Short-term Momentum

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We document a striking pattern in U.S. and international stock returns: double sorting on the previous month's return and share turnover reveals significant short-term reversal among low-turnover stocks, whereas high-turnover stocks exhibit *short-term momentum*. Short-term momentum is as profitable and as persistent as conventional price momentum. It survives transaction costs and is strongest among the largest, most liquid, and most extensively covered stocks. Our results are difficult to reconcile with models imposing strict rationality but are suggestive of an explanation based on some traders underappreciating the information conveyed by prices. (*JEL* G12, G14)

A key stylized fact in the asset pricing literature is that stock returns exhibit reversal at short horizons of 1 month (Jegadeesh 1990) but continuation—or *momentum*—at longer horizons between 2 and 12 months (Jegadeesh and Titman 1993, 2001). In this paper, we show that reversal and momentum *coexist* with striking magnitudes at the 1-month horizon. While the previous month's thinly traded stocks exhibit a strong short-term reversal effect, the previous month's heavily traded stocks exhibit an almost equally strong continuation effect, which we

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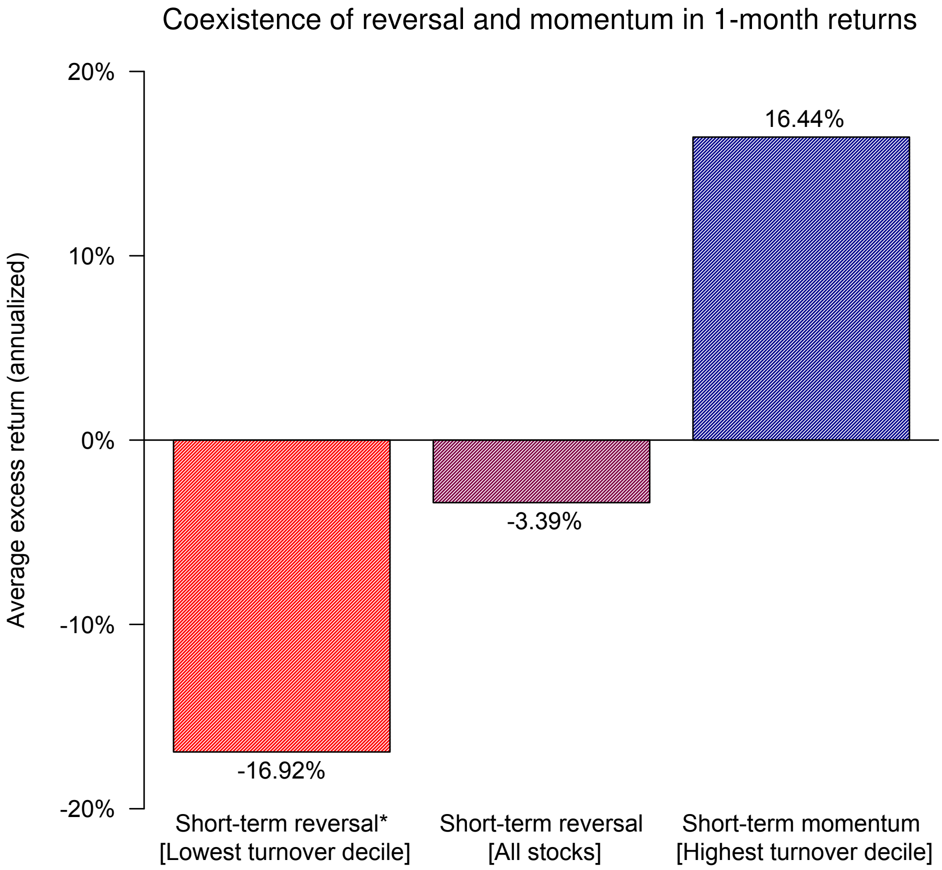

Figure 1
Coexistence of reversal and momentum in 1-month returns
This figure shows the average excess returns to three long-short strategies that buy the previous month's winners and short the losers among U.S. stocks. The conventional short-term reversal strategy (Jegadeesh, 1990) is from a univariate decile sort on the previous month's return using NYSE breakpoints. The *short-term reversal** and *short-term momentum* strategies trade the corner portfolios from double decile sorts on the previous month's return and the previous month's share turnover using NYSE breakpoints; short-term reversal* trades only in the lowest-turnover decile while short-term momentum trades only in the highest-turnover decile. The portfolios underlying all three strategies are value weighted and rebalanced at the end of each month. The performance of the portfolios underlying the short-term reversal* and short-term momentum strategies is provided in Table 1. The sample is all common nonfinancial shares on the NYSE, AMEX, and NASDAQ exchanges and covers July 1963 to December 2018.

dub *short-term momentum*. Figure 1 illustrates our main results for the United States.

To obtain our main results, we double decile sort stocks on the previous month's return and the previous month's share turnover using NYSE breakpoints and form value-weighted portfolios. We find, first, significant short-term reversal among stocks with *low* share turnover. The *short-term reversal** strategy, which buys the previous month's winners and shorts the losers within the lowest turnover decile, generates a negative and significant average return of -16.9% per annum (Figure 1, left bar). Second, our key finding is that short-term reversal is reversed among stocks with *high* share turnover. The short-term momentum strategy, which buys the previous month's winners and shorts the losers within the highest turnover decile, generates a positive and significant average return of +16.4% per annum (Figure 1, right bar). We show that both strategies generate significant abnormal returns relative to the standard factor models currently applied in the literature. We also show that short-term momentum persists for 12 months and is strongest among the largest and most liquid stocks. Finally, we show that our main findings extend to 22 developed markets outside the United States.

We provide additional results and robustness tests that shed light on the economic drivers of our findings. First, skipping the last few days of the formation month implies stronger short-term momentum (on average 22.0% per annum) because this mitigates end-of-month liquidity trading (Etula, Rinne, Suominen, and Vaittinen 2020). Second, short-term momentum survives conservative estimates of transaction costs (Novy-Marx and Velikov 2015). Third, while short-term momentum is naturally related to conventional price- and earnings-momentum strategies, its correlations with such strategies are moderate and do not appear to fully capture its average return, at least when judged by spanning tests. Fourth, short-term momentum does not appear to be driven by momentum in industry returns (Moskowitz and Grinblatt 1999) or by momentum in factor returns (Ehsani and Linnainmaa 2020). Fifth, it is not a result of any correlation between share turnover and size, liquidity, or volatility. Lastly, it exhibits far less crash risk than does conventional price momentum (Daniel and Moskowitz 2016).

Short-term momentum is difficult to reconcile with rational expectations equilibrium (REE) models of the volume-return relation. In Campbell, Grossman, and Wang (1993), noninformational trading due to liquidity demand causes temporary price pressure when absorbed by liquidity suppliers. As a result, returns coupled with high volume will subsequently reverse. This runs opposite to short-term momentum. In Wang (1994) and Llorente et al. (2002), informed trading due to private information causes persistent price movements that counteract temporary price pressure. Hence, among stocks with a high degree of information asymmetry, returns coupled with high volume will reverse less and may even continue. This would be an explanation for short-term momentum *if* it were driven by high-information-asymmetry stocks. However, while Wang (1994) and Llorente et al. (2002) argue that such stocks should be small, illiquid, and have low analyst coverage, short-term momentum is *strongest* among the largest, most liquid, and most extensively covered stocks.[1]

[1] Wang (1994) argues that contemporaneous evidence "is consistent with our model if we assume that there is more information asymmetry in the market for small-size firms than for large-size firms" (p. 151). Llorente et al. (2002) proxy for higher information asymmetry using smaller size, lower liquidity, and lower analyst coverage.

The literature on “boundedly rational” traders suggests an alternative mechanism that potentially explains short-term momentum: underinference from prices. When some traders fail to fully infer others’ information from prices, expected volume is higher and prices underreact to the available information relative to the case with solely rational traders. Underreaction in turn causes persistent price movements that counteract temporary price pressure.[2] Hence, an explanation based on bounded rationality suggests that short-term momentum should be stronger among stocks where any underinference from prices is not overwhelmed by noninformational trading. The cross-sectional variation in short-term momentum is suggestive of such an explanation: It is strongest among the largest and most liquid stocks, whose returns tend to be less affected by temporary price pressure (Avramov, Chordia, and Goyal 2006; Nagel 2012; Hendershott and Menkveld 2014), and it is also stronger among stocks with greater dispersion in analysts’ forecasts, a common proxy for disagreement among traders (Diether, Malloy, and Scherbina 2002; Verardo 2009; Banerjee 2011).

Lastly, to assist in differentiating between fully and boundedly rational explanations, we investigate how volume affects the ability of realized returns to predict firms’ fundamentals. Intuitively, “fully rational” volume ultimately emanates from noninformational trading. By contrast, “boundedly rational” volume reflects both underreaction to the available information and any noninformational trading. Hence, higher volume should decrease the ability of realized returns to predict fundamentals if all traders are fully rational, but should increase it if underinference has a detectable effect. Empirically, we find in cross-sectional regressions that the interaction of 1-month returns and turnover predicts the following year’s growth in gross profits and earnings with a positive and significant slope coefficient.

Because our findings are at the 1-month horizon, they differ from those in the extant literature on the volume-return relation, which has primarily focused on the weekly horizon. Conrad, Hameed, and Niden (1994) find that, among NASDAQ stocks, higher growth in the number of transactions is associated with more reversal in weekly returns. In contrast, Cooper (1999) finds that, among the largest NYSE/AMEX stocks, higher growth in trading volume is associated with less reversal in weekly returns.[3] Despite their opposing findings, both papers find

[2] Models of boundedly rational traders have been invoked to explain why volume greatly exceeds what is expected under REE and why patterns in returns and volume are tightly linked (see, e.g., Hong and Stein 2007; French 2008). Underreaction is often invoked as the mechanism underlying return continuation in models that relax the strict rationality assumption (see, e.g., Fama 1998; Daniel and Hirshleifer 2015).

[3] In his explanation of the opposing findings, Cooper (1999) conjectures that “in the context of Wang’s (1994) model, it may be that in periods of large price movements, high volume

only limited evidence of continuation. We conjecture that this is because temporary price pressure dominates other effects at the weekly horizon. Indeed, Avramov, Chordia, and Goyal (2006) find that, controlling for illiquidity, higher turnover implies more reversal at the weekly horizon but less reversal at the monthly horizon. They do not, however, document monthly continuation among high-turnover stocks, as we do, nor do they study their findings in the context of momentum effects. Moreover, we find that the returns to *weekly* short-term momentum strategies are on average *negative* (in line with our price-pressure conjecture) but become more negative with illiquidity, which shows that our evidence against the high-information-asymmetry mechanism also holds at the weekly horizon. We contribute to this literature by documenting the *coexistence* of significant reversal and momentum effects in 1-month returns separated by the level of turnover.[4,5]

Our paper is also related to a recent literature that sheds new light on the economic sources of momentum. Goyal and Jegadeesh (2018) find that time-series momentum, once stripped of its implicit time-varying investment in the market, has little incremental power beyond cross-sectional momentum in pricing tests (see also Huang et al., 2020). In turn, Ehsani and Linnainmaa (2020) find that conventional price momentum as well as industry momentum are spanned by momentum in factor returns. Theoretically, Luo, Subrahmanyam, and Titman (2021) propose an explanation for momentum based on sequential learning with overconfidence and skepticism, that is, a form of bounded rationality. We contribute to this literature by reconciling the strands of the literature that document reversal at the 1-month horizon but momentum at the 12-2 months horizon. In particular, we show that momentum coexists

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for smaller (larger) stocks represents a higher percentage of liquidity (informed) traders, resulting in greater subsequent reversals (continuations)" (p. 921). This contrasts with Wang's (1994) argument that high-information-asymmetry stocks should be *smaller*, not larger (see our footnote 1). While our evidence in principle supports Cooper's conjecture, we will argue in Section 3 that it is for reasons outside of the Wang model.

[4] Our asset pricing tests employ value-weighted portfolios from sorts based on NYSE breakpoints as well as weighted least squares (WLS) cross-sectional regressions with market capitalization as the weight. Llorente et al. (2002) use stock-by-stock, full-sample regressions of daily returns on the previous day's return and its interaction with de-trended log-turnover in their tests. Based on ex post cross-sectional variation in the interaction coefficients, they argue that high-volume days are followed by return continuation among the smallest and most illiquid stocks. Since their horizon is daily and their findings are not based on investable portfolios, their tests are inherently different from ours. Furthermore, the fact that any such daily return continuation is limited to the smallest and most illiquid stocks raises questions about its economic significance.

[5] Asness (1995) finds stronger 1-month reversal among low-volume stocks but does not document continuation among high-volume ones. Lee and Swaminathan (2000) study how volume affects the relation between the value and momentum effects, but consider longer formation periods of at least 3 months. Gervais, Kaniel, and Mingelgrin (2001) find that stocks with unusually high volume outperform those with unusually low volume. Cespa, Gargano, Riddiough, and Sarno (2020) find stronger reversal in daily returns among low-volume currencies but do not find continuation among high-volume currencies.

with reversal at the 1-month horizon, albeit confined to the stocks with the highest trading activity. In addition, we provide guidance as to which broader class of models (fully vs. boundedly rational) that is most plausible as an explanation for short-term momentum.

1. Main Results

This section presents our main results. We first show that double sorting on the previous month's return and turnover reveals strong reversal among low-turnover stocks but almost equally strong momentum among high-turnover stocks. We then show that standard factors cannot account for either effect; that the returns to the short-term momentum strategy persist for 12 months after formation; and that short-term momentum is strongest among the largest stocks. Finally, we show that our main results also hold internationally.

1.1 Data and key variables

Our main sample is all NYSE/AMEX/NASDAQ stocks on both CRSP and Compustat. We keep only ordinary common shares (share codes 10 or 11). Following Fama and French (1993, 2015), we impose a six month lag between annual accounting data and subsequent returns to avoid look-ahead bias. Hence, if a firm's fiscal year ends in December of calendar year $t-1$, we assume that these data are publicly available at the end of June of calendar year t. Following Hou, Xue, and Zhang (2015, 2020), we exclude financial firms, although retaining these does not affect our results. Our main sample covers July 1963 to December 2018. We will later show that our main results extend back to 1926.

