Why Does Financial Strength Forecast Stock Returns? Evidence from Subsequent Demand by Institutional Investors

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Using institutional investor demand as a proxy for revisions in sophisticated investors' expectations, we test whether financial strength information is gradually impounded over time. Consistent with the gradual incorporation of information, financial strength predicts both future returns and future institutional investor demand. Further consistent with the gradual incorporation of information, more sophisticated transient (high-turnover) institutions respond to financial strength signals prior to less sophisticated, nontransient institutions. A number of additional tests suggest that financial strength forecasts stock returns, at least in part, because it forecasts institutional demand, and institutional demand drives prices. (*JEL* G11, G12, G14)

Financial strength measures (e.g., accruals, return on equity [ROE], return on assets [ROA]) predict cross-sectional variation in stock returns. These patterns are often interpreted as arising because markets are slow to fully incorporate public information. As Fama and French (2006, 2008) and Chen, Novy-Marx, and Zhang (2011) point out, however, the standard valuation equation indicates that, controlling for book-to-market ratios and expected investment, higher expected profitability implies a higher discount rate (and, therefore, expected return). Because financial strength measures proxy for expected profitability, the relation between financial strength and future returns is also consistent with a risk-based argument.[1] Thus, as Fama and French summarize (2006,

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[1] See Fama and French (2006) for evidence that accruals proxy for future profitability and forecast returns, Haugen and Baker (1996) for evidence ROE proxies for future profitability and forecasts returns, and Fama and French (2006) and Chen, Novy-Marx, and Zhang (2011) for evidence ROA proxies for future profitability and forecasts returns.

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493), "tests based (explicitly or implicitly) on the valuation equations are generally powerless to determine whether observed relations between average returns and B_t/M_t, profitability, and investment are due to rational or irrational pricing."

Our goal is to overcome this limitation by developing a new test of whether investors' gradual incorporation of public information contributes to the relation between financial strength and subsequent returns. Although both the gradual incorporation of information and risk-based explanations predict that expected profitability will forecast subsequent returns, they do so for different reasons. Under the risk-based explanation, rational changes in investors' expectations are immediately impounded into prices, and financial strength predicts returns, because higher expected profitability is associated with greater risk (and therefore a higher required return). In contrast, the gradual incorporation of information explanation requires that financial strength forecasts the gradual incorporation of revision in investors' expectations into prices either because investors are slow to revise their expectations or because frictions prevent market participants from quickly incorporating their revised expectations.

Given that information (i.e., revisions in expectations) is impounded primarily through trading, the gradual incorporation of information explanation requires that over time, investors who recognize (i.e., have revised their expectations) that strong financial condition stocks are undervalued will initiate purchases of these stocks and drive prices higher.[2] And, analogously, investors who realize that weak financial condition stocks are overvalued will initiate sales of these stocks and drive prices lower. Because the financial strength signals are public, these investors need not be better informed; they need only recognize the remaining informational content of the public information. Following Griffin, Shu, and Topaloglu (2008), we designate investors who trade on public information that is not yet fully reflected in prices as "more sophisticated."

Because there is a buyer for every seller, sophisticated investors' demand must be offset by less-sophisticated investors' supply. Thus, the gradual incorporation of information implies that financial strength will predict not only returns but also *future* trading between more and less sophisticated investors. Following previous work and consistent with empirical evidence (e.g., Nofsinger and Sias 1999; Bartov, Radhakrishnan, and Krinsky 2000; Cohen, Gompers, and Vuolteenaho 2002; Jiambalvo, Rajgopal, and Venkatachalam 2002; Collins, Gong, and Hribar 2003; Gibson, Safieddine, and Sonti 2004; Hribar, Jenkins, and Wang 2005; Ke and Petroni 2004; Amihud and Li 2006), we use institutional and individual investors as proxies for more- and less-sophisticated investors, respectively.

[2] Some information may be incorporated into prices without trading as well (e.g., overnight price changes). Nonetheless, both theory and empirical work demonstrate that information is primarily incorporated into prices through trading (e.g., Kyle 1985; French and Roll 1986; Barclay and Warner 1993; Chakravarty 2001).

Related, a number of recent studies (e.g., Lev and Nissim 2006) purport that institutions that trade frequently ("transient" institutions) are, on average, more sophisticated and/or better informed than other institutions ("nontransient").[3] If, on average, transient institutions are more sophisticated than nontransient institutions, and nontransient institutions are more sophisticated than individual investors, then transient institutions will respond to financial condition information prior to nontransients, and both transients and nontransients will respond prior to individual investors.

Finally, it is possible that institutions are short-term momentum traders, and as a result, financial strength forecasts institutional demand because it forecasts returns. That is, even if financial strength forecasts institutional demand, the interpretation is subject to debate—is institutional demand driving returns (i.e., the gradual incorporation of information), are returns driving institutional demand (short-term institutional momentum trading), or is there some combination thereof?

Our central tests examine three issues. First, does financial strength predict subsequent institutional demand? Second, do transient institutions respond prior to nontransient institutions? And third, assuming that financial strength forecasts institutional demand, does the relation derive from institutions chasing intra-quarter lag returns or from institutions driving returns?

Our key empirical results are easily summarized—consistent with previous studies, financial strength forecasts returns. Consistent with the gradual incorporation of information explanation, financial strength also predicts institutional investor demand. Moreover, first transient institutions respond to financial strength information, then nontransient institutions respond, and both exploit individual investors. Finally, in general, our tests suggest that the relation between financial strength and subsequent returns is driven, at least in part, by subsequent institutional demand driving subsequent returns. We also exploit a large database of institutional investors' transactions to delve deeper into the causation question by evaluating the relations between daily institutional demand, returns the same day, and lag returns. The transaction data tests also support the explanation that institutional demand drives returns. It is possible, however, that very short-term (e.g., intraday) institutional momentum trading may drive our results.

The balance of the article is organized as follows. We discuss the data in the next section. Section 2 provides the primary empirical tests. Section 3 examines whether subsequent institutional demand drives subsequent returns. Section 4 further investigates transient versus nontransient investor behavior. Section 5 employs the institutional investor transaction data set to more fully explore the importance of returns driving institutional demand versus

[3] The relation between portfolio turnover and information/sophistication might arise because the incentive to trade increases with information/sophistication (Yan and Zhang 2009) or because although some (e.g., nontransient) investors may recognize a credible signal, they fail to exploit it due to their investment style (such as an indexer) or differences in trading costs (Ke and Ramalingegowda 2005).

institutional demand driving returns. The final section considers potential alternative interpretations of our results and provides conclusions.

1. Data

1.1 Financial strength: Piotroski's F-score

Piotroski's (2000, 2005) F-score is the sum of nine binary signals that form a "composite measure of firm strength" (Fama and French 2006, 496). Each "good" signal contributes one point to the F-score, while a "bad" signal contributes zero and, as a result, F-scores range from zero to nine points.[4] Specifically, firms are given one point each for (i) positive net income, (ii) positive cash flow from operation, (iii) an increase in net income, (iv) a positive difference between cash flow from operation and net income, (v) a decrease in the long-term debt-to-asset ratio, (vi) an increase in the current ratio, (vii) not issuing any common or preferred equity in the most recent fiscal year, (viii) an increase in gross margin, and (ix) an increase in asset turnover. We use F-score as the financial strength metric because (i) it forecasts returns even after accounting for other known stock return predictors such as size, book to market, and asset growth (Fama and French 2006); (ii) the F-score components are commonly used in financial statement analysis; and (iii) F-score forecasts profitability consistent with the explanation that F-score proxies for expected profitability (Fama and French 2006).

We calculate F-score at the end of each fiscal year following the definitions in Fama and French (2006) (see Appendix for details). Further following Fama and French, we (i) exclude financials, (ii) require firms to have Center for Research in Security Prices (CRSP) share codes 10 or 11 (i.e., ordinary shares), and (iii) require firms to have total assets of at least \$25 million and book equity of at least \$12.5 million.

For our sample period, firms had ninety days following the end of the fiscal year to file their 10-K statements. Some firms, however, experience delays in filing their financial statements (Stice 1991). To ensure that investors would have the necessary information to compute F-scores, Piotroski (2000, 2005) examines annual returns beginning in the fifth month following the fiscal year-end. Because we focus on how F-score relates to institutional demand, and comprehensive institutional ownership data are available only at calendar quarter-ends, we define the "post F-score period" as the year beginning six months following the fiscal year-end. To ensure consistency, we limit the sample to firms with fiscal year-ends in March, June, September, and December.[5]

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4 As Piotroski (2000, 2005) discusses, the signals can be theoretically ambiguous (e.g., an increase in leverage may reduce agency costs) and are not purported to be optimal. Rather, Piotroski (2005, 15) chooses the signals because they are "intuitive, easy-to-construct, and commonly used in financial statement analysis."

5 Following Compustat, for fiscal year-ends in March, we define the fiscal year as the prior calendar year. For June, September, and December fiscal year-ends, we define the fiscal year as the current calendar year.

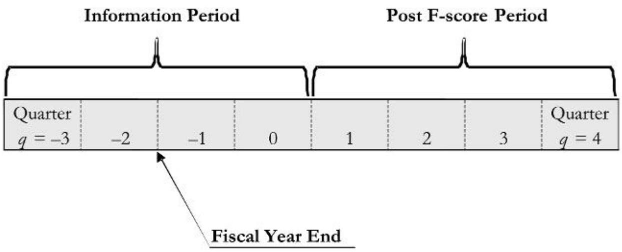

Figure 1
Timeline

We analogously define the "information period" as the year prior to the post F-score period. For a firm with a December 1984 fiscal year-end, for example, the information period covers July 1984–June 1985 (event quarters $q = -3$ to 0), and the post F-score period covers July 1985–June 1986 (event quarters $q = 1$ to 4). We use a year for the information period because much of the information captured by F-score would be available to investors prior to release of the fiscal year-end financial statements (e.g., information contained in quarterly financial statements). Figure 1 presents a timeline of the information period, the post F-score period, and the fiscal year-end date.

1.2 Institutional demand and returns

Aggregate institutional demand is computed from institutional investors' quarterly 13(f) reports (purchased from Thomson Financial) filed with the Securities and Exchange Commission (SEC) from March 1983 to September 2008.[6] We consider two measures of institutional demand—the change in the fraction of shares held by institutional investors and the change in the number of institutions holding shares. The advantage of the former metric is that the negative of 13(f) investors' demand is non–13(f) investors' supply. Following previous studies (e.g., Cohen, Gompers, and Vuolteenaho 2002), we denote non–13(f) investors as "individual investors." The 13(f) data, however, are an inexact measure of professional managers' ownership. Small institutions (less than \$100 million in assets) and positions (less than \$200,000), for example, may be excluded from the 13(f) filings.

We measure the net fraction of security i's shares purchased by institutions over quarter q as (where $q-1$ represents the end of quarter $q-1$):

$$\Delta Institutional\ Fraction_{i,q} = \frac{\#\, Shares\ Institutions\ Hold_{i,q}}{\#\, Shares\ Outstanding_{i,q}} - \frac{\#\, Shares\ Institutions\ Hold_{i,q-1}}{\#\, Shares\ Outstanding_{i,q-1}}. \quad (1)$$

[6] Institutions with \$100 million or more under management are required to disclose their equity holding of 10,000 shares or \$200,000 in value to the Securities and Exchange Commission (SEC) within forty-five days of the end of each calendar quarter.

