Review of Finance Advance Access published July 17, 2014

Review of Finance (2014) pp. 1–53
doi:10.1093/rof/rfu029

Short-Term Trading and Stock Return Anomalies: Momentum, Reversal, and Share Issuance

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Abstract. This article examines how the extent of short-term trading relates to the efficiency of stock prices. We employ a new duration measure based on quarterly institutional investors' portfolio holdings, next to existing proxies such as trading volume, the percentage of transient institutions, and fund turnover. Momentum returns and subsequent returns reversal are generally much stronger for stocks held primarily by short-term investors, especially if these investors recently had superior recent performance which could make them overconfident. Our results point toward the behavioral theory in Daniel, Hirshleifer and Subrahmanyam (1998) and seem inconsistent with short-term institutions improving efficiency.

JEL Classification: G12, G14, G23

1. Introduction

How is the efficiency of stock prices related to the short-term trading behavior of investors? As the evidence in the literature seems mixed,[1] in

*We wish to thank Nick Barberis, Bidisha Chakrabarty, Werner DeBondt, Thierry Foucault (the editor), Roger Ibbotson, Robert Korajczyk, Andrew Metrick, Ernst Schaumburg, Anna Scherbina, Erik Stafford, an anonymous referee, as well as participants at the American Finance Association 2011 Annual Meeting, Inaugural Miami Behavioral Finance Conference 2010, Florida State University, New York Society of Quantitative Analysts, University of Oregon, Temple University, DePaul Behavioral Finance Conference 2010, Eastern Finance Association 2010 Annual Meeting, Midwest Finance Association 2010 Annual Meeting, Global Finance Conference 2010, Chicago Quantitative Alliance (CQA) Academic Competition, and the Citigroup Global Quant Conference 2010 for their helpful comments and suggestions.

[1] On the one hand, there is evidence that short-term trading is related to a greater presence of anomalous pricing, most notably for momentum in Lee and Swaminathan (2000) and Hou, Peng, and Xiong (2008). Bushee (1998) shows that institutions with short investment horizons myopically price firms, overweighting short-term earnings potential and underweighting long-term earnings potential. On the other hand, several papers argue that

this article we provide a comprehensive overview of the association between short-term (institutional) trading and three of the best-known stock return anomalies: the 6-month price momentum, return reversal, and net issuance anomalies. We consider four different short-term trading proxies: stock turnover (i.e., trading volume divided by the shares outstanding), the percentage of transient investors (i.e., well-diversified and trading frequently, as defined by Bushee, 1998), fund turnover (based on quarterly holding changes, see Gaspar, Massa, and Matos, 2005), and a new measure of institutional holding duration also based on quarterly portfolio holdings, which we call Stock Duration.[2] We find that short-term trading is associated with significantly stronger anomalous pricing of stock returns. Fund Turnover and Stock Duration are the most relevant in explaining anomalies, while stock turnover and the percentage of transient investors are typically driven out once we control for Stock Duration.

In order to explain our surprising results we are guided by Daniel, Hirshleifer, and Subrahmanyam (1998, henceforth DHS), who propose a theory that market under- and overreactions are based on investor overconfidence and biased self-attribution, two well-documented psychological biases (see e.g., DeBondt and Thaler (1995) and De Long *et al*. (1991) for discussion of applications in finance). In the DHS theory, investors are quasi-rational, combining Bayesian learning with overconfidence about their private information. Overconfident investors thus overweight their valid private signals, causing the stock price to overreact. Investor self-attribution bias leads them to view subsequent public information as further confirming their own private information, strengthening and sustaining this overreaction. This could explain the momentum anomaly. DHS show that eventually, further public information gradually induces learning, such that prices revert back to fundamentals, explaining the reversal anomaly. Further, the flip side of overreaction to private signals is the underreaction

short-term trading, particularly by institutional investors, is associated with greater efficiency, see for example, Collins, Gong, and Hribar (2003), Ke and Ramalingegowda (2005), Bartov, Radhakrishnan, and Krinsky (2000) and Boehmer and Kelley (2009).

[2] We first calculate the holding duration at the stock-institution level for all the stocks in the given institutional investors' portfolio, that is the weighted number of years the stock has been held in the last 5 years in the portfolio. For each stock, we then aggregate the duration across all institutions using 13F holding reports holding that stock to yield the "Stock Duration" proxy for the investment horizon of institutional investors. We also compute the turnover of each institution and then compute its weighted average across all institutions holding the stock (i.e., the "fund turnover"). Stock Duration has rank correlations with turnover and weighted fund turnover of −57% and −66%, respectively. Here, "fund" refers to an investment company (e.g., Fidelity) and not to a particular mutual fund.

to public signals, which could theoretically explain positive (negative) future abnormal returns after an announcement that the firm believes their shares are under(over) valued and decides to buy back (issue) shares.

We test the ability of the DHS theory to explain the anomalies by focusing on the recent investment performance of the institutional investors holding the stock. Both DHS (1998) and Gervais and Odean (2001) argue that successful performance could lead to increased trader overconfidence. Statman, Thorley, and Vorkink (2006) show that stock turnover is positively related to past market returns, which supports the trading volume predictions of these overconfidence models. If traders with superior recent performance also have a self-attribution bias, that is, if they are more likely to take credit for good performance while blaming poor performance on other forces outside of their control, then their overconfidence may be particularly pronounced after their recent outperformance. Institutional arrangements may matter as well: fund managers who have done well typically receive significant fund inflows, positive media coverage, and higher compensation, all of which could strengthen overconfidence.

The DHS theory would thus predict that the presence of short-term investors with superior recent performance is particularly strongly related to anomalies such as momentum and reversal. The alternative "smart traders" hypothesis would predict the opposite: if short-term institutional investors are generally smart, then short-term institutions with superior past performance would seem especially likely to have skill and to be able to take advantage of and drive out any temporary pricing inefficiency.[3] Empirically, we find that these anomalies are stronger for stocks held by short-term investors with superior past abnormal performance than for stocks held by similarly short-term investors but with relatively poor past abnormal performance. We thus conclude that our results are consistent with DHS and inconsistent with the "smart traders" hypothesis.

Our results are generally both economically and statistically strong. For each anomaly, we independently sort stocks into groups based on a particular anomaly characteristic and based on one of the short-term trading proxies. The first anomaly considered is momentum, which involves sorting stocks based on their returns in the past 6 months (see Jegadeesh and Titman, 1993). We find that the momentum profits increase with decreasing Stock Duration and are insignificant for the highest duration

[3] To the extent such "smart traders" would not have been able to driven out inefficiencies, we would expect asymmetric alphas, that is only positive alphas for a long strategy. As we do not observe short positions of institutional investors, our measures do not capture such activity or the importance of short sale constraints.

group. For example, the equal-weighted long–short momentum returns using a 6-month holding period are a significant 0.61% per month (with a *t*-statistic of 2.46) higher for stocks in the lowest duration group compared to stocks in the top duration group. Conditioning on low Stock Duration thus significantly strengthens momentum.[4]

The strongest evidence that our results are driven by overconfident short-term traders is that the relationship between Stock Duration and momentum is substantially stronger for stocks held by short-term investors with superior past abnormal performance than for stocks held by similarly short-term investors but with relatively poor past abnormal performance. This is consistent with such past success strengthening overconfidence through a self-attribution bias, as some fraction of the past success will be due to luck but may be attributed by the traders to their own skill. For example, using independent triple sorts on past 6 month return, Stock Duration and institutional past DGTW-adjusted performance,[5] the long-short momentum returns are 0.55% per month (with a *t*-statistic of 2.48) higher if the short duration investors also had relatively good past DGTW-adjusted performance, relative to stocks where short duration investors had relatively poor past DGTW-adjusted performance.

Closely connected to the momentum anomaly, we next consider return reversals. Jegadeesh and Titman (2001) show that the returns of a long–short momentum portfolio are negative in the post-holding period and conclude that this evidence is consistent with a behavioral rather than a risk-based explanation for momentum. We find that the momentum return reversal is

[4] This association between momentum and Stock Duration is naturally related to the well-known relation between momentum and volume (Lee and Swaminathan, 2000). However, it is robust to controlling for stock turnover, that is, in cross-sectional regressions, the association between momentum and volume is completely subsumed by the association between momentum and Stock Duration.

[5] DGTW-adjusted performance refers to the method of Daniel *et al*. (1997) to adjust performance for size, value, and momentum characteristics. We start by calculating the institutional fund-level DGTW-adjusted abnormal returns by weighting the stock DGTW-adjusted returns with the portfolio weight of the stock in each institution's portfolio at the end of the previous quarter (assuming holdings are held constant from quarter-end to next quarter-end). The DGTW-adjusted return of each stock is calculated as the difference of the stock return and an equally weighted portfolio with similar size, value, and momentum as the stock in the portfolio (see Daniel *et al*. (1997) for details). We then aggregate the institutional fund-level DGTW-adjusted returns over the last four quarters to get the abnormal return of each institution for the past year. For each stock, we then weight the past year abnormal performance of the institutional investors holding that stock, using as weights the amount held by each institution. This provides the aggregate DGTW-adjusted past performance measure for the institutional investors holding that stock.

limited to stocks held primarily by short-term investors. For example, the difference in return reversal between stocks in the lowest versus the highest Stock Duration quintile is highly significant at 0.24% per month (*t*-statistic of 1.98). For the stocks in the lowest (i.e., shortest) Stock Duration quintile, the entire momentum profits (about 4% over the first 6 months after portfolio formation) are reversed within 3 years of portfolio formation. Moreover, the size and magnitude of return reversal for short duration investors is strongly related to their short-term trading performance. For example, focusing on stocks with low Stock Duration with the highest third of past-year DGTW-adjusted performance results in 0.31% per month (*t*-statistic of 2.68) higher reversal alphas compared to using institutions with the lowest third of past abnormal performance.

Finally, we consider the share issuance anomaly or the long-run abnormal returns following corporate events like seasoned equity offerings, share repurchase announcements, and stock mergers (e.g., Loughran and Ritter, 1995; Loughran and Vijh, 1997; Ikenberry, Lakonishok, and Vermaelen, 2005; Daniel and Titman, 2006; Pontiff and Woodgate, 2008). While momentum seems most likely to be based on investor overconfidence in their private signal, the share issuance anomaly is an example of an anomaly based on a public signal. Therefore, the theory in DHS could explain this anomaly based on investor underreacting to this public signal, that is, the flipside of their overreaction to their private signals. We again find that this anomaly is stronger for stocks held by short-term institutional investors. For example, the returns of a long–short portfolio (long low issuance stocks and short high issuance stocks) are a significant 0.45% per month (with a *t*-statistic of 2.33) higher for stocks in the lowest duration group compared to stocks in the top duration group.

Our various proxies of short-term trading are not that highly correlated. Stock Duration, our new measure of how long institutions have held the stock in their portfolio, has a rank correlation of −57% with stock turnover. Fund turnover, based on quarter-to-quarter changes in institutional portfolios, has a rank correlation of 53% with overall turnover and a rank correlation of −66% with Stock Duration. All three of these proxies are positively related to the strengths of all three of these anomalies.

There are two main differences between overall stock turnover and the proxies of institutional trading used in this article. First, because these proxies are based on quarterly holdings reports, they ignore all intra-quarterly trading. As a result, the recent phenomenon of high-frequency trading strongly affects turnover, which has significantly increased since 2000, but does not impact Stock Duration or the other holdings-based proxies. Second, the institutional trading proxies ignore all trading by noninstitutional investors. Consequently, they may be less appropriate for stocks with relatively low institutional holdings; therefore, we remove these from our sample.

Across the four different short-term trading proxies, the results are generally strongest for Stock Duration. Most notably, Stock Duration subsumes and even reverses the positive association between turnover and momentum documented in Lee and Swaminathan (2000). Turnover includes all intra-quarter roundtrip trades but Stock Duration does not, suggesting that within-quarter trades (including those of high-frequency traders) are unlikely to affect the anomalous pricing effects, which play out at longer intervals. Results for Stock Duration are also generally stronger than those for fund turnover and the percentage of transient investors. Their main difference between Stock Duration and the other proxies is that only Stock Duration allows for heterogeneity in the investment horizon across different stocks in a given institutional portfolio (i.e., a portfolio can have a long duration in some stocks but a short duration in others, while fund turnover and the transient investor proxy classify the whole fund as such). As we will show, in typical joint specifications, Stock Duration remains significant, while both fund turnover and (stock) turnover become insignificant, indicating that the institution-stock-specific information is important to retain.

The most closely related paper, Lee and Swaminathan (2000), already has shown that past trading volume predicts both the magnitude and persistence of future price momentum. However, turnover has not yet been considered in regard to reversal and net issuance anomalies, the two other anomalies investigated in this article. Further, turnover has been used as a proxy for various diverse and interesting concepts in the literature. This includes concepts that are behavioral in nature, such as investor underreaction (Lee and Swaminathan, 2000), as well as concepts like liquidity (Amihud, 2002), disagreement (Hong and Stein, 2007), and speed of adjustment to market-wide information (Chordia and Swaminathan, 2000). By using alternative proxies for investor trading horizons and relating them to momentum, we are able to clarify Lee and Swaminathan's (2000) results. Our article is further related to Hou, Peng, and Xiong (2008), who interpret turnover as a measure of investor attention and also show that price momentum profits are higher among high volume stocks, and Bushee (1998), who shows that institutions with short investment horizons myopically price firms, overweighting short-term earnings potential and underweighting long-term earnings potential.

The results in our article may be surprising in light of the literature finding that institutional investors are associated with greater efficiency. However, this literature has not focused on the short-term trading proxies we use. We further note that those results are all for different anomalies than studied in this article. For example, Collins, Gong, and Hribar (2003) show that accruals are priced correctly in stocks with a high level of institutional ownership. Similarly, Ke and Ramalingegowda (2005) show that transient institutional investors trade to exploit the earnings announcement anomaly, and Bartov, Radhakrishnan, and Krinsky (2000) document a negative association between the post-earnings announcement drift anomaly and institutional activity. We focus on the momentum, reversal and stock issuance anomalies, as these are some of the most studied anomalies in the finance literature that we can directly link to the DHS theory, and leave the other anomalies for future research.

Finally, if these well-known anomalies can partly be explained by the trading of overconfident investors, what prevents other investors to take advantage of this and bring prices back to fundamentals? In order to answer this question, we consider the role of short-sales constraints and liquidity. We find that our results for the momentum and reversal anomalies are strongest in the subsample of stocks that may be harder to short, and that momentum is stronger for less liquid stocks. As a result, limits to arbitrage may explain why these anomalies have persisted.

The remainder of this article is organized as follows. In the next section, we discuss the construction of the investment horizon measures used in this article and briefly describe the data sample. In Section 3, we test the relevance of the short-term trading proxies for the momentum, reversal, and share issuance anomalies. Section 4 concludes.

2. Data and Methodology

2.1 DATA

The institutional investor holdings data in this study comes from the Thomson Financial CDA/Spectrum database of SEC 13F filings. All institutional investors with greater than $100 million of securities under management are required to report their holdings to the SEC on form 13F. Holdings are reported quarterly; all common stock positions greater than 10,000 shares or $200,000 must be disclosed.

Stock returns data are obtained from monthly stock data files from the Center for Research in Securities Prices (CRSP), and accounting data are from COMPUSTAT. The analysis focuses only on US common stocks from January 1980 to December 2010. Return forecasting and stock selection analysis is performed from January 1985 onwards, as at least 5 years of data are required to calculate the institutional holding duration measure. Each quarter, we sort the stocks into three groups by institutional ownership and eliminate the stocks in the bottom institutional ownership tercile. We also eliminate the stocks in the bottom NYSE size quintile from the sample. These data screens ensure that our sample only includes the approximately largest 1,300 stocks most commonly held by institutional investors, and still covers about 90% of the CRSP common stock market capitalization.