Our asset pricing tests relate 1-month returns to the previous month's return ($r_{1,0}$) and trading volume. A 1-month holding period is standard in the literature and the previous month's return is the signal underlying Jegadeesh's (1990) short-term reversal strategy. To be consistent, we use the same 1-month horizon when measuring trading volume. Following Lo and Wang (2000) and Avramov, Chordia, and Goyal (2006), we deflate the total volume of trades by the number of shares outstanding to obtain share turnover ($TO_{1,0}$). Following Gao and Ritter (2010), we adjust the trading volume of NASDAQ stocks prior to 2004 to ensure comparability with NYSE and AMEX stocks, although our results are the same with or without this adjustment.[6] We will later show that our findings are robust to using longer formation periods of up to 6 months, but that the 1-month formation period produces the strongest results.

[6] Prior to February 2001, we divide NASDAQ volume by 2.0. From February 2001 to December 2001, we divide by 1.8. From January 2002 to December 2003, we divide by 1.6. From January 2004 and onward, NASDAQ volume no longer differs from NYSE and AMEX volume, and we apply no adjustment.

Table 1
Double sorts on the previous month's return and turnover

	$r_{1,0}$ deciles										$r_{1,0}$ strategies		
	Low	2	3	4	5	6	7	8	9	High	$\mathbb{E}[r^e]$	α_{FF6}	α_q
$TO_{1,0}$ deciles													
	Portfolio excess return												
Low	1.28	1.23	0.99	0.85	0.70	0.80	0.59	0.74	0.26	−0.14	−1.41	−1.45	−1.43
											(−7.13)	(−6.19)	(−5.95)
2	1.54	1.22	0.98	0.99	1.05	0.98	0.70	0.69	0.57	0.35	−1.19	−1.31	−1.34
											(−4.61)	(−4.04)	(−4.21)
3	1.71	1.53	0.96	1.11	0.99	0.94	0.75	0.60	0.64	0.36	−1.34	−1.62	−1.66
											(−5.02)	(−5.61)	(−4.87)
4	1.51	1.35	1.43	0.98	1.10	1.07	0.81	0.83	0.64	0.65	−0.85	−1.02	−0.91
											(−3.63)	(−4.15)	(−2.92)
5	1.11	1.10	1.26	1.17	1.10	1.00	0.60	0.92	0.90	0.66	−0.45	−0.63	−0.51
											(−1.94)	(−2.29)	(−1.54)
6	1.26	1.38	1.40	1.14	1.00	1.14	1.12	1.19	0.78	0.67	−0.59	−0.60	−0.41
											(−2.50)	(−2.35)	(−1.20)
7	1.39	1.06	1.12	1.22	0.84	1.05	0.83	0.98	0.96	0.73	−0.67	−0.85	−0.96
											(−2.52)	(−2.55)	(−2.37)
8	0.92	1.17	1.25	0.99	1.12	1.02	1.02	0.85	0.82	1.15	0.23	0.13	0.21
											(0.85)	(0.47)	(0.60)
9	0.71	1.37	1.29	1.24	1.21	1.22	1.00	1.12	1.02	0.75	0.05	0.00	0.19
											(0.21)	(0.01)	(0.55)
High	0.00	0.83	1.14	1.08	1.03	0.78	1.01	1.16	0.99	1.36	1.37	1.37	1.65
											(4.74)	(4.22)	(4.47)
$TO_{1,0}$ strategies													
$\mathbb{E}[r^e]$	−1.28	−0.41	0.15	0.23	0.33	−0.01	0.42	0.42	0.73	1.50			
	(−5.04)	(−1.75)	(0.59)	(0.80)	(1.34)	(−0.05)	(1.58)	(1.54)	(2.76)	(5.46)			
α_{FF6}	−1.26	−0.31	0.18	0.17	0.29	−0.02	0.34	0.57	0.81	1.56			
	(−4.71)	(−1.33)	(0.79)	(0.73)	(1.32)	(−0.09)	(1.48)	(2.12)	(3.29)	(5.34)			
α_q	−1.39	−0.14	0.21	0.05	0.33	0.02	0.28	0.42	0.91	1.70			
	(−4.98)	(−0.57)	(0.82)	(0.18)	(1.39)	(0.07)	(1.17)	(1.41)	(3.15)	(5.07)			

This table shows portfolios double sorted on the previous month's return ($r_{1,0}$) and turnover ($TO_{1,0}$). We use conditional sorts into deciles based on NYSE breakpoints, first on $r_{1,0}$ and then on $TO_{1,0}$. Portfolios are value weighted and rebalanced at the end of each month. The table also shows the performance of long-short strategies across the deciles. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Time-series averages of the portfolios' characteristics are provided in Table A.1 in the appendix. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 to December 2018, except for the q-factors, which are available from January 1967.

1.2 Double sorts on the previous month's return and turnover

Table 1 shows the average excess returns to portfolios double sorted on the previous month's return ($r_{1,0}$) and turnover ($TO_{1,0}$). We use conditional decile sorts based on NYSE breakpoints, first on $r_{1,0}$ and then on $TO_{1,0}$ within $r_{1,0}$ deciles. Hence, we first separate winners from losers and then separate heavily traded stocks from thinly traded ones among winners and losers. Portfolios are value weighted and rebalanced at the end of each month. We use deciles to account for any nonlinearities and conditional sorts because independent ones give a few empty portfolios before July 1969.[7] The table also shows the performance of high-minus-low strategies within each decile. Abnormal returns are relative to Fama and French's (2015) five-factor model plus the momentum factor (FF6) and Hou, Xue, and Zhang's (2015) q-factor model. Test statistics are adjusted for heteroscedasticity and autocorrelation (Newey and West, 1987).

The double sorts reveal a striking pattern in 1-month returns. The strategy that buys the previous month's winners and shorts the losers within the *lowest* turnover decile yields -1.41% per month with $t = -7.13$, which is evidence of strong reversal in 1-month returns for low-turnover stocks. We label this effect "short-term reversal*" (STREV*) to distinguish it from the conventional short-term reversal effect. In stark contrast, the winner-minus-loser strategy within the *highest* turnover decile yields $+1.37\%$ per month with $t = 4.74$, which is evidence of strong *continuation* in 1-month returns for high-turnover stocks. Consequently, we label this effect "short-term momentum" (STMOM).[8] The abnormal returns of the STMOM and STREV* strategies are as large and as strong as the strategies' average returns. On average, the STMOM strategy generates all its profits on the long side.

The double sorts also reveal significant 1-month reversal in the bottom-seven turnover deciles, although the magnitude of the reversal effect generally weakens with turnover before switching signs and

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[7] The models of Campbell, Grossman, and Wang (1993), Wang (1994), and Llorente et al. (2002) suggest a nonlinear relation between expected and realized returns for a given level of volume. Conditional sorts allow us to use the full sample period, but Table A.2 in the appendix shows similar results for independent sorts starting from July 1969. Sorting first on returns and then on turnover produces the largest spreads in holding-period returns, but the results are similar for the reverse sorting order. The average cross-sectional rank correlation between 1-month returns and turnover is 9.99% ($t = 8.29$), so the interpretation of the double sorts is largely unaffected by the sorting order. Our use of conditional decile sorts based on NYSE breakpoints follows Fama and French (1992). Fama and French (2015, 2016) also use conditional sorts based on NYSE breakpoints in some of their tests and Ken French maintains several decile double sorts on his website.

[8] For comparison, the conventional STREV strategy (from a univariate decile sort on $r_{1,0}$) yields -0.28% with $t = -1.68$ over our sample; see also Hou, Xue, and Zhang (2015, 2020). The corresponding conventional momentum strategy (from a univariate decile sort on the prior 12-2 month returns) yields 1.21% per month with $t = 4.77$.

Table 2
Short-term momentum's factor exposures and abnormal returns

	Intercepts, slopes, and test statistics (in parentheses) from time-series regressions of the form $y_t = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t$							
	Short-term momentum [WML, high turnover]				Short-term reversal* [WML, low turnover]			
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.37	1.56	1.37	2.21	−1.41	−1.29	−1.45	−0.93
	(4.74)	(5.54)	(4.22)	(7.54)	(−7.13)	(−6.57)	(−6.19)	(−4.43)
MKT		−0.38	−0.35	−0.14		−0.25	−0.16	−0.01
		(−4.53)	(−3.97)	(−1.96)		(−3.67)	(−2.87)	(−0.17)
SMB			0.00	0.04			−0.30	−0.19
			(−0.03)	(0.44)			(−2.59)	(−2.40)
HML			0.03	0.08			0.00	0.11
			(0.12)	(0.45)			(−0.04)	(0.91)
RMW			−0.40	−0.34			−0.09	−0.14
			(−1.56)	(−2.80)			(−0.86)	(−1.29)
CMA			0.18	−0.20			0.05	0.02
			(0.66)	(−0.98)			(0.24)	(0.07)
MOM			0.33	0.05			0.30	0.13
			(1.89)	(0.54)			(4.05)	(2.80)
STREV				−1.51				−0.97
				(−14.38)				(−11.11)
LTREV				0.34				−0.16
				(2.68)				(−1.12)
PSLIQ				0.08				−0.06
				(0.97)				(−0.99)
Adj. R^2		3.8%	6.8%	34.0%		3.6%	9.8%	35.1%

This table shows time-series regressions for the short-term momentum (STMOM) and short-term reversal* (STREV*) strategies from Table 1. The explanatory variables are the factors from Fama and French's (2015) five-factor model in addition to the momentum factor (MOM), the two reversal factors (STREV and LTREV), and the traded liquidity factor (PSLIQ). Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are at the monthly frequency and cover July 1963 to December 2018, except for specifications employing PSLIQ, which is available from January 1968.

becoming significantly positive in the highest turnover decile. Hence, momentum coexists with reversal at the 1-month horizon, although it is confined to the highest turnover decile in these benchmark results. Nonetheless, we will later show that the stocks that tend to exhibit short-term momentum are among the largest and most liquid, which emphasizes the economic importance of the effect. In addition, we will show that skipping the end of the formation month implies not only stronger short-term momentum but also significant continuation in the ninth turnover decile. As a result, (independent) quintile double sorts are in fact sufficient to document short-term momentum when skipping the end of the formation month. Lastly, we will show that the results of Table 1 are not limited to the United States but extend to 22 international developed markets.

1.3 Factor exposures and abnormal returns

Table 2 shows spanning tests for the STMOM and STREV* strategies. The explanatory variables are the FF6 factors as well as the conventional 1-month short-term reversal factor (STREV); the 60-13 month long-term reversal factor (LTREV; see De Bondt and Thaler, 1985); and Pástor and Stambaugh's (2003) traded liquidity factor (PSLIQ).

The STMOM strategy has a significantly negative market loading and a marginally significant, positive loading on the conventional momentum factor. It does not load significantly on the remaining FF6 factors. Controlling for the conventional reversal factors increases STMOM's abnormal return to 2.21% per month with $t = 7.54$. The STREV* strategy has only modest loadings on the FF6 factors, and controlling for the conventional reversal factors does not fully capture its average return. Neither strategy loads significantly on PSLIQ.[9]

1.4 Persistence and historical performance

Panel A of Figure 2 shows the average cumulative sums of post-formation returns to the STMOM and STREV* strategies along with 95% confidence bands. The average cumulative performance of STREV* is indistinguishable from zero just 3 months after formation. The short-lived nature of the average returns to STREV* suggest it is capturing the easing of strong but temporary price pressure among low-turnover stocks. In contrast, there is a much stronger drift in the average returns to STMOM, which on average persist for 12 months after formation. This is similar to conventional momentum strategies (see, e.g., Jegadeesh and Titman, 2001) and suggests that STMOM is capturing strong and persistent price movements among high-turnover stocks. In practical terms, it means that traders can build up positions in STMOM relatively slowly and reduce trading costs by rebalancing less frequently.

Panel B shows a time-series plot of cumulative sums of excess returns to the two strategies. STREV* returns are remarkably consistent until 2011, but have slightly tapered off more recently. We suspect that generally increasing market liquidity is responsible for this trend. STMOM earned low returns during 1975-79, but has otherwise delivered consistently positive returns with no other subsample significantly affecting its performance.

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[9] The STMOM strategy is not within the univariate span of the MOM factor (abnormal return of 1.13% with $t = 3.36$). The converse is also true. The STREV* strategy is not within the univariate span of the standard STREV factor (abnormal return of -0.91% with $t = -4.78$), but the standard STREV factor is, in fact, within the univariate span of the STREV* strategy (abnormal return of 0.03% with $t = 0.31$).

