parsimony, I omit the variables' stock i and month-year t subscripts. *SR* is short interest divided by total shares outstanding. *RET* is monthly stock return. *SUE* is seasonally adjusted earnings divided by the standard deviation of seasonally adjusted earnings over the prior eight quarters, following [7]. *TACC* is accruals calculated following [35], multiplied by negative one. *FSC* is *F_SCORE* from Piotroski (2000), calculated to range between 0 and 9. *FIN* is $\Delta XFIN$, the sum of external financing from equity and debt, from [5], multiplied by negative one. *MOM* is stock return from month -12 to month -2. *BTM* is book value of equity divided by lagged market value of equity. *SIGNAL* is the first principal component of *SUE, TACC, FSC, FIN, MOM,* and *BTM*. *SIGNALFUN* is the first principal component of *SUE, TACC, FSC,* and *FIN*. *SIGNALMKT* is the first principal component of *MOM* and *BTM*. *ACCRUALQ* is the standard deviation of residuals from accruals regressions calculated following [22], who augment the [17] model with the fundamental variables from the modified Jones model. *COMPARE* is the firm-specific measure of comparability $CompAcct4_{it}$ in [15], multiplied by negative one so that higher values are interpreted as more opaque earnings. *OPAQUE* is the first principal component of *ACCRUALQ* and *COMPARE*. *SIZE* is the log of market value of equity. *INSTOWN* is shares held by 13f institutions divided by total shares outstanding. *TURN* is the average of monthly trading volume divided by shares outstanding over the prior three months. *RETVOL* is the standard deviation of returns over the prior 12 months. *CONSEC* is an indicator for whether the firm has convertible securities outstanding. *NYSE* and *NASDAQ* are stock exchange dummies. *NOANALYST* (*NOGUIDANCE*) is an indicator for stocks that do not have any analyst forecasts of quarterly earnings (do not issue any earnings guidance) during the prior two years. All independent variables are measured at the end of the month prior to each observation of *SR* and *RET*. I assume market data are known immediately and accounting data are known four months after the end of the fiscal period. Continuous variables, except returns, are winsorized at the 1st and 99th percentiles within each year. The main sample consists of 295,019 stock-month observations in the period July 1988 - December 2012. Following [11], the *NOGUIDANCE* sample consists of 202,256 stock-month observations in the period January 2000 - December 2012.

Panel A: Distributional statistics

Variable	Mean	Std Dev	1st	25th	Median	75th	99th
SR(%)	2.94	3.85	0.00	0.32	1.52	4.01	18.83
RET(%)	1.50	13.97	-31.55	-5.28	0.75	7.10	45.25
SUE	0.22	1.99	-6.17	-0.38	0.16	0.95	5.61
TACC	0.01	0.04	-0.12	-0.01	0.01	0.03	0.15
FSC	5.05	1.75	1	4	5	6	8
FIN	-0.01	0.10	-0.48	-0.02	0.00	0.03	0.22
MOM	0.15	0.51	-0.71	-0.14	0.08	0.33	2.21
BTM	0.59	0.55	0.05	0.29	0.48	0.75	2.63
SIGNAL	0.02	0.98	-2.70	-0.55	0.06	0.62	2.29
SIGNALFUN	0.04	0.97	-2.97	-0.50	0.13	0.68	2.04
SIGNALMKT	-0.01	0.96	-2.90	-0.48	0.02	0.49	2.73
ACCRUALQ	0.06	0.05	0.01	0.03	0.05	0.08	0.26
COMPARE	0.01	0.02	0.00	0.00	0.00	0.01	0.08
OPAQUE	0.00	1.00	-1.00	-0.62	-0.31	0.25	4.16
SIZE	6.33	2.00	2.24	4.88	6.30	7.73	11.05
INSTOWN	0.55	0.27	0.02	0.33	0.58	0.77	0.98
TURN	0.13	0.14	0.01	0.04	0.08	0.17	0.73
RETVOL	0.41	0.25	0.11	0.24	0.35	0.51	1.34
CONSEC	0.20	0.40	0	0	0	0	1
NYSE	0.57	0.50	0	0	1	1	1
NASDAQ	0.36	0.48	0	0	0	1	1
NOANALYST	0.30	0.46	0	0	0	1	1
NOGUIDANCE	0.52	0.50	0	0	1	1	1