One limitation of this measure is that the absolute value of Equation (1) is positively correlated with capitalization and initial institutional ownership (see Sias 2007). Moreover, small stocks with low levels of institutional ownership are more likely to have extreme F-scores. To ensure that our results are not impacted by these patterns, we follow Sias and compute the adjusted percentage change in the fraction of shares held by institutions as the change in the fraction of shares held by institutions for security i in quarter q less the average quarter q change for securities within the same capitalization decile, normalized by the average fraction of shares held by institutional investors (at the end of quarter $q=0$) for securities within the same capitalization decile:

$$Adjusted\,\%\Delta Institutional\ Fraction_{i\in d,q}$$

$$= \frac{\Delta Institutional\ Fraction_{i\in d,q} - \overline{\Delta Institutional\ Fraction_{i\in d,q}}}{\%Shares\ Held\ by\ Institutions_{i\in d,\,q=0}}, \tag{2}$$

where security i is in capitalization decile d. We denote Equation (2) as the "adjusted" percentage change in the fraction of shares held by institutions because (i) we subtract the average change in the fraction of shares held by institutions in similar-size firms, (ii) we normalize by the average level of institutional ownership in similar-size firms rather than each firm's institutional ownership (to ensure that firms with very low levels of institutional ownership do not drive the results), and (iii) we maintain the same denominator (end of quarter $q=0$) so that the measure is additive over time.

We also compute the change in institutional breadth as the difference between the number of institutional investors holding the stock at the beginning and end of the quarter:

$$\Delta Institutional\ Breadth_{i,q}$$

$$= \#Institutional\ Shareholders_{i,q} - \#\,Institutional\ Shareholders_{i,q-1}. \tag{3}$$

As Sias, Starks, and Titman (2006) and Brown, Wei, and Wermers (2009) point out, this measure may better capture price moves associated with how information is impounded into prices—that is, many institutions entering a position provide a stronger signal than a single institution buying the same number of shares.

Because the absolute value of the change in institutional breadth is correlated with firm size and institutional breadth, we also compute the "adjusted" percentage change in institutional breadth as the difference between the change in institutional breadth for security i in quarter q and the average change in quarter q institutional breadth for securities within the same capitalization decile, normalized by the average number of institutional shareholders at the end of quarter $q=0$ for securities in the same capitalization decile:

$$Adjusted\,\%\Delta Institutional\ Breadth_{i\in d,q}$$
$$= \frac{\Delta Institutional\ Breadth_{i\in d,q} - \overline{\Delta Institutional\ Breadth_{i\in d,q}}}{\#\,Institutions\ Shareholders_{\,i\in d,\,q=0}}. \quad (4)$$

We require firms to have institutional ownership data available throughout the evaluation period (quarters $q = -3$ to 4).[7] To ensure that our results are not driven by outliers or errors in the 13(f) data, we Winsorize all four measures of institutional demand (over the information period and the post F-score period) at the 0.5% and 99.5% levels each fiscal year.[8]

Brian Bushee generously provided transient/nontransient institutional investor classifications that are updated annually throughout our sample period (the classifications are based on the factor and cluster analysis method detailed in Bushee 1998, 2001). Transient institutions hold well-diversified portfolios and exhibit high turnover. Nontransient institutions include those that hold large long-term positions in firms (“dedicated” institutions) and those that hold well-diversified low-turnover portfolios (“quasi-indexers”).

When computing the adjusted percentage change in the fraction of shares held by transient institutions, we subtract the demand for transient institutions in the same capitalization decile and normalize by the average fraction of shares held by transient institutions for securities within the same capitalization decile:

$$Adjusted\,\%\Delta Transient\ Inst.\ Fraction_{i\in d,q}$$
$$= \frac{\Delta Transient\ Inst.\ Fraction_{i\in d,q} - \overline{\Delta Transient\ Inst.\ Fraction_{i\in d,q}}}{\%Shares\ Held\ by\ Transient\ Institutions_{i\in d,q=0}}. \quad (5)$$

We analogously compute (i) the adjusted percentage change in the fraction of shares held by nontransient institutions, and (ii) the adjusted percentage change in institutional breadth for both transient and nontransient institutions.

We define market-adjusted returns as the firm’s buy-and-hold return less the CRSP value-weighted index buy and hold return over the same period. We require firms to have monthly returns for the information period (quarters $q = -3$ to 0). Following Bushee and Goodman (2007), we truncate the top and bottom 1% of firms with the highest and lowest market-adjusted returns over the information period (quarters $q = -3$ to 0) and the post F-score period (quarters $q = 1$ to 4) to ensure that our results are not driven by outliers.

Table 1 reports descriptive statistics for F-score, institutional demand, and returns. (We describe the transaction data set in Section 5.) Our sample covers twenty-four fiscal years (1983–2006) for which we have institutional

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7 In untabulated analysis, we repeat the tests without this restriction and find similar results.

8 The data are also cleaned of obvious reporting errors (e.g., lags in adjustment for stock splits).

Table 1
Descriptive statistics

	Mean	Standard deviation	25th percentile	Median	75th percentile
F-score	5.108	1.729	4.000	5.000	6.000
$\textit{Institutional Fraction}_{q=0}$	43.396%	24.478%	22.695%	42.169%	62.981%
$\Delta \textit{Institutional Fraction}_{q=-3\,to\,0}$	2.147%	8.863%	−1.769%	1.451%	5.649%
$\Delta \textit{Institutional Fraction}_{q=1\,to\,4}$	1.403%	9.602%	−2.175%	1.180%	5.307%
$\textit{Adj.}\%\Delta \textit{Institutional Fraction}_{q=-3\,to\,0}$	−1.413%	26.999%	−11.135%	−1.978%	8.265%
$\textit{Adj.}\%\Delta \textit{Institutional Fraction}_{q=1\,to\,4}$	−0.954%	29.523%	−10.146%	−0.313%	9.253%
$\textit{Institutional Breadth}_{q=0}$	96.464	133.810	19.000	49.000	119.000
$\Delta \textit{Institutional Breadth}_{q=-3\,to\,0}$	6.027	20.163	−3.000	2.000	12.000
$\Delta \textit{Institutional Breadth}_{q=1\,to\,4}$	5.162	21.897	−3.000	2.000	12.000
$\textit{Adj.}\%\Delta \textit{Institutional Breadth}_{q=-3\,to\,0}$	−1.431%	27.946%	−13.479%	−1.083%	12.276%
$\textit{Adj.}\%\Delta \textit{Institutional Breadth}_{q=1\,to\,4}$	−1.720%	32.277%	−16.382%	−2.433%	11.421%
$\textit{Market-Adjusted Return}_{q=-3\,to\,0}$	0.023%	45.155%	−28.618%	−5.795%	19.378%
$\textit{Market-Adjusted Return}_{q=1\,to\,4}$	−0.705%	44.914%	−29.191%	−6.112%	19.178%

This table reports summary statistics for F-score, institutional ownership levels, institutional demand measures, and market-adjusted returns for the sample covering fiscal years 1983–2006. F-score is the sum of nine binary signals derived from financial statements that measure financial strength. $\textit{Institutional Fraction}_{q=0}$ is number of shares held by institutional investors divided by number of total shares outstanding at the end of quarter $q = 0$. $\Delta \textit{Institutional Fraction}_{q=a\,to\,b}$ is the net fraction of a firm's outstanding shares moving from individual investors to institutional investors from the beginning of quarter a to the end of quarter b. *Adjusted* $\%\Delta \textit{Institutional Fraction}_{q=a\,to\,b}$ is defined as $\Delta \textit{Institutional Fraction}_{q=a\,to\,b}$ minus the average $\Delta \textit{Institutional Fraction}_{q=a\,to\,b}$ for firms in the same capitalization decile, normalized by average $\textit{Institutional Fraction}_{q=0}$ for the firms in the same capitalization decile at the end of quarter $q = 0$. $\textit{Institutional Breadth}_{q=0}$ is the number of institutions holding the stock at the end of quarter $q = 0$. $\Delta \textit{Institutional Breadth}_{q=a\,to\,b}$ is the number of institutional shareholders holding the security at the end of quarter b less the number holding the security at the beginning of quarter a. *Adjusted* $\%\Delta \textit{Institutional Breadth}_{q=a\,to\,b}$ is defined as $\Delta \textit{Institutional Breadth}_{q=a\,to\,b}$ less the average $\Delta \textit{Institutional Breadth}_{q=a\,to\,b}$ for the firms in the same capitalization decile, normalized by the average $\textit{Institutional Breadth}_{q=0}$ for firms in the same capitalization decile at the end of quarter $q = 0$. $\textit{Market-Adjusted Return}_{q=a\,to\,b}$ is the firm's buy and hold return minus the CRSP value-weighted index buy-and-hold return from the beginning of quarter a to the end of quarter b. The sample consists of 41,845 firm-year observations.

ownership data covering both the information period and the post F-score period (March 1983–September 2008). On average, we have complete data for 1,744 firms each fiscal year for a total sample of 41,845 company–fiscal year observations.[9]

2. Empirical Results

If markets incorporate some of the F-score information in a timely manner, then the gradual incorporation of information explanation requires that high F-score stocks outperform low F-score stocks, on average, when the information is revealed to the market. In contrast, high F-scores may convey good, bad, or no information (on average) under the risk-based explanation (e.g., a

9 Post F-score returns average slightly lower than information period returns primarily as a result of the minimum asset value and book equity filters—e.g., the July 2003–June 2004 return for a shrinking firm with $26 million in assets at December 2003 and $20 million in assets at December 2004 would be included in the post F-score period sample for fiscal year 2003 (when July 2003–June 2004 covers the post F-score period), but excluded from fiscal year 2004 (when July 2003–June 2004 covers the information period).

high F-score does not necessarily provide positive information because prices should adjust relative to expectations). Under the risk-based scenario, however, any information captured by F-scores is immediately impounded into prices.

The first column of Panel A in Table 2 reports the time-series average (over the twenty-four fiscal years) of the cross-sectional mean market-adjusted returns in the information period (quarters $q = -3$ to 0) for firms with high ($7 \leq$ F-score), medium ($3 <$ F-score < 7), and low (F-score ≤ 3) F-scores. The bottom two rows report a t-statistic (computed from the time series of the differences in the twenty-four cross-sectional means with Newey-West 1987 standard errors) and z-statistic (computed from Wilcoxon signed rank test of the differences in the twenty-four cross-sectional means) of the null hypothesis that returns do not differ across high and low F-score firms.

Consistent with the explanation that high F-scores convey good information and low F-scores convey bad information (on average), and at least some of this information is quickly impounded, we find a strong positive relation between F-score and information period returns. Specifically, the difference between high and low F-score group returns averages 25.73% (statistically significant at the 1% level).

Panel B reports the results for the post F-score period (quarters $q = 1$ to 4). As discussed above, this period begins after all information captured by F-scores is made public. Consistent with Piotroski (2000, 2005) and Fama and French (2006), the results reveal a strong positive relation between F-score and future returns—high F-score stocks ($\geq$7) average annual market-adjusted returns 8.35% greater (statistically significant at the 1% level) than low F-score stocks ($\leq$3).

2.1 Institutional investor demand

Information period returns reveal that high F-scores convey good information, low F-scores convey bad information (on average), and at least some of this information is quickly impounded into prices. If information is primarily incorporated by trading, and institutional investors are more sophisticated than individual investors, then institutional demand for high F-score stocks should exceed their demand for low F-score stocks during the information period. The last four columns in Panel A of Table 2 report the time-series average of the annual cross-sectional means (across the twenty-four fiscal years) of each of the four measures of institutional demand during the information period for securities with high ($7 \leq$ F-score), medium ($3 <$ F-score < 7), and low (F-score ≤ 3) F-scores. As with returns, the bottom two rows report t- and z-statistics of the null hypothesis that institutional demand does not differ across high and low F-score firms.