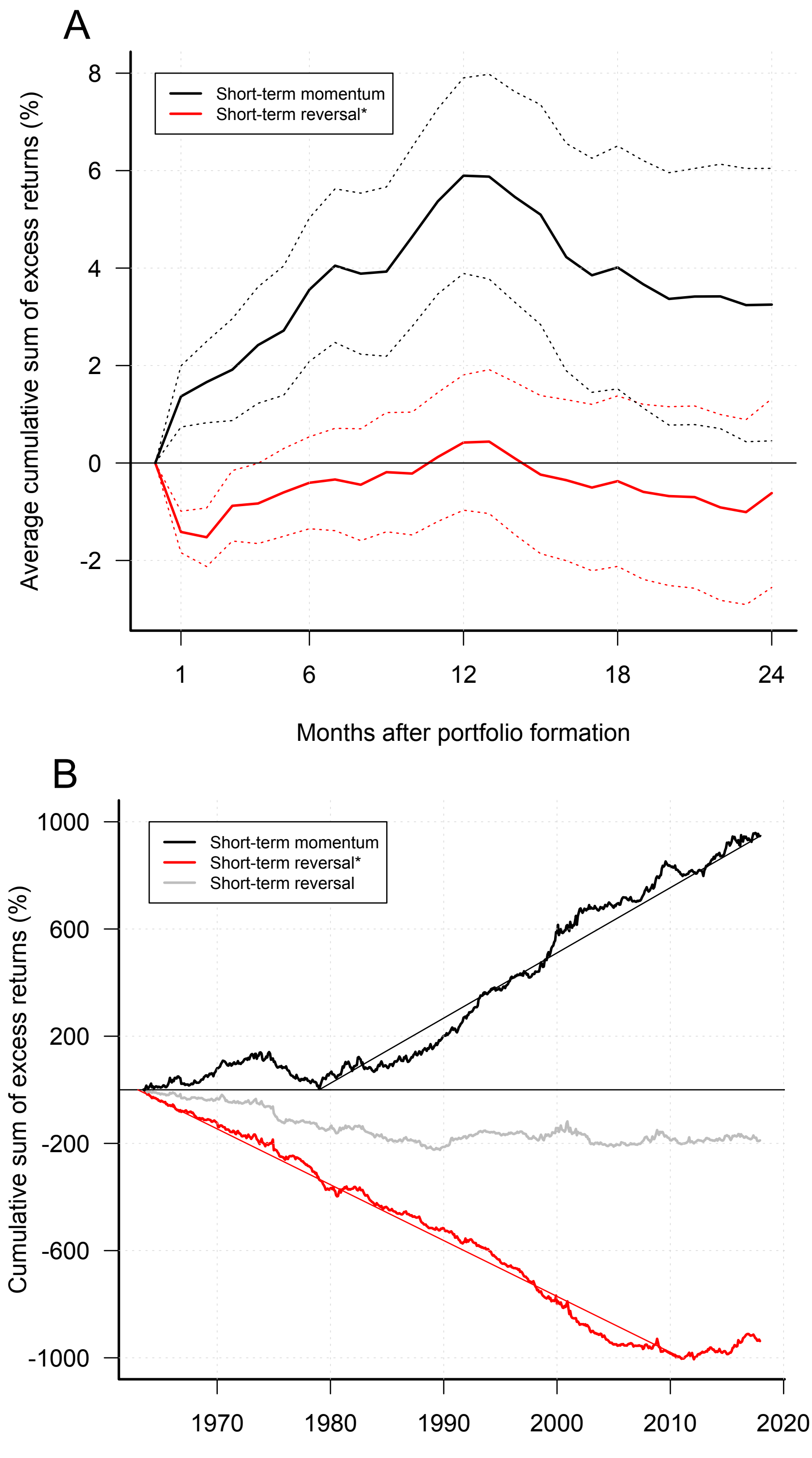

Figure 2
Short-term momentum's persistence and historical performance Panel A shows the average cumulative sums of post-formation excess returns to each of the short-term momentum and short-term reversal* strategies along with 95% confidence bands. Panel B shows a time-series plot of cumulative sums of excess returns to the two strategies as well as a conventional short-term reversal strategy. Data are at the monthly frequency and cover July 1963 to December 2018.

1.5 Short-term momentum and size

Table 3 shows the performance of size-conditional STMOM and STREV* strategies. In panel A, we use $2 \times 3 \times 3$ conditional sorts on

Table 3
Short-term momentum controlling for size

	Short-term momentum [WML, high turnover] controlling for size			Short-term reversal* [WML, low turnover] controlling for size		
Size group	$\mathbb{E}[r^e]$	α_{FF6}	α_q	$\mathbb{E}[r^e]$	α_{FF6}	α_q
A. Size breakpoint is NYSE median						
Small-cap	0.20	0.03	0.06	−1.41	−1.51	−1.53
	(0.89)	(0.12)	(0.17)	(−9.03)	(−7.59)	(−7.33)
Large-cap	0.62	0.52	0.64	−0.84	−0.92	−0.83
	(3.01)	(2.25)	(2.12)	(−5.45)	(−6.38)	(−5.00)
B. Size breakpoints are NYSE quintiles						
Microcap	−0.34	−0.49	−0.53	−2.04	−2.17	−2.17
	(−1.21)	(−1.35)	(−1.26)	(−10.28)	(−9.97)	(−8.56)
2	0.20	0.07	0.03	−1.19	−1.20	−1.26
	(0.77)	(0.26)	(0.07)	(−7.12)	(−7.01)	(−7.03)
3	0.40	0.29	0.44	−1.20	−1.28	−1.19
	(1.66)	(1.09)	(1.33)	(−6.93)	(−5.97)	(−5.32)
4	0.34	0.27	0.38	−1.23	−1.15	−1.01
	(1.40)	(1.08)	(1.22)	(−7.80)	(−6.71)	(−5.09)
Megacap	0.53	0.43	0.48	−0.74	−0.80	−0.72
	(2.53)	(2.21)	(2.01)	(−4.27)	(−4.77)	(−3.82)
C. 500 largest stocks						
Largest 500	0.42	0.43	0.41	−0.02	0.02	−0.02
	(4.91)	(4.99)	(4.19)	(−0.19)	(0.18)	(−0.10)

This table shows the performance of short-term momentum (STMOM) and short-term reversal* (STREV*) strategies constructed with a control for size (market capitalization). In panels A and B, the strategies are from $N \times 3 \times 3$ conditional sorts on size and the previous month's return and turnover, in that order, where the breakpoints for returns and turnover are the 20th and 80th percentiles for NYSE stocks. In panel A, $N = 2$ and the size breakpoint is the NYSE median; in panel B, $N = 5$ and the size breakpoints are NYSE quintiles. In panel C, the strategies are from 2×2 independent sorts on returns and turnover among the 500 largest stocks by monthly market capitalization, where the breakpoints for returns and turnover are the 250th rank. All portfolios are value weighted and rebalanced at the end of each month. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 to December 2018, except when applying the q-factors, which are available from January 1967.

the previous month's size (market capitalization), return, and turnover, in that order. The breakpoint for size is the median for NYSE stocks, while the breakpoints for returns and turnover are the 20th and 80th percentiles for NYSE stocks. Portfolios are value weighted and rebalanced at the end of each month. STREV* yields −0.84% per month among large-caps ($t = -5.45$) but a considerably larger −1.41% per month among small-caps ($t = -9.03$). STMOM, on the other hand, yields a significant 0.62% per month among large-caps ($t = 3.01$) but an insignificant 20 basis points per month among small-caps. The strategies' abnormal returns tell a similar story.

In panel B, we use a finer size sort according to NYSE quintiles but maintain the breakpoints for returns and turnover as in panel A. STREV* yields an extremely large −2.04% per month among microcaps ($t = -10.28$) but a comparably much smaller −0.74% per month among megacaps ($t = -4.27$). In contrast, the average return to STMOM is almost monotonically increasing with size: −0.34% per month among microcaps ($t = -1.21$), around 0.30% per month for the intermediate quintiles (t-statistics between 0.77 and 1.66), and a statistically and economically significant 0.53% per month with $t = 2.53$ among megacaps.

Lastly, we consider the strategies' performance when constructed exclusively from the 500 largest stocks by monthly market capitalization. At the end of each month, we rank these stocks on the previous month's return and form two portfolios using the 250th rank as the breakpoint. Independently, we use the same procedure to form two portfolios based on the previous month's share turnover. The intersection produces four portfolios, which are value weighted and rebalanced at the end of each month. Panel C shows that the largest-500 STMOM strategy yields 0.42% per month with $t = 4.91$, along with equally large and strong abnormal returns. The largest-500 STREV* strategy, however, yields just −2 basis points per month.[10]

Table 3 shows that the lion's share of STREV* returns come from microcaps. This is not surprising, since short-term reversal is often attributed to temporary price pressure (as a result of liquidity demand or other microstructure issues), which tend to have a greater impact on the returns of smaller stocks (Avramov, Chordia, and Goyal 2006; Nagel 2012; Hendershott and Menkveld 2014). By the same logic, it is not surprising that STMOM derives the majority of its performance from megacaps, whose returns tend to be much less affected by temporary price pressure.[11]

However, we stress that our results are *not* mechanically driven by any correlation between turnover and size. While the two are positively correlated in the cross section (average cross-sectional rank correlation of 28.8% with $t = 4.43$), Table IA.2 in the Internet Appendix shows that using turnover orthogonal to size does not affect our main results from Table 1 and that replacing turnover with size does not lead to any

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[10] The largest-500 STMOM strategy trades in an average of 129 and 121 stocks on its long and short sides with average market capitalizations of \$14.0 billion and \$13.7 billion. In December 2018 (the end of our sample), the top-five holdings on the long side were Alphabet, Exxon, Walmart, AT&T, and Home Depot, while the top-five holdings on the short side were Microsoft, Johnson & Johnson, Pfizer, Verizon, and Procter & Gamble.

[11] Hendershott and Menkveld (2014), for instance, study price pressure across NYSE size quintiles and find that "[p]rice pressure for the quintile of largest stocks is 17 basis points with a half life of 0.54 days. For the smallest-stocks quintile, it is 118 basis points with a half life of 2.11 days. These price pressures are roughly the size of the (effective) bid-ask spread" (p. 406).

continuation. We will later show that our results are also not driven by any correlation between turnover and each of liquidity and volatility.

As we will discuss in Section 3, the results of Table 3 are at odds with the "high-information-asymmetry" mechanism in the models of Wang (1994) and Llorente et al. (2002), which counterfactually predicts stronger STMOM performance among smaller stocks. In practical terms, the results of Table 3 mean that STMOM is considerably cheaper to implement and more scalable than is STREV*. In Section 2.2, we will study the performance of the large-caps and megacaps STMOM strategies net of transaction costs and with an implementation lag.

1.6 Cross-sectional regressions

Tables 1–3 illustrate our main results using strategies from corner portfolios. Here, we use regressions to show that similar results hold more broadly in the cross section.

Table 4 shows the average slopes from Fama and MacBeth (1973) cross-sectional regressions of monthly returns on the previous month's return, turnover, and their interaction ($r_{1,0} \times TO_{1,0}$). As such, these regressions mimic the approximate functional form of the theoretical volume-return relation in the models of Campbell, Grossman, and Wang (1993), Wang (1994), and Llorente et al. (2002). We control for prior 12-2 months return ($r_{12,2}$), book-to-market ($\log(B/M)$), *Size* (log of market capitalization as of prior June), cash-based operating profitability (COP/A_{-1}), and asset growth (dA/A_{-1}). Independent variables are trimmed at the 1st and 99th percentiles, then standardized by their cross-sectional average and standard deviation. The interaction is the product of the standardized variables. We show results for all stocks as well as separately within NYSE size quintiles (Fama and French 2010) and we estimate the regressions using weighted least squares (WLS) with market capitalization as the weight (Hou, Xue, and Zhang 2020).[12]

[12] Following Fama and French (2015), we define book equity, B, as shareholder's equity plus deferred taxes minus preferred stock. In the definition of B, shareholder's equity is SEQ. If SEQ is missing, we substitute it by common equity (CEQ) plus preferred stock (defined below), or else by total assets minus total liabilities (AT − LT). Deferred taxes is deferred taxes and investment tax credits (TXDITC) or else deferred taxes and/or investment tax credit (TXDB and/or ITCB). Finally, preferred stock is redemption value (PSTKR) or else liquidating value (PSTKL) or else carrying value (PSTK). B/M is book equity divided by market capitalization (CRSP's PRC times SHROUT) as of prior December, where the lagging is to avoid taking unintentional positions in conventional momentum. dA/A_{-1} is the year-over-year change in total assets divided by 1-year-lagged total assets. Following Ball et al. (2016), COP is total revenue (REVT) minus cost of goods sold (COGS), minus selling, general, and administrative expenses (XSGA), plus R&D expenditures (XRD, zero if missing), minus the change in accounts receivable (RECT), minus the change in inventory (INVT), minus the change in prepaid expenses (XPP), plus the change in deferred revenue (DRC + DRLT), plus the change in trade accounts payable (AP), plus the change in accrued expenses (XACC). All changes are annual, and missing changes are set to zero.

Table 4
Cross-sectional regressions to predict returns

	Average slopes (×100) and test statistics (in parentheses) from monthly WLS regressions of the form $r_{it} = \boldsymbol{\beta}_t' \mathbf{X}_{it} + \epsilon_{it}$											
	All		Microcaps		Size quintile 2		Size quintile 3		Size quintile 4		Megacaps	
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$r_{1,0}$	−0.32	−0.59	−0.50	−0.63	−0.42	−0.62	−0.46	−0.65	−0.47	−0.73	−0.25	−0.52
	(−4.16)	(−8.05)	(−6.76)	(−8.21)	(−5.62)	(−8.29)	(−5.88)	(−8.82)	(−5.15)	(−7.28)	(−2.36)	(−5.08)
$TO_{1,0}$	0.06	−0.05	0.10	0.10	−0.02	−0.01	−0.01	−0.01	0.06	0.02	0.09	0.01
	(0.64)	(−0.82)	(1.39)	(1.31)	(−0.33)	(−0.17)	(−0.13)	(−0.21)	(0.91)	(0.25)	(0.67)	(0.12)
$r_{1,0} \times TO_{1,0}$	0.19	0.29	0.20	0.19	0.16	0.18	0.18	0.23	0.26	0.33	0.35	0.57
	(5.45)	(9.06)	(6.21)	(6.04)	(5.23)	(5.06)	(5.66)	(5.17)	(5.10)	(5.26)	(4.01)	(5.74)
$r_{12,2}$		0.36		0.39		0.35		0.48		0.41		0.28
		(3.24)		(6.28)		(3.88)		(4.57)		(3.50)		(2.17)
$\log(B/M)$		0.21		0.30		0.21		0.24		0.17		0.18
		(3.06)		(4.22)		(2.71)		(2.97)		(2.12)		(2.24)
Size		−0.09		−0.27		−0.32		0.07		0.30		−0.02
		(−1.30)		(−2.17)		(−1.91)		(0.29)		(1.64)		(−0.20)
COP/A_{-1}		0.35		0.33		0.29		0.31		0.33		0.31
		(5.17)		(7.63)		(4.26)		(4.12)		(2.87)		(3.65)
dA/A_{-1}		−0.20		−0.24		−0.25		−0.28		−0.22		−0.14
		(−3.57)		(−6.58)		(−4.29)		(−3.97)		(−2.15)		(−1.24)
Adj. R^2	4.8%	12.7%	1.9%	4.3%	2.4%	5.6%	3.5%	7.0%	3.9%	8.6%	6.9%	16.5%

This table shows Fama and MacBeth (1973) cross-sectional regressions of monthly returns on the previous month's return ($r_{1,0}$), the previous month's turnover ($TO_{1,0}$), and their interaction ($r_{1,0} \times TO_{1,0}$). Regressions are estimated using weighted least squares (WLS) with market capitalization as the weight. Independent variables are trimmed at the 1st and 99th percentiles and then standardized by their cross-sectional average and standard deviation. The interaction is the product of the standardized variables. The controls are prior 12-2 month performance ($r_{12,2}$), cash-based operating profits-to-lagged assets (COP/A_{-1}), asset growth (dA/A_{-1}), book-to-market equity ($\log(B/M)$, where M is market equity as of prior December), and *Size* (log of market capitalization as of prior June). Specifications 1 and 2 are for all stocks, while the remaining specifications are within NYSE size quintiles. Test statistics are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms and firms with negative book equity. Data are at the monthly frequency and cover July 1963 to December 2018.