Panel B: Pearson (above) and Spearman (below) correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	*SR(%)*		-0.02	-0.02	-0.01	-0.09	-0.11	0.01	-0.10	0.00	-0.08	0.08	0.05
2	*RET(%)*	-0.01		-0.01	0.01	0.01	0.01	-0.02	0.06	-0.02	0.01	-0.04	0.01
3	*SUE*	0.00	0.01		-0.10	0.25	0.04	0.20	-0.16	0.62	0.53	0.21	-0.02
4	*TACC*	-0.01	0.01	-0.10		0.05	0.12	-0.01	0.02	-0.05	0.14	-0.02	-0.02
5	*FSC*	-0.06	0.03	0.27	0.05		0.24	0.13	-0.05	0.59	0.78	0.11	-0.15
6	*FIN*	-0.06	0.02	0.05	0.19	0.25		0.00	0.04	0.30	0.59	-0.02	-0.14
7	*MOM*	0.00	0.00	0.29	-0.01	0.17	0.05		-0.29	0.54	0.15	0.72	0.03
8	*BTM*	-0.23	0.03	-0.22	0.02	-0.03	-0.01	-0.33		-0.45	-0.07	-0.72	-0.01
9	*SIGNAL*	0.05	0.01	0.63	-0.03	0.61	0.26	0.58	-0.45		0.73	0.68	-0.09
10	*SIGNALFUN*	-0.03	0.03	0.52	0.14	0.82	0.50	0.21	-0.10	0.74		0.15	-0.15
11	*SIGNALMKT*	0.14	-0.03	0.28	-0.01	0.12	0.05	0.71	-0.76	0.67	0.19		0.01
12	*ACCRUALQ*	-0.01	-0.02	-0.03	-0.04	-0.14	-0.10	-0.03	-0.05	-0.08	-0.13	0.00	
13	*COMPARE*	-0.03	-0.01	-0.07	0.04	-0.11	-0.10	0.01	0.13	-0.13	-0.13	-0.09	0.25
14	*OPAQUE*	-0.06	-0.02	-0.05	-0.02	-0.14	-0.11	-0.03	0.01	-0.11	-0.15	-0.02	0.86
15	*SIZE*	0.37	0.01	0.14	0.00	0.17	0.12	0.15	-0.37	0.30	0.20	0.31	-0.38
16	*INSTOWN*	0.54	0.01	0.06	-0.01	0.10	0.08	0.04	-0.14	0.16	0.13	0.13	-0.16
17	*TURN*	0.71	-0.01	0.04	-0.01	-0.03	-0.04	0.06	-0.24	0.13	0.02	0.20	0.04
18	*RETVOL*	0.13	0.00	-0.09	0.03	-0.17	-0.16	-0.10	0.03	-0.11	-0.17	0.00	0.36
19	*CONSEC*	0.10	0.00	-0.01	0.02	0.00	-0.05	-0.02	-0.04	-0.01	-0.03	0.02	0.00
20	*NYSE*	-0.01	0.03	0.06	0.01	0.17	0.09	0.04	-0.02	0.12	0.12	0.06	-0.32
21	*NASDAQ*	0.16	-0.02	-0.04	-0.01	-0.16	-0.08	-0.03	-0.04	-0.07	-0.10	-0.01	0.26
22	*NOANALYST*	-0.33	-0.02	-0.05	0.00	-0.06	-0.05	-0.02	0.12	-0.11	-0.08	-0.10	0.11
23	*NOGUIDANCE*	-0.19	-0.02	-0.04	0.01	-0.11	-0.10	-0.02	0.07	-0.10	-0.11	-0.04	0.13