Limiting our sample to stocks with relatively high institutional ownership means that the evidence for the unconditional anomalies is weaker than if we had used a sample with more "small cap" stocks and less liquid stocks (in which the anomalies considered are typically stronger). This limit also significantly decreases the number of stocks in our sample, especially at the beginning of our sample period; however, with 1,300 stocks on average, the number of stocks is sufficient for independent 5×5 double sorts into twenty-five portfolios. We choose this limit because it enables the Stock Duration proxy to more accurately measure the average investment horizon of investors for the stocks in our sample compared to, for example, turnover (which may include added noise, such as the turnover of individual investors or day traders who are unlikely to be marginal investors for the stocks in our sample). Our sample is thus especially suitable for testing the "smart traders" hypothesis, as our sample does not include the illiquid or small stocks that large institutions find hardest to trade.

We require a stock to be present in CRSP for at least 2 years before it is included in the sample to make sure that IPO-related anomalies do not affect the results. We also require an institutional investor to be present for 2 years before it is included in the sample to eliminate any bias in the sample, as new institutions by construction have a short past holding duration for each stock in their portfolios. Table I shows summary statistics for the stock sample used in this study. Panel A presents a summary of stock data over time. The number of stocks varies from 1,100 in 2005 to 1,713 in 1995. The mean number of stocks across all the quarters is 1,317, which represents 33% of the CRSP common stocks but 89% of the CRSP market capitalization.

2.2 METHODOLOGY: STOCK DURATION

We calculate the duration of ownership of each stock for every institutional investor by calculating a weighted measure of buys and sells by an institutional investor, weighted by the duration the stock was held. For each stock

Table I. Summary statistics

Panel A reports the summary statistics for the sample used in this article. For stock characteristics, the time-series averages of the quarterly sample mean, median, standard deviation, 25th percentile, and 75th percentile values are reported. The sample period is from 1985 to 2010. Stock Duration is the weighted average of the holding durations across all institutional investors holding that stock and is calculated according to Equation (1) in the text. Fund Duration is calculated by averaging the institutional investor portfolio's duration across all institutional investors holding a stock. An institutional investor portfolio's average holding duration is calculated by averaging duration across all stocks included in the portfolio. Fund Turnover is defined as the weighted average of the mean turnover of the institutional investors holding a given stock calculated over the past four quarters. Daily stock turnover is the average of the daily percentage of turnover of a stock in the previous quarter. Market cap is the market capitalization of the stock at the beginning of the quarter. BM ratio is measured by the ratio of the book value of the firm from the end of the last year and market capitalization of the firm at the end of the most recent quarter. Transient is the percentage of the stock owned by transient institutional investors, according to the classification of Bushee (1998, 2001). PrcPressure is the absolute value of price pressure due to institutional investor flow. Other relevant stock-level variables are stock price (Prc), number of analysts (NumAnalyst), and idiosyncratic volatility (IdioRisk). Panel B reports the Spearman's rank correlations. In Panel C, we present results of pooled panel regressions using Stock Duration as the dependent variable. In this panel, the *t*-statistics are based on robust standard errors independently clustered in both the firm and time (quarter) dimensions. Significance at 5% level is denoted in bold, and t-statistics are given in parentheses. In Panel D, we document the persistence of the various duration measures over time.

Panel A

	Mean	Stdev	p25	Median	p75
Number of stocks	1,317	262	1,131	1,318	1,517
Percentage of CRSP stocks	33.4	3.2	36.2	32.5	30.6
Percentage of CRSP market cap	89.3	3.6	88.0	89.8	91.8
Stock duration (years)	1.45	0.53	1.09	1.43	1.77
Fund duration (years)	1.66	0.26	1.50	1.65	1.80
Fund turnover (%)	27.84	7.05	23.19	26.61	31.22
Transient (%)	14.1	8.5	7.9	12.5	18.7
Daily stock turnover (%)	0.68	0.67	0.31	0.48	0.81
PrcPressure (%)	1.18	1.98	0.26	0.62	1.36
Market cap ($ million)	4,924	14,192	572	1,253	3,489
BM	0.49	0.36	0.26	0.42	0.63
Past 12 months return (%)	23.85	56.20	−4.89	14.12	38.08
Institutional ownership (%)	59.4	16.6	47.0	60.7	72.2
IdioRisk (%)	2.01	0.94	1.36	1.81	2.45

(continued)

Table I. (Continued)

Panel B

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Stock duration	1.00						
(2)	Fund duration	0.70	1.00					
(3)	Turnover	−0.57	−0.49	1.00				
(4)	Fund turnover	−0.66	−0.86	0.53	1.00			
(5)	Transient	−0.45	−0.63	0.53	0.63	1.00		
(6)	PrcPressure	−0.23	−0.26	0.33	0.32	0.30	1.00	
(7)	DGTW_Inst_Ret_1Y	−0.04	−0.07	0.01	0.07	0.05	0.00	1.00
(8)	IdioRisk	−0.48	−0.41	0.56	0.41	0.26	0.16	0.03
(9)	Num analyst	0.05	0.09	0.20	−0.08	0.10	0.06	−0.07
(10)	Market cap	0.26	0.26	0.00	−0.23	0.02	0.02	−0.05
(11)	BM	0.17	0.18	−0.20	−0.19	−0.22	−0.08	−0.08
(12)	Mom6	−0.08	−0.19	0.06	0.23	0.21	0.08	0.31
(13)	IO	−0.07	−0.19	0.32	0.14	0.55	0.21	0.02

Panel C

Independent variable	1	2	3	4	5
	Dependent variable: log(Stock Duration)				
log(Turnover)	**−0.182**	**−0.208**	**−0.182**	**−0.181**	**−0.179**
	(−15.76)	**(−23.34)**	**(−20.28)**	**(−19.79)**	**(−20.28)**
log(Transient)		**−0.141**	**−0.137**	**−0.139**	**−0.137**
		(−14.27)	**(−14.27)**	**(−14.19)**	**(−14.38)**
log(Market Cap)		**0.106**	**0.097**	**0.098**	**0.095**
		(37.37)	**(25.38)**	**(25.20)**	**(25.32)**
log(IO)		**0.316**	**0.299**	**0.302**	**0.297**
		(17.61)	**(16.87)**	**(16.90)**	**(16.87)**
log(BM)		**0.087**	**0.075**	**0.078**	**0.073**
		(14.53)	**(12.52)**	**(12.38)**	**(12.30)**
log(Prc)			0.003	−0.002	0.003
			(0.31)	(−0.30)	(0.34)
MOM6			**−0.054**		**−0.048**
			(−4.77)		**(−4.46)**
log(IdioRisk)			**−0.084**	**−0.081**	**−0.084**
			(−7.02)	**(−6.77)**	**(−7.18)**
LOG(1 + Num Analyst)			**−0.013**	**−0.012**	**−0.014**
			(−2.85)	**(−2.67)**	**(−2.98)**
Nasdaq	**−0.104**	**0.061**	**0.065**	**0.064**	**0.063**
	(−8.90)	**(6.25)**	**(6.74)**	**(6.61)**	**(6.56)**
MOM6_Q1				**−0.015**	
				(−2.66)	
MOM6_Q2				0.002	
				(0.80)	

(continued)

Table I. (Continued)

Panel C

Independent variable	Dependent variable: log(Stock Duration) 1	2	3	4	5
MOM6_Q4				−0.004	
				(−1.10)	
MOM6_Q5				**−0.034**	
				(−6.56)	
ISSUANCE_Q1					0.000
					(0.06)
ISSUANCE_Q2					**−0.025**
					(−3.09)
ISSUANCE_Q4					−0.011
					(−1.83)
ISSUANCE_Q5					**−0.048**
					(−7.21)
R^2 (%)	19.9	40.4	41.2	41.1	41.5
Clustered(Firm,Qtr)	Yes	Yes	Yes	Yes	Yes
N	118,890	118,890	118,890	118,890	118,810

Panel D

Stock duration Quarter t group	Percent in Group – Quarter $t+4$ 1	2	3	Percent in Group – Quarter $t+12$ 1	2	3
1	78.5	20.6	0.9	63.6	28.2	8.2
2	18.5	62.3	19.2	26.8	46.3	27.0
3	3.0	17.2	79.8	9.5	25.7	64.8
Fund duration	1	2	3	1	2	3
1	84.3	15.5	0.2	72.1	22.2	5.6
2	13.6	72.2	14.2	22.8	55.0	22.2
3	1.4	12.4	86.2	5.0	22.8	72.1

in a given fund manager's portfolio, the holding duration measure is calculated by looking back to determine how long that particular stock has been held continuously in that fund's portfolio.[6]

[6] We also calculated the average duration for *all* stocks in the last 5 years, not just the stocks held continuously in the institutional portfolio. We wanted to consider cases in which funds went in and out of the same stock multiple times within the recent period, which could make our consideration of only stocks currently held continuously misleading. This alternative proxy has a 98% correlation with Stock Duration and results are unchanged if it is used instead.

We calculate the duration for stock i that is included in the institutional portfolio j at time $T-1$, for all stocks $i=1\ldots\mathrm{I}$ and all institutional investors $j=1\ldots\mathrm{J}$, by using the following equation:

$$Duration_{i,j,T-1} = d_{i,j,T-1} = \sum_{t=T-W}^{T-1} \left(\frac{(T-t-1)\alpha_{i,j,t}}{H_{i,j}+B_{i,j}} \right) + \frac{(W-1)H_{i,j}}{H_{i,j}+B_{i,j}}, \qquad (1)$$

where

$B_{i,j}$ = total percentage of shares of stock i bought by institution j between $t=T-W$ and $t=T-1$; t, T are in quarters.

$H_{i,j}$ = percentage of total shares outstanding of stock i held by institution j at time $t=T-W$.

$\alpha_{i,j,t}$ = percentage of total shares outstanding of stock i bought or sold by institution j between time $t-1$ and t, where $\alpha_{i,j,t}>0$ for buys and <0 for sells.

This measure for duration takes into account cases of tax selling and other kinds of temporary adjustments in the portfolio, because the intermediate sells are cancelled by immediate buybacks, with only a small effect on the duration of current holdings. The literature does not provide clear guidance on the value of W or the time period over which to calculate holding changes. We choose $W=20$ quarters because, beyond that, any informational or behavioral effects would seem to be marginal. If stock i is not included in institutional portfolio j at time $T-1$, then $Duration_{i,j,T-1}=0$.

We can illustrate the construction of the holding duration measure with a simple example. Suppose the institutional portfolio of Fidelity owns two stocks: IBM and Ford. It owns 5% of total shares of IBM, 2% of which it bought three quarters back, with the remaining 3% shares bought five quarters back. The weighted age of IBM today in Fidelity's portfolio is (2%/5% × 3 quarters + 3%/5% × 5 quarters) = 4.2 quarters. Also, suppose it currently owns 1% shares of Ford, having bought 5% shares six quarters back and having sold 4% of them one quarter back. At this point, the portfolio has thus held 1% for six quarters, but previously held another 4% for five quarters, such that over the past 5 years the weighted average duration (weighted across the percentages of stock owned over time) of Ford is thus (4%/5% × 5 quarters + 1%/5% × 6 quarters) = 5.2 quarters. Similarly, we calculate this duration measure for every stock-institutional investor pair. The measure thus represents the weighted duration of the holding experience that the institutional investor had in its past for a given stock currently in its portfolio.

Next, we compute the "Stock Duration" proxy by averaging $\text{Duration}_{i,j,T-1}$ over all stocks and institutions currently holding the stock, using as weights the total current holdings of each institution. Similarly, we compute the "Fund Duration" as follows. First, for each institutional fund j, we average $\text{Duration}_{i,j,T-1}$ over all stocks, computing each institution's weighted portfolio duration. Second, for each stock, we average the weighted portfolio duration of each institutional fund over all funds currently holding the stock, using as weights the total current holdings of each fund.[7] As we observe holdings at the aggregate institutional level, "fund" refers to an investment management company (e.g., Fidelity) rather than to a particular mutual fund.

In Figure 1, we compare the distribution of the Stock Duration with that of stock turnover. As Panel A shows, turnover has increased steadily and significantly over the years, whereas the variation in Stock Duration has been more cyclical and holdings duration has only slightly lengthened over time. In Panel B of Figure 1, we further illustrate the difference between Stock Duration and turnover by comparing them for two stocks: GE and APPLE. The Stock Duration for GE is higher at around 3 years and its turnover is lower than APPLE's. Both Stock Duration and turnover are more stable over time for GE than for APPLE, whose turnover is particularly volatile.

Figure 2 shows the distribution of turnover and duration at the fund level. The median Fund Duration has been close to one and a half years and very stable over our full time period, while the median fund turnover (calculated from quarterly holdings changes) has been much more volatile, though also without a clear time trend. However, for any given fund, Fund Duration tends to increase steadily in the initial life of the fund before stabilizing, as exemplified by the individual fund series for Fidelity and Vanguard. The Fund Duration for Vanguard has been high, at above 3 years, compared

[7] Only considering institutions currently holding the stock does not mean that we ignore the impact of institutions exiting and selling all stock holdings, as that will be captured by the change in Stock Duration. Also, stocks that are owned by fewer institutional investors will not have by construction a shorter Stock Duration, as this depends on how long those fewer institutions have held the stock in their portfolios. For example, if a few large institutions sell all their holdings in a stock, then the new Stock Duration may go up or down. The Stock Duration will go up if the remaining institutions have held the stock for longer (on average) than the large selling institutions, and Stock Duration will go down if the remaining institutions have held the stocks for on average a shorter length of period. Several of our results control for the level of institutional ownership, such as the Residual Stock Duration measure and the Fama–MacBeth regressions.

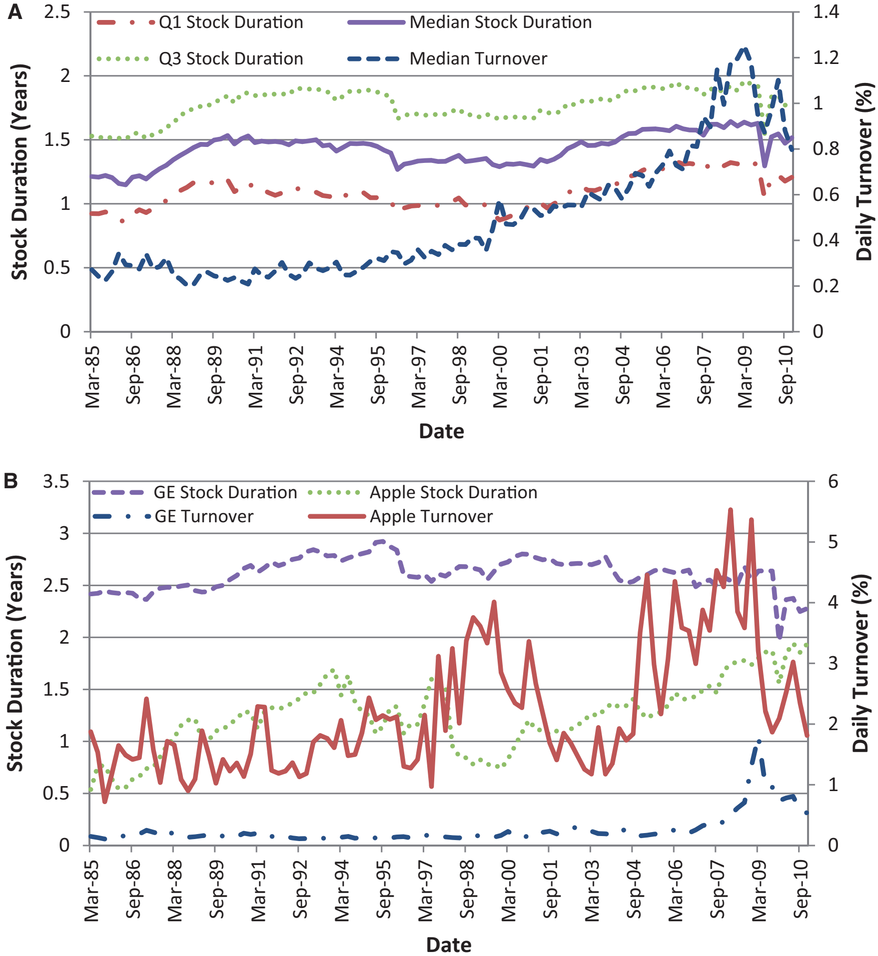

Figure 1. Stock Duration versus Stock Turnover. In (A), we compare the distribution of the Stock Duration (showing the median, the 25th, and the 75th percentiles) with the median stock turnover in our quarterly sample. In (B), we further illustrate the difference between Stock Duration and turnover by comparing them for two stocks: GE and APPLE.

to about 2 years for an average fund. This is consistent with the long-term investment philosophy of Vanguard.