The all-stock regressions show that $r_{1,0}$ predicts the cross section of monthly returns with a negative and significant slope (t-statistic of -4.16 without controls and -8.05 with controls). They also show that $r_{1,0} \times TO_{1,0}$ has roughly the same predictive power as $r_{1,0}$ itself, albeit with a *positive* slope (t-statistics of 5.45 and 9.06). Similar results hold within each size quintile, although the slope on $r_{1,0}$ generally decreases in magnitude with size while that on $r_{1,0} \times TO_{1,0}$ tends to increase with size. This suggests that low-turnover reversal becomes weaker with size and, conversely, that high-turnover continuation becomes stronger with size, consistent with the size-conditional strategy performance in Table 3. Taken literally, the regressions suggest that 1-month returns are positively autocorrelated when turnover is $0.50/0.20 = 2.5$ standard deviations above average among microcaps, but that $0.25/0.35 = 0.7$ standard deviations are enough for the same relation among megacaps.

We caution, however, against reading too much into the magnitudes of the slope estimates or taking the parametric relations literally. Cross-sectional regressions are useful for studying return predictability in a multivariate setting but, unlike portfolio sorts, they impose a potentially misspecified functional form and are sensitive to outliers (Fama and French, 2010). Furthermore, the R^2 values in Table 4 imply that over 80% of the variation in monthly returns is not captured by the parametric relations. A more careful interpretation (cf. Fama, 1976) is that each slope is the average return to a long-short strategy that trades on a unit spread in the part of the variation in the independent variable that is orthogonal to all other independent variables. Under that interpretation, each t-statistic is proportional to the Sharpe ratio of the implied long-short strategy. The regressions in Table 4 thus show that the long-short strategy that trades on orthogonal variation in $r_{1,0} \times TO_{1,0}$ generates a positive Sharpe ratio that is roughly equal in magnitude to the negative Sharpe ratio on the strategy that trades on orthogonal variation in $r_{1,0}$.[13]

1.7 International evidence

We conclude this section with out-of-sample evidence using international stock market data. The sample is from the Compustat Global Securities database and comprises the 22 developed markets considered by Fama and French (2017).[14]

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[13] This interpretation is applicable here because the interaction is far from perfectly correlated with the straight variables: if we let $z(\cdot)$ denote standardization, then the average cross-sectional rank correlation between $z(r_{1,0}) \times z(TO_{1,0})$ and each of $z(r_{1,0})$ and $z(TO_{1,0})$ is -17.34% ($t = -35.22$) and -4.00% ($t = -12.10$), respectively.

[14] The countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Great Britain (the United Kingdom), Greece, Hong Kong, Italy, Ireland, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, and Switzerland.

Table 5
Double sorts on 1-month returns and turnover: International evidence

	$r_{1,0}$ deciles										$r_{1,0}$ strategies	
	Low	2	3	4	5	6	7	8	9	High	$\mathbb{E}[r^e]$	α_{DMFF6}
$TO_{1,0}$ deciles												
	Portfolio excess return											
Low	1.28	0.57	0.42	−0.14	0.21	−0.43	−0.27	−0.55	−1.06	−1.97	−3.25	−3.06
											(−6.36)	(−5.83)
2	1.66	0.69	0.25	0.21	0.17	0.09	0.11	0.02	−0.40	−0.88	−2.53	−2.09
											(−4.63)	(−2.90)
3	1.02	0.59	0.39	0.24	0.29	0.06	−0.31	−0.03	−0.57	−1.37	−2.40	−2.09
											(−5.16)	(−4.50)
4	0.63	0.87	0.44	0.30	0.39	0.41	0.20	−0.10	−0.18	−0.52	−1.14	−0.74
											(−2.73)	(−1.71)
5	1.27	0.75	0.31	0.37	0.27	0.43	0.60	0.33	0.31	−0.54	−1.81	−1.47
											(−4.13)	(−2.24)
6	0.46	0.62	0.38	0.47	0.61	0.27	0.46	0.32	−0.20	−0.15	−0.61	−0.10
											(−1.58)	(−0.22)
7	0.91	0.62	0.04	0.51	−0.11	0.42	0.39	0.20	0.21	0.08	−0.83	−0.93
											(−2.01)	(−1.65)
8	0.38	0.46	0.24	0.33	0.33	0.25	0.25	0.81	0.40	0.37	−0.01	−0.04
											(−0.03)	(−0.08)
9	−0.06	0.16	0.38	0.36	−0.27	0.52	0.26	0.63	0.38	0.26	0.32	0.46
											(1.13)	(1.41)
High	−1.03	−1.30	−0.63	−0.21	−1.04	−0.11	−0.22	−0.24	0.10	0.36	1.39	1.36
											(3.65)	(3.45)
$TO_{1,0}$ strategies												
$\mathbb{E}[r^e]$	−2.30	−1.87	−1.05	−0.07	−1.25	0.32	0.05	0.31	1.16	2.33		
	(−4.74)	(−4.69)	(−2.08)	(−0.14)	(−3.17)	(0.76)	(0.10)	(0.64)	(2.08)	(3.77)		
α_{DMFF6}	−2.75	−2.11	−1.42	−0.43	−1.52	0.07	−0.43	−0.09	0.78	1.67		
	(−5.97)	(−4.82)	(−2.74)	(−0.92)	(−3.25)	(0.18)	(−0.94)	(−0.19)	(1.38)	(2.85)		

This table shows international portfolios from double sorts on the previous month's return ($r_{1,0}$) and turnover ($TO_{1,0}$). We use independent double sorts to form country-specific portfolios that are value weighted and rebalanced at the end of each month. We then weight each country's portfolio by the country's total market capitalization for the previous month to form each international portfolio. All returns and market values are in U.S. dollars and excess returns are above the monthly U.S. Treasury-bill rate. The table also shows the raw and risk-adjusted returns to long-short strategies within the deciles, where risk-adjustment is relative to Fama and French's (2017) developed markets five-factor model including the momentum factor (DMFF6). Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are at the monthly frequency and cover January 1993 to December 2018.

Table 5 shows international portfolios double sorted on the previous month's return and share turnover. Following Asness, Frazzini, and Pedersen (2019), we use independent double sorts to form country-specific portfolios that are value weighted and rebalanced at the end of each month, and then weight each country's portfolio by the country's total market capitalization for the most recent month to form each international portfolio. We consider only common shares and compute all returns and market values in U.S. dollars. The sample period is January 1993 to December 2018.

The international STREV* strategy yields an extremely large −3.25% per month ($t = -6.36$). This is over twice as large as its U.S. counterpart, presumably because of the on average less liquid markets outside the United States. For comparison, the international counterpart of the conventional STREV strategy yields −0.37% per month with $t = -1.29$ (untabulated). Despite this extreme reversal among low-turnover stocks, high-turnover stocks still exhibit strong short-term momentum, as the international STMOM strategy yields 1.39% per month with $t = 3.65$, which is comparable to its U.S. counterpart. The strategies' abnormal returns relative to Fama and French's (2017) developed markets six-factor model are about as large and strong as the average returns. Figure IA.1 in the Internet Appendix shows that the returns to the international STMOM strategy persist for 24 months after formation, while those to the international STREV* strategy stagnate after 3 months.

Figure 3 shows the annualized Sharpe ratios of the country-specific STMOM and STREV* strategies. The STMOM strategy yields positive average returns in all 22 markets. The STREV* strategy yields negative average returns in all countries but the United Kingdom.

Lastly, Table IA.3 in the Internet Appendix shows that our results on the size-conditional performance of the STMOM and STREV* strategies for the United States (Table 3) carry over to the international sample. The average return to the international STMOM strategy is almost monotonically increasing across size quintiles: −0.23% per month in the quintile with the smallest stocks ($t = -0.36$), around 0.65% in the intermediate size quintiles (t-statistics between 1.16 and 1.90), and 1.12% per month with $t = 4.01$ in the quintile with the largest stocks. Moreover, a value-weighted STMOM strategy based on the largest 100 stocks in each country yields 0.62% per month with $t = 3.25$.[15]

[15] The long and short sides of the international largest-100-per-country STMOM strategy trade in an average of 499 and 470 stocks. In December 2018, the top holdings from the top-five countries on the long side were NTT DoCoMo (Japan), BMW (Germany), China Mobile (Hong Kong), Banco Santandar (Spain), and AB InBev (Belgium), while the top holdings from the top-five countries on the short side were Toyota (Japan), Nestle (Switzerland), Allianz (Germany), Citic (Hong Kong), and AstraZeneca (the United Kingdom).

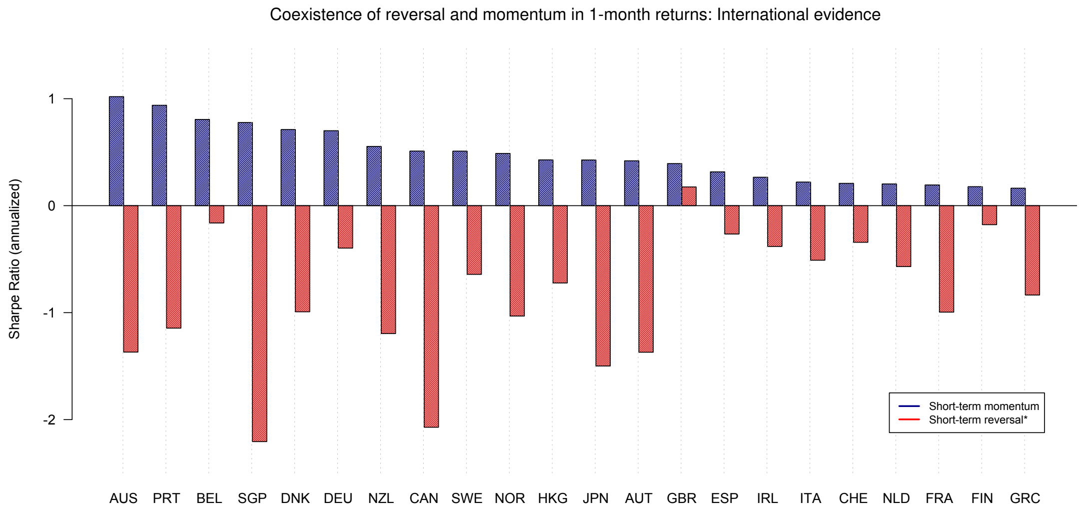

Figure 3
International short-term momentum returns This figure shows the annualized Sharpe ratios of the country-specific international short-term momentum and short-term reversal* strategies. The underlying portfolios are from independent double sorts into deciles based on the previous month's return and turnover. Portfolios are value weighted and rebalanced at the end of each month. All returns and market values are in U.S. dollars. Data are at the monthly frequency and cover January 1993 to December 2018.

2. Additional Results and Robustness

This section provides additional results and robustness tests. We show that short-term momentum is stronger when purged of liquidity-related trades at the end of the formation month; survives transaction costs; generates abnormal returns relative to standard implementations of popular stock-level momentum strategies; does not appear to be driven by earnings announcements, industry momentum, factor momentum, or volatility; and exhibits far less crash risk than conventional momentum.

2.1 End-of-month liquidity trading and implementation lag

Etula et al. (2020) document that end-of-month trading is dominated by institutional demand for cash and associated with systematic price pressure and subsequent reversal. We employ this seasonality in liquidity demand as an instrument to understand the impact of noninformational trading on short-term momentum performance. If short-term momentum is driven by informed trading, then skipping the last few days of the formation month and purging the signals of noninformational trading should result in stronger performance. Skipping the last few days of the formation month also serves as an implementation lag, facilitating a more realistic assessment of the strategy's implementability.

Panel A of Table 6 shows the performance of winner-minus-loser strategies similar to those in Table 1, except that we skip the sorting variables' values for the last 3 trading days in each month. Hence, if month $t-1$ has d trading days, the sorting variables at the end of month

Table 6
Short-term momentum and end-of-month effects

A Performance of $r_{1,0-\text{EOM}}$ strategies within $TO_{1,0-\text{EOM}}$ deciles				B Performance of r_{EOM} strategies within TO_{EOM} deciles			
$TO_{1,0-\text{EOM}}$	$\mathbb{E}[r^e]$	α_{FF6}	α_q	TO_{EOM}	$\mathbb{E}[r^e]$	α_{FF6}	α_q
Low	−0.41	−0.49	−0.41	Low	−2.36	−2.45	−2.56
	(−2.16)	(−2.58)	(−1.75)		(−11.51)	(−11.13)	(−11.59)
2	−0.38	−0.48	−0.48	2	−1.72	−1.80	−1.81
	(−1.64)	(−1.98)	(−1.76)		(−7.12)	(−6.61)	(−6.55)
3	−0.28	−0.47	−0.52	3	−1.73	−1.90	−2.04
	(−1.22)	(−1.83)	(−1.56)		(−6.17)	(−6.96)	(−6.55)
4	−0.21	−0.24	−0.11	4	−1.66	−1.75	−1.77
	(−0.81)	(−0.75)	(−0.29)		(−6.06)	(−5.60)	(−5.64)
5	0.39	0.30	0.46	5	−1.72	−1.99	−1.92
	(1.40)	(0.90)	(1.35)		(−6.78)	(−6.75)	(−6.77)
6	0.22	0.08	0.16	6	−1.86	−1.97	−2.06
	(0.89)	(0.27)	(0.39)		(−7.45)	(−7.00)	(−7.56)
7	0.27	0.33	0.50	7	−1.16	−1.17	−1.20
	(1.00)	(0.91)	(1.29)		(−4.86)	(−4.54)	(−4.42)
8	0.38	0.34	0.53	8	−1.67	−1.72	−1.79
	(1.26)	(1.11)	(1.35)		(−5.60)	(−5.01)	(−4.58)
9	0.72	0.58	0.72	9	−1.16	−1.29	−1.29
	(2.89)	(2.09)	(2.13)		(−4.74)	(−4.91)	(−4.41)
High	1.83	1.80	2.10	High	−0.65	−0.86	−0.87
	(5.52)	(5.22)	(5.16)		(−2.25)	(−2.63)	(−2.41)

This table shows the performance of winner-minus-loser strategies based on the previous month's return within deciles of the previous month's share turnover. In panel A, the sorting variables skip their end-of-month values ($r_{1,0-\text{EOM}}$ and $TO_{1,0-\text{EOM}}$) measured at the month's last 3 trading days. In panel B, the sorting variables are just the end-of-month values (r_{EOM} and TO_{EOM}) measured at the month's last 3 trading days. Portfolios are from conditional sorts into deciles based on NYSE breakpoints, first on returns and then on turnover, and are value weighted and rebalanced at the end of each month. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 to December 2018, except when applying the q-factors, which are available from January 1967.