	Variable	13	14	15	16	17	18	19	20	21	22	23
1	*SR(%)*	0.03	0.02	0.15	0.38	0.58	0.14	0.09	-0.10	0.19	-0.20	-0.09
2	*RET(%)*	0.02	0.02	-0.05	-0.03	-0.02	0.12	0.00	0.00	0.00	0.00	0.00
3	*SUE*	-0.01	-0.03	0.12	0.04	0.01	-0.10	-0.01	0.05	-0.03	-0.03	-0.02
4	*TACC*	0.02	0.00	-0.01	-0.01	-0.01	0.03	0.01	0.01	-0.01	0.00	0.01
5	*FSC*	-0.05	-0.13	0.18	0.11	-0.04	-0.17	0.00	0.18	-0.17	-0.06	-0.12
6	*FIN*	-0.05	-0.12	0.11	0.10	-0.09	-0.18	-0.04	0.12	-0.11	-0.06	-0.13
7	*MOM*	0.07	0.05	0.07	-0.01	0.13	0.11	0.00	-0.02	0.03	0.01	0.02
8	*BTM*	0.03	0.03	-0.36	-0.13	-0.13	0.12	-0.03	-0.07	0.01	0.12	0.08
9	*SIGNAL*	-0.03	-0.08	0.29	0.15	0.09	-0.09	-0.02	0.11	-0.07	-0.10	-0.10
10	*SIGNALFUN*	-0.05	-0.14	0.20	0.14	-0.02	-0.18	-0.03	0.14	-0.12	-0.08	-0.13
11	*SIGNALMKT*	0.02	0.02	0.29	0.11	0.18	0.06	0.02	0.05	0.00	-0.09	-0.03
12	*ACCRUALQ*	0.12	0.74	-0.34	-0.20	0.05	0.28	0.01	-0.30	0.24	0.12	0.12
13	*COMPARE*		0.67	-0.19	-0.11	0.03	0.22	0.08	-0.08	0.04	0.11	0.13
14	*OPAQUE*	0.56		-0.37	-0.24	0.02	0.35	0.09	-0.21	0.13	0.17	0.17
15	*SIZE*	-0.36	-0.44		0.58	0.24	-0.37	0.08	0.48	-0.31	-0.36	-0.38
16	*INSTOWN*	-0.16	-0.22	0.58		0.39	-0.19	0.05	0.24	-0.06	-0.43	-0.38
17	*TURN*	0.02	-0.02	0.39	0.58		0.29	0.09	-0.12	0.21	-0.18	-0.10
18	*RETVOL*	0.35	0.42	-0.40	-0.12	0.26		0.06	-0.29	0.25	0.10	0.18
19	*CONSEC*	0.13	0.08	0.07	0.05	0.09	0.06		0.08	-0.07	0.01	0.00
20	*NYSE*	-0.18	-0.25	0.49	0.21	-0.04	-0.32	0.08		-0.85	-0.18	-0.23
21	*NASDAQ*	0.12	0.17	-0.32	-0.05	0.19	0.28	-0.07	-0.85		0.05	0.14
22	*NOANALYST*	0.17	0.16	-0.35	-0.41	-0.30	0.07	0.01	-0.18	0.05		0.39
23	*NOGUIDANCE*	0.24	0.19	-0.39	-0.36	-0.21	0.18	0.00	-0.23	0.14	0.39	

Table 2. Estimated arbitrage capital devoted to strategies

This table shows OLS estimates of equation (1) for each trading strategy. *SIGNAL1-SIGNAL10* are indicators for each decile of the signal variable, and *SIGNAL5* is the omitted base decile. While other *SIGNAL* variables are ranked into deciles, I create only five *FSC* groups of roughly equal size with $FSC < 4$ making up the lowest group, $FSC > 6$ making up the highest group, and *FSC* of 4, 5, and 6 making up the other three intermediate groups. Variables are defined in Table 1. Independent variables are measured at the end of the month prior to each observation of the dependent variable. I assume market data are known immediately and accounting data are known four months after the end of the fiscal period. Continuous variables, except returns, are winsorized at the 1st and 99th percentiles within each year. Decile ranks are determined by sorting variables each year and are scaled to vary between zero and one. The prefix *R_* denotes that a variable is ranked into deciles. For parsimony, I omit the variables' stock i and month-year t subscripts. The t-statistics reported in parentheses below each coefficient are based on standard errors that are adjusted for correlation across firms and time by clustering by both stock and year following the procedure developed by [36]. All regressions include untabulated stock, year, month, and exchange fixed effects. ***, **, *, indicate significance at the 1, 5, and 10 percent level, respectively.