We report the summary statistics for the Stock Duration and other stock characteristics in Panel A of Table I. The mean Stock Duration for the sample is 1.45 years. In Panel B of Table I, we report the rank correlations between the Stock Duration and other stock characteristics. Stock Duration

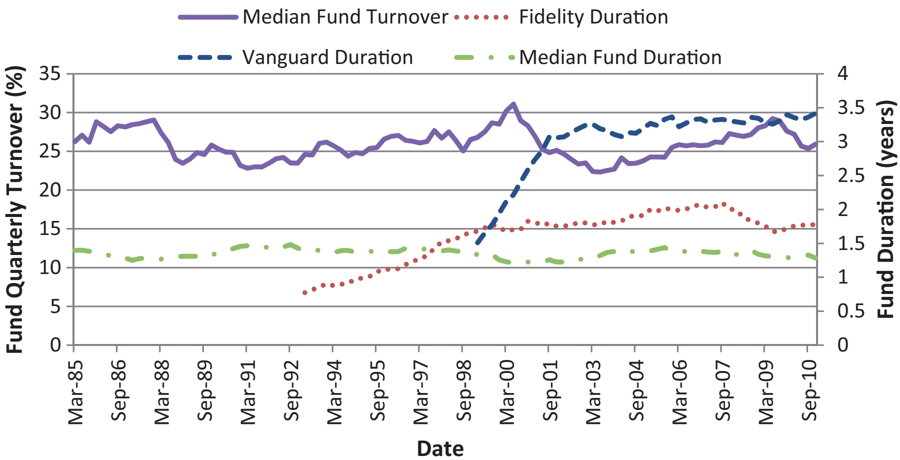

Figure 2. Distribution of Fund Duration. The figure shows the median of Fund Turnover and Fund Duration over time. As examples, we also show the quarterly holding duration for two of the largest institutional investors: Fidelity and Vanguard.

is negatively correlated with turnover, with a rank correlation of −57%. In our sample, we only consider stocks that have very high institutional ownership, with an average institutional ownership of 43.8% in 1985 and of 75.4% in 2005. Therefore, Stock Duration may more accurately measure the horizon of the marginal investors as compared to stock turnover, which also includes the trades of individual investors, day traders, high-frequency (program) traders, and other "noise traders". In addition, turnover has been used in the literature as a proxy for several interesting concepts not related to holding duration, such as liquidity, disagreement, attention, and speed of information diffusion. In Figure 3, we plot the cross-sectional mean of Stock Duration along with the means of other stock characteristics over time. Both average turnover and institutional ownership have increased steadily over time, whereas both Stock Duration and average idiosyncratic volatility have undergone periods of increases and decreases.

We also employ two other closely related measures of investor horizon. The first "Transient" measure was introduced by Bushee (1998, 2001), who used a methodology based on factor and clustering analysis to classify institutional investors into three groups: "transient" investors with high portfolio turnover and diversified portfolios, "dedicated" institutions with low turnover and more concentrated portfolio holdings, and "quasi-indexer" institutions with low turnover and diversified portfolio holdings. We

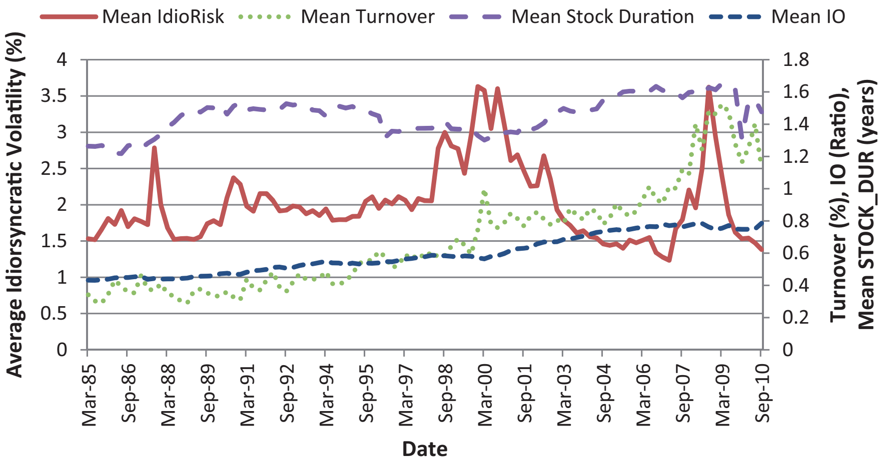

Figure 3. Stock Duration and Stock Characteristics. The figure plots the time-series variation in the mean of Stock Duration along with the means of the following stock characteristics: Institutional Ownership (IO), Idiosyncratic Volatility (IdioRisk), and daily turnover. We use a quarterly estimation window to calculate stock characteristics because the mutual fund holdings-based independent variables used to explain stock volatility are calculated at a quarterly frequency. Idiosyncratic volatility for a given stock is calculated as the standard deviation of residuals from the three-factor Fama–French model using daily data.

obtain the institutional investor classification data from Brian Bushee's web site and calculate Transient as the percentage of a firm owned by transient institutional investors.

The second alternative measure is "(average) fund turnover" introduced by Gaspar, Massa, and Matos (2005). It is defined as the weighted average turnover of the institutional investors holding a given stock. The average turnover is calculated using changes in the quarterly holdings over the past four quarters and the weights are calculated using the current holdings of each fund. The rank correlation between Stock Duration and the percentage of ownership by transient investors is −45%, and the correlation between fund turnover and Stock Duration equals −66%, such that both of these alternative measures are distinct from Stock Duration.

Stock Duration and our alternative measures of investor horizon—the percentage of transient investors and institutional fund turnover—have one major difference: these two latter measures are calculated at the institutional fund level rather than at the fund-stock level (before either is aggregated across all institutions holding the stock). As a result, Transient investors and fund turnover do not allow for heterogeneity in the investment horizon across different stocks in a given institutional portfolio. In contrast, Stock Duration is calculated by aggregating the fund-stock level holding durations, thus allowing the same institutional investor to be short-term for some but long-term for other stocks in its portfolio.[8]

We also examine the relation between Stock Duration and large institutional investor flows, which we estimate using changes in the aggregate holdings of each institution. Fund flows could mechanically reduce the Stock Duration if inflows lead to funds scaling up the investment in existing positions, reducing Stock Duration. Similarly, outflows could reduce Stock Duration as managers are forced to sell their long held positions. Using the methodology in Coval and Stafford (2007) though applied at the institutional level rather than the mutual fund level, we calculate the price pressure due to fund flows by:

$$PRESSURE = \left(\begin{array}{l} \sum_j (\max(0, \Delta Holdings_{j,i,t}) \mid flow_{j,t} > Percentile(90\text{th})) \\ -\sum_j (\max(0, -\Delta Holdings_{j,i,t}) \mid \text{flow}_{j,t} < Percentile(10\text{th})) \end{array} \right) / (\text{Shares Outstanding}_{i,t-1}), \tag{2}$$

where the net flow of funds to institutional investor j during quarter t is estimated by:

$$flow_{j,t} = \left(\text{TEV}_{j,t} - \text{TEV}_{j,t-1} \cdot \left(1 + R_{j,t}\right)\right)/\text{TEV}_{j,t-1}, \tag{3}$$

[8] This may be important for different reasons. The institutional holdings are at the most aggregate level within these institutions, which may often combine very different businesses and many different portfolio managers. And even if the institutional portfolio were under the control of a single portfolio manager, allowing for heterogeneity within the portfolio might still be useful. One motivation for this could involve the Narrow Framing-based preferences proposed by Barberis, Huang, and Thaler (2006), who find that the trader's decision utility depends on the outcome of the individual gamble in addition to what that outcome implies for total wealth risk. Therefore, the same trader who is prudent and has a long-horizon for most of her portfolio could narrowly frame risky short-term investments in the remainder of her portfolio and be overconfident while choosing to accept them. Using a sample of currency trades by global institutional money managers, O'Connell and Teo (2009) show that these institutional investors narrow frame their investments at the individual account level rather than aggregating at the fund level. One of the reasons proposed for Narrow Framing in the literature is that in certain situations, traders or decision makers may make decisions intuitively, rather than by using effortful reasoning (see Kahneman, 2003).

where $\mathrm{TEV}_{j,t}$ is the total equity value of the aggregate holdings of institution j in quarter t, and R is the holdings-based return from $t-1$ to t based on the aggregate holdings at time $t-1$ ($\mathrm{TEV}_{j,t-1}$).

The average rank correlation between Stock Duration and the absolute value of price pressure due to flows is negative as expected, but relatively low at −23%, confirming that Stock Duration is not mechanically driven by flows. As we show later, the relationship between stock return anomalies and Stock Duration is robust and not driven by investor flows.

In Panel C of Table I, we present results of pooled panel regressions using the log of Stock Duration as the dependent variable. We cluster the robust standard errors in both firm and time (quarter) dimensions. In the first column, log turnover and a Nasdaq dummy are the only regressors, resulting in a coefficient of log turnover of −0.18 and an R^2 of 19.9%. Adding log Transient and additional controls raises the R^2 to 40.4% in column 2. Adding further controls in column 3 reduces their coefficients, but both turnover and Transient remain economically and statistically quite important.

In columns 4 and 5, we include dummy variables corresponding to momentum and issuance quintiles. This allows us to examine whether short-term traders are more likely to hold anomaly stocks in either direction, such as stocks with high or low momentum, or stocks with high or low issuance. The coefficients corresponding to both MOM6_Q1 and MOM6_Q5 are negative but with quite low economic significance (showing that short-term traders are a bit more likely to hold stocks with both negative and positive past returns, compared to long-term investors). In column 5, the negative and highly significant coefficient on ISSUANCE_Q5 shows that firms with high stock issuance activity are held more by short-term investors, which could be explained by newly issued shares having, by definition, short holding durations.

Panel D of Table I documents the persistence of the various duration measures over time. Institutions classified as short-term (the bottom third of the fund duration group) tend to remain short-term in the future, as more than 84% (72%) of the institutions classified as short-term are still in the bottom fund duration group 1 year (3 years) hence. Similarly, the majority of institutions classified as long-term remain long-term in the future. Stock Duration is also persistent over time. More than 78% (63%) of the stocks with a low Stock Duration measure (i.e., in the lowest third) remain short-term 1 year (3 years) into future. Likewise, around 65% of the high Stock Duration stocks remain long-term or in the group with the highest third of Stock Duration after 3 years.

3. Short-Term Trading and Anomalies

3.1 MOMENTUM

In this section, we consider stock return momentum strategies conditional on different proxies for the investment horizon of institutional investors. Table II reports the returns for an unconditional momentum strategy and for conditional momentum strategies based on past returns and different investor horizon measures. Again, we only consider stocks with high institutional ownership and eliminate stocks in the bottom NYSE size quintile and stocks priced below $5.

Each quarter, we sort the stocks into five equal groups based on their past 6-month returns and then calculate the returns of these portfolios for a holding period of next 6 months. We leave a gap of 2 month between the formation and holding periods to account for any microstructure issues. We also leave a gap of one quarter between the calculation of the holding duration measure and the return calculation to account for the delay in the disclosure of institutional investor portfolio holdings. We do the same for the alternative proxies for the presence of short-term traders. As shown in the first column of Table II, Panel A, the monthly equal-weighted long–short raw return for an unconditional momentum strategy is 0.37% for a holding period of 6 months, with a *t*-statistic of 1.26.[9]

To examine the effect of the investment horizon on momentum returns, at the beginning of each quarter we first sort stocks into quintiles based on the past 6-month returns and then independently sort the stocks into quintiles based on Stock Duration measured one quarter prior to the current quarter. Panel A of Table II present the raw returns and Fama–French three-factor alphas for each of the twenty-five equal-weighted portfolios measured each month over the holding period of the next 6 months. A long–short momentum strategy earns an equal-weighted three-factor monthly alpha of 0.89% for the bottom Stock Duration group, and an equal-weighted monthly alpha of 0.30% for the top Stock Duration group. The difference in equal-weighted momentum returns between the top and bottom Stock Duration groups is 0.59%, which is highly significant with a *t*-statistic of 2.34. These results show that momentum returns are associated with short

[9] The reason that the momentum anomaly has become so weak is largely due to the recent "momentum crash" in 2009 (see Daniel and Moskowitz, 2012). If we end the return estimation for our sample in 2008, the monthly equal-weighted long–short raw return for an unconditional momentum strategy is 0.59% for a holding period of 6 months (with a *t*-statistic of 2.14), which is consistent with the return on momentum strategies for large cap stocks found in previous literature (see, e.g., Jegadeesh and Titman, 2001).

Table II. Stock Duration and Momentum Returns

This table presents the results corresponding to the effect of the institutional investors' Stock Duration on future momentum profits. In Panel A, stocks are first sorted into quintiles based on Stock Duration calculated according to Equation (1). A gap of one quarter is left between the calculation of the holding duration measure and portfolio formation to account for the delay in the disclosure of institutional investor portfolio holdings. Stocks are further independently sorted into quintiles based on the past 6-month returns. The returns for an unconditional momentum strategy based on past 6-month returns is reported in the first column of Panel A. In Panel A, we report the equal-weighted raw returns and Fama–French three-factor alphas for the twenty-five portfolios. Panels B and C report the equal-weighted raw returns and Fama–French three-factor returns for the portfolios formed by independently sorting the stocks on past 6-month returns and one of the following variables: turnover, weighted Fund Turnover, or Transient ownership. All the returns are in monthly percentages. Significance at the 5% level is denoted in bold, and t-statistics are given in parentheses.