Panel A reveals substantial differences in institutional demand between high and low F-score stocks when the F-score information is revealed to the public—the average high F-score firm experiences an increase of 11.15 institutions and 2.77% of outstanding shares moving from individuals to

Table 2
Market-adjusted return and institutional demand over information period (Quarters $q = -3$ to 0) and post F-score period (Quarters $q = 1$ to 4)

	Market-Adjusted Return	*ΔInstitutional Fraction*	*Adjusted % ΔInstitutional Fraction*	*ΔInstitutional Breadth*	*Adjusted % ΔInstitutional Breadth*
	Panel A: Information period (Quarters $q = -3$ to 0)				
All firms	−0.253%	2.160%	−1.412%	6.034	−1.447%
High (F-score ≥ 7)	10.891%	2.773%	0.828%	11.153	5.123%
Medium (3 < F-score < 7)	0.058%	2.356%	−0.833%	6.045	−0.862%
Low (F-score ≤ 3)	−14.833%	0.824%	−6.029%	−0.047	−11.080%
High–Low	25.724%	1.948%	6.857%	11.200	16.203%
(t-statistic)	(18.12)***	(11.52)***	(11.87)***	(9.84)***	(13.91)***
(z-statistic)	(4.28)***	(4.29)***	(4.29)***	(4.29)***	(4.29)***
	Panel B: Post F-score period (Quarters $q = 1$ to 4)				
All firms	−0.971%	1.408%	−0.959%	5.152	−1.660%
High (F-score ≥ 7)	2.363%	1.533%	0.155%	7.040	0.411%
Medium (3 <F-score < 7)	−0.960%	1.477%	−0.844%	5.289	−1.377%
Low (F-score ≤ 3)	−5.985%	1.048%	−2.816%	2.343	−5.309%
High–Low	8.348%	0.485%	2.971%	4.697	5.720%
(t-statistic)	(4.42)***	(2.63)**	(5.78)***	(5.09)***	(7.01)***
(z-statistic)	(3.31)***	(2.14)**	(3.66)***	(4.09)***	(4.20)***

This table reports the time-series average of the cross-sectional mean of the four measures of institutional demand over the information period (quarters $q = -3$ to 0) and post F-score period (quarters $q = 1$ to 4) covering fiscal years 1983–2006. F-score is the sum of nine binary signals derived from financial statements that measure financial strength (see Appendix for details). The four institutional demand metrics are defined in Table 1. The bottom two rows in each panel report a t-statistic (computed from the time series of the twenty-four cross-sectional means with Newey-West 1987 standard errors) and z-statistic (computed from Wilcoxon signed rank test of the twenty-four cross-sectional means) of the null hypothesis that means do not differ across high and low F-score firms. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

institutions over the information period. In contrast, the average low F-score firm experiences a decrease of 0.05 institutional investors and 0.82% of outstanding shares moving from individual investors to institutions. We find the same pattern across the adjusted percentage change metrics. Differences are statistically significant at the 1% level in all cases. The results are consistent with the explanation that information captured by F-scores is primarily incorporated by trading between more- and less-sophisticated investors when that information is made public.

The last four columns in Panel B of Table 2 report the institutional demand figures for the post F-score period (quarters $q = 1$ to 4). Consistent with the gradual incorporation of information, we find a positive relation between F-score and each of the four measures of future institutional demand (statistically significant at the 5% level or better).

2.2 Trading by transient and nontransient institutions

Previous studies suggest that high-turnover transient institutional investors are more sophisticated than nontransient institutional investors. If so, and if F-score's ability to forecast returns is driven, at least in part, by the gradual incorporation of information, then more-sophisticated transient institutions should respond to the informational content of F-scores prior to less-sophisticated nontransient institutions.

Table 3 reports the time-series average of the cross-sectional means of the two adjusted percent change metrics of institutional demand for transient and nontransient institutions in the information period and the post F-score period. (To conserve space, the balance of the study focuses on these two metrics.)[10]

Table 3 reveals that although demand by both transient and nontransient institutions for high F-score stocks is greater than their demand for low F-score stocks (statistically significant at the 1% level in all cases) in the information period (Panel A), only nontransient institutions continue to demand high F-score stocks to a much greater extent than low F-score stocks in the post F-score period (Panel B). The results support the hypothesis that F-score predicts returns, at least in part, due to the gradual incorporation of public information. In short, the results paint a mosaic where transient institutions act first to incorporate much of the information, slower-acting nontransient institutions continue to incorporate the information into prices over time, and both exploit less-sophisticated individual investors.

2.3 Does return momentum and institutional momentum trading explain F-scores' ability to predict returns and institutional demand?

It is possible that F-score predicts both subsequent returns and subsequent institutional demand because F-score is correlated with information period

10 The other demand metrics yield similar results.

Table 3
Demand by transient and nontransient institutions

	Adjusted % ΔInstitutional Fraction		*Adjusted % ΔInstitutional Breadth*	
	Transient	Nontransient	Transient	Nontransient
	Panel A: Information period (Quarters $q=-3$ to 0)			
High (F-score ≥ 7)	5.422%	−0.282%	9.412%	3.768%
Medium (3 < F-score < 7)	−1.336%	−0.589%	−0.259%	−1.047%
Low (F-score ≤ 3)	−11.351%	−4.703%	−14.335%	−10.193%
High-Low	16.773%	4.420%	23.747%	13.961%
(t-statistic)	(7.27)***	(7.43)***	(11.99)***	(11.78)***
	Panel B: Post F-score period (Quarters $q=1$ to 4)			
High (F-score ≥ 7)	−1.763%	0.706%	−2.042%	1.416%
Medium (3 < F-score < 7)	−0.454%	−0.991%	−1.899%	−1.206%
Low (F-score ≤ 3)	−0.543%	−3.527%	−3.011%	−5.942%
High–Low	−1.220%	4.234%	0.969%	7.357%
(t-statistic)	(−0.90)	(6.85)***	(0.64)	(10.24)***

This table reports the time-series average (over twenty-four fiscal years) of the cross-sectional mean transient and nontransient institutional demand over the information period (Panel A, quarters $q=-3$ to 0) and the post F-score period (Panel B, quarters $q=1$ to 4). Δ*Transient Fraction*$_{q=a\,to\,b}$ is the net fraction of a firm's outstanding shares moving to transient institutional investors from the beginning of quarter a to the end of quarter b. *Adjusted* %Δ*Institutional Fraction*$_{q=a\,to\,b}$ (transient) is defined as Δ*Transient Fraction*$_{q=a\,to\,b}$ minus the average Δ*Transient Fraction*$_{q=a\,to\,b}$ for firms in the same capitalization decile, normalized by average *Transient Fraction*$_{q=0}$ for the firms in the same capitalization decile at the end of quarter $q=0$. Δ*Transient Breadth*$_{q=a\,to\,b}$ is the number of transient institutional shareholders holding the security at the end of quarter b less the number holding the security at the beginning of quarter a. *Adjusted* %Δ*Institutional Breadth*$_{q=a\,to\,b}$ (transient) is defined as Δ*Transient Breadth*$_{q=a\,to\,b}$ less the average Δ*Transient Breadth*$_{q=a\,to\,b}$ for the firms in the same capitalization decile, normalized by the average *Transient Breadth*$_{q=0}$ for firms in the same capitalization decile at the end of quarter $q=0$. Nontransient institutional demand metrics are analogously defined. The t-statistics are based on the Newey-West (1987) standard error of the time series of the twenty-four annual cross-sectional means. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

returns and stocks exhibit return momentum (e.g., Jegadeesh and Titman 1993), and institutional investors are long-term momentum traders (e.g., Sias 2007). In this section, we further evaluate the 13(f) data to examine whether return momentum and institutional momentum trading can fully explain the relations between F-score, subsequent returns, and subsequent institutional demand.

If return momentum and institutional momentum trading fully drive our results, then subsequent returns and subsequent institutional demand will not differ when comparing high and low F-score firms with similar lag returns. Thus, each fiscal year, we sort all securities into 100 portfolios by their market-adjusted return over the six months prior to the post F-score period ($q = -1$ to 0). Given an average of 1,744 firms each fiscal year, each percentile averages 17.4 firms. We then match high F-score (≥ 7) firms in each lag return percentile with low F-score (≤ 3) firms in the same lag return percentile. This would yield 100 paired comparisons each fiscal year if there were high and low F-score firms in every lag return percentile. However, there are a few cases where a lag return percentile has either no low F-score firms or no high F-score firms. As a result, on average, there are ninety-four comparisons each year of high F-score firms with similar lag return low F-score firms.

We compute the average F-score, lag market-adjusted return ($q = -1$ to 0), future market-adjusted return ($q = 1$ to 4), and subsequent institutional demand for high F-score firms, the paired similar lag return low F-score firms, and their difference for each lag return percentile (that has both high and low F-score firms) each fiscal year. We then compute the cross-sectional average of these figures across lag return percentiles each fiscal year. Table 4 reports the time-series average (and associated t-statistic computed from the Newey-West 1987 standard error) of these cross-sectional averages over the twenty-four fiscal years in our sample.

The results in Table 4 support the hypothesis that stock return momentum and institutional momentum trading do not fully explain the relations between F-score, subsequent returns, and subsequent institutional demand. Even though the samples exhibit similar lag returns in the six months prior to the post F-score period (second column of Panel A), high F-score firms average returns 7.26% percent higher (statistically significant at the 1% level) than low F-score firms in the post F-score period. Moreover, as shown in Panel B, institutional investors' demand for high F-score stocks is significantly greater (at the 5% level or better) than their demand for low F-score stocks for both demand metrics even though the high and low F-score stocks exhibit nearly identical lag returns.

Nonetheless, both return differences and institutional demand differences are smaller when comparing the results in Table 4 with the corresponding figures in Table 2. Thus, return momentum and institutional momentum trading appear to play some role in explaining the relations between F-score, subsequent returns, and subsequent institutional demand.

Table 4
Institutional demand and returns for high and low F-score firms with similar lag return

	F-score	*Lag Market-Adjusted Return*$_{q=-1\,to\,0}$	*Market-Adjusted Return*$_{q=1\,to\,4}$
	Panel A: F-scores and returns		
High F-score (≥7)	7.376	2.447%	2.270%
Low F-score (≤3)	2.500	2.501%	−4.986%
Difference	4.877	−0.054%	7.256%
	(227.20)***	(−0.67)	(4.06)***

	Adjusted %ΔInstitutional Fraction$_{q=1\,to\,4}$	*Adjusted %ΔInstitutional Breadth*$_{q=1\,to\,4}$
	Panel B: All institutions	
High F-score (≥7)	0.049%	0.033%
Low F-score (≤3)	−1.593%	−3.677%
Difference	1.641%	3.709%
	(2.77)**	(4.43)***
	Panel C: Nontransient institutions	
High F-score (≥7)	0.640%	1.000%
Low F-score (≤3)	−2.768%	−4.520%
Difference	3.408%	5.520%
	(5.06) ***	(7.35) ***
	Panel D: Transient institutions	
High F-score (≥7)	−2.178%	−2.381%
Low F-score (≤3)	1.980%	−0.696%
Difference	−4.158%	−1.685%
	(−2.74)***	(−0.93)

Each fiscal year we sort all stocks into 100 lag (quarters $q = -1$ to 0) market-adjusted return groups. Within each lag return percentile/fiscal year, we compute the average lag return, post F-score return ($q = 1$ to 4), and institutional demand in the post F-score period for high F-score (≥7) stocks, low F-score (≤3) stocks, and their difference. We then compute the cross-sectional average of these figures each fiscal year. Panel A reports the time-series average (over twenty-four fiscal years) of the cross-sectional mean F-score, lag market adjusted return, and post F-score return for high and low F-score firms with similar lag returns. Panels B, C, and D report the post F-score period institutional demand metrics for these portfolios for all institutions, nontransient institutions, and transient institutions, respectively. The t-statistics are computed from the time series of the twenty-four cross-sectional means with Newey-West (1987) standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

We next estimate two regressions, each year, of annual market-adjusted returns in the post F-score period on (i) F-score and (ii) F-score, market-adjusted returns over the prior two quarters ($q = -1$ and 0), and three other variables known to explain cross-sectional variation in stock returns: the natural logarithm of firm size, the natural logarithm of book to market ratios, and lag asset growth (as a proxy for expected investment following Fama and French 2006). To allow direct comparisons across regressions and variables, we rescale, each fiscal year, all the variables to have unit variance and zero mean.