Dependent Variable =				*SR(%)*			
SIGNAL Variable =	*SUE*	*TACC*	*FSC*	*FIN*	*MOM*	*BTM*	*SIGNAL*
SIGNAL1	0.32***	0.07	0.21***	0.21	0.33***	0.49***	0.36**
	(7.28)	(1.30)	(5.33)	(1.56)	(3.66)	(4.47)	(2.52)
SIGNAL2	0.19***	0.13***	0.08***	-0.03	0.21***	0.14	0.22***
	(4.89)	(3.18)	(4.74)	(-0.46)	(3.54)	(1.56)	(4.05)
SIGNAL3	0.15***	0.05		-0.11	0.17***	0.00	0.16***
	(3.31)	(1.67)		(-1.53)	(3.51)	(0.00)	(4.19)
SIGNAL4	0.06	0.02		-0.19**	0.09***	-0.02	0.09***
	(1.50)	(0.66)		(-2.42)	(3.60)	(-0.39)	(2.75)
SIGNAL6	-0.04**	0.02		-0.17***	-0.05**	0.10**	-0.10***
	(-2.38)	(0.51)		(-2.99)	(-2.32)	(2.35)	(-4.39)
SIGNAL7	-0.10***	0.02		-0.20***	-0.12***	0.16***	-0.17***
	(-2.75)	(0.49)		(-3.18)	(-3.05)	(3.76)	(-5.25)
SIGNAL8	-0.16***	0.01		-0.21***	-0.21***	0.27***	-0.23***
	(-3.59)	(0.52)		(-3.03)	(-3.23)	(4.00)	(-7.22)
SIGNAL9	-0.14***	0.04	-0.06***	-0.21***	-0.29***	0.38***	-0.36***
	(-3.15)	(1.05)	(-2.72)	(-2.83)	(-4.82)	(4.19)	(-4.33)
SIGNAL10	-0.14	0.06**	-0.14***	-0.21**	-0.44***	0.50***	-0.43***
	(-1.29)	(2.14)	(-10.35)	(-2.14)	(-3.97)	(2.85)	(-3.71)
R_SIZE	0.67	0.51	0.58	0.49	1.10*	0.91	1.08*
	(1.26)	(0.95)	(1.07)	(0.90)	(1.94)	(1.62)	(1.87)
R_INSTOWN	2.98***	3.00***	3.00***	2.99***	2.94***	2.99***	2.94***
	(3.61)	(3.59)	(3.60)	(3.57)	(3.63)	(3.65)	(3.62)
R_TURN	3.91***	3.89***	3.89***	3.86***	3.96***	3.90***	3.95***
	(9.41)	(9.49)	(9.52)	(9.41)	(9.36)	(9.34)	(9.39)
R_RETVOL	0.41**	0.41**	0.40**	0.39**	0.45***	0.39**	0.43**
	(2.45)	(2.40)	(2.38)	(2.37)	(2.73)	(2.34)	(2.59)
CONSEC	0.55***	0.55***	0.55***	0.55***	0.55***	0.54***	0.55***
	(4.53)	(4.48)	(4.51)	(4.48)	(4.48)	(4.40)	(4.56)
N	295,019	295,019	295,019	295,019	295,019	295,019	295,019
R^2	0.118	0.116	0.117	0.117	0.119	0.117	0.119

Table 3. Earnings opacity and strategy-level arbitrage capital

This table shows OLS estimates of equation (2) for the high and low terciles of *OPAQUE*. Variables are defined in Table 1. Independent variables are measured at the end of the month prior to each observation of the dependent variable. I assume market data are known immediately and accounting data are known four months after the end of the fiscal period. Continuous variables, except returns, are winsorized at the 1st and 99th percentiles within each year. Decile ranks are determined by sorting variables each year and are scaled to vary between zero and one. The prefix *R_* denotes that a variable is ranked into deciles. For parsimony, I omit the variables' stock i and month-year t subscripts. The t-statistics reported in parentheses below each coefficient are based on standard errors that are adjusted for correlation across firms and time by clustering by both stock and year following the procedure developed by [36]. All regressions include untabulated stock, year, month, and exchange fixed effects. ***, **, *, indicate significance at the 1, 5, and 10 percent level, respectively.