Panel A

	Equal-weighted raw returns							Equal-weighted three-factor alpha						
		Average Stock Duration							Average Stock Duration					
Momentum	Uncond.	1	2	3	4	5	5-1	Uncond.	1	2	3	4	5	5-1
1	**0.94**	0.71	**0.88**	**0.95**	**1.12**	**1.12**	0.41	−0.32	**−0.61**	−0.37	−0.29	−0.12	−0.11	**0.50**
	(2.20)	(1.35)	**(2.04)**	**(2.40)**	**(3.03)**	**(3.09)**	(1.31)	(−1.51)	**(−2.27)**	(−1.70)	(−1.40)	(−0.64)	(−0.54)	**(2.29)**
2	**1.11**	0.71	**0.99**	**1.23**	**1.26**	**1.13**	0.42	0.00	**−0.43**	−0.15	0.13	0.17	0.08	**0.51**
	(3.72)	(1.83)	**(2.96)**	**(4.09)**	**(4.46)**	**(4.26)**	(1.86)	(0.04)	**(−3.00)**	(−1.12)	(1.09)	(1.53)	(0.71)	**(3.61)**
3	**1.15**	**0.93**	**1.21**	**1.19**	**1.20**	**1.14**	0.20	0.11	−0.19	0.11	0.15	0.16	**0.19**	**0.37**
	(4.24)	**(2.53)**	**(3.86)**	**(4.38)**	**(4.57)**	**(4.81)**	(0.95)	(1.29)	(−1.42)	(0.99)	(1.51)	(1.67)	**(1.99)**	**(2.79)**
4	**1.14**	**1.02**	**1.14**	**1.16**	**1.16**	**1.15**	0.13	0.13	−0.06	0.09	0.14	0.16	**0.24**	**0.30**
	(4.18)	**(2.75)**	**(3.69)**	**(4.22)**	**(4.47)**	**(4.93)**	(0.60)	(1.67)	(−0.53)	(0.91)	(1.45)	(1.62)	**(2.48)**	**(2.18)**
5	**1.30**	**1.38**	**1.33**	**1.24**	**1.33**	**1.18**	−0.20	**0.26**	0.28	**0.27**	0.18	**0.31**	0.20	−0.09
	(3.71)	**(3.12)**	**(3.64)**	**(3.75)**	**(4.44)**	**(4.27)**	(−0.79)	**(2.22)**	(1.84)	**(1.99)**	(1.43)	**(2.56)**	(1.65)	(−0.55)
5-1	0.37	**0.67**	0.46	0.29	0.21	0.06	**−0.61**	**0.58**	**0.89**	**0.64**	0.47	0.43	0.30	**−0.59**
	(1.26)	**(2.01)**	(1.57)	(1.00)	(0.80)	(0.20)	**(−2.46)**	**(2.00)**	**(2.69)**	**(2.18)**	(1.62)	(1.68)	(1.11)	**(−2.34)**

(continued)

Table II. (Continued)

Panel B												
	Equal-weighted raw returns						Equal-weighted three-factor alpha					
	Turnover						Turnover					
Momentum	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	**1.11**	**1.13**	**0.95**	0.81	0.82	−0.28	−0.05	−0.10	−0.32	**−0.49**	−0.47	−0.42
	(3.41)	**(3.20)**	**(2.47)**	(1.88)	(1.56)	(−0.87)	(−0.29)	(−0.55)	(−1.61)	**(−2.23)**	(−1.81)	(−1.88)
5	**1.29**	**1.29**	**1.25**	**1.25**	**1.40**	0.11	**0.29**	0.26	0.17	0.17	0.32	0.03
	(4.75)	**(4.34)**	**(3.96)**	**(3.56)**	**(2.95)**	(0.34)	**(2.12)**	(1.83)	(1.45)	(1.36)	(1.91)	(0.15)
5-1	0.19	0.16	0.30	0.44	0.58	0.39	0.34	0.35	0.50	**0.66**	**0.78**	0.45
	(0.84)	(0.61)	(1.13)	(1.53)	(1.83)	(1.66)	(1.50)	(1.41)	(1.86)	**(2.30)**	**(2.47)**	(1.87)

Panel C												
	Equal-weighted three-factor alpha						Equal-weighted three-factor alpha					
	Weighted fund turnover						Transient					
Momentum	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	−0.21	−0.12	−0.31	−0.36	**−0.58**	**−0.37**	−0.14	−0.36	−0.28	−0.42	**−0.47**	−0.33
	(−0.99)	(−0.60)	(−1.50)	(−1.38)	**(−2.48)**	**(−2.16)**	(−0.57)	(−1.61)	(−1.36)	(−1.83)	**(−1.98)**	(−1.83)
5	**0.33**	0.18	**0.27**	**0.30**	**0.31**	−0.02	**0.28**	**0.27**	**0.31**	0.22	0.36	0.07
	(2.43)	(1.58)	**(2.12)**	**(2.25)**	**(1.96)**	(−0.10)	**(2.18)**	**(2.24)**	**(2.44)**	(1.58)	(2.24)	(0.42)
5-1	0.54	0.30	**0.58**	**0.66**	**0.89**	0.36	0.42	**0.62**	**0.60**	**0.64**	**0.83**	0.41
	(1.90)	(1.17)	**(2.02)**	**(1.96)**	**(2.85)**	(1.60)	(1.30)	**(2.06)**	**(2.04)**	**(2.09)**	**(2.73)**	(1.85)

horizons of institutional investors. The momentum returns are insignificant for the stocks in the top Stock Duration quintile, the majority of which are held by long-term investors.

In Panels B and C, we present the three-factor alphas for momentum strategies conditional on the other three short-term trading proxies: turnover, fund turnover, and the percentage of stocks held by transient institutional investors. We find that momentum returns are stronger for all three of these alternative proxies as well, although the statistical and economic significance is lower than when using Stock Duration. For example, momentum returns increase with increasing turnover, confirming Lee and Swaminathan (2000) findings. The difference in the three-factor momentum alpha for stocks in the top versus bottom turnover quintile equals 0.45% per month, with a *t*-statistic of 1.87. Supplementary Appendix Table A1 provides the corresponding and similar results using raw returns rather than three-factor alphas.

From previous literature, we know that certain stock characteristics are related to momentum, such as turnover (Lee and Swaminathan, 2000) and idiosyncratic volatility (Zhang, 2006). For robustness, we therefore show all of the main results using both the "raw" proxy and the proxy orthogonalized with respect to turnover and other basic stock characteristics (market capitalization, book-to-market, idiosyncratic volatility, and the percentage of institutional ownership). We label these orthogonalized proxies the "residual" versions of each proxy, and calculate these by quarterly cross-sectional regressions of the proxy on the stock characteristics mentioned above. Table III considers the relevance that our new proxies add relative to stock turnover and other stock characteristics. We find that the results for Stock Duration and fund turnover in Table II are largely robust to controlling for stock turnover. Using "Residual Stock Duration" (constructed by regressing Stock Duration on log turnover and other stock characteristics such as market capitalization, the book-to-market ratio, institutional ownership, and idiosyncratic volatility), the difference in the three-factor momentum alpha for stocks in the top versus bottom Residual Stock Duration quintile equals −0.46% per month, with a *t*-statistic of 2.35. The results for "residual fund turnover" are similar to using fund turnover. The only exception is that Residual Transient is not related to the momentum anomaly.

Interestingly, Stock Duration subsumes and even reverses the association between turnover and momentum documented in Lee and Swaminathan (2000). Using "residual turnover" (constructed by regressing log turnover on log Stock Duration and the log of other stock characteristics), we find that the momentum anomaly is stronger for stocks with low residual

Table III. Residual measures and momentum returns

This table presents monthly momentum returns from portfolio strategies based on past 6-month returns and either Residual Stock Duration, Residual Turnover, Residual Fund Turnover, or Residual Transient ownership. The regression used to calculate each residual is given at the top of each panel. For example, in Panel A, Residual Stock Duration is defined as the residual from the regression of the log of Stock Duration on the log of the following stock characteristics: Turnover, Transient, market capitalization, BM, institutional ownership (IO), and idiosyncratic risk (IDIORISK). Equal-weighted Fama–French three-factor alphas are calculated. All returns are in monthly percentages. Significance at the 5% level is denoted in bold, and *t*-statistics are given in parentheses.

Panel A												
	Residual: log(STOCK_DUR) = log(Turnover), log(MCAP), log(BMRATIO), log(IO), log(IDIORISK)						Residual: log(Turnover) = log(STOCK_DUR), log(MCAP), log(BMRATIO), log(IO), log(IDIORISK)					
	Equal-weighted three-factor alpha						Equal-weighted three-factor alpha					
Momentum	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	−0.44	−0.16	−0.07	−0.05	0.00	**0.44**	−0.23	−0.13	−0.13	−0.24	−0.02	0.21
	(−1.74)	(−0.70)	(−0.35)	(−0.26)	(−0.02)	**(2.66)**	(−1.12)	(−0.63)	(−0.60)	(−1.05)	(−0.07)	(1.31)
5	**0.32**	0.25	**0.29**	0.23	**0.29**	−0.03	**0.42**	**0.29**	0.24	0.22	0.18	−0.24
	(2.11)	(1.77)	**(2.00)**	(1.59)	**(2.39)**	(−0.19)	**(3.13)**	**(2.13)**	(1.81)	(1.47)	(1.12)	(−1.52)
5-1	**0.76**	0.41	0.36	0.28	0.30	**−0.46**	**0.65**	0.42	0.37	0.45	0.20	**−0.45**
	(2.32)	(1.36)	(1.24)	(0.94)	(1.03)	**(−2.35)**	**(2.26)**	(1.45)	(1.28)	(1.47)	(0.62)	**(−2.17)**

Panel A												
	Residual: log(Fund_Turnover) = log(Turnover), log(MCAP), log(BMRATIO), log(IO), log(IDIORISK)						Residual: log(TRANSIENT) = log(Turnover), log(MCAP), log(BMRATIO), log(IO), log(IDIORISK)					
	Equal-weighted three-factor alpha						Equal-weighted three-factor alpha					
Momentum	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	0.06	−0.13	−0.23	−0.20	−0.27	**−0.33**	0.06	−0.13	−0.22	−0.27	−0.21	**−0.28**
	(0.26)	(−0.59)	(−1.05)	(−0.86)	(−1.26)	**(−2.19)**	(0.29)	(−0.56)	(−1.02)	(−1.13)	(−1.03)	**(−1.97)**
5	**0.37**	0.21	0.22	0.21	**0.39**	0.02	**0.36**	**0.42**	**0.29**	0.18	0.21	−0.15
	(2.70)	(1.56)	(1.63)	(1.47)	**(2.59)**	(0.12)	**(2.73)**	**(2.85)**	**(2.11)**	(1.26)	(1.41)	(−1.06)
5-1	0.31	0.34	0.45	0.41	**0.66**	0.34	0.29	0.54	0.51	0.45	0.42	0.13
	(1.07)	(1.12)	(1.51)	(1.29)	**(2.24)**	(1.86)	(0.99)	(1.76)	(1.72)	(1.40)	(1.53)	(0.76)

turnover as opposed to high residual turnover, or a reversal of the positive association between turnover and momentum. Turnover includes all intra-quarter roundtrip trades but Stock Duration does not, suggesting that within-quarter trades (including those of high frequency traders) are unlikely to affect the anomalous pricing effects, which play out at longer intervals.

Next, we examine the effect of the investor horizon on momentum returns using a multivariate regression setting. We use the Fama–MacBeth (1973) methodology. Here and throughout the article, we run the Fama–MacBeth regressions at a quarterly frequency, as that is the frequency that the holdings data are updated. We estimate predictive cross-sectional regressions of the next 6-month returns on the past 6-month returns, and past returns interacted with our proxies for the (institutional) investment horizon such as Stock Duration and turnover, while controlling for other stock characteristics. Table IV presents the results. Newey–West (1987) adjusted *t*-statistics are based on two lags to control for serial correlation due to overlapping quarterly time periods.

In general, the regression results are consistent with the portfolio results. The coefficient on the interaction term between momentum and the logarithm of Stock Duration is negative and significant in all specifications in which it is included. It remains significant even after controlling for turnover and its interaction with past momentum in column 3.[10] It likewise remains significant after further adding the presence of transient investors, idiosyncratic volatility, the number of analysts, and extreme fund flow and all of their interactions with past momentum in column 7. In this most inclusive specification, both Stock Duration and fund turnover are economically and statistically strongly related to momentum, but turnover and analyst coverage are not. This result means that Stock Duration and fund turnover subsume (though do not reverse) the effects documented in previous studies that both turnover (Lee and Swaminathan, 2000) and analyst coverage (Hong, Lim, and Stein, 2000) affect momentum returns.

[10] The results in Table IV are also economically significant. For example using column 3, when LOG(STOCK_DUR) is one standard deviation below (above) its mean, a two standard deviation decrease in MOM6 predicts a return of 3.13% (5.93%) over the next 6 months, that is, a difference in negative momentum return of −2.80% over the next 6 months. Similarly, when LOG(STOCK_DUR) is one standard deviation below (above) its mean, a two standard deviation increase in MOM6 predicts a return of 9.31% (7.65%) over the next 6 months, that is a difference in positive momentum return of 1.66% over next 6 months. The difference in long–short momentum returns over the next 6 months when Stock Duration is one standard deviation below versus above the mean is 4.46% over next 6 months, which is highly economically and statistically significant.

Table IV. Momentum returns: regression evidence

This table presents results of quarterly Fama–MacBeth regressions of future 6-month stock returns (RET6MONTH) on the past 6-month returns (MOM6), Stock Duration, Turnover, Fund Turnover, Transient, and their interaction with past 6-month returns (MOM6) plus controls. Firm characteristics of BM, size (Market Cap), stock price (Prc), Num Analyst, PrcPressure, Idiosyncratic Risk (IDIORISK), and institutional ownership (IO) are included as control variables. See Table I for variable descriptions. Significance at the 5% level is denoted in bold, and Newey–West (1987) adjusted *t*-statistics based on two lags are given in parentheses.

Independent variable	1 RET6MONTH	2	3	4	5	6	7
MOM6	0.022	0.069	0.036	−0.190	−0.130	−0.194	−0.229
	(0.85)	(1.86)	(0.52)	(−1.36)	(−1.00)	(−1.39)	(−1.39)
MOM6*LOG(STOCK_DUR)		**−0.031**	**−0.046**	**−0.056**	**−0.037**	**−0.053**	**−0.043**
		(−2.10)	**(−2.76)**	**(−3.19)**	**(−2.12)**	**(−3.03)**	**(−2.31)**
LOG(STOCK_DUR)		0.006	0.011	0.012	**0.018**	**0.013**	**0.021**
		(0.64)	(1.80)	(1.88)	**(4.40)**	**(2.39)**	**(4.59)**
MOM6*LOG(TURNOVER)			−0.014	−0.007	−0.010	−0.011	−0.018
			(−1.09)	(−0.62)	(−0.81)	(−0.86)	(−1.46)
LOG(TURNOVER)			0.001	0.006	0.004	0.005	0.005
			(0.21)	(1.09)	(0.73)	(1.00)	(0.79)
MOM6*LOG(FUNDTURNOVER)					**0.063**		**0.084**
					(2.13)		**(2.47)**
LOG(FUNDTURNOVER)					0.016		0.025
					(1.24)		(1.81)
MOM6*LOG(IDIORISK)				−0.042	−0.041	−0.039	−0.035
				(−1.67)	(−1.63)	(−1.58)	(−1.37)
LOG(IDIORISK)				−0.013	−0.013	−0.014	−0.015
				(−1.19)	(−1.21)	(−1.25)	(−1.38)
MOM6*LOG(IO)				0.030	0.025	0.023	0.032
				(1.75)	(1.46)	(1.21)	(1.45)

(continued)

Table IV. (Continued)

Independent variable	1 RET6MONTH	2	3	4	5	6	7
LOG(IO)				−0.006	−0.005	−0.006	−0.003
				(−0.70)	(−0.69)	(−0.79)	(−0.28)
MOM6*LOG(TRANSIENT)						0.010	−0.0003
						(1.04)	(−0.03)
LOG(TRANSIENT)						0.001	−0.006
						(0.25)	(−1.54)
MOM6*LOG(ABS(PRCPRESSURE)							−0.002
							(−0.53)
LOG(ABS(PRCPRESSURE))							0.0002
							(0.21)
MOM6*LOG(NUMANALYST)							0.001
							(0.06)
LOG(NUMANALYST)							**0.007**
							(2.12)
MOM6*LOGMCAP							0.005
							(0.92)
LOG(BK/MKT)	0.009	0.009	0.009	0.008	0.008	0.008	0.008
	(1.43)	(1.46)	(1.60)	(1.57)	(1.57)	(1.50)	(1.47)
LOG(MCAP)	−0.001	−0.002	−0.002	−0.003	−0.003	−0.003	−0.005
	(−0.60)	(−0.85)	(−0.91)	(−1.30)	(−1.26)	(−1.40)	(−1.69)
Average R^2 (%)	4.78	6.11	7.43	8.93	9.31	9.23	10.62
Average number of stocks	1,284	1,284	1,284	1,284	1,284	1,284	1,284
Number of quarters	101	101	101	101	101	101	101

Overall, the robustness after controlling for related proxies and other firm characteristics provides strong confirmation that momentum is more prevalent in stocks with more short-term trading.