$t-1$, used to predict returns over month t, are based on days $1,2,\dots,d-3$ of month $t-1$. We only consider stocks with at least 15 nonmissing daily returns and turnover each month. Skipping the end of the formation month implies a clear shift toward stronger high-turnover continuation and weaker low-turnover reversal compared to Table 1. The STMOM strategy (in the highest turnover decile) now yields 1.83% per month with $t=5.52$ (compared to 1.37% with $t=4.74$ in the benchmark case). In addition, there is a significant continuation effect in the ninth turnover decile: 0.72% per month with $t=2.82$. By contrast, the STREV* strategy (in the lowest turnover decile) yields just −0.41% per month (compared to −1.41% per month in the benchmark case). The abnormal returns tell a very similar story. These results suggest that skipping the end of the formation month effectively purges the sorting variables of end-of-month liquidity trades, leading to stronger high-turnover continuation but weaker low-turnover reversal. In the following, we provide two pieces of evidence that corroborate this explanation.

First, we consider a complementary version of this exercise where we sort *only* on the signals' end-of-month values, that is, only on returns and turnover occurring on days $d-2$,$d-1$, and d of month $t-1$. Based on the same reasoning as above, the last days in a month should be dominated by noninformational demand for liquidity, and we therefore expect to see stronger low-turnover reversal but weaker high-turnover momentum. Panel B of Table 6 shows that this is indeed the case. The resultant STREV* strategy now yields a very large -2.36% per month with $t=-11.51$, while the corresponding STMOM strategy's average return is now a *negative* -0.65% per month.[16]

Second, we repeat the tests of Table 6 on different days during the month. Panel A of Figure 4 shows the performance of STMOM and STREV* strategies formed on day d of each month, based on prior return and turnover over $d-20$ to $d-3$, and held from $d+1$ to $d+21$. Skipping 3 days only significantly improves the performance of STMOM when these days lie at the end of the month, and the performance of the corresponding STREV* strategies is weakest around the end of the month. Panel B shows the complementary version of this exercise. Sorting on just the prior 3 days' signal values is only associated with stronger STREV* performance when these days lie at the end of the month, while the corresponding STMOM strategies generate large *negative* returns around the end of the month.

Taken together, these results suggest that the performance of STMOM and STREV* is indeed affected by noninformational demand for liquidity, but in opposite directions. Practitioners implementing STMOM should skip the last few days of the formation month to purge the signals of end-of-month liquidity trades. Conversely, researchers and practitioners looking into price pressure and the returns to liquidity provision should pay attention to STREV* near the end of the month.

Lastly, the fact that skipping the end of the formation month implies a significant continuation effect in the ninth turnover decile (panel A of Table 6) suggests that *quintile* double sorts should be sufficient to document significant short-term momentum. Table A.3 in the appendix confirms this: using independent quintile double sorts and skipping the last 3 days of the formation month yields an STMOM strategy with

[16] Table IA.4 in the Internet Appendix shows that the results from Table 6 also hold in our international sample. In untabulated tests, we find very similar results when focusing on the last 5 (instead of 3) trading days for month $t-1$ (the formation period) and, furthermore, that these results are robust to also excluding the first 1–3 trading days from the return for month t (the holding period).

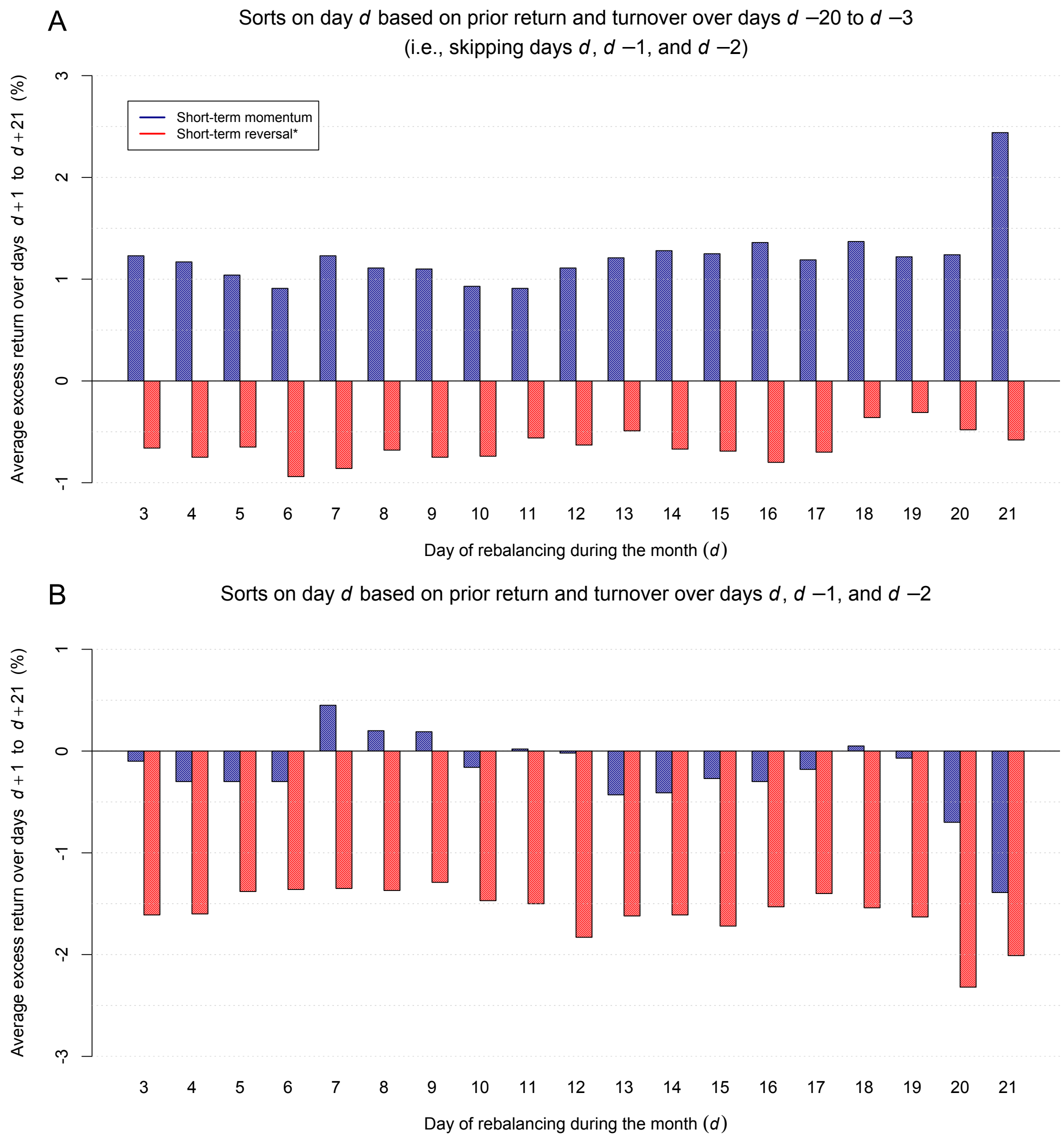

Figure 4
Short-term momentum and end-of-month effects This figure shows the average excess returns to STMOM and STREV* strategies formed on different days (d) during the month. Panel A shows strategies formed on day d based on prior return and turnover over days $d-20$ to $d-3$, skipping the most recent 3 days (i.e., days $d-2, d-1$, and d). Panel B shows strategies formed on day d based only on prior return and turnover over the most recent 3 days (i.e., days $d-2, d-1$, and d). We use conditional sorts into deciles based on NYSE breakpoints, first on returns and then on turnover. Portfolios are value weighted and returns are calculated over days $d+1$ to $d+21$. The sample excludes financial firms. Data are at the daily frequency and cover the end of July 1963 to the end of December 2018.

an average return of 0.74% per month with $t = 4.21$. The strategy's abnormal returns are about as large and as strong as its average return. It trades in an average of 222 and 180 stocks on its long and short sides with average market capitalizations of \$1.22 billion and \$1.01 billion. As such, short-term momentum exists for a substantially larger subset of the market than in our benchmark results.

2.2 Transaction costs

Strategies from sorts on 1-month returns tend to have high turnover and can be expensive to trade (Da, Liu, and Schaumburg 2012; Novy-Marx and Velikov 2015). Nonetheless, this section shows that short-term momentum survives conservative estimates of transaction costs.

Following Koijen et al. (2018) and Bollerslev et al. (2018), we estimate average transaction costs using average turnover and average "half-spreads" (one-half of the proportional bid-ask spread).[17] For a given portfolio, let $w_{i,t-1} \geq 0$ be the value weight of stock i in the sort at the end of month $t-1$ and let r_{it} be the stock's return over month t. The portfolio's (one-way) turnover in month t is then

$$\frac{1}{2}\sum_{i}\left|(1+r_{it})w_{i,t-1}-w_{it}\right|, \tag{1}$$

where the sum is taken over all stocks in the portfolio in months $t-1$ or t and is divided by 2 to avoid double counting buys and sells. The product $(1+r_{it})w_{i,t-1}$ is the weight of stock i just before rebalancing at the end of month t. We set $w_{i,t-1}=0$ if stock i is not in the portfolio in month $t-1$, and similarly for w_{it}. The portfolio's half-spread in any given month is the value-weighted average of $\frac{1}{2}(\text{ASK}-\text{BID})/(\frac{1}{2}(\text{ASK}+\text{BID}))$.

Table 7 shows strategy performance net of transaction costs. The benchmark STMOM strategy (Table 1) turns over 89% and 90% of its long and short sides each month on average, yet these incur relatively modest average half-spreads of 0.17% and 0.24% per month. Table A.4 in the appendix explains why: for every $1 investment, each side puts on average just 9 cents into microcaps but around 30 cents into megacaps. The strategy's average monthly cost is therefore just $0.89\times0.17+0.90\times0.24=0.37\%$, implying a net average return of 1.00% per month with $t=3.47$. Its FF6 net abnormal return is equally large and strong, while its net information ratio relative to a "FF8" model (FF6 plus the two conventional reversal factors) is 0.92. The benchmark STREV* strategy turns over more often and incurs higher half-spreads because it puts much more weight on microcaps (Table A.4). Its average monthly cost of 1.94% therefore subsumes its average gross return when judged by our conservative approach.

[17] Half-spreads are simpler than the "effective bid-ask spread" proposed by Hasbrouck (2009) and used by Novy-Marx and Velikov (2015), but the resultant costs are still conservative, especially for large institutional traders. Like effective spreads, half-spreads do not account for the price impact of large trades and should be interpreted as the costs faced by a small liquidity demander. The resultant costs are nonetheless conservative (an upper bound) because they assume market orders and immediate liquidity demand, instead of limit orders, an assumption that likely overstates the actual average costs associated with implementing a strategy. Frazzini, Israel, and Moskowitz (2015) find that the actual trading costs faced by a large institutional trader are an order of magnitude smaller than those estimated for the average trader because a large institutional trader will attempt to trade within the spread, use limit orders, and supply, rather than demand, liquidity.

Table 7
Short-term momentum and transaction costs

		Long side		Short side				FF6 (net)		FF8 (net)	
Strategy	$\mathbb{E}[r^e_{\text{gross}}]$	TO	HS	TO	HS	Cost	$\mathbb{E}[r^e_{\text{net}}]$	α	IR	α	IR
Short-term momentum	1.37 (4.74)	0.89	0.17	0.90	0.24	0.37	1.00 (3.47)	1.00 (3.09)	0.44	1.78 (6.11)	0.92
Short-term reversal*	−1.41 (−7.13)	0.96	0.84	0.94	1.22	1.94					
Short-term momentum (excl. EOM)	1.83 (5.52)	0.89	0.18	0.91	0.24	0.38	1.45 (4.38)	1.42 (4.12)	0.61	2.18 (6.95)	1.11
Short-term momentum (5×5, excl. EOM)	0.74 (4.21)	0.83	0.17	0.85	0.21	0.32	0.42 (2.40)	0.45 (2.35)	0.33	1.03 (6.61)	1.07
Short-term momentum (large-caps, excl. EOM)	0.77 (3.90)	0.83	0.08	0.84	0.10	0.15	0.62 (3.14)	0.59 (2.78)	0.38	1.22 (7.07)	1.01
Short-term momentum (megacaps, excl. EOM)	0.72 (3.76)	0.84	0.07	0.85	0.08	0.13	0.59 (3.10)	0.59 (2.66)	0.34	1.24 (6.46)	0.90

This table shows strategy performance net of transaction costs. "TO" is average turnover, computed as the time-series average of one-half of the sum of absolute monthly changes in the portfolio weights (Eq. (1)). "HS" (in % per month) is the average half-spread, computed as the time-series average of the portfolios' monthly value-weighted average half-spreads. "Cost" (in % per month) is the sum of the average turnover times the average half-spread for the long and short sides. "FF8" is FF6 plus the conventional short-term and long-term reversal factors. "IR" is the information ratio, computed as the abnormal return over the residual standard error. "EOM" is end of month. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are at the monthly frequency and cover July 1963 to December 2018, but the half-spreads are computed starting from 1983 because of data availability in CRSP.