Table 5 reports the time-series average coefficients (over the twenty-four fiscal years) and associated t-statistics (computed from the Newey-West 1987 time-series standard error of the estimated coefficients). Consistent with Fama

Table 5
Predicting returns and institutional demand regressions

Dependent variable	F-score$_{q=0}$	*Market-Adjusted Return*$_{q=-1\,to\,0}$	*ln(capitalization)* $_{q=-2}$	*ln(Book/Market)*$_{q=-2}$	*Asset Growth*$_{q=-6\,to\,-2}$	Adjusted R^2
Market-Adjusted Return$_{q=1\,to\,4}$	0.072					1.04%
	(4.55)***					
Market-Adjusted Return$_{q=1\,to\,4}$	0.065	0.040	0.026	0.052	–0.046	4.14%
	(4.97)***	(2.29)**	(1.23)	(2.73)**	(–4.53)***	
Adjusted %Δ*Institutional Fraction*$_{q=1\,to\,4}$	0.035					0.16%
	(5.67)***					
Adjusted %Δ*Institutional Fraction*$_{q=1\,to\,4}$	0.026	0.131	0.009	−0.014	0.004	2.26%
	(4.28)***	(9.59)***	(1.05)	(−1.24)	(0.66)	
Adjusted %Δ*Institutional Breadth*$_{q=1\,to\,4}$	0.062					0.46%
	(7.94)***					
Adjusted %Δ*Institutional Breadth*$_{q=1\,to\,4}$	0.045	0.224	0.015	−0.024	0.014	5.92%
	(5.91)***	(18.12)***	(1.95)*	(−2.84)***	(2.20)*	

This table presents the time-series average coefficients and associated t-statistics for twenty-four annual regressions (covering fiscal years 1983–2006) of subsequent annual market-adjusted returns and measures of subsequent institutional demand on (i) F-score and (ii) F-score, lag market-adjusted return (firm's buy-and-hold return less CRSP's value-weighted index return over the quarters $q=-1$ to $q=0$), the natural logarithm of market capitalization and book-to-market ratios (measured at fiscal year-end, $q=-2$), and asset growth from previous fiscal year-end (end of quarter $q=-6$ to end of quarter $q=-2$). The institutional demand metrics are defined in Table 1. The associated t-statistics are computed from the time-series Newey-West (1987) standard error of the twenty-four coefficient estimates. All variables are standardized (i.e., rescaled to zero mean, unit variance) each fiscal year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

and French (2006), the results in the first two rows confirm a positive relation between subsequent returns and F-score regardless of whether we control for momentum, size, book-to-market ratios, and investment.

The bottom four rows in Table 5 confirm that F-score predicts subsequent institutional demand (statistically significant at the 1% level or better in all cases). The results also reveal a reduction in the average coefficient associated with F-score when including the control variables arising primarily from the positive relation between institutional demand and lag returns. Nonetheless, the results suggest that institutional momentum trading does not fully explain the relation between F-score and subsequent institutional demand.

3. Is Subsequent Institutional Demand Driving Subsequent Returns?

There are two possible (non–mutually exclusive) reasons F-score predicts institutional demand—institutions are short-term momentum traders (i.e., post F-score returns drive post F-score institutional demand) and/or aggregate institutional demand drives returns (i.e., in aggregate, institutions are net liquidity demanders). In this section, we further investigate these possibilities using the 13(f) data.

3.1 Quarterly analysis

Following Piotroski (2000, 2005) and Fama and French (2006), we focus on return (and institutional demand) over the post F-score year. The 13(f) data, however, allow us to examine results over each quarter in the post F-score period. Thus, we begin by reporting returns and institutional demand, by event quarter, in the post F-score period. If the relation between F-score and subsequent annual returns is driven, at least in part, by the gradual incorporation of information into prices by institutional investors, then differences in returns between high and low F-score firms should accrue primarily in the quarters with the largest differences in demand. Alternatively, if the relation between F-score and subsequent institutional demand is fully driven by short-term institutional momentum trading, then the largest differences in institutional demand should *follow* the largest differences in returns.

Table 6 reports the time-series average (across the twenty-four fiscal years) difference in mean (Panel A) and median (Panel B) market-adjusted returns and institutional demand between high ($\geq$7) and low ($\leq$3) F-score firms, by quarter, in the post F-score period. The t-statistics are based on Newey-West (1987) standard errors of the time series of twenty-four means or medians.

The estimates in Table 6 provide mixed support for the gradual incorporation of information explanation. On the negative side, mean and median return differences (between high and low F-score firms) are concentrated in the first two quarters. Institutional demand differences, however, show up in all four quarters. On the plus side, the ranks somewhat line up. The second quarter,

Table 6
Quarterly institutional demand and returns in high F-score firms (≥7) less quarterly institutional demand and returns in low F-score firms (≤3)

	Quarter +1	Quarter +2	Quarter +3	Quarter +4
	Panel A: Means (high F-score firms less low F-score firms)			
Market-Adjusted Return$_q$	1.702%	2.211%	−0.027%	0.741%
	(2.84)***	(2.16)**	(−0.03)	(0.76)
Adjusted %ΔInstitutional Fraction$_q$	0.573%	0.771%	0.370%	1.257%
	(2.00)*	(3.10)***	(1.75)*	(3.64)***
Adjusted %ΔInstitutional Breadth$_q$	1.868%	1.137%	1.219%	1.495%
	(8.23)***	(3.62)***	(3.42)***	(4.61)***
	Panel B: Medians (high F-score firms less low F-score firms)			
Market-Adjusted Return$_q$	2.897%	3.855%	1.241%	2.308%
	(5.12)***	(4.72)***	(1.50)	(2.86)***
Adjusted %ΔInstitutional Fraction$_q$	0.188%	0.496%	0.417%	0.629%
	(1.71)	(4.04)***	(3.70)***	(3.45)***
Adjusted %ΔInstitutional Breadth$_q$	1.332%	1.394%	1.088%	1.248%
	(7.58)***	(6.87)***	(4.06)***	(4.26)***
	Panel C: Regression of (calendar) quarterly return difference (high F-score firms less low F-score firms) on (calendar) quarterly demand difference			
Dependent variable	Intercept	*Adjusted %ΔInstitutional Fraction$_q$*	*Adjusted %ΔInstitutional Breadth$_q$*	Adjusted R^2
Market-Adjusted Return$_q$	0.004	1.025		6.12%
	(0.53)	(3.37)***		
Market-Adjusted Return$_q$	−0.013		1.708	18.16%
	(−1.35)		(3.92)***	

Panels A and B report the time-series average of the cross-sectional mean and median return and institutional demand difference between high F-score (≥7) firms and low F-score (≤3) firms for each of the four event quarters in the post F-score period for fiscal years 1983–2006. Panel C reports results from regression of the quarterly market-adjusted return difference (cross-sectional average quarterly return for high F-score firms less average quarterly return for low F-score firms) on the quarterly institutional demand difference (cross-sectional average institutional demand for high F-score firms less average institutional demand for low F-score firms) estimated over the ninety-seven calendar quarters in our post F-score period. F-score is the sum of nine binary signals derived from financial statements that measure financial strength (see Appendix for details). The institutional demand metrics are defined in Table 1. All t-statistics are based on Newey-West (1987) standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

for example, exhibits the highest return difference, and institutional demand differences are either the highest or second highest for three of the four measures that quarter. Similarly, the third quarter exhibits the lowest return difference, and all four demand differences are smallest or second smallest that quarter. There are a number of reasons this test may not provide strong support for the gradual incorporation of information explanation. For instance, different securities may incorporate the information at different rates, how quickly the information is incorporated into prices may vary over time, and a number of other factors, no doubt, influence stock returns and institutional demand.

As a further test, we examine whether quarterly return differences are related to the contemporaneous quarterly institutional demand differences for the ninety-seven calendar quarters in the post F-score period in our sample.[11] Specifically, we regress mean (calendar) quarterly return differences (between high and low F-score stocks) on mean institutional demand differences. Regression results, reported in Panel C of Table 6, provide support for the gradual incorporation of information explanation. The results reveal that post F-score return differences (between high and low F-score stocks) tend to be larger in quarters when institutional demand differences are larger—that is, the coefficient associated with institutional demand differs meaningfully from zero (at the 1% level) in both cases.

3.2 Market frictions and the gradual incorporation of information

Although Fama and French (2006) denote the risk-based explanation the "rational asset pricing" explanation, investors may not fully and quickly impound all information even when they are fully rational for many reasons. An investor's ability to trade on a signal, for example, is a function of trading costs, the size of the signal, the decay function of the signal, the costs of gathering information, and the covariance matrix of expected returns (e.g., Garleanu and Pedersen 2009). Moreover, a number of models (e.g., Allen, Morris, and Shin 2006; Banerjee, Kaniel, and Kremer 2009; Barbosa 2010) and empirical work (e.g., Chen, Hong, and Stein 2002; Zhang 2006; Verardo 2009) suggest that differences in opinion slow the price adjustment process. As a result, we hypothesize that if the relations are driven, at least in part, by the gradual incorporation of information by sophisticated traders, then post F-score return and institutional demand patterns should be stronger when limits to arbitrage and information uncertainty are higher.

We use nine common limits to arbitrage/information uncertainty metrics: (i) the number of institutions holding shares, (ii) the fraction of shares held by institutional investors, (iii) market capitalization, (iv) total return volatility (weekly return standard deviation over the information period), (v) idiosyncratic return volatility (standard deviation of residuals from regression of weekly stock return on weekly market return over the information period), (vi) Amihud's (2002) illiquidity measure (ratio of absolute daily return to daily dollar volume averaged over the information period), (vi) Amihud's (2002) modified illiquidity measure (ratio of difference between daily high and low price to daily dollar volume averaged over the information period), (viii) dollar

[11] Because we aggregate at calendar quarters, the mean return (or demand) each calendar quarter arises from different fiscal year-ends. For instance, the quarter ending December 1991 is quarter +2 for a firm with a December 1990 fiscal year-end (recall that the post F-score period begins six months following fiscal year-end) but quarter +4 for a firm with a June 1990 fiscal year-end. In addition, given that our last fiscal year-end is 200703, the last calendar quarter in the post F-score period is 200812. Because there are relatively few firms with fiscal year-end 200703, there are even fewer firms with high ($\geq$7) or low ($\leq$3) F-scores (less than twenty in each case). As a result, we exclude the quarter ending 200812 from these tests.

volume of trading (measured over the information period), and (ix) firm age (number of months since first appearing on CRSP).[12]

Each fiscal year, we sort all securities in our sample into five portfolios based on each of the nine arbitrage costs/information uncertainty measures. We then compute the difference in subsequent returns and subsequent institutional demand between high (≥7) and low (≤3) F-score stocks for firms in the highest friction portfolio and firms in the lowest friction portfolio. Because the arbitrage costs metrics are correlated with size, we report capitalization-adjusted returns in Table 7.[13]

The first two rows of each panel in Table 7 report the time-series average of the twenty-four cross-sectional means of the *difference* in subsequent returns or institutional demand (analogous to the "high–low" row in Panel B of Table 2) for securities within the highest arbitrage cost/information uncertainty portfolio (first row in each panel) and the lowest arbitrage cost/information uncertainty portfolio (second row in each panel). The third row in each panel reports the difference between the first two rows and associated t-statistic computed from the Newey-West (1987) standard error. If the patterns in subsequent returns and institutional demand are driven, at least in part, by the gradual incorporation of information, then differences between high and low F-score stocks will tend to be larger when arbitrage costs/information uncertainty are higher—that is, the values in the third row of each panel will tend to be positive.