Dependent Variable =	*SR(%)*	
OPAQUE Tercile =	High	Low
R_SIGNAL	-0.91***	-0.17
	(-3.19)	(-0.62)
*R_SIZE*R_SIGNAL*	-0.43	0.78**
	(-1.33)	(2.30)
R_SIZE	0.72	1.23*
	(1.04)	(1.71)
*R_INSTOWN*R_SIGNAL*	0.53	-0.77**
	(1.36)	(-2.36)
R_INSTOWN	2.28**	3.88***
	(2.58)	(4.60)
*R_TURN*R_SIGNAL*	-0.52	-1.73***
	(-1.13)	(-2.75)
R_TURN	4.30***	4.59***
	(7.66)	(6.28)
*R_RETVOL*R_SIGNAL*	0.69**	-0.21
	(2.31)	(-0.51)
R_RETVOL	0.30	0.27
	(0.94)	(0.81)
*CONSEC*R_SIGNAL*	0.05	0.68***
	(0.30)	(3.03)
CONSEC	0.56**	-0.07
	(2.22)	(-0.29)
N	98,344	98,323
R^2	0.105	0.143

Test equality of *R_SIGNAL* coefficients

p-value =	0.031

Table 4. Earnings opacity and strategy returns

This table shows OLS estimates of equation (2) with *RET(%)* as the dependent variable. Variables are defined in Table 1. Independent variables are measured at the end of the month prior to each observation of the dependent variable. I assume market data are known immediately and accounting data are known four months after the end of the fiscal period. Continuous variables, except returns, are winsorized at the 1st and 99th percentiles within each year. Decile ranks are determined by sorting variables each year and are scaled to vary between zero and one. The prefix *R_* denotes that a variable is ranked into deciles. For parsimony, I omit the variables' stock *i* and month-year *t* subscripts. The t-statistics reported in parentheses below each coefficient are based on standard errors that are adjusted for correlation across firms and time by clustering by both stock and year following the procedure developed by [36]. All regressions include untabulated stock, year, month, and exchange fixed effects. *, **, *, indicate significance at the 1, 5, and 10 percent level, respectively.**

Dependent Variable =	*RET(%)*	
OPAQUE Tercile =	High	Low
R_SIGNAL	7.17***	2.93***
	(10.10)	(5.08)
*R_SIZE*R_SIGNAL*	-2.94***	-2.87***
	(-3.11)	(-3.41)
R_SIZE	-12.88***	-8.16***
	(-7.86)	(-6.00)
*R_INSTOWN*R_SIGNAL*	-0.80	0.90
	(-1.31)	(1.25)
R_INSTOWN	0.43	-0.44
	(0.50)	(-0.75)
*R_TURN*R_SIGNAL*	2.79***	1.31*
	(3.35)	(1.86)
R_TURN	-4.51***	-1.78**
	(-4.77)	(-2.14)
*R_RETVOL*R_SIGNAL*	-11.42***	-7.96***
	(-7.79)	(-4.21)
R_RETVOL	11.39***	7.03***
	(5.60)	(3.24)
*CONSEC*R_SIGNAL*	1.35***	0.51
	(2.84)	(1.19)
CONSEC	-0.88***	-0.39
	(-2.79)	(-1.34)
N	98,344	98,323
R^2	0.045	0.042

Test equality of *R_SIGNAL* coefficients

p-value =	0.000

Table 5. Shifting capital across strategy types

This table compares OLS estimates of equation (2) for fundamental-based strategies (*SUE* and *SIGNALFUN*) and market-based strategies (*MOM* and *SIGNALMKT*). Panel A compares *SUE* and *MOM*. Panel B compares *SIGNALFUN* and *SIGNALMKT*. Variables are defined in Table 1. Independent variables are measured at the end of the month prior to each observation of the dependent variable. I assume market data are known immediately and accounting data are known four months after the end of the fiscal period. Continuous variables, except returns, are winsorized at the 1st and 99th percentiles within each year. Decile ranks are determined by sorting variables each year and are scaled to vary between zero and one. The prefix *R_* denotes that a variable is ranked into deciles. For parsimony, I omit the variables' stock i and month-year t subscripts. The t-statistics reported in parentheses below each coefficient are based on standard errors that are adjusted for correlation across firms and time by clustering by both stock and year following the procedure developed by [36]. All regressions include untabulated stock, year, month, and exchange fixed effects. ***, **, *, indicate significance at the 1, 5, and 10 percent level, respectively.