The STMOM strategy with an implementation lag (panel A of Table 6) earns 1.45% per month with $t = 4.38$ after costs and has a net FF8 information ratio of 1.11. The coarser version of this strategy from quintile double sorts (Table A.3) earns 0.42% per month with $t = 2.40$ after costs, but its net FF8 information ratio is largely undiminished and its investment capacity is over four times higher (Table A.4).[18]

Lastly, the large-caps and megacaps STMOM strategies with an implementation lag (as in Table 3 but excluding end-of-month values) have almost identical performance at around 0.60% per month after costs with a t-statistic above 3. The reason is that the large-caps strategy on average puts over 55 cents of every invested dollar into megacaps. The megacap strategy's investment capacity is on average 4.24% of aggregate market capitalization and totaled $1.24 trillion in December 2018.

2.3 Other stock-level momentum strategies: Price-, earnings-, and ROE-based momentum

Table 8 analyzes the STMOM strategy in the context of four other stock-level momentum strategies: A conventional momentum strategy based on prior 12-2 months performance ($r_{12,2}$), a post-earnings announcement drift (PEAD) strategy based on cumulative 3-day abnormal return around quarterly earnings announcements dates (CAR_3), a PEAD strategy based on standardized unexpected earnings (SUE), and an earnings-momentum strategy based on quarterly return on equity (ROE). The strategies trade value-weighted portfolios from decile sorts using NYSE breakpoints and are rebalanced at the end of each month.[19]

Panel A shows the strategies' average excess returns and characteristic tilts, defined as the time-series average of the long-short difference in the portfolios' monthly value-weighted average characteristics. The characteristics are the strategies' main sorting variables. STMOM has a sizable tilt toward the CAR_3 signal but only modest tilts toward the other momentum signals (negative for ROE). Conversely, the other momentum strategies have only modest tilts toward the $r_{1,0}$ signal (insignificant for conventional momentum and ROE), with the exception

[18] For comparison, the conventional momentum strategy incurs an average cost of 0.26% per month and its net return is 0.95% per month ($t = 3.74$). Moskowitz and Grinblatt's (1999) industry momentum strategy incurs an average cost of 0.34% per month and its net return is 0.64% per month ($t = 3.02$). The average cost of the conventional STREV strategy is 0.56% per month, which subsumes its average gross return.

[19] We employ quarterly earnings starting from the end of the month of the announcement date (Compustat's RDQ). CAR_3 is the 3-day cumulative return minus the value-weighted market return around earnings announcements. SUE is the year-over-year change in split-adjusted earnings per share (EPSPXQ/AJEXQ) divided by its standard deviation over the latest eight announcements (minimum of six) excluding the current announcement. ROE is total quarterly earnings (IBQ) deflated by one-quarter-lagged book equity.

of the CAR_3 strategy.[20] Nonetheless, panel B shows that the correlation between STMOM and the CAR_3 strategy is a modest 18% (t=2.72), equal in magnitude and strength to the correlation between STMOM and conventional momentum. For comparison, the correlation between conventional momentum and each of the PEAD strategies is 36% and 53% with t-statistics exceeding 5.00.

The modest correlations suggest that STMOM's average return is not spanned by the other momentum strategies. Panel C confirms this: STMOM's abnormal return relative to the other momentum strategies is 0.96% per month with t=2.30 and the regression's adjusted R^2 is just 5.3%. In these tests, the only other strategy with an abnormal return t-statistic exceeding 2.00 is the CAR_3 strategy. We caution, however, that spanning tests are not conclusive about the redundancy of one effect relative to others: for one, they can be fragile to the choice of right-hand-side strategies and to the details of the strategy construction.

2.4 Directly controlling for earnings announcement dates

Section 2.3 shows that the STMOM strategy is only moderately correlated with strategies based on post-earnings announcement drift (PEAD). Here, we show more generally that our main results are not mechanically driven by the high trading volume and persistent price drifts associated with earnings announcements (for a review, see, e.g., Hong and Stein 2007; see also Medhat and Schmeling 2018).

Panel A of Table IA.6 in the Internet Appendix shows the performance of winner-minus-loser strategies similar to those in Table 1, except that we exclude firms whose most recent announcement date fell in the previous month. With the exclusion of announcers, STMOM yields 1.31% (t=2.75) while STREV* yields −1.82% per month (t=−5.99) over the period from January 1972 for which we have announcement dates. Panel B shows an alternative version of this exercise where we keep announcers but exclude the 3 days around announcements from the return and turnover signals. In this case, STMOM yields 1.16% (t=3.30) while STREV* yields −1.80% (t=−7.32) per month. In sum, the profitability of short-term momentum is largely undiminished when explicitly excluding earnings announcements.

[20] Table IA.5 in the Internet Appendix shows additional characteristic tilts as well as average portfolio overlap for the five momentum strategies. An interesting observation is that, while conventional momentum has the well-known strong tilt toward growth stocks, short-term momentum has a slight but significant *value* tilt. The two strategies' average portfolio overlap is 34% for winners and 20% for losers.

Table 8
Short-term momentum and other stock-level momentum strategies

A. Excess returns and characteristic tilts

Strategy	$\mathbb{E}[r^e]$	Time-series average of long-short difference in portfolio characteristics (all in %) $r_{1,0}$	$r_{12,2}$	CAR_3	SUE	ROE
STMOM	1.37	45.95	3.20	5.85	0.19	−0.21
	(4.74)	(36.21)	(2.19)	(11.13)	(3.31)	(−0.80)
MOM	1.21	0.26	111.20	2.48	1.63	3.14
	(4.77)	(0.78)	(19.38)	(12.17)	(20.50)	(6.17)
CAR_3	0.91	7.49	14.45	21.29	0.74	1.62
	(6.46)	(24.08)	(20.62)	(10.18)	(11.51)	(8.38)
SUE	0.53	1.31	24.57	1.73	6.14	8.52
	(4.02)	(10.88)	(15.88)	(16.35)	(36.12)	(9.62)
ROE	0.75	0.34	12.90	1.25	3.52	23.21
	(3.18)	(1.38)	(4.08)	(10.04)	(20.84)	(9.55)

B. Time-series correlations

	MOM	CAR	SUE	ROE
STMOM	0.18	0.18	0.06	−0.01
	(2.50)	(2.72)	(1.24)	(−0.12)
MOM		0.36	0.53	0.23
		(5.18)	(9.09)	(1.59)
CAR_3			0.29	0.13
			(4.17)	(1.49)
SUE				0.51
				(6.06)

C. Spanning tests

Intercepts, slopes, and test statistics (in parentheses) from time-series regressions of the form $y_t = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t$

Dependent strategy	α	STMOM	MOM	CAR_3	SUE	ROE	Adj. R^2
STMOM	0.96		0.25	0.34	−0.13	−0.07	5.3%
	(2.30)		(2.44)	(2.07)	(−0.86)	(−0.49)	
MOM	0.22	0.10		0.41	0.87	−0.06	34.4%
	(0.94)	(2.35)		(3.29)	(7.55)	(−0.38)	
CAR_3	0.63	0.04	0.13		0.13	0.00	15.2%
	(4.63)	(2.18)	(2.96)		(2.45)	(−0.07)	
SUE	−0.04	−0.01	0.23	0.11		0.29	44.6%
	(−0.32)	(−0.87)	(7.14)	(2.25)		(7.37)	
ROE	0.44	−0.02	−0.04	−0.01	0.74		26.0%
	(1.92)	(−0.47)	(−0.37)	(−0.07)	(6.25)		

This table studies the benchmark STMOM strategy (Table 1) in the context of four other stock-level momentum strategies: a conventional momentum strategy (MOM) based on prior 12-2 months performance ($r_{12,2}$), a post-earnings announcement drift (PEAD) strategy based on cumulative 3-day abnormal return around quarterly earnings announcements dates (CAR_3), a PEAD strategy based on standardized unexpected earnings (SUE), and an earnings-momentum strategy based on the quarterly return on equity (ROE). The strategies trade value-weighted portfolios from decile sorts using NYSE breakpoints and are rebalanced at the end of each month. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms, and the sorts on ROE exclude firms with negative book equity. Data are at the monthly frequency and cover July 1963 to December 2018, but the PEAD and ROE strategies start from January 1972 because of data availability in Compustat.

2.5 Industry momentum

Moskowitz and Grinblatt (1999) find that industry momentum is strongest at the 1-month horizon (see also Asness, Porter, and Stevens 2000). Nonetheless, the profitability of short-term momentum does not appear to be mechanically driven by industry effects.

Table IA.7 in the Internet Appendix shows spanning tests employing STMOM and a 1-month industry momentum (IMOM) strategy based on the 49 industries from Fama and French (1997) but excluding financials. STMOM is not within the span of the IMOM strategy, with or without controlling for the FF6 or q-factors. On the other hand, IMOM is in fact within the combined span of STMOM and the q-factors.

Table A.5 in the appendix shows the performance of the winner-minus-loser strategies similar to those in Table 1 except that we consider industry-adjusted signals or performance. Panel A shows strategies from sorts where the sorting variables are demeaned by their value-weighted average industry values. With industry-demeaned signals, STMOM yields 1.18% ($t=4.08$) while STREV* yields −2.00% per month ($t=-10.25$). That is, the profitability of short-term momentum remains largely undiminished when the strategy is constructed in a way that explicitly sorts *against* the 1-month industry-momentum signal.[21]

Panel B shows a decomposition of Table 1's benchmark strategies into an industry-hedged ("within-industry") component and the industry hedge. The industry-hedged strategies are from sorts on unadjusted variables, but each stock's position is combined with an offsetting position of equal size in the corresponding value-weighted industry portfolio. The industry hedges are these offsetting positions in the value-weighted industry portfolios. This follows Novy-Marx (2013) and allows us to quantify how much of the benchmark strategies' performance is due to industry exposure. The benchmark STMOM strategy's average monthly return of 1.37% ($t=4.74$) decomposes into 0.89% ($t=3.35$) from the within-industry component and 0.48% ($t=5.65$) from the industry hedge. Similar results hold for abnormal returns. That is, roughly two-thirds of the strategy's performance is unrelated to industry exposure and hedging industry exposure does not increase its Sharpe or information ratios.

[21] Moskowitz and Grinblatt (1999) argue that "[o]ne possible explanation for the discrepancy between short-term (one-month) reversals for individual stocks and short-term continuations for industries is that the one-month return reversal for individual stocks is generated by microstructure effects (such as bid-ask bounce and liquidity effects), which are alleviated by forming industry portfolios" (p. 1274). Our results suggest that conditioning on high turnover is an alternative and equally effective way of alleviating microstructure effects.

2.6 Factor momentum

Ehsani and Linnainmaa (2020) construct "factor momentum" strategies which are long winners and short losers based on prior 12-1 (not 12-2) month return from a set of 20 U.S. and international factors. They find that factor momentum subsumes conventional price momentum in spanning tests (see also Lewellen, 2002). Table IA.8 in the Internet Appendix shows that this is not the case for short-term momentum. The STMOM strategy yields significant abnormal returns relative to both the time-series factor-momentum strategy and the cross-sectional factor-momentum strategy, whether employed alone or together and with or without controlling for the FF6 factors. The table also shows that while factor momentum explains over 40% of the variation in conventional momentum, it explains under 5% of that in short-term momentum.

2.7 Longer formation periods

Our main results use past short-term performance and turnover measured over the previous month. Here, we show that our results are robust to using longer formation periods of up to 6 months, although the 1-month horizon produces the strongest results.

Table IA.9 in the Internet Appendix shows the performance of alternative short-term momentum and short-term reversal* strategies constructed as in Table 1, except that the sorting is on cumulative return and average monthly turnover for the previous 2,…,6 months. The alternative short-term momentum strategies generate significant average returns between 0.99% and 1.24% per month, although lower and statistically weaker than the 1.37% for the benchmark strategy. The average returns to the alternative short-term reversal* strategies are decreasing with the formation period and insignificant at the 5-month horizon. Each alternative strategy is within the univariate span of the corresponding benchmark strategy.

2.8 Volatility and residual turnover

Bandarchuk and Hilscher (2013) argue that "characteristic screens" lead to elevated profits for conventional price-momentum strategies because they identify stocks with more volatile past returns. In particular, they find that the part of share turnover which is unrelated to volatility no longer has the ability to elevate the profits of conventional momentum strategies. Here, we show that volatility is not driving our main results.

Table IA.10 in the Internet Appendix shows the performance of winner-minus-loser strategies similar to those in Table 1, except that we replace the previous month's share turnover with "residual turnover" ($RTO_{1,0}$; panel A) or volatility ($\sigma_{1,0}$; panel B). Here, $RTO_{1,0}$ is the residual from cross-sectional regressions of the previous month's share turnover on $\sigma_{1,0}$, estimated using weighted least squares (WLS) with market capitalization as the weight, while $\sigma_{1,0}$ is the standard deviation of the previous month's daily stock returns using a minimum of 15 daily observations. Panel A shows that using residual turnover does not materially alter our main results. Panel B shows that, while there is significant 1-month reversal among low-volatility stocks, there is no 1-month continuation among high-volatility stocks. In untabulated tests, we find very similar results using idiosyncratic volatility relative to the FF6 or q-factors.

2.9 Pre-1963 performance and sample splits

As is now standard in the literature, we focus on the post-1963 sample for our main results. However, the availability of CRSP data going back to 1926 allows us to verify the robustness of our main results to adding an additional 37 years to the sample.

Table IA.11 in the Internet Appendix shows spanning tests for the STMOM and STREV* strategies starting from July 1926. The explanatory factors are the three Fama-French factors (MKT, SMB, HML) in addition to the momentum factor (MOM) and the two reversal factors (STREV and LTREV). Over the full sample period (July 1926 to December 2018), the average STMOM return is 1.02% per month with $t = 4.23$ while the average STREV* return is −2.82% per month with $t = -5.40$. The corresponding abnormal returns are 2.16% per month ($t = 9.03$) for STMOM and −1.80% per month ($t = -6.83$) for STREV*.