The results reveal that for six of the nine metrics, subsequent return differences (first column) between high and low F-score stocks are larger (statistically at the 10% level or greater) when the arbitrage costs/information uncertainty proxies are higher. As shown in the next two columns, the difference between high and low F-score firms' subsequent institutional demand also tends to be greater when arbitrage costs/information uncertainty proxies are higher (statistically significant at the 5% level or better in fifteen of eighteen cases). In several cases (e.g., Panel C), however, we find differences in returns are not statistically significant, while differences in demand are meaningful.

3.3 Subsequent earnings announcements and F-scores

Related, it is also possible that the gradual incorporation of information occurs through subsequent corporate announcements and sophisticated investors' demand follows earnings shocks. Bernard and Thomas (1989) find, for example, that a disproportionate share of returns associated with post-earnings drift occurs around subsequent earnings announcements. To examine this possibility, we compute each firm's post F-score period market-adjusted

[12] See Ali, Hwang, and Trombley (2003), Baker and Wurgler (2006), Brav, Heaton, and Li (2010), and Lam and Wei (2011) for discussion of these proxies.

[13] The demand metrics are already capitalization adjusted because they are de-meaned and standardized by firms in the same capitalization decile.

Table 7
Post F-score returns and institutional demand in high F-score firms (≥7) less returns and institutional demand in low F-score firms (≤3) for high and low limits to arbitrage/ information uncertainty portfolios

		All institutions		Transient institutions		Nontransient institutions	
Limits to arbitrage/ Information Uncertainty (LTA/IU)	*Capitalization-Adjusted* $Return_{q=1\,to\,4}$	*Adjusted*%Δ *Institutional* $Fraction_{q=1\,to\,4}$	*Adjusted*%Δ *Institutional* $Breadth_{q=1\,to\,4}$	*Adjusted*%Δ *Institutional* $Fraction_{q=1\,to\,4}$	*Adjusted*%Δ *Institutional* $Breadth_{q=1\,to\,4}$	*Adjusted*%Δ *Institutional* $Fraction_{q=1\,to\,4}$	*Adjusted*%Δ *Institutional* $Breadth_{q=1\,to\,4}$
Panel A: Number of institutional shareholders							
Few institutions	8.917%	2.401%	4.014%	0.052%	−1.681%	2.403%	5.608%
Many institutions	5.010%	−1.355%	3.775%	−8.863%	−2.489%	0.953%	6.122%
High–Low LTA/IU	3.907%	3.756%	0.239%	8.915%	0.808%	1.450%	−0.514%
	(1.72)*	(2.98)***	(0.11)	(3.10)***	(0.23)	(1.00)	(0.25)
Panel B: Fraction of shares held by institutions							
Low %institution	10.915%	1.777%	6.398%	2.382%	5.433%	1.658%	6.975%
High %institution	5.169%	4.697%	5.089%	−2.206%	−0.412%	7.022%	7.236%
High–Low LTA/IU	5.746%	−2.920%	1.309%	4.589%	5.844%	−5.364%	−0.261%
	(2.63)**	(−2.24)**	(0.80)	(1.16)	(1.90)*	(−4.24)***	(−0.18)
Panel C: Market capitalization							
Small firms	7.493%	6.639%	8.917%	2.448%	4.490%	7.167%	9.930%
Large firms	5.640%	−1.038%	2.815%	−7.009%	−2.628%	0.755%	4.756%
High–Low LTA/IU	1.854%	7.676%	6.102%	9.458%	7.118%	6.413%	5.174%
	(0.64)	(5.78)***	(3.19)***	(3.20)***	(1.66)	(4.56)***	(3.13)***
Panel D: Total return volatility							
High volatility	6.099%	5.968%	7.777%	1.580%	2.722%	7.012%	9.539%
Low volatility	1.620%	−0.069%	1.295%	−1.062%	−0.157%	0.799%	2.093%
High–Low LTA/IU	4.479%	6.037%	6.482%	2.641%	2.879%	6.213%	7.445%
	(2.79)**	(3.15)***	(3.12)***	(0.55)	(0.89)	(3.78)***	(3.82)***

(continued)

Table 7
(Continued)

		All institutions		Transient institutions		Nontransient institutions	
Limits to arbitrage/ Information Uncertainty (LTA/IU)	*Capitalization-Adjusted* $Return_{q=1\,to\,4}$	*Adjusted%Δ Institutional* $Fraction_{q=1\,to\,4}$	*Adjusted%Δ Institutional* $Breadth_{q=1\,to\,4}$	*Adjusted%Δ Institutional* $Fraction_{q=1\,to\,4}$	*Adjusted%Δ Institutional* $Breadth_{q=1\,to\,4}$	*Adjusted%Δ Institutional* $Fraction_{q=1\,to\,4}$	*Adjusted%Δ Institutional* $Breadth_{q=1\,to\,4}$
	Panel E: Idiosyncratic volatility						
High volatility	6.764%	5.951%	7.700%	1.392%	1.336%	7.002%	9.730%
Low volatility	3.384%	−0.535%	1.768%	−1.138%	−0.538%	−0.071%	2.939%
High–Low LTA/IU	3.380%	6.485%	5.931%	2.530%	1.874%	7.073%	6.791%
	(2.32)**	(3.51)***	(3.10)***	(0.63)	(0.64)	(4.29)***	(3.63)***
	Panel F: Amihud's illiquidity measure						
Less liquid	8.261%	5.449%	7.042%	3.337%	2.931%	5.683%	7.930%
More liquid	5.718%	−1.197%	4.083%	−8.722%	−1.463%	1.220%	6.073%
High–Low LTA/IU	2.543%	6.646%	2.959%	12.060%	4.394%	4.463%	1.857%
	(1.02)	(4.16)***	(1.58)***	(3.33)***	(1.21)	(2.85)***	(1.17)
	Panel G: Amihud's modified illiquidity measure						
Less liquid	8.261%	4.467%	6.629%	4.777%	5.290%	4.385%	7.141%
More liquid	3.853%	−2.756%	3.210%	−11.710%	−3.138%	0.275%	5.552%
High–Low LTA/IU	4.407%	7.223%	3.419%	16.487%	8.428%	4.110%	1.589%
	(2.16)**	(4.84)***	(2.30)**	(3.55)***	(2.14)**	(3.85)***	(1.32)

(continued)

Table 7
(Continued)

Limits to arbitrage/ Information Uncertainty (LTA/IU)	All institutions: *Capitalization-Adjusted* $Return_{q=1\,to\,4}$	All institutions: *Adjusted%Δ Institutional* $Fraction_{q=1\,to\,4}$	All institutions: *Adjusted%Δ Institutional* $Breadth_{q=1\,to\,4}$	Transient institutions: *Adjusted%Δ Institutional* $Fraction_{q=1\,to\,4}$	Transient institutions: *Adjusted%Δ Institutional* $Breadth_{q=1\,to\,4}$	Nontransient institutions: *Adjusted%Δ Institutional* $Fraction_{q=1\,to\,4}$	Nontransient institutions: *Adjusted%Δ Institutional* $Breadth_{q=1\,to\,4}$
	Panel H: Dollar volume of trading						
Low $ volume	6.849%	3.058%	4.683%	4.590%	1.430%	2.958%	5.471%
High $ volume	7.265%	−0.811%	4.896%	−8.687%	−0.937%	1.601%	6.910%
High–Low LTA/IU	−0.416%	3.869%	−0.213%	13.277%	2.367%	1.358%	−1.439%
	(−0.13)	(2.44)***	(−0.13)	(3.17)***	(0.73)	(0.81)	(−0.87)
	Panel I: Firm age						
Young firms	8.329%	4.860%	9.074%	0.104%	7.435%	6.488%	9.837%
Mature firms	2.733%	−1.204%	1.965%	−6.343%	−3.951%	0.892%	4.025%
High–Low LTA/IU	5.596%	6.065%	7.109%	6.447%	11.386%	5.597%	5.811%
	(2.80)***	(3.26)***	(3.51)***	(1.24)	(3.08)***	(3.58)***	(3.44)***

Each fiscal year, all firms are sorted into five groups based on nine proxies for limits to arbitrage/information uncertainty. We then compute the post F-score capitalization adjusted return and institutional demand for high F-score stocks (≥7), low F-score stocks (≤3), and their difference, for stocks within the highest limits to arbitrage/information uncertainty portfolio and stocks in the lowest limits to arbitrage/information uncertainty portfolio. The first two rows in each panel report, respectively, the time-series average of the twenty-four cross-sectional means for securities within the highest limits to arbitrage/information uncertainty portfolio and the lowest limits to arbitrage/information uncertainty portfolio. The third row in each panel reports the difference between the first two rows and associated t-statistic computed from the Newey and West (1987) standard error of the time series of the twenty-four cross-sectional means. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Post F-score returns and earnings announcements (Quarters $q = 1$ to 4)

	Market-Adjusted Return$_{q=1\,to\,4}$	Earnings announcement return	Not around earnings announcement
High (F-score $\geq$ 7)	2.363%	1.145%	1.218%
Medium (3 $<$ F-score $<$ 7)	−0.960%	0.552%	−1.512%
Low (F-score $\leq$ 3)	−5.985%	−0.295%	−5.691%
High–Low	8.348%	1.440%	6.908%
(t-statistic)	(4.42)***	(3.63)***	(2.82)***
(z-statistic)	(3.31)***	(2.94)***	(3.06)***

This table reports the time-series average of annual (fiscal year) cross-sectional mean market-adjusted returns, market-adjusted returns around earnings announcements, and market-adjusted returns not around earnings announcements for high (F-score $\geq$ 7), medium (3 $<$ F-score $<$ 7), and low (F-score $\leq$ 3) F-score stocks in the post F-score period. The sample spans twenty-four fiscal years (1983–2006). For each firm year in the sample, we define the market-adjusted return in the four days (days –1, 0, 1, and 2 relative to day 0 announcement) around all earnings announcements in the post F-score period as the "Earnings announcement return." The return "Not around earnings announcements" is defined as the difference between the total market adjusted return in the post F-score period and the earnings announcement return. F-score is the sum of nine binary signals derived from financial statements that measure financial strength (see Appendix for details). The bottom two rows report a t-statistic (computed from the time series of the twenty-four cross-sectional means with Newey-West 1987 standard errors) and z-statistic (computed from Wilcoxon signed rank test of the twenty-four cross-sectional means) of the null hypothesis that returns do not differ across high and low F-score firms. The fiscal year-end occurs at the end of quarter $q = –2$. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

return around earnings announcement dates as the four-day period beginning the day prior to the earnings announcement date (dates are from Compustat), the day of the earnings announcement, and the two days following the earnings announcement.[14] For most firms, these dates make up sixteen trading days (i.e., four days for each quarterly announcement) during the post F-score year.[15] We define the difference between the market-adjusted return in the post F-score period, and the market-adjusted return around earnings announcements in the post F-score period as the non-earnings-announcement return.