Panel A: *SUE* and *MOM*

Dependent Variable =	*SR(%)*			
SIGNAL Variable =	*SUE*		*MOM*	
OPAQUE Tercile =	High	Low	High	Low
R_SIGNAL	-0.60***	0.06	-0.96***	-0.49**
	(-5.73)	(0.38)	(-4.03)	(-2.08)
*R_SIZE*R_SIGNAL*	0.47*	0.52*	0.21	1.08
	(2.00)	(1.69)	(0.48)	(1.68)
R_SIZE	-0.08	0.95	0.50	1.03
	(-0.12)	(1.30)	(0.69)	(1.57)
*R_INSTOWN*R_SIGNAL*	0.25	-0.80***	0.38	-0.30
	(1.19)	(-2.85)	(0.98)	(-0.47)
R_INSTOWN	2.46***	3.86***	2.32**	3.66***
	(2.99)	(4.37)	(2.61)	(4.45)
*R_TURN*R_SIGNAL*	-0.62	-0.98*	-0.64	-1.99***
	(-1.30)	(-1.81)	(-1.67)	(-3.04)
R_TURN	4.33***	4.20***	4.39***	4.66***
	(7.64)	(6.09)	(7.83)	(6.54)
*R_RETVOL*R_SIGNAL*	0.32	-0.28	0.61***	0.30
	(1.12)	(-1.01)	(4.14)	(0.61)
R_RETVOL	0.44	0.32	0.35	0.01
	(1.48)	(1.18)	(1.41)	(0.02)
*CONSEC*R_SIGNAL*	0.15	0.51***	0.08	0.47**
	(1.27)	(3.88)	(0.43)	(2.25)
CONSEC	0.51**	0.04	0.55*	0.06
	(2.41)	(0.23)	(1.98)	(0.36)
N	98,344	98,323	98,344	98,323
R^2	0.104	0.140	0.105	0.141

Test equality of *R_SIGNAL* coefficients

p-value =	0.000	0.081

Panel B: *SIGNALFUN* and *SIGNALMKT*

Dependent Variable =	*SR(%)*			
SIGNAL Variable =	*SIGNALFUN*		*SIGNALMKT*	
OPAQUE Tercile =	High	Low	High	Low
R_SIGNAL	-0.24***	0.04	-1.17***	-0.81**
	(-3.07)	(0.19)	(-2.78)	(-2.25)
*R_SIZE*R_SIGNAL*	-0.74***	0.19	-0.03	1.02
	(-2.90)	(0.60)	(-0.06)	(1.67)
R_SIZE	0.45	0.98	0.49	1.41**
	(0.75)	(1.21)	(0.64)	(2.10)
*R_INSTOWN*R_SIGNAL*	0.52*	-0.32	0.48	-0.42
	(1.84)	(-1.25)	(1.03)	(-0.51)
R_INSTOWN	2.35***	3.65***	2.26***	3.67***
	(2.64)	(3.98)	(2.63)	(4.71)
*R_TURN*R_SIGNAL*	-1.12***	-1.26***	0.20	-1.42**
	(-3.03)	(-3.31)	(0.50)	(-2.19)
R_TURN	4.48***	4.33***	3.97***	4.40***
	(9.32)	(7.07)	(6.66)	(6.24)
*R_RETVOL*R_SIGNAL*	0.56***	-0.20	0.63	0.02
	(2.67)	(-0.79)	(1.33)	(0.03)
R_RETVOL	0.30	0.28	0.36	0.19
	(1.21)	(1.15)	(0.95)	(0.46)
*CONSEC*R_SIGNAL*	0.21	0.51***	-0.14	0.58**
	(0.95)	(2.91)	(-0.50)	(2.19)
CONSEC	0.49**	0.03	0.67**	-0.01
	(2.42)	(0.13)	(2.07)	(-0.04)
N	98,344	98,323	98,344	98,323
R^2	0.105	0.139	0.104	0.141

Test equality of *R_SIGNAL* coefficients

p-value =	0.126	0.258

Table 6. Holding constant other sources of earnings information

Panel A (Panel B) compares OLS estimates of equation (2) for *SUE* and *MOM* among a sample of stocks that do not have any analyst earnings forecasts (do not issue any earnings guidance). Variables are defined in Table 1. Independent variables are measured at the end of the month prior to each observation of the dependent variable. I assume market data are known immediately and accounting data are known four months after the end of the fiscal period. Continuous variables, except returns, are winsorized at the 1st and 99th percentiles within each year. Decile ranks are determined by sorting variables each year and are scaled to vary between zero and one. The prefix *R_* denotes that a variable is ranked into deciles. For parsimony, I omit the variables' stock i and month-year t subscripts. The t-statistics reported in parentheses below each coefficient are based on standard errors that are adjusted for correlation across firms and time by clustering by both stock and year following the procedure developed by [36]. All regressions include untabulated stock, year, month, and exchange fixed effects. ***, **, *, indicate significance at the 1, 5, and 10 percent level, respectively.