As an aside, the coefficient on past momentum by itself in column 1 of Table IV is insignificant, which indicates that the unconditional momentum anomaly is quite weak during our time period. This weakness is largely due to the "momentum crash" in 2009 (see Daniel and Moskowitz, 2012) and is again consistent with the results in the first column of Table II, Panel A.

3.2 RETURN REVERSAL

We next consider the reversal anomaly. The main empirical prediction that distinguishes behavioral theories (e.g., Daniel, Hirshleifer, and Subrahmanyam (1998); Hong and Stein (1999)) from the rational explanation (e.g., Conrad and Kaul (1998)) of momentum returns is the suggestion of post-holding period reversal. In the behavioral models, initial underreaction or overreaction in prices is followed by further overreaction and subsequent reversal to the fundamental value. In contrast, Conrad and Kaul's (1998) rational explanation predicts that momentum profits should remain positive in the post-ranking period. Jegadeesh and Titman (2001) provide empirical evidence of post-holding period reversal in momentum returns. They also find that return reversal is limited to the winner portfolio and within small stocks. If short-term investors were more likely to be affected by the behavioral biases studied in Daniel, Hirshleifer, and Subrahmanyam (1998), we would expect return reversal to be stronger for stocks held by short-horizon investors. If short-term investors are more likely to represent "smart traders" or to be rational, then, based on Conrad and Kaul (1998), the reversal anomaly should be weaker for stocks with more short-term trading.

To investigate this, we sort the stocks independently into quintiles based on past 6-month returns and Stock Duration, and calculate the average monthly returns for the 2 years (year+2 and year+3) following portfolio formation. We account for overlapping portfolios by following the methodology in Jegadeesh and Titman (1993) such that the stocks ranked in each of the eight quarters form one-eighth of the portfolio. Each quarter, one-eighth of the portfolio ranked twelve quarters ago is replaced by the stocks ranked four quarters back. Returns from each of the eight subportfolios are equally weighted to calculate the monthly returns for the portfolio.

As shown in Panel A of Table V, the momentum returns for the bottom Stock Duration quintile show a reversal of around 0.30% per month with a t-statistic of 2.29. The top Stock Duration quintile shows basically no reversal in year+2 and year+3 following the holding period, with a momentum return of −0.05% per month and a *t*-statistic of 0.43. The difference in momentum returns between the top and bottom Stock Duration quintiles equals 0.24% per month and is statistically significant with a *t*-statistic of 1.98. Using three-factor alphas also gives a corresponding difference of 0.24% per month with a *t*-statistic of 1.94.

Panels B and C show that the reversal anomaly is likewise stronger using the other three proxies of turnover, fund turnover, and Transient. For all three alternative proxies, the difference in momentum (i.e., reversal) returns in year+2 and year+3 following the holding period across stocks in the top and bottom quintiles are all economically meaningful, and only statistically insignificant for the percentage of transient investors. Supplementary Appendix Table A2 provides the corresponding and similar results using raw returns rather than three-factor alphas.

We next calculate residual measures by controlling for turnover and other firm characteristics. Using Residual Transient actually improves the evidence using Transient, as shown in Panel B of Table VI, while the results for Residual Stock Duration and Residual Turnover become weaker (see Panel A of Table VI). This finding suggests that part of the effect of Stock Duration and turnover on return reversals comes from their common component.

The regression evidence in Table VII corroborates the main result that the return reversal anomaly is driven by stocks with more short-term trading or that are held more by short-term institutions. The statistically strongest proxy is again Stock Duration, whose interaction with past 6-month momentum is positive and statistically significant in columns 1–6. In column VII, our most inclusive specification, the interaction of momentum and fund turnover is significant with a *t*-statistic of 1.83, though the interaction with Stock Duration becomes insignificant.

3.3 CONDITIONING ON PAST INSTITUTIONAL PERFORMANCE

DHS (1998) and Gervais and Odean (2001) argue that self-attribution bias would lead to increased trader overconfidence following successful performance. According to DHS, such increasing overconfidence implies a stronger overreaction to traders' short-term private signals, and thus to a greater correction when more public information is revealed subsequently. The consequences of increasing overconfidence following positive trading performance would be higher volatility and return continuation at shorter horizons and stronger return reversal in the longer-run. If short-horizon traders are

Table V. Stock Duration and momentum reversal

This table reports the long-run returns for momentum strategies based on past returns and Stock Duration for a period of 2 years (year+2 and year+3) starting 1 year after the portfolio's formation. At the beginning of each quarter, stocks are independently sorted into quintiles based on the past 6-month returns, and Stock Duration and average monthly returns are calculated for 2 years (year+2 and year +3) following portfolio formation. To account for overlapping portfolios, we follow the methodology in Jegadeesh and Titman (1993) such that the stocks ranked in each of the eight quarters form one-eighth of the portfolio. Each quarter, one-eighth of the portfolio ranked twelve quarters ago is replaced by the stocks ranked four quarters back. Returns from each of the eight subportfolios are equally weighted to calculate the monthly returns for the portfolio. Average monthly portfolio raw returns for the twenty-five portfolios are then regressed on the three Fama–French factors to estimate the three-factor alphas. The results are reported in Panel A. Similarly, Panels B and C present the reversal returns for the portfolio strategy based on past returns and one of the following: the stock's average daily turnover, weighted Fund Turnover, or ownership by Transient investors. Significance at the 5% level is denoted in bold, and *t*-statistics are given in parentheses.

Panel A

	Equal-weighted raw returns							Equal-weighted three-factor alpha						
		Average Stock Duration							Average Stock Duration					
Momentum	Uncond.	1	2	3	4	5	5-1	Uncond.	1	2	3	4	5	5-1
1	**1.26**	**1.33**	**1.23**	**1.23**	**1.25**	**1.17**	−0.16	0.07	0.11	0.00	0.04	0.11	0.06	−0.05
	(3.36)	**(2.94)**	**(3.08)**	**(3.42)**	**(3.82)**	**(3.76)**	(−0.68)	(0.64)	(0.64)	(0.00)	(0.34)	(1.04)	(0.57)	(−0.30)
2	**1.11**	**1.16**	**1.12**	**1.14**	**1.14**	**1.04**	−0.12	0.04	0.02	0.00	0.06	0.09	0.03	0.01
	(3.68)	**(2.96)**	**(3.27)**	**(3.71)**	**(2.97)**	**(3.90)**	(−0.53)	(0.44)	(0.11)	(−0.01)	(0.58)	(0.94)	(0.31)	(0.09)
3	**1.09**	**1.08**	**1.10**	**1.10**	**1.16**	**1.04**	−0.04	0.06	−0.02	0.04	0.05	0.14	0.07	0.09
	(3.81)	**(2.87)**	**(3.42)**	**(3.76)**	**(4.19)**	**(4.09)**	(−0.18)	(0.76)	(−0.18)	(0.40)	(0.57)	(1.57)	(0.80)	(0.73)
4	**1.13**	**1.20**	**1.12**	**1.12**	**1.15**	**1.07**	−0.13	0.11	0.11	0.06	0.08	0.16	0.12	0.02
	(3.86)	**(3.18)**	**(3.43)**	**(3.80)**	**(4.18)**	**(4.16)**	(−0.67)	(1.32)	(0.91)	(0.61)	(0.84)	(1.77)	(1.40)	(0.13)
5	**1.09**	**1.04**	**1.09**	**1.17**	**1.09**	**1.12**	0.08	0.03	−0.07	0.01	0.11	0.08	0.13	0.19
	(3.04)	**(2.34)**	**(2.91)**	**(3.47)**	**(3.63)**	**(3.85)**	(0.35)	(0.26)	(−0.42)	(0.08)	(0.99)	(0.91)	(1.28)	(1.33)
5-1	−0.17	**−0.30**	−0.14	−0.06	−0.16	−0.05	**0.24**	−0.05	−0.18	0.01	0.07	−0.02	0.06	0.24
	(−1.65)	**(−2.29)**	(−1.18)	(−0.52)	(−1.41)	(−0.43)	**(1.98)**	(−0.52)	(−1.51)	(0.10)	(0.65)	(−0.23)	(0.54)	(1.94)

(continued)

Table V. (Continued)

Panel B												
	Equal-weighted raw returns						Equal-weighted three-factor alpha					
	Turnover						Turnover					
Momentum	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	**1.05**	**1.14**	**1.11**	**1.22**	**1.43**	0.37	−0.06	−0.02	−0.09	0.00	0.23	0.29
	(3.47)	**(3.51)**	**(3.18)**	**(3.18)**	**(3.02)**	(1.30)	(−0.52)	(−0.23)	(−0.81)	(−0.03)	(1.26)	(1.47)
5	**1.04**	**1.00**	**1.16**	**1.10**	**1.14**	0.10	0.05	−0.03	0.09	−0.01	0.07	0.02
	(3.81)	**(3.34)**	**(3.58)**	**(2.97)**	**(2.43)**	(0.34)	(0.49)	(−0.29)	(0.83)	(−0.04)	(0.41)	(0.10)
5-1	−0.02	−0.14	0.05	−0.12	**−0.29**	**−0.27**	0.11	−0.01	0.18	0.00	−0.16	−0.27
	(−0.13)	(−1.27)	(0.45)	(−1.10)	**(−2.23)**	**(−1.97)**	(1.02)	(−0.06)	(1.86)	(−0.02)	(−1.41)	(−1.95)

Panel C												
	Equal-weighted three-factor alpha						Equal-weighted three-factor alpha					
	Weighted Fund Turnover						Transient					
Momentum	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	0.02	0.12	0.14	0.05	0.02	0.00	0.05	0.10	0.11	0.03	0.06	0.01
	(0.17)	(1.00)	(1.16)	(0.32)	(0.11)	(−0.02)	(0.39)	(0.84)	(0.93)	(0.26)	(0.40)	(0.09)
5	0.14	0.06	0.17	0.09	−0.12	−0.26	0.11	0.12	0.04	0.05	−0.06	−0.17
	(1.53)	(0.63)	(1.68)	(0.75)	(−0.76)	(−1.79)	(1.01)	(1.17)	(0.38)	(0.43)	(−0.38)	(−1.37)
5-1	0.12	−0.06	0.03	0.04	−0.13	**−0.26**	0.06	0.01	−0.07	0.01	−0.12	−0.18
	(1.13)	(−0.53)	(0.27)	(0.40)	(−1.11)	**(−2.03)**	(0.51)	(0.12)	(−0.74)	(0.15)	(−1.02)	(−1.33)

Table VI. Residual measures and reversal returns

This table reports the long-run returns for momentum strategies based on past 6-month returns and either Residual Stock Duration, Residual Turnover, Residual Fund Turnover, or Residual Transient ownership for a period of 2 years (year+2 and year+3) starting 1 year after the portfolio's formation. The regression used to calculate each residual is given at the top of each panel. For example, in Panel A, Residual Stock Duration is defined as the residual from the regression of the log of Stock Duration on the log of the following stock characteristics: Turnover, Transient, market capitalization, BM, institutional ownership (IO), and idiosyncratic risk (IDIORISK). To account for overlapping portfolios, we follow the methodology in Jegadeesh and Titman (1993) such that the stocks ranked in each of the eight quarters form one-eighth of the portfolio. Each quarter, one-eighth of the portfolio ranked twelve quarters ago is replaced by the stocks ranked four quarters back. Returns from each of the eight subportfolios are equally weighted to calculate the monthly returns for the portfolio. Average monthly portfolio raw returns for the twenty-five portfolios are then regressed on the three Fama–French factors to estimate the three-factor alphas. All returns are in monthly percentages. Significance at the 5% level is denoted in bold, and *t*-statistics are given in parentheses.

Panel A												
	Residual: log(STOCK_DUR) = log(Turnover), log(MCAP), log(BMRATIO), log(IO), log(IDIORISK)						Residual: log(Turnover) = log(STOCK_DUR), log(MCAP), log(BMRATIO), log(IO), log(IDIORISK)					
	Equal-weighted three-factor alpha						Equal-weighted three-factor alpha					
Momentum	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	0.18	0.21	**0.26**	0.13	**0.29**	0.11	0.22	0.13	**0.24**	0.22	0.22	0.00
	(1.19)	(1.75)	**(2.15)**	(1.12)	**(2.40)**	(0.93)	(1.87)	(1.17)	**(2.04)**	(1.78)	(1.48)	(0.01)
5	−0.04	0.06	0.12	0.17	**0.27**	0.31	0.05	0.08	0.07	0.14	0.21	0.16
	(−0.29)	(0.53)	(1.06)	(1.57)	**(2.56)**	(3.27)	(0.39)	(0.75)	(0.58)	(1.16)	(1.50)	(1.34)
5-1	−0.22	−0.14	−0.13	0.04	−0.02	0.20	−0.17	−0.05	−0.17	−0.07	−0.01	0.16
	(−1.93)	(−1.36)	(−1.24)	(0.42)	(−0.19)	(1.69)	(−1.64)	(−0.50)	(−1.56)	(−0.73)	(−0.12)	(1.32)

(continued)

Table VI. (Continued)

Panel B												
	Residual: log(Fund_Turnover) = log(Turnover), log(MCAP), log(BMRATIO), log(IO), log(IDIORISK)						Residual: log(TRANSIENT) = log(Turnover), log(MCAP), log(BMRATIO), log(IO), log(IDIORISK)					
	Equal-weighted three-factor alpha						Equal-weighted three-factor alpha					
Momentum	1	2	3	4	5	5-1	1	2	3	4	5	5-1
1	0.21	0.21	**0.25**	0.19	0.18	−0.03	**0.28**	0.16	0.26	0.20	0.17	−0.11
	(1.67)	(1.77)	**(2.05)**	(1.50)	(1.51)	(−0.29)	**(2.22)**	(1.32)	(1.94)	(1.55)	(1.44)	(−1.04)
5	0.19	**0.23**	**0.24**	0.07	−0.09	**−0.28**	**0.27**	0.17	0.18	0.10	−0.08	**−0.35**
	(1.81)	**(2.02)**	**(2.19)**	(0.57)	(−0.69)	**(−3.16)**	**(2.53)**	(1.56)	(1.48)	(0.82)	(−0.64)	**(−3.69)**
5-1	−0.02	0.02	−0.01	−0.12	**−0.27**	**−0.25**	−0.01	0.01	−0.08	−0.10	**−0.25**	**−0.24**
	(−0.20)	(0.17)	(−0.12)	(−1.12)	**(−2.39)**	**(−2.13)**	(−0.10)	(0.13)	(−0.71)	(−0.86)	**(−2.46)**	**(−2.20)**

Table VII. Return reversal: regression evidence

This table presents results of quarterly Fama–MacBeth regressions of future 2 year stock returns (measured in the second and third year after the portfolio formation) on past 6-month returns (MOM6), Stock Duration, Fund Turnover, Transient, and their interaction with past 6-month returns (MOM6) plus controls. Firm characteristics of BM, size (Market Cap), turnover, stock price (Prc), Num Analyst, PrcPressure, and institutional ownership (IO) are included as control variables. See Table 1 for variable descriptions. Significance at the 5% level is denoted in bold, and Newey–West (1987) adjusted *t*-statistics based on two-lags are given in parentheses.