The table also shows the performance of the strategies in three nonoverlapping subperiods: July 1926 to June 1963, July 1963 to June 1991, and July 1991 to December 2018. The STMOM strategy's average return is monotonically increasing across the subperiods, from 0.60% per month ($t = 1.61$) in the pre-1963 era to 2.03% per month ($t = 4.80$) in the post-1991 era. The opposite is true for STREV*, for which the average return decreases monotonically in magnitude from −3.96% to −1.15% per month across the subperiods. We conjecture that generally increasing market liquidity is responsible for these trends.

2.10 Crash risk

Daniel and Moskowitz (2016) show that conventional price momentum can experience infrequent but persistent strings of negative returns—or *crashes*—that are contemporaneous with market rebounds, in that the strategy "will have significant negative market exposure following bear markets precisely when the market swings upward" (p. 229). Here, we show that short-term momentum exhibits far less crash risk than conventional momentum. Following Daniel and Moskowitz, we use the extended sample going back to January 1927.

Table A.6 in the appendix presents the results. Panel A shows that STMOM exhibits a mild negative skew and a moderate kurtosis, similar to those observed for the market but orders of magnitude lower than those observed for conventional momentum. It also shows that while conventional momentum exhibits negative and significant coskewness (Harvey and Siddique 2000; Schneider, Wagner, and Zechner 2020) and downside beta (Henriksson and Merton 1981), both are positive albeit small and statistically insignificant for STMOM.

Panel B shows results from Daniel and Moskowitz's regressions,

$$r_t^e = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + (\beta_B + \beta_{B,U} I_{U,t}) I_{B,t-1}) r_{mt}^e + \epsilon_t, \tag{2}$$

where r_t^e is a strategy's excess return, r_{mt}^e is the market excess return, $I_{B,t-1}$ is an ex ante 24-month "bear market" indicator, and $I_{U,t}$ is a contemporaneous 1-month "up-market" indicator. Here, β_B captures the difference in beta during bear markets, while $\beta_{B,U}$ captures the difference in beta in rebounds *after* bear markets. Conventional momentum has a bear-market beta of $\widehat{\beta}_0 + \widehat{\beta}_B = -0.34$ when the contemporaneous market return is negative but $\widehat{\beta}_0 + \widehat{\beta}_B + \widehat{\beta}_{B,U} = -1.06$ when the contemporaneous market return is positive. In contrast, STMOM's bear-market beta is -0.51 when the contemporaneous market return is negative but just $+0.05$ when the contemporaneous market return is positive. That is, STMOM is a better hedge in bear markets and has no negative market exposure in rebounds.

2.11 VIX and volatility risk

Drechsler, Moreira, and Savov (2018) find that the CBOE Volatility Index (VIX) predicts larger returns to daily reversal strategies, especially among larger stocks (see also Nagel 2012). They also find that daily reversal strategies are exposed to volatility risk, in that they suffer loses when the contemporaneous change in the VIX is higher, again especially among larger stocks. We show that the monthly strategies we consider exhibit little predictability by the VIX and only insignificant exposure to volatility risk after controlling for market exposure.

Table IA.12 in the Internet Appendix shows time-series regression results for the small- and large-cap STMOM and STREV* strategies from Table 3. The explanatory variables are the 1-month-lagged VIX, the contemporaneous monthly change in VIX, and the contemporaneous market return. The period covered is January 1990 to December 2018, where the start date is determined by the availability of the VIX. Only the small-cap STREV* strategy is predictable by the VIX. Its average return in the post-1990 period is -1.03% per month ($t = -4.92$) and a one-point increase in the VIX predicts a 9 basis points more negative monthly return ($t = -2.13$) with an R^2 of 2.3%. Without controlling for the market return, all four strategies load positively and significantly on contemporaneous VIX changes, with 25–30 basis points added to each strategy's monthly return for every one-point increase in the contemporaneous VIX change. That is, ignoring market exposure, a larger VIX change is associated with losses to the STREV* strategies but *gains* to the STMOM strategies. Controlling for the market return, however, renders the strategies' volatility-risk exposure insignificant.

3. Testing Theories of the Volume-Return Relation

In this section, we study short-term momentum in the context of models of the volume-return relation, that is, models of how expected returns depend on realized returns and volume. We first consider prominent rational expectations equilibrium (REE) models. Since short-term momentum proves difficult to reconcile with these models, we conclude by briefly discussing the potential of models of "boundedly rational" traders to explain short-term momentum.

3.1 REE models of the volume-return relation

In the model of Campbell, Grossman, and Wang (1993), noninformational trading due to liquidity demand causes temporary price pressure when absorbed by liquidity suppliers. As a result, returns coupled with high trading volume will subsequently reverse. This runs opposite to short-term momentum and rules out purely noninformational trading as an explanation.

In the models of Wang (1994) and Llorente et al. (2002), trading due to private information causes persistent price movements that counteract temporary price pressure. As a result, returns coupled with high volume will reverse among stocks with low information asymmetry (similar to Campbell, Grossman, and Wang 1993) but will reverse less and may even continue among stocks with high information asymmetry.[22,23] Wang (1994) and Llorente et al. (2002) argue that high-information-asymmetry stocks should be small, illiquid, and have low analyst coverage (see our footnote 1). As such, high-information-asymmetry is

[22] Wang (1994) assumes long-lived private information and that liquidity-related trading is due to hedging a nontraded asset which is correlated with the risky asset, that is, that liquidity-related trading is "endogenous." Inspired by Wang (1994), Llorente et al. (2002) also assume endogenous liquidity-related trading but drop the assumption of long-lived private information. As a result, higher volume is *always* associated with more reversal in their model, but the effect of volume decreases in magnitude with information asymmetry.

[23] We focus on the models' predictions for return autocorrelation conditional on *high* volume because their predictions for return autocorrelation conditional on *low* volume are less clear-cut and receive less attention. In Campbell, Grossman, and Wang's (1993) model, the sign of return autocorrelation conditional on low volume is ambiguous (equation (16), p. 929). In Llorente et al.'s (2002) model, which simplifies that of Wang (1994), return autocorrelation conditional on low volume is captured by θ_1, about which they write "the result on θ_1 can be sensitive to the simplifying assumptions of our model. For example, when motives for hedging trade [...] are persistent, the returns can become positively serially correlated (even in the absence of trading). In addition, when private information is long-lived, the behavior of return autocorrelation is more involved, and the impact of information asymmetry on θ_1 becomes more complex (see, e.g., Wang 1994)" (p. 1015–6).

an explanation for short-term momentum *if* it is strongest among small, illiquid, and low-coverage stocks.

The performance of the size-conditional strategies in Table 3 is at odds with the high-information-asymmetry mechanism, given that STMOM is stronger among larger stocks. Since larger stocks tend be more liquid and have greater analyst coverage, we would a priori expect stronger STMOM performance among liquid and high-coverage stocks. If so, this would be further evidence at odds with the mechanism. In the following, we verify this by constructing STMOM strategies with an explicit control for illiquidity and analyst coverage.

3.1.1 Short-term momentum and illiquidity. Panel A of Table 9 shows the performance of STMOM and STREV* strategies constructed with a control for the Amihud (2002) illiquidity measure. The strategies are from 5×3×3 conditional sorts on the previous month's illiquidity, return, and turnover. The breakpoints for illiquidity are NYSE quintiles while the breakpoints for the return and turnover signals are the 20th and 80th percentiles for NYSE stocks. Portfolios are value weighted and rebalanced at the end of each month. The STMOM strategies' average returns are monotonically *decreasing* with illiquidity; from 0.88% per month (t=3.55) among the most liquid stocks to −0.77% per month (t=−2.38) among the most illiquid ones. Similar results hold for abnormal returns. As such, high-turnover continuation is strongest among the most liquid stocks, a result that directly opposes the high-information-asymmetry mechanism. The STREV* strategies' average returns are all negative, but become monotonically more negative with illiquidity; from −0.64% to −1.67% per month. Both sets of results are consistent with those for the size-conditional strategies in Table 3.

Avramov, Chordia, and Goyal (2006) find that, with a control for illiquidity, higher turnover implies less reversal at the monthly horizon but more reversal at the weekly horizon.[24] Despite the different roles of turnover at the monthly and weekly horizons, Table 9 shows that our evidence against the high-information-asymmetry mechanism also holds at the weekly horizon. In panel B, we consider strategies constructed similarly to those in panel A, except that we rebalance the portfolios each Tuesday, skipping signals and holding-period returns over Tuesday itself to avoid undue influence from bid-ask bounce. The STMOM strategies' average returns are negative but again

[24] Avramov et al. (2006) argue that the different roles of turnover "could arise because demand shocks are attenuated at the monthly frequency as compared to the weekly frequency, which would suggest that turnover may be a poor proxy for noninformational trades at the monthly frequency." (p. 2367). Table IA.13 in the Internet Appendix shows that using turnover orthogonal to illiquidity does not affect our main results and that replacing turnover with illiquidity in our double sorts does not lead to significant continuation.

Table 9
Short-term momentum controlling for illiquidity

	Short-term momentum [WML, high turnover] controlling for illiquidity		Short-term reversal* [WML, low turnover] controlling for illiquidity	
$\text{Illiq}_{1,0}$ quintile	$\mathbb{E}[r^e]$	α_{FF6}	$\mathbb{E}[r^e]$	α_{FF6}
A. Monthly sorts				
Liquid	0.88	0.67	−0.64	−0.72
	(3.55)	(2.51)	(−3.62)	(−3.83)
2	0.38	0.32	−1.02	−0.97
	(1.43)	(1.15)	(−5.12)	(−4.42)
3	0.21	0.11	−1.24	−1.26
	(0.85)	(0.36)	(−7.05)	(−6.21)
4	−0.04	−0.15	−1.44	−1.44
	(−0.16)	(−0.53)	(−7.22)	(−4.90)
Illiquid	−0.77	−1.11	−1.67	−1.90
	(−2.38)	(−2.92)	(−7.32)	(−6.94)
B. Weekly sorts (rebalanced Tuesday, skipping Tuesday)				
Liquid	−0.18	−0.19	−0.34	−0.32
	(−3.15)	(−3.26)	(−8.37)	(−7.94)
2	−0.50	−0.49	−0.45	−0.45
	(−8.26)	(−7.99)	(−11.02)	(−10.71)
3	−0.55	−0.54	−0.41	−0.40
	(−9.59)	(−9.11)	(−8.68)	(−8.56)
4	−0.79	−0.77	−0.43	−0.41
	(−13.64)	(−13.42)	(−9.35)	(−9.06)
Illiquid	−1.00	−1.00	−0.37	−0.36
	(−14.84)	(−15.15)	(−8.15)	(−7.98)

This table shows the performance of short-term momentum and short-term reversal* strategies constructed with a control for the Amihud (2002) illiquidity measure. Panel A shows results for monthly sorts, while panel B shows results for weekly sorts. The strategies are from $5\times3\times3$ conditional sorts on illiquidity ($\text{Illiq}_{1,0}$), returns, and turnover, in that order, measured over the previous month or week. $\text{Illiq}_{1,0}$ is the average absolute daily return relative to the daily dollar trading volume. The breakpoints for illiquidity are NYSE quintiles, while the breakpoints for returns and turnover are the 20th and 80th percentiles for NYSE stocks. Portfolios are value weighted. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. In panel A, portfolios are rebalanced at the end of each month and $\text{Illiq}_{1,0}$ is computed using a minimum of 15 daily observations. In panel B, portfolios are rebalanced each Tuesday, skipping signals and holding-period returns over Tuesday itself to avoid undue influence from bid-ask bounce. That is, for the sort on Tuesday of week t, the sorting variables are returns, turnover, and illiquidity measured from Wednesday of week $t-1$ to Monday of week t, both inclusive, and the holding-period return is computed from Wednesday of week t to Monday of week $t+1$, both inclusive. For the weekly sorts, $\text{Illiq}_{1,0}$ is computed using a minimum of four daily observations. Data are at the monthly or weekly frequency and cover the beginning of July 1963 to the end of December 2018.

monotonically decreasing with illiquidity; from −0.18% per week among the most liquid stocks to −1.00% per week among the most illiquid ones, and similarly for the abnormal returns. Hence, even though there is no high-turnover continuation in any illiquidity quintile at the weekly horizon, returns coupled with high turnover *still* reverse much less among the most liquid stocks compared to the most illiquid ones. These weekly-horizon results are consistent with the findings of Avramov, Chordia, and Goyal (2006) but, again, directly oppose the high-information-asymmetry mechanism. We conjecture that the performance of the weekly STMOM strategies is due to temporary price pressure dominating other effects at the weekly horizon, but less so for more liquid stocks.

3.1.2 Short-term momentum and analysts' forecasts. Table 10 shows the performance of STMOM and STREV* strategies constructed with a control for analysts' forecast variables. The strategies are from $3\times 3\times 3$ conditional sorts on the control variable and the previous month's return and turnover. The breakpoints are the 20th and 80th percentiles for NYSE stocks. Portfolios are value weighted and rebalanced at the end of each month. The sample starts in January 1985 because of the availability of data on analysts' forecasts.[25]

The table's first specification controls for the number of analysts covering a stock. The STMOM strategy yields 1.14% per month ($t=3.20$) among high-coverage stocks but a comparably much weaker 0.62% ($t=1.52$) per month among low-coverage stocks. This again runs opposite to the high-information-asymmetry mechanism. The second specification shows that these results are not mechanically driven by the fact that larger stocks tend to be covered by more analysts: Using analyst coverage orthogonal to size yields qualitatively similar results. Since STREV* is stronger among smaller stocks (Table 3) and smaller stocks tend to have lower analyst coverage, we would expect to see the strongest STREV* performance among low-coverage stocks. The first two specifications confirm this.

Following Diether, Malloy, and Scherbina (2002), a large literature uses measures of the dispersion in analysts' forecasts as proxies for heterogeneity or "disagreement" in beliefs among *traders*.[26] While this interpretation comes with many caveats, there is some consensus that forecast dispersion is at least positively correlated with the underlying, unobservable heterogeneity in beliefs (Verardo 2009; Banerjee 2011). Since short-term momentum is strongest among high-coverage stocks (presumably those with low information asymmetry), it is interesting to examine whether it is also strongest among high-dispersion stocks

[25] Analysts' forecast data come from the Institutional Brokers' Estimate System (I/B/E/S), but we use only unadjusted forecasts to mitigate the reporting inaccuracies, rounding errors, and look-ahead-biases identified in previous studies (Diether, Malloy, and Scherbina 2002). Our tests use earnings-per-share forecasts for the month closest to, but preceding, the month in which a firm announces its quarterly earnings (Compustat's RDQ).