Panel A: No analyst coverage sample

Dependent Variable =	*SR(%)*			
SIGNAL Variable =	*SUE*		*MOM*	
OPAQUE Tercile =	High	Low	High	Low
R_SIGNAL	-0.51**	-0.13	-1.04**	-0.28
	(-2.54)	(-0.47)	(-2.19)	(-0.45)
*R_SIZE*R_SIGNAL*	0.87**	0.46	0.84	0.30
	(2.43)	(0.94)	(1.03)	(0.54)
R_SIZE	1.83**	1.75**	2.34***	2.05**
	(2.42)	(2.06)	(2.79)	(2.24)
*R_INSTOWN*R_SIGNAL*	-0.48	-0.37	-0.21	-0.75
	(-1.16)	(-1.12)	(-0.45)	(-1.37)
R_INSTOWN	1.35*	1.64*	1.11	1.81*
	(1.73)	(1.86)	(1.47)	(2.01)
*R_TURN*R_SIGNAL*	-0.18	-0.13	0.00	0.67
	(-0.58)	(-0.20)	(0.00)	(1.71)
R_TURN	2.13***	2.74***	2.12***	2.32***
	(7.80)	(4.23)	(7.28)	(4.62)
*R_RETVOL*R_SIGNAL*	0.29	-0.19	0.20	-0.49
	(1.14)	(-0.34)	(0.37)	(-0.62)
R_RETVOL	0.77***	0.77**	0.94**	0.94**
	(3.07)	(2.23)	(2.12)	(2.19)
*CONSEC*R_SIGNAL*	-0.01	0.34	0.28	0.29
	(-0.03)	(1.39)	(0.77)	(0.73)
CONSEC	0.36	-0.16	0.22	-0.15
	(1.32)	(-0.71)	(0.82)	(-0.46)
N	29,421	29,421	29,421	29,421
R^2	0.052	0.071	0.055	0.072

Test equality of *R_SIGNAL* coefficients

p-value =	0.125	0.168

Panel B: No earnings guidance sample

Dependent Variable =	*SR(%)*			
SIGNAL Variable =	*SUE*		*MOM*	
OPAQUE Tercile =	High	Low	High	Low
R_SIGNAL	-0.41	-0.12	-1.05***	-0.17
	(-1.33)	(-0.39)	(-3.62)	(-0.30)
*R_SIZE*R_SIGNAL*	0.09	0.81	0.13	1.24
	(0.16)	(1.40)	(0.17)	(1.69)
R_SIZE	1.80	1.95	2.43*	2.89**
	(1.59)	(1.61)	(2.08)	(2.48)
*R_INSTOWN*R_SIGNAL*	0.03	-0.29	0.12	-1.52
	(0.04)	(-0.46)	(0.17)	(-1.31)
R_INSTOWN	3.75***	4.45***	3.55***	4.99***
	(3.67)	(2.97)	(3.19)	(3.50)
*R_TURN*R_SIGNAL*	0.20	-1.59*	0.10	-1.56*
	(0.31)	(-1.82)	(0.30)	(-1.87)
R_TURN	3.92***	5.43***	4.02***	5.30***
	(4.51)	(6.43)	(5.48)	(6.17)
*R_RETVOL*R_SIGNAL*	0.16	0.14	0.55***	-0.02
	(0.31)	(0.18)	(4.20)	(-0.02)
R_RETVOL	0.65	0.29	0.58	0.40
	(1.30)	(0.43)	(1.32)	(0.54)
*CONSEC*R_SIGNAL*	-0.62***	0.35	-0.59*	-0.10
	(-4.13)	(0.82)	(-1.93)	(-0.17)
CONSEC	0.76**	0.18	0.76	0.39
	(2.20)	(0.67)	(1.65)	(0.89)
N	35,378	35,377	35,378	35,377
R^2	0.079	0.114	0.080	0.118