Table 8 reports the time-series mean (across the twenty-four fiscal years) of the average market-adjusted returns in the post F-score period (identical to the figures in Table 2), total market adjusted returns around earnings announcements in the post F-score period, and their difference (market-adjusted returns not around earnings announcements). The last two rows report the associated t-statistic (computed from the time series of the twenty-four cross-sectional means based on Newey-West 1987 standard errors) and z-statistic (computed from Wilcoxon signed rank test of the twenty-four cross-sectional means). Consistent with the gradual incorporation of information by sophisticated institutions, on average, more than 82% (6.908%/8.348%) of the difference between high and low F-score stocks' returns in the post F-score period arises outside the earnings announcement period.

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14 If a firm announces on a non–trading day, we define the four-day earnings announcement period as two days prior to the earnings announcement to two days post announcement.

15 On average, Compustat identifies four earnings announcement dates for more than 91% of our sample of 41,845 firm-years.

4. Understanding the Behavior of Transient and Nontransient Institutions

Although the patterns in Table 3 are consistent with the gradual incorporation of information explanation, it is curious that transient institutions do not continue buying high F-score stocks and selling low F-score stocks until the information is fully incorporated into prices. One possibility is that, as Ke and Ramalingegowda (2005) propose, transient institutions may begin to unwind positions prior to the full incorporation of information because they believe they have better opportunities—that is, the perceived risk/reward trade-off may be higher elsewhere.

A second possibility is that differences between transient and nontransient institutional investors' momentum trading primarily drive the differences in responses to F-score information. To examine this possibility, we repeat the comparison of securities with similar lag returns but different F-scores, but examine demand by transient and nontransient institutions. The results in Panels C and D of Table 4 match those in Table 3—even when comparing securities with similar lag returns, post F-score aggregate institutional demand is driven by the nontransient institutional demand.[16]

A third possibility is that limits to arbitrage/information uncertainty play a role in driving differences between transient and nontransient investors. Specifically, we predict that the delayed response by nontransient institutions will be greater in firms with greater market frictions. Moreover, if transients reverse positions to move on to more attractive opportunities, we expect the inverse relation between F-score and subsequent transient demand to be driven by low friction stocks. Thus, we examine transient and nontransient institutions' demand across the arbitrage cost/information uncertainty portfolios.

The results, reported in the last four columns of Table 7, are largely consistent with the gradual incorporation of information. First, regardless of arbitrage costs, most of the post F-score period institutional demand arises from nontransient institutions. Second, nontransient institutions' demand differences in the post F-score period tend to be larger when frictions are larger. Specifically, the third row ("High–Low") is positive and differs significantly from zero (at the 1% level or better) for nontransient institutions (last two columns) in ten of the eighteen tests. Third, evidence that transients tend to reverse positions in the post F-score period is largely limited to low arbitrage costs/information uncertainty portfolios.

A fourth possibility is that early trading institutions fully incorporate the information captured by F-scores in a timely manner, but nontransient institutions blindly follow other institutions' trades and therefore drive prices

[16] We also estimate the regressions in Table 5 for transient and nontransient institutions. Consistent with Table 4, F-score continues to forecast nontransient institutional demand (statistically significant at the 1% level in all cases) even when controlling for lag returns and the other independent variables. Further consistent with Table 4, the relation between F-score and subsequent transient institutional demand is not statistically meaningful or negative when controlling for lag returns and the other independent variables.

from fundamental values. We ran two sets of tests to investigate this possibility. First, we estimate standardized regressions (annually for each institutional demand measure) of nontransient institutional demand in the post F-score period on both F-score and information period institutional demand. Although we do not report specific results (to conserve space), the analysis reveals that nontransient institutions following other institutions' trades does not fully explain our results. Specifically, F-score continues to forecast nontransient institutional demand (statistically significant at the 5% level or better in all cases) even when accounting for nontransient institutions following other institutions' information period trades.

In addition, if nontransient herding drives prices from value, then we should see an eventual return reversal. Thus, we investigate high and low F-score stocks' returns in the year following the post F-score period (i.e., quarters $q =$ 5 to 8). Neither high nor low F-score stocks exhibit reversals (market-adjusted returns do not differ meaningfully from zero), and we find no evidence that high and low F-score firms exhibit meaningfully different returns in the year following the post F-score period.

5. Institutional Transaction Data Analysis

The primary limitation of the 13(f) data is its coarseness—we cannot infer institutional demand over any period less than a quarter. Thus, although the analyses in Section 3 suggest that the relation between F-score and subsequent returns is driven, at least in part, by subsequent institutional demand, it is still possible that the relation is driven primarily by very short-term (e.g., intra-quarter) institutional momentum trading. To further investigate this possibility, we exploit a proprietary database of institutional investor trades provided by ANcerno Ltd. (formerly Abel Noser Corporation).[17] The limitations of the ANcerno data are that (i) the data are for a shorter period than the 13(f) data, and (ii) the data include only institutional investors who are ANcerno clients.[18]

The ANcerno data begin in 1999, and our institutional ownership data end in September 2008, yielding nine fiscal years (1998–2006) with both data sets. On average, we have 1,905 firms in our F-score (i.e., 13(f)) sample during those nine fiscal years, yielding a total of 17,142 firm-year observations. Of those 17,142 firm-years in the overlapping period, we eliminate firms from the ANcerno data that we cannot match with CRSP data (based on CUSIP) and those firms with less than ten days of ANcerno transactions in the post F-score period. This yields a total sample of 15,729 firm-years (approximately

[17] ANcerno is a consulting firm that provides "trade costs analysis" to institutional investors. The ANcerno data have been used in a number of recent studies—e.g., Goldstein et al. 2009; Puckett and Yan 2011; Jegadeesh and Tang 2010; Jame 2010.

[18] Puckett and Yan (2011) provide a thorough discussion of the ANcerno data in their paper. As Puckett and Yan note, ANcerno clients include such institutions as CalPERS, YMCA retirement, Putman Investments, and Lazard Asset Management.

92% of our original sample for the 1998–2006 fiscal years) that we use in our analysis based on the ANcerno data. Table 9 reports descriptive statistics for the ANcerno data.

In total, the ANcerno data include nearly 57 million transactions, accounting for 438 billion shares worth more than $13.52 *trillion* from 874 different institutional investors for our sample (Panel A). Moreover, given an average of 251 trading days per year (over those nine fiscal years), we have 3,953,764 firm-day observations in our F-score/ANcerno sample (251 trading days * 15,729 firm-years). More than 68% of those firm-days have at least one ANcerno transaction (Panel B). As shown in Panel C, on firm-days with ANcerno data, the ANcerno transactions account for, on average, more than 15% of the CRSP reported volume. The average (median) firm-day includes 20.97 (7) ANcerno transactions for 161,216 shares (23,564 shares) with a value of $4,980,680 ($444,511).

Given that the ANcerno institutions are a subset of all institutions, we begin by examining whether ANcerno demand in the post F-score period is related to 13(f) demand in the post F-score period. Specifically, for each firm-year, we compute two measures of ANcerno demand analogous to our 13(f) demand metrics. We define the adjusted percent change in the fraction of shares held by ANcerno institutions (over the post F-score period) as the change in the fraction of shares held by ANcerno institutions less the average for firms in the same capitalization decile, normalized by the fraction of shares held by all (i.e., 13(f)) institutions (at the end of quarter $q = 0$) for securities within the same capitalization decile:

$$Adjusted\,\%\Delta ANcerno\,Fraction_{i\in d,q=1\,to\,4}$$
$$= \frac{\Delta ANcerno\,Fraction_{i\in d,q=1\,to\,4} - \overline{\Delta ANcerno\,Fraction_{i\in d,q=1\,to\,4}}}{\%\,Shares\,Held\,by\,13\,(f)\;\,Institutions_{i\in d,q=0}}, \quad (6)$$

where security i is in capitalization decile d. We normalize by ownership of all 13(f) institutions rather than ANcerno institutions because although the ANcerno transaction data allow us to compute changes in the levels of ANcerno ownership, we cannot measure the levels themselves.

We analogously compute the adjusted percentage change in the number of ANcerno buyers over the post F-score period normalized by the number of 13(f) shareholders at the beginning of the post F-score period:[19]

$$Adjusted\,\%\Delta\;ANcerno\,Buyers_{i\in d,q=1\,to\,4}$$
$$= \frac{Net\,\#\,of\;ANcerno\,Buyers_{i\in d,q=1\,to\,4} - \overline{Net\,\#\,of\;ANcerno\,Fraction_{i\in d,q=1\,to\,4}}}{\#\,Institutional\,13\,(f)\;\,Shareholders_{i\in d,q=0}}. \quad (7)$$

Analogous to our 13(f) data, we Winsorize each of the ANcerno demand metrics at the 0.50% and 99.50% levels for each fiscal year. For each of the

[19] This measure is not exactly analogous to the adjusted percent change in the 13(f) institutional breadth metric because the change in breadth measure focuses on the net number of 13(f) institutions entering or leaving the stock, whereas this measure computes the net number of ANcerno institutions buying the security.

Table 9
Descriptive statistics for ANcerno transaction data sample (fiscal years 1998–2006)

Panel A: Aggregate ANcerno data statistics

Number of ANcerno institutions	Number of ANcerno transactions	Total shares traded by ANcerno institutions	Total dollar value of ANcerno trades
874	56,931,902	437,606,498,744	$13.52 trillion

Panel B: Merging the F-score sample with ANcerno transaction data

	Firm-years			Firm-days	
Number of firm-years in F-score sample	Number of matching firm-years in ANcerno data	% of F-score firm-years matched with ANcerno data	Number of firm-days in matching sample	Number of firm-days with ANcerno transactions	% of post F-score firm-days with ANcerno trades
17,142	15,729	91.76%	3,953,764	2,714,409	68.65%

Panel C: Descriptive statistics across the 2,714,409 firm-days with both F-score and ANcerno data

	Mean	Standard deviation	25th percentile	Median	75th percentile
Transactions	20.97	64.92	2.00	7.00	19.00
Volume	161,216	632,710	4,551	23,564	104,120
Dollar volume	$4,980,680	$18,981,037	$66,300	$444,511	$2,621,048
% CRSP volume	15.37%	17.70%	2.74%	8.92%	21.56%
#ANcerno institutional trading	5.21	5.56	2.00	3.00	7.00

Panel D: Average correlation between annual ANcerno institutional demand and 13(f) institutional demand

	13(f) Adjusted $\%\Delta$*Institutional Fraction*$_{q=1\,to\,4}$	*13(f) Adjusted* $\%\Delta$*Institutional Breadth*$_{q=1\,to\,4}$
Adjusted $\%\Delta$*ANcerno Fraction*$_{q=1\,to\,4}$	0.340 (29.14)***	
Adjusted $\%\Delta$*ANcerno Buyers*$_{q=1\,to\,4}$		0.529 (27.77)***

This table reports summary statistics for ANcerno institutional transaction data for January 1999–September 2008 (the post F-score period covering fiscal years 1998–2006). Panel A presents descriptive statistics for the ANcerno data that match the F-score sample over this period. Panel B reports statistics regarding the merging of the F-score and ANcerno samples. Panel C reports descriptive statistics for the 2.71 million firm-days in the F-score sample with ANcerno trades. Panel D reports the time-series ($n = 9$ fiscal years) average cross-sectional correlation between institutional demand metrics computed from the ANcerno data and from the 13(f) data (see Table 1 for descriptions of the 13(f) demand metrics). The ANcerno demand metrics are: (i) the change in the fraction of share held by ANcerno institutions less the average change in the fraction of shares held by ANcerno institutions in similar capitalization firms normalized by the fraction of shares held by 13(f) institutions (*Adjusted* $\%\Delta$ *ANcerno Fraction*) and (ii) the net number of ANcerno institutions purchasing shares less the average net number purchasing shares in similar-size firms normalized by the number of 13(f) institutions holding shares in the firm (*Adjusted* $\%\Delta$ *ANcerno Buyers*). The associated t-statistics are computed from the Newey-West (1987) standard error of the time series of the nine cross-sectional correlations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

nine fiscal years that the 13(f) and ANcerno data sets overlap, we compute the cross-sectional correlation between each of the 13(f) institutional demand measures and corresponding ANcerno institutional demand measures. The time-series averages of the nine cross-sectional correlations, reported in Panel D of Table 9, reveal that the ANcerno demand metrics are strongly related to the 13(f) demand metrics (t-statistics are based on the Newey-West 1987 standard error of the nine time-series observations).