Independent variable	1	2	3	4	5	6	7
	RET(YEAR + 2, YEAR + 3)						
MOM6	−0.033	**−0.190**	−0.208	−0.137	−0.154	−0.117	−0.092
	(−1.10)	**(−3.45)**	(−1.94)	(−0.40)	(−0.43)	(−0.34)	(−0.28)
MOM6*LOG(STOCK_DUR)		**0.105**	**0.116**	**0.120**	0.094	**0.106**	0.068
		(3.04)	**(2.75)**	**(2.61)**	(1.68)	**(2.16)**	(1.32)
LOG(STOCK_DUR)		−0.034	0.002	0.009	−0.005	−0.001	0.012
		(−1.35)	(0.14)	(0.60)	(−0.24)	(−0.06)	(0.74)
MOM6*LOG(TURNOVER)			0.001	0.035	0.049	0.043	0.033
			(0.04)	(0.87)	(1.15)	(1.08)	(1.06)
LOG(TURNOVER)			0.035	0.023	0.023	0.028	0.032
			(1.93)	(1.66)	(1.56)	(1.83)	(1.55)
MOM6*LOG(FUNDTURNOVER)					−0.107		−0.212
					(−1.22)		(−1.83)
LOG(FUNDTURNOVER)					−0.046		0.025
					(−0.91)		(0.92)
MOM6*LOG(IDIORISK)				−0.068	−0.072	−0.069	−0.056
				(−1.19)	(−1.14)	(−1.20)	(−0.95)
LOG(IDIORISK)				0.059	0.061	0.059	0.046
				(1.74)	(1.74)	(1.80)	(1.91)
MOM6*LOG(IO)				−0.033	−0.035	0.003	−0.031
				(−0.48)	(−0.49)	(0.03)	(−0.36)
LOG(IO)				−0.025	−0.023	−0.009	−0.010
				(−1.23)	(−1.15)	(−0.60)	(−0.59)
MOM6*LOG(TRANSIENT)						−0.039	−0.021
						(−1.20)	(−0.54)
LOG(TRANSIENT)						−0.021	**−0.023**
						(−1.56)	**(−2.14)**
MOM6*LOG(ABS(PRCPRESSURE)							0.022
							(1.16)
LOG(ABS(PRCPRESSURE))							−0.006
							(−0.80)
MOM6*LOG(NUMANALYST)							−0.003
							(−0.14)
LOG(NUMANALYST)							**0.030**
							(4.66)
MOM6*LOGMCAP							0.001
							(0.05)
LOG(BK/MKT)	0.014	0.018	0.024	0.029	0.027	0.026	0.023
	(0.70)	(1.08)	(1.53)	(1.88)	(1.72)	(1.68)	(1.44)
LOG(MCAP)	−0.004	−0.001	−0.004	0.006	0.005	0.007	−0.005
	(−0.55)	(−0.20)	(−0.57)	(0.69)	(0.69)	(0.81)	(−0.53)
Average R^2 (%)	3.23	3.84	4.87	5.92	6.30	6.24	7.80
Average number of stocks	1,155	1,155	1,155	1,155	1,155	1,155	1,155
Number of quarters	91	91	91	91	91	91	91

more likely to be overconfident and increasingly so if they experienced better past performance, then the relationship between investor horizon and stock return anomalies like momentum would also become stronger for stocks held by short-term investor with superior past performance. In other words, stocks which are largely held by successful short-term investors should have the most anomalous momentum pricing.

To test this, we construct a stock-level measure for aggregate past performance by calculating the weighted average past abnormal performance for the institutional investors holding each stock. We start by calculating the institutional fund-level DGTW-adjusted abnormal returns by weighting the stock DGTW-adjusted returns with the portfolio weight of the stock in each institution's portfolio at the end of the previous quarter (assuming holdings are held constant from quarter-end to next quarter-end). The DGTW-adjusted return of each stock is calculated as the difference of the stock return and an equally weighted portfolio with similar size, value, and momentum as the stock in the portfolio (see Daniel *et al.* (1997) for details). We then aggregate the institutional fund-level DGTW-adjusted returns over the last four quarters to get the abnormal return of each institution for the past year. For each stock, we then weight the past year abnormal performance of the institutional investors holding that stock, using as weights the amount held by each institution. This provides the aggregate DGTW-adjusted past performance measure for the institutional investors holding that stock, denoted by DGTW_Inst_Ret_1y.

Next, we test whether momentum returns and reversals are likely to be more significant for stocks held by short-term investors with positive past performance. We present the results in Table VIII. In Panel A, we independently triple sort all stocks: into three groups based on their past 6-month returns, into three groups each by Stock Duration, and finally into three groups based on the weighted past 12-month institutional investor abnormal performance (DGTW_Inst_Ret_1y).[11]

For the stocks with low Stock Duration, the difference in three-factor momentum returns between the stocks held by institutional investors with high and low past abnormal performance (DGTW_Inst_Ret_1y) is 0.55% (=1.00% − 0.45%) per month and is highly significant with a *t*-statistic of 2.48, whereas the difference is −0.11% (=0.18% − 0.29%) and insignificant

[11] We verify that sorting on the recent performance of institutional investor portfolios is substantially different from sorting on past momentum. We compute the formation period stock returns for all cells in panel A of Table VIII, and find that—controlling for past momentum—the past stock returns are almost identical across the institutional performance terciles. These results are included in Supplementary Appendix Table A3.

Table VIII. Stock Duration, institutional investors' past performance: momentum and reversal returns

This table presents the results corresponding to the effect of Stock Duration and weighted past abnormal performance of the institutional investors holding a given stock on future momentum profits. Panel A presents the Fama–French (1993) equal-weighted three-factor alphas for momentum strategies based on past returns, Stock Duration, and the weighted past DGTW-adjusted abnormal performance of the institutional investors holding that stock. At the beginning of each quarter, stocks are independently sorted into three groups each based on past 6 month returns, Stock Duration (calculated according to Equation (1)) and weighted institutional investors past abnormal performance. Average monthly portfolio raw returns for the twenty-seven portfolios are then regressed on Fama–French three factors to estimate the three-factor alphas. Panel B reports the long-run three-factor alphas for momentum (R) strategies based on past returns, Stock Duration (D), and the weighted past DGTW-adjusted abnormal performance (P) of institutional investors holding that stock, for a period of 2 years (year+2 and year+3) starting 1 year after the portfolio formation. To account for overlapping portfolios, we follow the methodology in Jegadeesh and Titman (1993) such that the stocks ranked in each of the eight quarters form one-eighth of the portfolio. All the alphas are in monthly percentage. 5% significance level is denoted in bold and *t*-statistics are given in parentheses.

Panel A													
	Equal-weighted three-factor alpha												
	D1				D2				D3				
Momentum	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	D3-D1
R1	−0.38	**−0.43**	**−0.62**	−0.24	−0.20	−0.06	−0.20	0.00	−0.09	0.09	0.06	0.14	0.38
	(−1.48)	**(−2.07)**	**(−3.12)**	(−1.02)	(−1.06)	(−0.38)	(−1.33)	(−0.01)	(−0.51)	(0.66)	(0.38)	(1.00)	(1.67)
R2	−0.03	−0.08	−0.17	−0.14	0.13	0.17	0.18	0.05	0.09	**0.19**	**0.32**	**0.23**	**0.37**
	(−0.22)	(−0.61)	(−1.50)	(−0.83)	(1.13)	(1.67)	(1.85)	(0.45)	(0.92)	**(2.10)**	**(2.99)**	**(2.09)**	**(2.18)**
R3	0.06	0.20	**0.37**	0.31	0.06	0.15	0.22	0.16	0.20	0.18	**0.24**	0.04	−0.27
	(0.42)	(1.47)	**(2.39)**	(1.49)	(0.48)	(1.32)	(1.85)	(1.02)	(1.61)	(1.62)	**(2.11)**	(0.27)	(−1.32)
R3-R1	0.45	**0.64**	**1.00**	**0.55**	0.26	0.22	**0.42**	0.16	0.29	0.09	0.18	−0.11	**−0.66**
	(1.69)	**(2.41)**	**(3.84)**	**(2.48)**	(1.26)	(1.04)	**(2.03)**	(0.87)	(1.38)	(0.50)	(1.04)	(−0.66)	**(−2.58)**

(continued)

Table VIII. Continued

	Panel B												
	Equal-weighted three-factor alpha												
	D = 1 (low stock duration)				D = 2				D = 3 (high stock duration)				
Momentum	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	D3-D1
R1	0.06	−0.05	0.04	−0.02	0.05	0.07	−0.05	−0.10	0.11	0.05	−0.02	−0.14	−0.11
	(0.43)	(−0.39)	(0.26)	(−0.20)	(0.42)	(0.66)	(−0.41)	(−0.86)	(1.12)	(0.57)	(−0.22)	(−1.40)	(−0.84)
R2	0.11	0.02	−0.02	−0.13	0.04	0.10	0.03	−0.01	0.14	0.07	0.08	−0.06	0.07
	(1.08)	(0.18)	(−0.15)	(−1.08)	(0.45)	(1.11)	(0.32)	(−0.15)	(1.48)	(0.86)	(0.94)	(−0.78)	(0.62)
R3	0.18	0.08	−0.15	**−0.33**	0.20	0.11	−0.01	−0.20	**0.23**	0.13	0.12	−0.11	0.22
	(1.59)	(0.66)	(−0.94)	**(−2.36)**	(1.84)	(1.09)	(−0.08)	(−1.93)	**(2.42)**	(1.58)	(1.23)	(−1.28)	(1.60)
R3-R1	0.12	0.13	−0.19	**−0.31**	0.15	0.04	0.04	−0.11	0.11	0.08	0.14	0.03	**0.34**
	(1.02)	(1.47)	(−1.86)	**(−2.68)**	(1.69)	(0.54)	(0.49)	(−0.95)	(1.24)	(1.14)	(1.69)	(0.29)	**(2.25)**

for the stocks in the highest Stock Duration group. The difference of 0.66% (=0.55% − −0.11%) is again highly economically and statistically significant with a *t*-statistic of 2.58.

We conduct several robustness checks. First, in Panel A of Supplementary Appendix Table A4, we show triple sorts using stock turnover rather than Stock Duration, and find similar results. For stocks with high turnover, momentum returns are significantly higher (0.49% per month with a *t*-statistic of 2.28) if those are also held by institutional investors with high abnormal performance in the past year. Second, Panel B of Supplementary Appendix Table A4 shows analogous results using fund turnover. Third, in order to show that our Stock Duration results are not driven by some other stock characteristic, as a robustness check we use Residual Stock Duration (i.e., the residual of regressing log Stock Duration on the log of turnover, market capitalization, book-to-market, institutional ownership, and idiosyncratic risk) and present the corresponding results in Panel A of Supplementary Appendix Table A5. These are results are very similar to the results in Panel A of Table VIII.

Overall, these results are consistent with short-term institutional investors becoming more overconfident after positive past abnormal performance. However, for stocks held by institutional investors with longer horizons, we find that their past performance is not systematically related to positive or negative momentum returns. This suggests that the portfolio decisions of long-term institutional investors may not be affected by self-attribution bias.

The results documented in section 3.2, of stronger return reversal for stocks held by short-term investors, is limited to the stocks held by short-term institutional investors with superior past abnormal performance. The corresponding independent triple sort results are reported in Panel B of Table VIII. Using equal-weighted, three-factor alphas, the return reversal for the stock held by short-term institutions with superior past performance equals −0.19% per month, with a *t*-statistic of 1.86. The difference in return reversal three-factor alphas for stocks with short-term institutions with superior versus inferior past performance equals −0.31% per month and is strongly significant with a *t*-statistic of 2.68. Corresponding results using turnover and fund turnover are presented in Supplementary Appendix Table A6.

In Figure 4, we plot the time series of momentum profits in event time (Panel A) and in calendar time (Panel B). Panel A plots event-time cumulative alphas of the long–short momentum up to 3 years after portfolio formation. The figure confirms our earlier findings that there is strong momentum and reversal for the stocks held by short-term institutions with

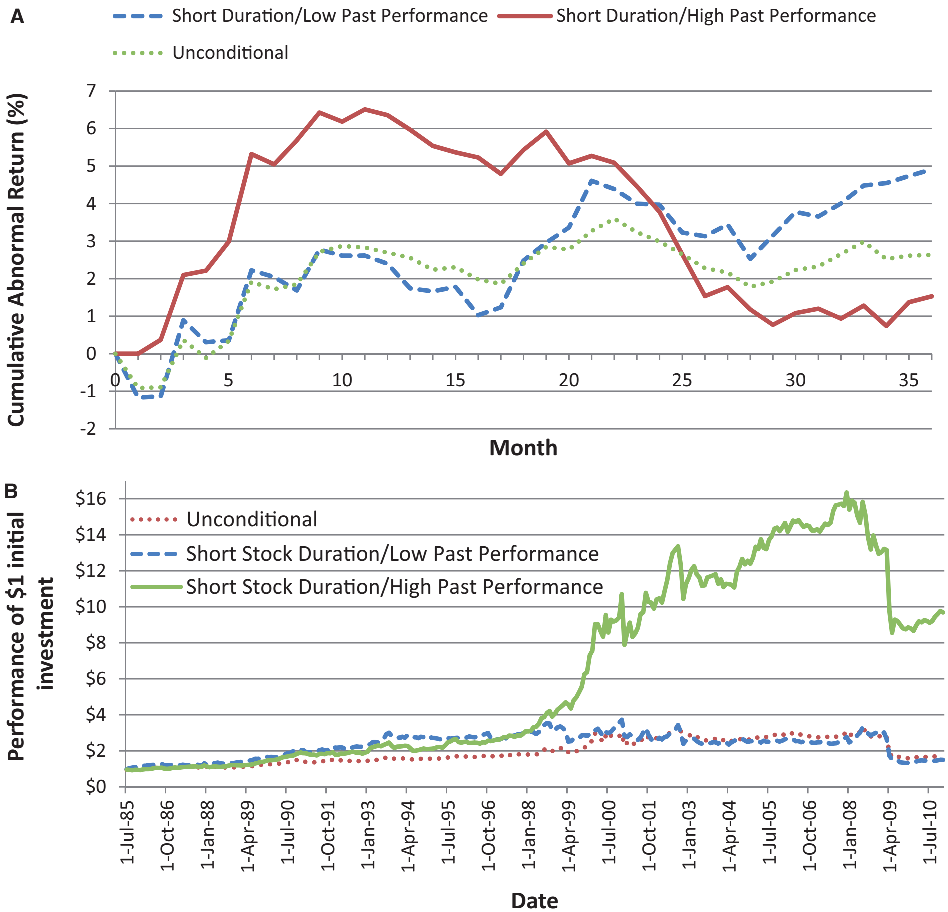

Figure 4. Cumulative Momentum Profits. This figure plots the cumulative abnormal performance of momentum profits. (A) presents the returns in event time (after portfolio formation, averaged across all quarters) and (B) in calendar time (for a $1 initial investment at the start of our sample period) from July 1985 to December 2010. The returns for an unconditional momentum strategy and for momentum strategies conditional on Stock Duration and past performance (measured as the 1 year DGTW-adjusted institutional performance) are reported.

high past performance, whereas momentum is weaker both for an unconditional momentum strategy and for the momentum strategy implemented on the stocks held by short-term institutional investors with low average past performance. Further, neither of those latter strategies shows any evidence for reversal, while the presence of strong reversal for stocks held by short-term investors with high past performance is consistent with our behavioral explanation for momentum.