Test equality of *R_SIGNAL* coefficients

p-value =	0.252	0.087

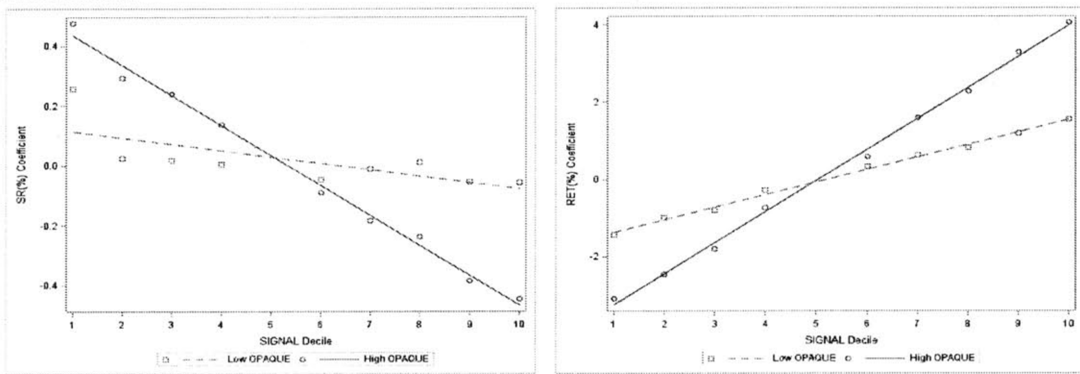
Appendix B

Figures

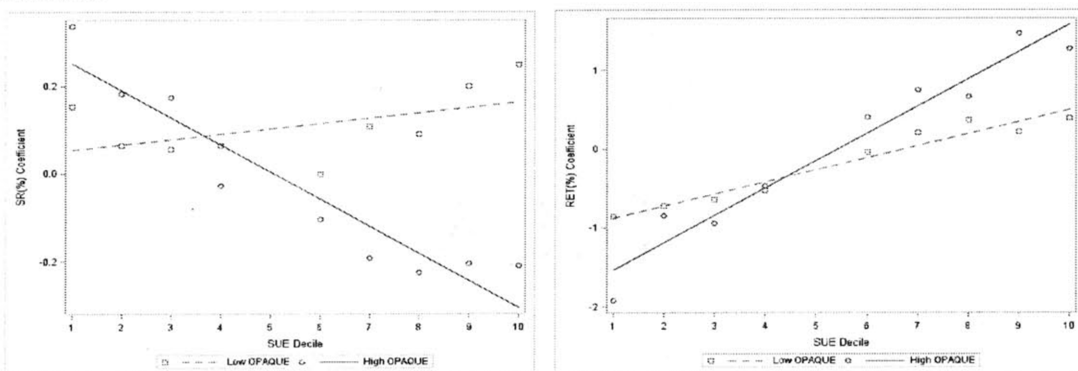
Figure 1. Earnings opacity, strategy-level capital, and strategy returns

Figure 1 shows estimates of the amount of capital devoted to quantitative equity arbitrage strategies (coefficients from $SR(\%)$ regressions) and the returns to signal variables (coefficients from $RET(\%)$ regressions) across $SIGNAL$ deciles for the high and low $OPAQUE$ terciles.

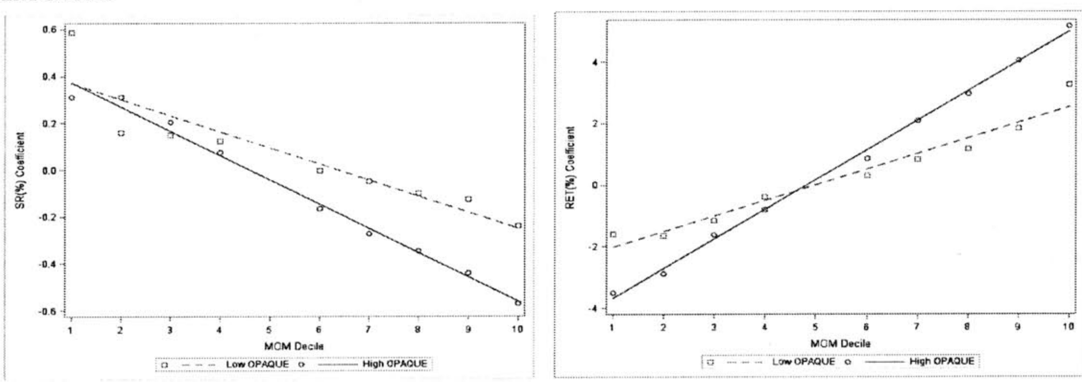
Panel A: *SIGNAL*



Panel B: *SUE*



Panel C: *MOM*



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