5.1 Does F-score predict returns and institutional demand for the overlapping period?

Because the 13(f) and ANcerno data sets overlap period is limited to nine fiscal years, we examine whether F-score predicts returns and 13(f) institutional demand when the sample is limited to these nine fiscal years. We also investigate whether F-score predicts ANcerno demand over this period. Specifically, we repeat the annual regressions in Table 5 but limit the sample to the nine overlapping fiscal years and include only those firms that have 13(f) and ANcerno data (i.e., the 15,729 firm-years with overlapping data). Following Table 5, all variables are standardized (rescaled to zero mean, and unit variance) each fiscal year. The t-statistics are computed from the Newey-West (1987) time-series standard errors based on the nine annual regression coefficients.

Panel A in Table 10 reveals evidence that F-score continues to predict returns in the overlapping period. The t-statistic associated with F-score is 2.25, but given only nine coefficient estimates, the significance level is 0.06. In addition, as shown in Panel B, F-score continues to predict 13(f) institutional demand (statistically significant at the 5% level) over the restricted sample. Panel C in Table 10 reveals evidence that F-score also predicts ANcerno demand—the coefficient on both metrics differs meaningfully from zero (at the 10% level or better).

5.2 ANcerno demand, contemporaneous returns, and lag returns

We next use the ANcerno data to examine whether the correlation between institutional demand and returns in the post F-score period is driven by institutions' short-term momentum trading or price changes associated with institutional demand. Thus, this section does not specifically focus on F-scores and institutional demand, but rather centers on the question of whether our results are likely explained by short-term institutional positive feedback trading within the post F-score period or by price changes associated with institutional demand in the post F-score period.

We begin by measuring ANcerno institutional demand, as above, but rather than computing ANcerno demand for each security over the entire annual post F-score period, we compute ANcerno institutional demand for each firm-day in the post F-score period. Thus, for example, the adjusted percent change in

Table 10
Predicting returns, 13(f) institutional demand, and ANcerno institutional demand (fiscal years 1998–2006 only)

Dependent variable	F-score$_{q=0}$	*Market-Adjusted Return*$_{q=-1\ to\ 0}$	*ln(Capitalization)*$_{q=-2}$	*ln(Book/Market)*$_{q=-2}$	*Asset Growth*$_{q=-6\ to\ -2}$	Adjusted R^2
	Panel A: Predicting market-adjusted returns in post F-score period					
Market-Adjusted Return$_{q=1\ to\ 4}$	0.055	0.009	−0.018	0.084	−0.054	6.00%
	(2.25)*	(0.31)	(−0.49)	(2.57)**	(−2.16)*	
	Panel B: Predicting 13(f) demand					
Adjusted %Δ*Institutional Fraction*$_{q=1\ to\ 4}$	0.035	0.181	−0.003	−0.031	0.006	3.40%
	(3.22)**	(18.30)***	(−0.17)	(−3.30)**	(1.66)	
Adjusted %Δ *Institutional Breadth*$_{q=1\ to\ 4}$	0.046	0.257	0.012	−0.021	0.013	7.49%
	(3.21)**	(12.74)***	(0.85)	(−2.12)*	(1.03)	
	Panel C: Predicting ANcerno demand					
Adjusted %Δ *ANcerno Fraction*$_{q=1\ to\ 4}$	0.027	0.114	−0.045	−0.052	0.019	1.68%
	(2.61)**	(15.09)***	(−9.36)***	(−5.41)***	(4.53)***	
Adjusted %Δ *ANcerno Buyers*$_{q=1\ to\ 4}$	0.027	0.166	−0.038	−0.014	0.006	3.18%
	(1.97)*	(11.57)***	(−8.51)***	(−1.69)	(1.17)	

This table presents the time-series average coefficients and associated t-statistics for nine annual regressions (covering fiscal years 1998–2006) of subsequent annual market-adjusted returns, measures of subsequent 13(f) institutional demand, and measures of ANcerno institutional demand on (i) F-score and (ii) F-score, lag market-adjusted return (firm's buy-and-hold return less CRSP's value-weighted index return over the quarters $q = -1$ to 0), the natural logarithm of market capitalization and book-to-market ratios (measured at fiscal year-end, $q = -2$), and asset growth from previous fiscal year-end (end of quarter $q = -6$ to end of quarter $q = -2$). The 13(f) institutional demand metrics are defined in Table 1. The ANcerno demand metrics are defined in Table 9. The associated t-statistics are computed from the time-series Newey-West (1987) standard error of the nine coefficient estimates. All variables are standardized (i.e., rescaled to zero mean, unit variance) for each fiscal year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

the fraction of shares held by ANcerno institutions on day t (in the post F-score period) for security i is given by

$$Adjusted\,\%\Delta ANcerno\,Fraction_{i\in d,t} = \frac{\Delta ANcerno\,Fraction_{i\in d,t} - \overline{\Delta ANcerno\,Fraction_{i\in d,t}}}{\%Shares\;Held\,by\,13\,(f)\;\;Institutions_{i\in d,q=0}}. \quad (8)$$

Our total sample size is the 2.714 million firm-days (see Panel B of Table 9) that have ANcerno trades and F-score data in the post F-score period. As before, we Winsorize the daily ANcerno demand metrics at the 0.5% and 99.5% levels each fiscal year. We then examine the relation between daily ANcerno demand, same day returns, and lag returns. Specifically, each fiscal year, we run a pooled cross-sectional time-series regression of the ANcerno daily institutional demand metrics on returns the same day and returns over the previous twenty days.[20] To allow direct comparison between the coefficients, the variables are rescaled to unit variance and zero mean each fiscal year (bars indicate that the variables are standardized):

$$\overline{ANcerno\,Institutional\,Demand}_{i,t=0} = \beta_1\overline{Market\;Adj.Return}_{i,t=0} + \beta_2\overline{Market\;Adj.Return}_{i,t=1\,to\,-20} + \varepsilon_{i,t}\,. \quad (9)$$

If the relation between institutional investors' demand and post F-score returns is driven, at least in part, by institutional demand impacting prices, then institutional demand will be positively related to same-day returns. Alternatively, if the relation is fully driven by short-term institutional momentum trading, then daily ANcerno institutional demand will be related only to lag market-adjusted returns.

Table 11 reports the time-series average coefficient and associated t-statistics (computed from the Newey-West 1987 standard error based on the time series of estimated coefficients) from the nine fiscal years in the ANcerno data. The third column reports the average difference between the coefficient associated with contemporaneous daily market-adjusted returns (β_1) and the coefficient associated with market-adjusted returns over the previous twenty days (β_2) and associated t-statistic. The results reveal that daily ANcerno institutional demand is strongly related to both same-day returns and returns over the previous twenty days (all coefficients are statistically significant at the 1% level). As shown in the third column, however, the relation between ANcerno demand and same-day returns is substantially stronger (statistically significant at the 5% level or better) than the relation between ANcerno demand and lag returns.

[20] In untabulated analysis, we repeat the regressions but use lag returns over the previous day or the previous five days rather than returns over the previous twenty days. In all cases, the relation between ANcerno demand and returns the same day remains meaningfully stronger than the relation between ANcerno demand and lag returns.

Table 11
Standardized regressions of daily ANcerno institutional demand on contemporaneous and lag market-adjusted returns

Dependent variable	*Market-Adjusted Return$_t$*	*Market-Adjusted Return$_{t-1 \text{ to } t-20}$*	*Difference*	Adjusted R^2
Adjusted %ΔANcerno Fraction$_t$ (in percent)	0.070	0.041	0.028	0.70%
	(9.04)***	(13.63)***	(4.52)***	
Adjusted %ΔANcerno Buyers$_t$ (in percent)	0.066	0.048	0.018	0.68%
	(34.12)***	(7.45)***	(2.62)**	

For each firm-day in the ANcerno sample with at least one ANcerno transaction, we compute two measures of ANcerno institutional demand: (i) the daily change in the fraction of shares held by ANcerno institutions less the average change in the fraction of shares held by ANcerno institutions in similar capitalization firms the same day normalized by the fraction of shares held by 13(f) institutions (*Adjusted %Δ ANcerno Fraction*), and (ii) the net number of ANcerno institutions purchasing shares that day less the average net number purchasing shares in similar-size firms that day normalized by the number of 13(f) institutions holding shares in the firm (*Adjusted %Δ ANcerno Buyers*). We then estimate a pooled cross-sectional time-series regression, each fiscal year, of daily ANcerno demand on returns the same day and returns over the previous twenty trading days. To allow direct comparison between the coefficients, all variables are rescaled to unit variance, zero mean, each fiscal year. The first two columns report the time-series mean of the regression coefficients and associated *t*-statistics. The third column reports the time-series mean of the difference between the same-day return coefficient and the lag return coefficient and associated *t*-statistics. The *t*-statistics are computed from the time-series Newey-West (1987) standard error of the nine coefficient estimates. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

It is important to recognize, however, that our results may be driven by very short-term (i.e., intraday) institutional momentum trading. In fact, Griffin, Harris, and Topaloglu (2003) find just such a pattern for a sample of Nasdaq 100 securities over a ten-month period (i.e., institutional investors chasing intraday returns). In sum, our tests suggest that either (i) the relation between institutional demand and returns in the post F-score period is driven, at least in part, by price changes associated with the gradual incorporation of information by sophisticated institutions, or (ii) institutions engage in intraday momentum trading and their demand does not impact prices.

5.3 Does F-score predict returns associated with ANcerno demand?

Given (i) the positive relation between ANcerno demand and same-day returns (Table 11) and (ii) evidence that F-score forecasts both ANcerno demand and returns (Table 10), we examine whether F-score predicts the portion of return associated with subsequent ANcerno demand or the portion of return independent of subsequent ANcerno demand. We begin by estimating, each fiscal year, the portion of each firm-day's return associated with ANcerno demand. Specifically, each fiscal year we estimate a pooled cross-sectional time-series regression of daily returns on daily ANcerno demand:[21]

[21] To ensure that our results are not influenced by institutional momentum trading, we also ran the analysis using institutional demand orthogonal to lag returns—that is, we replace institutional demand in Equation (10) with the residual from annual regressions of institutional demand on returns over the previous twenty days. Our results remain virtually identical.