In Panel B of Figure 4, we present the cumulative performance of several momentum strategies over calendar time. One dollar initial investment in March 1985 in long–short momentum strategy for stocks held by short-term institutional investors with high past performance would have increased to a peak of \$16.35 in December 2007 and then dropped to a still economically significant amount of \$9.69 in December 2010. In contrast, the performance in our sample of both the unconditional momentum strategy and the momentum strategy for the stocks held by short-term institutions with low past performance was relatively poor during the 1985–2010 period. One dollar initial investment increased to \$1.71 in December 2010 for the unconditional momentum strategy and to \$1.49 for the momentum strategy using stocks held by short-term institutional investors with low past performance.

Panel A of Table IX presents an alternative approach using multivariate regressions. Each quarter we divide the institutions into two groups based on positive or negative DGTW-adjusted performance in the past 1 year. We then calculate average Stock Duration and weighted fund turnover separately for these two groups of institutions. DHS would predict, assuming positive past performance leads to an increase in overconfidence because of self-attribution bias, that the effect of trading by institutional investors with positive past performance has a stronger effect on momentum returns and return reversal compared to trading by institutions with negative past performance. This idea is supported by the data. In column 1, we find a strong association between momentum returns and Stock Duration of the institutions with positive past performance. However, the coefficient corresponding to the interaction term between past 6 month returns and Stock Duration of institutions with negative past performance is insignificant. Subsequent return reversal is also stronger conditional on the Stock Duration of institutions with positive past performance as shown in Columns 3 and 4.

In conclusion, the evidence that momentum and reversal anomalies are stronger with shorter investor trading horizons is itself stronger if these institutions recently had successful performance. This is consistent with DHS (1998) and Gervais and Odean (2001), who argue that self-attribution biased short-horizon traders become more overconfident if they experienced better past performance, and that this overconfidence can lead to exactly the anomalous pricing behavior we document here.

3.4 ROLE OF SHORT-SALES CONSTRAINTS

If the strength of momentum returns and subsequent reversal can partly be explained by the presence of overconfident investors, as suggested by DHS

Table IX. Institutional investors' horizon and stock return anomalies: effects of past performance and short−sales constraints

Panel A reports the results for return predictability corresponding to different stock return anomalies conditional on average stock duration and weighted fund turnover calculated separately for the institutions with positive and negative DGTW-adjusted abnormal returns over the past 1 year (STOCK_DUR_POS, STOCK_DUR_NEG). Following the Fama–MacBeth approach, the regressions are performed quarterly and time-series averages of the quarterly coefficients are reported. Firm characteristics of past 6 month returns (MOM6), BK/MKT, and size (Market Cap) are also included as independent variables. In Panel B, we report the results corresponding to Fama–MacBeth regressions estimated separately for the stocks with high and low short interest ratio. Each quarter stocks are divided into two equal groups based on their most recently reported short interest ratio calculate as the ratio of short interest and the number of shares outstanding. Significance level at the 5% level is denoted in bold, and Newey–West (1987) adjusted *t*-statistics based on two-lags are given in parentheses.

Panel A

Independent variable	MOMENTUM 1 RET6MONTH	2	REVERSAL 3 RET(YEAR + 2, YEAR + 3)	4	ISSUANCE 5 RET3MONTH	6
MOM6	0.074	**0.130**	**−0.239**	−0.147	0.018	0.018
	(1.91)	**(2.32)**	**(−4.36)**	(−1.73)	(1.83)	(1.82)
ISSUE_QTR					**−0.208**	**−0.461**
					(−2.14)	**(−2.58)**
MOM6*LOG(STOCK_DUR_POS)	**−0.047**		**0.096**			
	(−3.59)		**(1.97)**			
MOM6*LOG(STOCK_DUR_NEG)	0.012		0.034			
	(0.84)		(0.75)			
ISSUE_QTR*LOG(STOCK_DUR_POS)					0.061	
					(1.05)	
ISSUE_QTR*LOG(STOCK_DUR_NEG)					0.055	
					(0.98)	
LOG(STOCK_DUR_POS)	0.008		−0.030		0.000	
	(1.39)		(−1.06)		(−0.10)	
LOG(STOCK_DUR_NEG)	−0.002		−0.007		0.000	
	(−0.29)		(−0.53)		(0.00)	
MOM6*LOG(FUNDTURNOVER_POS)		**0.064**		−0.078		
		(3.08)		(−1.57)		
MOM6*LOG(FUNDTURNOVER_NEG)		0.014		−0.017		
		(0.62)		(−0.25)		
ISSUE_QTR*LOG(FUNDTURNOVER_POS)						**−0.206**
						(−2.14)
ISSUE_QTR*LOG(FUNDTURNOVER_NEG)						−0.112
						(−0.98)
LOG(FUNDTURNOVER_POS)		−0.001		0.007		0.002
		(−0.36)		(0.43)		(0.32)
LOG(FUNDTURNOVER_NEG)		0.011		0.014		0.006
		(1.19)		(0.70)		(1.28)
LOG(BK/MKT)	0.008	0.010	0.020	0.016	0.004	0.004
	(1.45)	(1.65)	(1.05)	(0.76)	(1.45)	(1.49)
LOG(MCAP)	−0.002	−0.001	−0.001	−0.003	−0.001	−0.001
	(−0.94)	(−0.36)	(−0.09)	(−0.42)	(−1.27)	(−1.01)
Average R^2 (%)	6.57	6.35	4.23	4.08	5.95	5.65
Average number of stocks	1,120	1,120	1,017	1,017	1,133	1,133
Number of quarters	101	101	91	91	102	102

(continued)

Table IX. (Continued)

Panel B								
	MOMENTUM				REVERSAL		ISSUANCE	
	1	2	3	4	5	6	7	8
	Short interest ratio							
	Low	High	Low	High	Low	High	Low	High
Independent variable	RET6MONTH				RET(YEAR + 2, YEAR + 3)		RET3MONTH	
MOM6_LOW	−0.002	**−0.059**			−0.010	0.070		
	(−0.08)	**(−2.55)**			(−0.21)	(0.94)		
MOM6_HIGH	0.005	0.033			−0.004	**−0.142**		
	(0.20)	(1.36)			(−0.09)	**(−2.16)**		
MOM6			−0.007	**0.095**			0.010	**0.022**
			(−0.11)	**(2.13)**			(1.03)	**(1.97)**
ISSUE_HIGH							−0.024	−0.009
							(−1.53)	(−0.88)
ISSUE_LOW							0.005	**0.035**
							(0.33)	**(2.57)**
MOM6_LOW*LOG(STOCK_DUR)	0.002	**0.029**			0.010	−0.030		
	(0.23)	**(2.34)**			(0.48)	(−0.72)		
MOM6_HIGH*LOG(STOCK_DUR)	−0.004	−0.020			0.004	**0.101**		
	(−0.37)	(−1.59)			(0.16)	**(2.84)**		
MOM6*LOG(STOCK_DUR)			−0.001	**−0.049**				
			(−0.05)	**(−2.04)**				
ISSUE_LOW*LOG(STOCK_DUR)							−0.001	**−0.014**
							(−0.12)	**(−1.97)**
ISSUE_HIGH*LOG(STOCK_DUR)							0.012	0.006
							(1.49)	(1.00)
LOG(STOCK_DUR)	−0.005	0.0004	0.004	0.009	−0.027	−0.041	−0.006	0.000
	(−0.73)	(0.03)	(0.47)	(0.89)	(−1.54)	(−1.44)	(−1.41)	(−0.05)
LOG(BK/MKT)	0.004	0.012	0.004	**0.011**	0.025	**0.045**	0.002	**0.007**
	(0.93)	(1.98)	(0.97)	**(1.96)**	(1.46)	**(2.49)**	(0.64)	**(2.38)**
LOG(MCAP)	−0.002	−0.001	−0.002	−0.001	0.004	0.004	−0.002	−0.001
	(−0.98)	(−0.17)	(−0.99)	(−0.18)	(0.41)	(0.32)	(−1.34)	(−0.48)
Average R^2 (%)	6.61	7.24	6.38	7.32	7.00	6.06	6.84	6.92
Average number of stocks	765	765	765	765	679	679	775	775
Number of quarters	101	101	101	101	91	91	102	102

and the results in the previous subsection, what prevents other investors to quickly come in and bring prices back to fundamentals? We address this question by examining the role of short-sales constraints and liquidity. We expect the future momentum and reversal returns to be stronger when the short-sales constraints are binding, and likewise momentum and reversal alphas to be generally lower when stocks are more liquid. *Ex ante*, short-sales constraints may especially lead to stronger results for positive momentum and subsequent negative reversal, as the constraints may have prevented short sellers from trading more aggressively and thereby from tempering the positive momentum if that is caused by short-term overconfident about their positive information. For negative momentum stocks, short-sales constraints may likewise prevent short sellers from incorporating their negative information sooner. Any subsequent positive reversal for these stocks may potentially be explained by short sellers themselves being overconfident about their negative information. Finally, greater liquidity will make it easier for arbitrageurs to step in and reduce mispricing and thus any evidence of the anomalies.

We first consider short-sales constraints. Asquith, Pathak, and Ritter (2005) show that short-selling is likely to be more expensive for stocks with low institutional ownership and high short interest. As our sample mostly consists of stocks with relatively high institutional ownership, our proxy for the difficulty of shorting is the short interest ratio. Assuming that the supply of shares available for short lending is fairly similar across the stocks in our sample with any differences controlled for by for example, institutional ownership, we interpret stocks with a high short interest ratio as being more difficult or expensive to short (also because we do not have data on actual rebate rates).

Using short interest data from Compustat, for each firm we measure the short interest ratio as the ratio of the number of shares held short as of the latest settlement date to the number of shares outstanding. At the end of each quarter, we divide the stocks into two groups depending on their short interest ratio and separately examine the association of Stock Duration with the various stock return anomalies in these two subgroups. As the prediction for short sales constraints is asymmetric—these would allow future negative rather than future positive alphas—we construct a dummy variable "MOM6_HIGH" ("MOM6_LOW") that is equal to 1 if the stock's past 6-month momentum return is in the top (bottom) tercile. We construct dummies for the reversal and issuance anomalies analogously.[12]

The results are presented in Panel B of Table IX. As shown in columns 1 and 2, we only find momentum returns over next 6 months for stocks held by short-term investors when the short interest is also high. This indicates that our previous results are driven by stocks that are more likely to be subject to short-sales constraints. Consistent with short-sales constraints, we find that the short interest ratio has a strong relation to negative momentum returns (i.e., for the "MOM6_LOW" variables). For example, the interaction of the

[12] The only difference is that for the reversal dummies, we use dummies based on quintiles rather than terciles, as the reversal anomaly is driven only be stocks with extreme past momentum. Results for the reversal dummies using tercile groups are economically similar but lack statistical significance, are available upon request.

low momentum dummy and Stock Duration is insignificant in the low short interest ratio sample (see column 1) and strongly significant in the high short interest ratio sample (see column 2, with a coefficient of 0.029 and a *t*-statistic of 2.34).

Also consistent with the short-sales constraints prediction is that the evidence for positive momentum—which the panel shows is generally weaker than that for negative momentum in our sample—is unrelated to the short-sales ratio, as the coefficients involving the "MOM6_HIGH" dummies are insignificant and not statistically different across the different short interest ratio samples in columns 1 and 2. The results in columns 3 and 4 in panel B of Table IX confirm that the momentum anomaly generally only exists for stocks with a high short interest ratio, using the same specification as in column 2 of Table IV.

We find similar results for the reversal anomaly in columns 5 and 6 (panel B of Table IX), which again is only significant in the sample of stocks with high short interest and where again the short interest ratio matters only for stocks with negative reversal anomaly alphas (i.e., using the "MOM6_HIGH" dummy). In particular, Stock Duration only relates to the reversal anomaly for stocks that are harder to short, as the interaction of past positive momentum and Stock Duration is only significant in column 6 with a coefficient of 0.101 and a *t*-statistic of 2.84 (and is insignificant in column 5 with a coefficient very close to zero).

Next, we consider how stock liquidity as measured by the Amihud (2002) illiquidity ratio matters for our main results, as presented in the Supplementary Appendix Table A8 using 6-month predictive return regressions. Each period we split our sample evenly depending on whether the stock has an illiquidity ratio that is above or below the sample median. We find that the Amihud illiquidity ratio only relates to the momentum anomaly. Specifically, the interaction between past 6-month momentum and Stock Duration is only negative and significant in the sample of illiquid stocks (see column 2). For the reversal anomaly, results are similar across illiquidity subsamples. We thus conclude that our results for the momentum and reversal anomalies are only found for stocks where arbitrage opportunities seem more limited.

3.5 SHARE ISSUANCE

A number of studies provide evidence of long-run abnormal returns following corporate events like seasoned equity offerings, share repurchase announcements, and stock mergers (see, e.g., Loughran and Ritter, 1995; Ikenberry, Lakonishok, and Vermaelen, 1995; Loughran and Vijh, 1997).

In this article, we use "share issuance" as a general term to refer to these events. Using a stock-level annual share issuance measure that captures the corporate events corresponding to variation in the number of outstanding shares over time, Pontiff and Woodgate (2008) show that the annual share issuance measure strongly predicts the cross-section of future stock returns. This annual share issuance measure was first introduced in Daniel and Titman (2006).

Following the methodology in Pontiff and Woodgate (2008), we construct a quarterly share issuance measure for each stock. For each firm, we obtain the number of shares outstanding and the "Factor to Adjust Shares Outstanding" from monthly CRSP data. We compute the number of real shares outstanding, which adjusts for distribution events such as splits and rights offerings, as follows. We first compute a total factor at the end of month t, which represents the cumulative product of the CRSP-provided factor f up to month t inclusive:

$$TotalFactor_t = \prod_{i=1}^{t}(1 + f_i). \tag{4}$$

We compute the number of shares outstanding adjusted for splits and other events as:

$$Adjusted\ Shares_t = Shares\ Outstanding_t / TotalFactor_t \tag{5}$$

We use this measure of adjusted shares to compute the quarterly share issuance measure at the end of month t as:

$$ISSUE\_QTR_{t,t-3} = Ln(Adjusted\ Shares_t) - Ln(Adjusted\ Shares_{t-3}). \tag{6}$$

We use the quarterly share issuance measure at the end of each quarter in further return predictability analysis. At the beginning of each quarter, stocks are first divided into five groups based on the quarterly share issuance measure and then independently divided into three groups based on Stock Duration. A gap of one quarter is left between the calculations of Stock Duration and the return estimation to allow for institutional holdings to become public.

Table X presents the results. The raw returns for the unconditional portfolio strategy based only on the quarterly share issuance measure are reported in the first column of Panel A, with the corresponding four-factor alphas in the sixth column. A long–short portfolio with a long position in low share issuance stocks and a short position in high share issuance stocks earns a monthly equal-weighted return of 0.35% (t-statistic

Table X. Stock Duration and issuance anomaly

This table presents monthly equal-weighted raw returns and four-factor Fama–French alphas from portfolio strategies based on an independent two-way sort based on the quarterly share issuance measure (Issue_Qtr) and measures of investor horizon. Quarterly share issuance is calculated from the quarterly CRSP data by using the definition given in Equation (6) in the text. At the beginning of each quarter, stocks are first divided into five groups based on the quarterly share issuance measure and then independently divided into three groups based on Stock Duration calculated using Equation (1) in the text. Average equal-weighted raw returns and Fama–French four-factor alphas for these fifteen portfolios are reported in panel A of the table. The returns for the unconditional portfolio strategy based on the quarterly share issuance measure are reported in the first column. Similarly, Panels B and C report the average equal-weighted Fama–French four-factor alphas for portfolio strategies conditional on the quarterly issuance measure and one of the following: average daily Turnover, Fund Turnover, or Transient Institutional Ownership. All the returns are in monthly percentages. Significance at the 5% level is denoted in bold, and *t*-statistics are given in parentheses. In Panel B, Newey–West (1987) adjusted *t*-statistics based on two lags are reported in parentheses.