Table 12
Predicting returns and institutional demand regressions

	Panel A: Regression coefficient (*100) associated with ANcerno demand		
	Adjusted %Δ ANcerno Fraction$_t$	*Adjusted %Δ ANcerno Buyers$_t$*	*Adjusted R^2*
Daily *Market-Adjusted Return$_t$*	0.747 (8.71)***		0.52%
Daily *Market-Adjusted Return$_t$*		0.078 (15.87)***	0.43%
	Panel B: Does F-score predict return associated with ANcerno institutional demand or return independent of ANcerno institutional demand?		
Average correlation between F-score and future *Market-Adjusted Returns$_{q=1\text{ to }4}$*	0.052 (1.57)		0.052 (1.57)
Return associated with ANcerno demand	0.020 (3.77)***		0.022 (3.30)**
Return independent of ANcerno demand	0.032 (0.94)		0.030 (0.85)

We estimate a pooled cross-sectional time-series regression, each fiscal year, of daily market-adjusted returns on both measures of ANcerno institutional demand (see Table 11 for definitions) the same day. Panel A presents the time-series average of these regression coefficients and associated t-statistics. We then compound the fitted value from the regression for each firm-year to estimate the portion of post F-score period return associated with ANcerno demand. The difference between the post F-score market adjusted return and the compound fitted value is the estimate of the portion of post F-score return independent of ANcerno demand. Finally, each fiscal year, we partition the cross-sectional correlation between F-score and subsequent return into (i) the portion due to the return associated with ANcerno demand and (ii) the portion due to return independent of ANcerno demand. Panel B reports the time-series average of these nine (fiscal years 1998–2006) correlation coefficients and the two components. All t-statistics are computed from Newey-West (1987) standard errors from the time series of the nine estimates.

$$\begin{aligned} &Market\ Adjusted\ Return_{i,t} \\ &\quad = \alpha + \beta_1 ANcerno\ Institutional\ Demand_{i,t} + \varepsilon_{i,t}\,. \end{aligned} \tag{10}$$

Panel A of Table 12 reports the time-series average coefficients (and associated t-statistics computed from the Newey-West 1987 standard errors of the nine annual regressions) from Equation (10).

We next compound the daily predicted value (over the post F-score period) from Equation (10) as the estimate of the portion of security i's return during the post F-score period associated with ANcerno demand in the post F-score period:

$$\begin{aligned} &Return\ Associated\ with\ ANcerno\ Demand_{i,q=1\,to\,4} \\ &\quad = \prod_{t=1}^{T_i} \left(1 + \overline{\overline{Market\ Adjusted\ Return_{i,t}}}\right) - 1\,, \end{aligned} \tag{11}$$

where the double bars indicate the fitted market-adjusted return for security i on day t based on Equation (10) and security i has T_i days with ANcerno trades in the post F-score period that fiscal year.

We compute the portion of security i's return not associated with ANcerno demand as the difference between the post F-score market-adjusted return ($Return_{i,q=1to4}$) and the market-adjusted return associated with ANcerno demand in the post F-score period (Equation (11)). As a result, stock i's market-adjusted return over the post F-score year is simply the sum of the portion of its return attributed to ANcerno demand and the portion independent of ANcerno demand:

$$R_{i,t=1\,to\,4} = Return\ Associated\ with\ ANcerno\ Demand_{i,q=1\,to\,4} + Return\ Independent\ of\ ANcerno\ Demand_{i,q=1\,to\,4}. \quad (12)$$

Given that the post F-score market-adjusted return is the sum of the two components, the correlation between F-score and market-adjusted returns in the post F-score period can be decomposed into the relation between F-score and the portion of future return associated with future ANcerno demand and the relation between F-score and the portion of future return independent of future ANcerno demand:

$$\rho\left(f-score,\ R_{i,q=1\,to\,4}\right) = \frac{cov\left(f-score,\ Return\ Associated\ with\ ANcerno\ Demand_{i,q=1\,to\,4}\right)}{\sigma\left(f-score\right)\sigma\left(R_{i,q=1\,to\,4}\right)} + \frac{cov\left(f-score,\ Return\ Independent\ of\ ANcerno\ Demand_{i,q=1\,to\,4}\right)}{\sigma\left(f-score\right)\sigma\left(R_{i,q=1\,to\,4}\right)}. \quad (13)$$

The top row of Panel B in Table 12 reports the time-series average of the cross-sectional correlation between F-score and subsequent return over the post F-score period for the nine fiscal years that have both ANcerno and F-score data. The next two rows report the time-series average portion of the correlation accounted for by subsequent returns associated with ANcerno demand (i.e., the first term on the right-hand side of Equation (13)) and the portion of the correlation attributed to subsequent returns independent of ANcerno demand (i.e., the second term on the right-hand side of Equation (13)). Only the portion of return attributed to demand by ANcerno institutions is statistically significant (at the 5% level or better). In short, the results suggest that high F-score firms subsequently outperform low F-score firms, at least in part, because F-score predicts returns that are associated with subsequent demand by ANcerno institutions the same day.

6. Discussion and Conclusions

6.1 Can the risk-based hypothesis explain the results?

Another potential interpretation of the relation between F-score, subsequent returns, and subsequent institutional demand is that F-score is positively correlated with risk (i.e., the risk-based explanation) and institutional investors are attracted to higher-risk stocks and repelled from lower-risk stocks. Consider, for instance, a scenario where institutional investors are more risk-tolerant than individual investors, but due to transaction costs adjust positions slowly over time. This scenario, however, does not fit our empirical results. Specifically, this interpretation requires that high F-scores imply an *increase* in risk (and low F-scores imply a decrease). That is, if risk does not change, then existing institutional ownership levels will already reflect preferences/risk-tolerances and future institutional demand should be independent of F-score. The strong positive relation between F-score and returns during the information period does not, however, support the changing risk interpretation—for example, if a high F-score implied an increase in risk (that attracts institutions and increases expected returns), then high F-score stocks should underperform low F-score stocks in the information period.

Related to the risk-based explanation, one could argue that institutional demand is associated with high contemporaneous returns because it "causes" a decline in the discount rate due to increased liquidity, better corporate governance, or broader ownership (e.g., Merton's [1987] investor recognition hypothesis). This explanation, however, implies a positive relation between institutional demand and contemporaneous returns and an *inverse* relation between institutional demand and subsequent returns—that is, the contemporaneous relation is driven by a decline in the discount rate.

One may propose that some "story" other than the gradual incorporation of information could explain the relation between F-score, subsequent returns, and subsequent institutional demand. If institutional investors are usually the price-setting marginal investors (i.e., institutional demand "drives" price changes), then a positive relation between F-score, subsequent institutional demand, and subsequent returns implies either the gradual incorporation of information or that institutional demand shocks (related to F-scores) drive prices from fundamentals. Inconsistent with the demand shocks story, there is no evidence of an inverse relation between F-score and future returns (see Section 4; Piotroski 2000, 2005; Fama and French 2006).

Finally, it is possible that institutions do not revise their beliefs in response to F-score directly, but rather some other variable(s) correlated with F-score. Institutions, for example, may be attracted to the high lag returns (i.e., information period returns) associated with high F-scores. Or perhaps high F-score stocks subsequently experience analyst upgrades or positive earnings surprises that attract institutional investors. The gradual incorporation of information explanation, however, does not require that institutions update their beliefs based only on the information directly captured by F-score. Rather, the explanation requires only that whatever causes institutions to update their beliefs is correlated with the information captured by F-score or, equivalently, the information captured by F-score is not quickly fully impounded into prices.

6.2 Conclusions

Financial strength measures garnered from current financial statements forecast stock returns. Fama and French (2006) point out, however, that the relation between financial strength and future returns is consistent with two explanations: (i) financial strength proxies for expected profitability and, controlling for book-to-market ratios and investment, the standard valuation equation requires that more profitable firms must have higher expected returns; and (ii) markets gradually incorporate public information. As a result, Fama and French (2006, 496) conclude that it is "impossible" for traditional asset pricing tests to differentiate these explanations.

Focusing on Piotroski's (2000, 2005) F-score, we take a different approach to testing whether public information is gradually incorporated into prices. Specifically, under the risk-based explanation, profitability metrics are independent of subsequent changes in investors' expectations. In contrast, under the gradual incorporation of information explanation, financial strength forecasts the gradual incorporation of revision in investors' expectations into prices over time. Our proposal is straightforward—given that information (i.e., revised expectations) is incorporated through trading, the gradual incorporation of information explanation requires that F-score forecast not only future returns, but also future demand by more sophisticated investors.

Consistent with the gradual incorporation of information explanation, financial strength forecasts not only returns, but also subsequent institutional investor demand. Moreover, more sophisticated transient institutions respond to the information prior to less sophisticated nontransient institutions, and both exploit individual investors. Additional tests suggest that short-term institutional momentum trading cannot fully explain the relation between subsequent returns and subsequent institutional demand (although it is possible that intraday institutional momentum trading may explain our results). In sum, our tests imply that profitability proxies predict returns, at least in part, because they predict demand by institutional investors who, in aggregate, drive prices and incorporate public information with their trading.

Appendix

Piotroski's (2000, 2005) F-score is the sum of nine binary variables that collectively measure financial strength. We follow Fama and French (2006) in defining the F-score variables. Specifically, each component contributes one point if the following condition holds and zero otherwise:

1. Positive net income before extraordinary items (Compustat item IB).
2. Positive cash flow from operations:

    a. If a company files a statement of working capital (Compustat format code for statement of cash flows equals l), cash flow from operations is funds from operations less other changes in working capital (Compustat item WCAPC, if available). Funds from operations (Op_t) is defined as the sum of earnings before extraordinary items (Compustat item IB), income statement deferred taxes

(Compustat item TXDI, if available), and equity's share of depreciation expense. Equity's share of depreciation expense is calculated as depreciation expense (Compustat item DP) times the ratio of market capitalization to the sum of market capitalization and the difference between total assets (Compustat item AT) and book value of equity. Book value of equity is defined as total assets (Compustat item AT) less liabilities (Compustat item LT) plus deferred taxes and investment tax credits (Compustat item TXDITC) less preferred stocks liquidity value (if available, Compustat item PSTKL) or preferred stock redemption value (if available, Compustat item PSTKRV), or preferred stocks carrying value (if available, Compustat item PSTK).

b. If a company files a statement of cash flows (Compustat format code equals 7), cash flow from operations is defined as net cash flow from operating activities (Compustat item OANCF).

c. For all other Compustat format codes, cash flow from operations is defined as the sum of funds from operations (Op_t) and changes in working capital (Compustat item WCAPC).

3. Cash flow from operations greater than net income, i.e., (2)>(1).
4. Growth in net income (scaled by total assets) from the prior fiscal year-end:
   Net income before extraordinary items (Compustat item IB) divided by total assets (Compustat item AT).
5. Decrease in leverage from prior fiscal year-end:
   Leverage is defined as long-term debt (the sum of Compustat items DLTT and DD1) divided by total assets (Compustat item AT).
6. Increase in liquidity (current ratio) from prior fiscal year-end:
   Liquidity is defined as the ratio of current assets (Compustat item ACT) to current liabilities (Compustat item LCT).
7. No new common or preferred stock issued over the previous year:
   If sales from common and preferred stocks (Compustat item SSTK) are zero.
8. Increase in gross margin from prior fiscal year-end:
   Gross margin is defined as one less the ratio of cost of goods sold (Compustat item COGS) to sales (Compustat item SALE).
9. Increase in asset turnover from prior fiscal year-end:
   Asset turnover is defined as the ratio of sales (Compustat item SALE) to total assets at the beginning of the year (Compustat item AT from prior fiscal year).

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