Panel A

	Equal-weighted four-factor alpha					Equal-weighted raw returns				
		Stock Duration					Stock Duration			
Issue_Qtr	Uncond.	D1	D2	D3	D3-D1	Uncond.	D1	D2	D3	D3-D1
R1	**0.39**	**0.50**	**0.48**	**0.25**	−0.25	**1.31**	**1.40**	**1.41**	**1.17**	−0.23
	(4.24)	**(3.90)**	**(4.21)**	**(2.40)**	(−1.78)	**(4.70)**	**(3.92)**	**(4.92)**	**(4.68)**	(−1.12)
R2	0.11	−0.14	0.07	**0.26**	**0.40**	**1.06**	**0.82**	**1.05**	**1.17**	0.35
	(1.07)	(−0.84)	(0.58)	**(2.52)**	**(2.42)**	**(3.46)**	**(2.09)**	**(3.31)**	**(4.50)**	(1.65)
R3	0.20	0.16	0.21	0.10	−0.06	**1.17**	**1.11**	**1.21**	**1.08**	−0.04
	(1.95)	(0.93)	(1.61)	(0.87)	(−0.35)	**(3.57)**	**(2.52)**	**(3.73)**	**(3.85)**	(−0.14)
R4	0.06	−0.08	0.07	0.18	0.26	**1.05**	**0.94**	**1.06**	**1.16**	0.22
	(0.62)	(−0.62)	(0.70)	(1.67)	(1.93)	**(3.25)**	**(2.29)**	**(3.45)**	**(4.40)**	(0.96)
R5	−0.06	−0.13	0.04	0.07	0.19	**0.96**	**0.89**	**1.07**	**1.10**	0.22
	(−0.79)	(−1.05)	(0.41)	(0.63)	(1.20)	**(2.70)**	**(2.02)**	**(3.37)**	**(4.06)**	(0.78)
R5-R1	**−0.45**	**−0.63**	**−0.44**	−0.18	**0.44**	**−0.35**	**−0.52**	**−0.34**	−0.07	**0.45**
	(−4.25)	**(−4.01)**	**(−3.79)**	(−1.65)	**(2.61)**	**(−2.12)**	**(−2.60)**	**(−2.50)**	(−0.61)	**(2.33)**

(continued)

Table X. (Continued)

Panel B

	Equal-weighted raw returns				Equal-weighted four-factor alpha			
	Turnover				Turnover			
ISSUE_QTR	1	2	3	3-1	D1	D2	D3	D3-D1
R1	**1.22**	**1.26**	**1.50**	0.29	**0.27**	**0.31**	**0.64**	**0.37**
	(5.04)	**(4.41)**	**(3.97)**	(1.21)	**(2.62)**	**(2.80)**	**(4.56)**	**(2.27)**
R5	**1.11**	**1.10**	**0.93**	−0.19	0.09	−0.01	−0.06	−0.14
	(4.38)	**(3.59)**	**(2.05)**	(−0.61)	(0.82)	(−0.15)	(−0.46)	(−0.83)
R5-R1	−0.10	−0.16	**−0.57**	**−0.47**	**−0.18**	**−0.33**	**−0.70**	**−0.51**
	(−1.09)	(−1.25)	**(−2.81)**	**(−2.48)**	**(−2.06)**	**(−3.14)**	**(−4.09)**	**(−2.94)**

Panel C

	Equal-weighted four-factor alpha				Equal-weighted four-factor alpha			
	Fund turnover				Transient			
ISSUE_QTR	D1	D2	D3	D3-D1	D1	D2	D3	D3-D1
R1	**0.33**	**0.41**	**0.51**	0.18	**0.36**	**0.31**	**0.57**	0.21
	(3.29)	**(3.85)**	**(3.73)**	(1.34)	**(3.69)**	**(3.19)**	**(3.98)**	(1.59)
R5	0.07	0.07	−0.17	−0.24	0.09	0.02	−0.18	−0.27
	(0.68)	(0.90)	(−1.36)	(−1.54)	(0.86)	(0.20)	(−1.41)	(−1.66)
R5-R1	**−0.25**	**−0.33**	**−0.68**	**−0.43**	−0.26	**−0.29**	**−0.74**	**−0.48**
	(−2.15)	**(−2.92)**	**(−4.22)**	**(−2.43)**	(−1.84)	**(−2.21)**	**(−4.93)**	**(−2.71)**

of 2.12) and a four-factor alpha of 0.45% (with a highly significant t-statistic of 4.25).

Panel A also presents the raw returns and four-factor alphas for the $5 \times 3 = 15$ portfolios formed by independent double sorts based on annual share issuance and Stock Duration. A long–short trading strategy with a long position in low share issuance stocks and a short position in high share issuance stocks earns an equal-weighted four-factor monthly alpha of 0.63% (t-statistic of 4.01) for the bottom Stock Duration group and an equal-weighted monthly alpha of 0.18% (t-statistic of 1.65) for the top Stock Duration group. The difference in equal-weighted low–high share issuance returns between the bottom and top Stock Duration groups is 0.44% per month, which is positive and significant with a t-statistic of 2.61. These results provide evidence that the returns following a share issuance are stronger for stocks held by short-horizon institutional investors.

In Panels B and C, we present the average four-factor alphas for the fifteen portfolios formed by independent double sorts based on annual share issuance and the other three proxies for short-term trading: turnover, fund turnover, and the percentage held by transient investors. Corresponding raw returns are presented in Supplementary Appendix Table A7. Each of these proxies confirms that the share issuance anomaly is stronger if stocks are traded more frequently or held by institutions that do so.[13]

Table XI presents the robustness results using multivariate regressions. The dependent variable is the next 3-month return. Newey–West (1987) adjusted t-statistics (based on two lags) are reported in parentheses. In specification 2, we find that the coefficient corresponding to the interaction term between the logarithm of Stock Duration and share issuance is positive and highly significant with a t-statistic of 2.62, confirming that the share issuance is driven by stocks held by institutions who have held these stocks for short durations. In column 3, we also include the coefficient corresponding to the interaction between the logarithm of turnover and the quarterly share

[13] Supplementary Appendix Table A7 shows that Stock Duration and the percentage of transient investors seem to be better proxies than turnover for finding stocks that are driving the share issuance anomaly. For example, a portfolio strategy based on share issuance measure and the Residual Stock Duration (the residual obtained by Stock Duration on turnover and other firm characteristics) gives very similar results as using Stock Duration. Results using the percentage of transient investors are likewise robust to controlling for turnover and the other firm characteristics in this way. However, results for residual turnover and residual fund turnover become insignificant. That means that the anomaly is strongest for stocks for which the common component of turnover and Stock Duration (or fund turnover) points to frequent trading.

Table XI. Issuance anomaly: regression evidence

This table presents results of quarterly Fama–MacBeth regressions of future 3-month stock returns (RET3MONTH) on the quarterly share issuance measure (ISSUE_QTR), Stock Duration, Turnover, Fund Turnover, and Transient as well as their interaction with the quarterly share issuance measure plus controls. Firm characteristics of BM, size (Market Cap), stock price (Prc), Num Analyst, PrcPressure, Idiosyncratic Risk (IDIORISK), and institutional ownership (IO) are included as control variables. See Table I for variable descriptions. Significance level at the 5% level is denoted in bold, and Newey–West (1987) adjusted *t*-statistics based on two-lags are given in parentheses.

Independent variable	1 RET3MONTH	2	3	4	5	6
ISSUE_QTR	−0.032	**−0.223**	**−0.397**	**−0.505**	−0.616	−0.614
	(−1.18)	**(−2.62)**	**(−2.40)**	**(−3.11)**	(−1.16)	(−0.75)
ISSUE_QTR*LOG(STOCK_DUR)		**0.118**	0.066		−0.026	−0.048
		(2.62)	(1.43)		(−0.34)	(−0.51)
LOG(STOCK_DUR)		0.000	0.003		0.002	0.004
		(−0.04)	(0.93)		(0.97)	(1.43)
ISSUE_QTR*LOG(FUNDTURNOVER)				**−0.235**	**−0.333**	−0.333
				(−2.57)	**(−2.53)**	(−1.92)
LOG(FUNDTURNOVER)				−0.003	−0.001	0.004
				(−0.54)	(−0.17)	(0.76)
ISSUE_QTR*LOG(TURNOVER)			−0.052	−0.033	−0.034	−0.087
			(−1.44)	(−1.03)	(−0.75)	(−1.49)
LOG(TURNOVER)			0.002	0.002	0.002	0.001
			(0.72)	(0.56)	(0.79)	(0.41)
ISSUE_QTR*LOG(IDIORISK)					0.069	0.104
					(0.98)	(1.18)
LOG(IDIORISK)					0.000	0.000
					(0.05)	(0.05)
ISSUE_QTR*LOG(IO)					0.067	0.096
					(0.74)	(0.65)
LOG(IO)					0.001	0.002
					(0.21)	(0.35)
ISSUE_QTR*LOG(TRANSIENT)						−0.025
						(−0.30)
LOG(TRANSIENT)						−0.003
						(−1.46)
ISSUE_QTR*LOG(ABS(PRCPRESSURE)						0.004
						(0.22)
LOG(ABS(PRCPRESSURE))						0.001
						(1.53)
ISSUE_QTR*LOG(NUMANALYST)						**0.133**
						(2.09)
LOG(NUMANALYST)						**0.005**
						(3.53)
ISSUE_QTR*LOGMCAP						−0.030
						(−0.84)
LOG(BK/MKT)	0.004	0.004	0.004	0.004	0.004	0.004
	(1.35)	(1.44)	(1.54)	(1.54)	(1.47)	(1.37)
LOG(MCAP)	−0.001	−0.001	−0.002	−0.002	−0.002	**−0.004**
	(−1.15)	(−1.27)	(−1.40)	(−1.22)	(−1.56)	**(−2.43)**
MOM6	0.018	0.018	**0.020**	**0.020**	**0.022**	**0.022**
	(1.76)	(1.87)	**(2.16)**	**(2.22)**	**(2.49)**	**(2.60)**
Average R^2 (%)	4.42	5.56	6.74	6.72	8.24	9.36
Average number of stocks	1,297	1,297	1,297	1,297	1,297	1,297
Number of quarters	102	102	102	102	102	102

issuance variable in the regression, which renders both interactions insignificant. This suggests that the common component of Stock Duration and turnover is driving the result in column 2. In column 4, we further add the coefficient corresponding to the interaction between the logarithm of fund turnover and the quarterly share issuance variable in the regression. The interaction is negative and strongly statistically significant with a t-statistic of 2.57. This interaction remains negative and significant even after adding further controls and interactions in columns 5 and 6. As a result, the multivariate regressions confirm that the share issuance anomaly is stronger for stocks with more trading or more short-term institutions. In Table IX, we find some evidence that the association between the issuance anomaly and short-term investors is stronger for institutions with positive past performance (Panel A, columns 5 and 6) and is also stronger for stocks with a high short interest ratio compared to the stocks with lower short ratio (Panel B, columns 7 and 8).

4. Conclusion

In this article, we investigate whether trading frequency and investor horizons can be linked to asset pricing anomalies. We measure investor horizons using share turnover, the percentage of transient investors, institutional fund turnover, and a new measure of institutional investors' investment horizons based on quarterly institutional investor portfolio holdings. Our new stock-level proxy, Stock Duration, is the weighted average of the duration that the stock has been in the institutional portfolios, that is, weighted by the total amount invested in each institutional portfolio.

We examine whether three well-known stock return anomalies are related to the presence of short-term investors, namely the momentum, reversal, and share issuance anomalies. For each anomaly, we independently sort stocks into groups based on a particular stock characteristic and based on one of the short-term trading proxies. The first anomaly considered is momentum, which involves sorting stocks based on their returns over the past 6 months (see Jegadeesh and Titman, 1993). We present strong evidence that the momentum profits increase with decreasing Stock Duration and are insignificant for the highest Stock Duration group. For example, the equal-weighted long–short momentum returns, using the three-factor (Fama–French) model and a 6-month holding period, are a significant 0.59% per month (with a t-statistic of 2.34) higher for stocks in the lowest duration group compared to stocks in the top duration group. Conditioning on low Stock Duration thus significantly strengthens momentum. This association between momentum and Stock Duration is naturally related to the well-known relation between momentum and volume (Lee and Swaminathan, 2000), but it is robust to controlling for stock turnover, that is, using Residual Stock Duration, which is orthogonalized with respect to turnover. We likewise find that momentum returns are stronger for stocks that are more heavily traded, or owned by institutions that trade more, or are held more by transient institutions.

We next consider return reversals, which are closely connected to the momentum anomaly. Jegadeesh and Titman (2001) show that the returns of a long–short momentum portfolio are negative in the post-holding period. We find that momentum return reversal is limited to stocks held primarily by short-term investors. For example, the difference in the return reversal three-factor alpha between stocks in the lowest versus the highest Stock Duration quintile is highly significant at 0.24% per month (*t*-statistic of 1.94).

Finally, we consider the share issuance anomaly or the long-run abnormal returns following corporate events like seasoned equity offerings, share repurchase announcements, and stock mergers (see, e.g., Loughran and Ritter, 1995; Ikenberry, Lakonishok, and Vermaelen, 1995; Loughran and Vijh, 1997; Daniel and Titman, 2006; Pontiff and Woodgate, 2008). This anomaly is positively related to short-term trading as well. For example, the difference in the long–short share issuance four-factor alpha (i.e., buying stocks with high share issuance and selling stocks with low share issuance) between stocks in the lowest versus highest Stock Duration equals 0.45% per month with a *t*-statistic of 2.61.

Our results are hard to reconcile with efficient markets. Rather, our results seem more likely to be explained by a behavioral interpretation. In particular, we test the ability of the DHS theory to explain the anomalies by focusing on the recent investment performance of the institutional investors holding the stock. Both DHS (1998) and Gervais and Odean (2001) argue that successful performance could lead to increased trader overconfidence due to a self-attribution bias, that is, if traders are more likely to take credit for good performance while blaming poor performance on other forces outside of their control.

DHS' theory thus predicts that successful short-term investors are particularly strongly related to anomalies such as momentum, reversal, and share issuance. The alternative "smart traders" hypothesis would predict the opposite: if short-term institutional investors are generally smart, then successful short-term institutions are especially likely to have skill and to drive out any temporary pricing inefficiencies. Empirically, we find that all three anomalies are stronger for stocks held by short-term investors with superior past abnormal performance than for stocks held by similarly short-term investors but with relatively poor past abnormal performance. We thus conclude that the DHS theory seems consistent with our results.

Our results also shed light on two recent theory papers linking the efficiency of markets and investment horizons. Our findings are consistent with the predictions of Albagli (2012) that longer investor horizon leads to more price informativeness and higher market efficiency. The main mechanism is that long-term investors are more likely to be informed. Suominen and Rinne (2012) on the other hand predict that longer horizons mean that investors are less frequently present in the market, leading to less efficient pricing. These predictions are not consistent with our findings as we find that the stock return anomalies are stronger for stocks with more short-term investors.

We find that our results for the momentum and reversal anomalies are strongest in the subsample of stocks that may be harder to short. That may explain why it is hard for other investors to quickly come in and bring prices back to fundamentals, such that the anomalies have persisted.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

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