[26] This literature includes Johnson (2004), Verardo (2009), Banerjee (2011), Cen, Wei, and Yang (2017), Cujean and Hasler (2017), and Loh and Stulz (2018), among many others.

Table 10
Short-term momentum controlling for analysts' forecast

	Control variable	Quintile	Short-term momentum [WML, high turnover] controlling for analysts' forecasts $\mathbb{E}[r^e]$	α_{FF6}	Short-term reversal* [WML, low turnover] controlling for analysts' forecasts $\mathbb{E}[r^e]$	α_{FF6}
(1)	N^{Analysts}	High	1.14	1.12	−0.58	−0.59
			(3.20)	(2.84)	(−2.41)	(−2.31)
		Low	0.62	0.50	−0.88	−0.86
			(1.52)	(1.18)	(−3.69)	(−2.58)
(2)	$N^{\text{Analysts}} \perp M$	High	0.84	0.99	−0.41	−0.70
			(2.50)	(2.68)	(−1.27)	(−1.98)
		Low	0.47	0.52	−0.97	−0.94
			(1.15)	(1.14)	(−3.21)	(−2.71)
(3)	$\text{SD}(\widehat{\text{EPS}})$	High	1.38	1.28	−0.28	−0.23
			(2.69)	(2.31)	(−0.99)	(−0.79)
		Low	0.32	0.39	−1.13	−1.10
			(1.00)	(1.32)	(−4.29)	(−3.20)
(4)	$\text{SD}(\widehat{\text{EPS}})/P$	High	1.08	1.16	−0.95	−1.24
			(2.06)	(2.17)	(−2.51)	(−3.08)
		Low	0.01	0.21	−1.27	−1.26
			(0.03)	(0.71)	(−5.45)	(−5.54)
(5)	$\text{SD}(\widehat{\text{EPS}})/\lvert\text{Med}(\widehat{\text{EPS}})\rvert$	High	0.97	1.07	−0.74	−0.91
			(2.24)	(1.98)	(−1.65)	(−1.93)
		Low	−0.25	−0.39	−1.45	−1.61
			(−0.70)	(−1.07)	(−4.69)	(−4.89)
(6)	$\text{Max}(\widehat{\text{EPS}}) - \text{Min}(\widehat{\text{EPS}})$	High	1.49	1.53	−0.40	−0.38
			(3.20)	(2.53)	(−1.17)	(−1.19)
		Low	−0.13	−0.03	−1.16	−1.12
			(−0.36)	(−0.08)	(−4.14)	(−2.74)

This table shows the performance of short-term momentum and short-term reversal* strategies constructed with a control for analysts' forecast variables. The strategies are from $3 \times 3 \times 3$ conditional sorts on the control variable and the previous month's return and turnover, in that order. The breakpoints are the 20th and 80th percentiles for NYSE stocks. Portfolios are value weighted and rebalanced at the end of each month. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. All analysts' forecast variables are for the month closest to, but preceding, the month in which a firm announces its quarterly earnings (Compustat's RDQ). N^{Analysts} is the number of analysts following a stock. $N^{\text{Analysts}} \perp M$ is the residual from monthly cross-sectional regressions of $\log(N^{\text{Analysts}})$ on $\log(M)$, where M is market equity from CRSP, estimated using weighted least squares (WLS) with market capitalization as the weight. $\widehat{\text{EPS}}$ is analysts' forecasts of firms' earnings-per-share and P is price per share from CRSP. "SD" denotes standard deviation, and "Med" denotes median. The sample excludes financial firms. Data are at the monthly frequency and cover January 1985 to December 2018, where the start date is determined by the availability of analysts' forecast data.

(presumably those with strong disagreement among traders). The table's remaining four specifications show that this is indeed the case. In contrast, STREV* is strongest among low-dispersion stocks.

3.2 Models of boundedly rational traders

The literature on "boundedly rational" traders suggests an alternative mechanism that potentially explains short-term momentum: underinference from prices.[27] In the following, we relate our results to general features of models that relax the strict rationality assumption.

Under REE, traders condition on prices so as to infer each others' information up to any noise introduced by noninformational trading. However, when boundedly rational traders fail to fully infer others' information from prices, expected volume is higher and prices underreact to the available information relative to the case with solely rational traders. Underreaction in turn induces positive return autocorrelation that counteracts the negative one induced by noninformational trading. Hence, if there is underinference from prices but no noninformational trading, return autocorrelation will be positive and increasing in volume. Hong and Stein (2007), for instance, show that "the magnitude of the momentum effect will be increasing with average trading volume" (p. 122) in a simple setup where trading is solely due to private information and where there is no conditioning on prices. More generally, if there is some underinference from prices as well as some noninformational trading (e.g., Banerjee 2011; Eyster, Rabin, and Vayanos 2019), high volume will be associated with return continuation so long as underinference is not overwhelmed by noninformational trading.

As such, the cross-sectional variation in short-term momentum is suggestive of an explanation based on underinference prices: It is strongest among the largest and most liquid stocks, whose returns tend to be less affected by temporary price pressure (Avramov, Chordia, and Goyal 2006; Nagel 2012; Hendershott and Menkveld 2014), and it is also stronger among stocks with greater dispersion in analysts' forecasts, which is a common proxy for disagreement among traders (Diether, Malloy, and Scherbina 2002; Verardo 2009; Banerjee 2011).

Lastly, to assist in differentiating between fully and boundedly rational explanations, we investigate how trading volume affects the ability of realized returns to predict firms' fundamentals. The idea is

[27] Examples include Odean's (1998) "overconfident" traders who condition on prices but exaggerate the precision of their own signals (see also Daniel, Hirshleifer, and Subrahmanyam 1998); Hong and Stein's (1999) "newswatchers" that trade on their private information but do not condition on prices (see also Hong and Stein 2007); Hirshleifer, Lim, and Teoh's (2011) "inattentive" traders who condition on a subset of publicly available information, but not on prices; Banerjee's (2011) "dismissive" traders who condition on prices but downplay the precision of others' signals; Eyster, Rabin, and Vayanos' (2019) "cursed" traders who do not fully condition on prices; and Mondria, Vives, and Yang's (2020) "unsophisticated" traders who condition on a noisy version of the price for inference purposes.

that, in models that allow for both underinference and noninformational trading (e.g., Banerjee 2011; Eyster, Rabin, and Vayanos 2019), volume will have different effects on the relation between realized returns and subsequent fundamental values depending on the relative strength of underinference versus noninformational trading, just as discussed above for the effects of volume on return autocorrelation in such models. Because fully rational traders use prices to infer each others' information up to any noise introduced by noninformational trading, "rational volume" ultimately emanates from noninformational trading. Higher rational volume should therefore decrease the predictive ability of returns for fundamentals. By contrast, because boundedly rational traders underappreciate the information conveyed by prices, "boundedly rational" volume will reflect both underreaction to the available information and any noninformational trading. Higher boundedly rational volume should therefore increase the predictive ability of returns for fundamentals *if* underinference is not overwhelmed by noninformational trading.

To test this prediction, we use Fama and MacBeth predictive regressions of firms' fundamental growth rates (at horizons of 1, 3, and 5 years) on 1-month returns, turnover, and their interaction ($r_{1,0} \times TO_{1,0}$). We consider the growth in gross profits (REVT − COGS) in Table 11 and the growth in earnings (IB) in Table 12 and control for predictors commonly employed in the literature. All independent variables are measured at the end of firms' fiscal years. We use weighted least squares (WLS) with market capitalization as the weight. Dependent and independent variables are trimmed at the 1st and 99th percentiles. Independent variables are standardized by their cross-sectional average and standard deviation. The interaction is the product of the standardized variables.

The slope on $r_{1,0}$ is positive in all specifications and also significant, except for 5-year earnings growth when employed alongside the controls. The slope of the interaction should be positive if there is detectable underinference from prices, but otherwise should be negative. As such, the regressions are suggestive of detectable underinference. At the 1-year horizon, the slope on the interaction is positive and significant, with or without controls, for both gross-profit growth and earnings growth. At the 3- and 5-year horizons, although the slope on the interaction loses its significance, its point estimate never becomes negative. The fact that the slope on the interaction loses its significant at longer horizons suggests that the interaction reveals information about fundamentals in the relatively near term, and is broadly consistent with our previous result that short-term momentum returns on average persist for a year after portfolio formation (Figure 2).

Table 11
Cross-sectional regressions to predict the growth in gross profits

	Average slopes (×100) and test statistics (in parentheses) from WLS regressions of the form $\frac{GP_{i,t+\tau}-GP_{it}}{A_{it}}=\boldsymbol{\beta}_t'\mathbf{X}_{it}+\epsilon_{it}$					
	1-year		3-year		5-year	
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
$r_{1,0}$	0.79	0.70	1.24	0.86	1.51	0.95
	(5.15)	(9.57)	(3.67)	(4.98)	(2.71)	(3.15)
$TO_{1,0}$	0.76	−0.04	1.90	−0.18	2.98	−0.52
	(4.30)	(−0.35)	(2.49)	(−0.39)	(2.18)	(−0.57)
$r_{1,0} \times TO_{1,0}$	0.19	0.15	0.14	0.12	0.36	0.40
	(2.54)	(2.96)	(0.52)	(0.66)	(0.96)	(1.47)
$r_{12,2}$		1.54		2.00		2.76
		(8.33)		(5.90)		(5.27)
$\text{Illiq}_{1,0}$		−0.19		−1.00		−1.00
		(−1.55)		(−1.74)		(−1.09)
GP/A		1.94		6.38		11.78
		(10.97)		(8.45)		(8.12)
IB/B		−1.10		−2.50		−3.65
		(−5.37)		(−3.72)		(−3.17)
$D\&R/B$		−0.50		−1.91		−3.64
		(−9.41)		(−9.01)		(−9.40)
dA/A_{-1}		1.49		2.88		5.16
		(7.85)		(7.36)		(5.97)
$\log(B/M)$		−1.75		−5.34		−9.58
		(−16.64)		(−14.67)		(−20.09)
Size		−0.26		−1.49		−3.04
		(−2.67)		(−6.70)		(−4.66)
Adj. R^2	3.5%	29.1%	2.9%	32.0%	2.6%	35.4%

This table shows Fama and MacBeth cross-sectional regressions of firms' growth in gross profits on 1-month returns, turnover, and their interaction ($r_{1,0} \times TO_{1,0}$). All independent variables are measured at the end of firms' fiscal years. Regressions are estimated using weighted least squares (WLS) with market capitalization as the weight. Dependent and independent variables are trimmed at the 1st and 99th percentiles. Independent variables are standardized by their cross-sectional average and standard deviation. The interaction is the product of the standardized variables. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Controls are 12-2 months performance ($r_{12,2}$), 1-month Amihud illiquidity ($\text{Illiq}_{1,0}$), gross profits-to-assets (GP/A), earnings-to-book equity (IB/B), dividends and repurchases-to-book equity ($D\&R/B$, where $D\&R$ is DVC + PRSTKCC, both set to zero if missing), asset growth (dA/A_{-1}), book-to-market equity ($\log(B/M)$), and *Size* (log of market capitalization). The sample excludes financial firms and firms with negative book equity. Data are at the annual frequency and cover 1963 to 2018.

Table 12
Cross-sectional regressions to predict the growth in earnings

	Average slopes ($\times 100$) and test statistics (in parentheses) from WLS regressions of the form $\frac{IB_{i,t+\tau} - IB_{it}}{B_{it}} = \boldsymbol{\beta}_t' \mathbf{X}_{it} + \epsilon_{it}$					
	1-year		3-year		5-year	
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
$r_{1,0}$	0.85	0.77	1.00	0.75	0.87	0.37
	(4.87)	(5.08)	(4.79)	(3.29)	(2.62)	(1.21)
$TO_{1,0}$	0.06	−0.37	−0.13	−0.65	0.02	−0.92
	(0.38)	(−2.38)	(−0.27)	(−1.28)	(0.04)	(−1.83)
$r_{1,0} \times TO_{1,0}$	0.28	0.23	0.00	0.09	0.24	0.25
	(2.83)	(2.31)	(0.00)	(0.52)	(1.19)	(1.74)
$r_{12,2}$		2.06		1.07		0.98
		(9.06)		(2.91)		(5.07)
$\text{Illiq}_{1,0}$		−0.41		−0.51		−0.95
		(−2.13)		(−1.38)		(−2.15)
GP/A		0.87		1.36		1.90
		(4.41)		(2.90)		(3.00)
IB/B		−9.02		−12.22		−14.60
		(−4.16)		(−4.04)		(−3.46)
D&R$/B$		0.42		0.31		−0.04
		(5.66)		(1.34)		(−0.12)
dA/A_{-1}		−0.65		−0.65		−0.03
		(−2.81)		(−1.69)		(−0.05)
$\log(B/M)$		−1.67		−3.30		−4.82
		(−7.14)		(−10.33)		(−16.50)
Size		0.98		0.95		0.87
		(2.78)		(1.03)		(0.99)
Adj. R^2	2.3%	16.7%	2.6%	14.7%	2.2%	14.5%

This table shows Fama and MacBeth cross-sectional regressions of firms' growth in earnings on 1-month returns, turnover, and their interaction ($r_{1,0} \times TO_{1,0}$). All independent variables are measured at the end of firms' fiscal years. Regressions are estimated using weighted least squares (WLS) with market capitalization as the weight. Dependent and independent variables are trimmed at the 1st and 99th percentiles. Independent variables are standardized by their cross-sectional average and standard deviation. The interaction is the product of the standardized variables. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Controls are 12-2 months performance ($r_{12,2}$), 1-month Amihud illiquidity ($\text{Illiq}_{1,0}$), gross profits-to-assets (GP/A), earnings-to-book equity (IB/B), dividends and repurchases-to-book equity (*D&R*$/B$, where *D&R* is DVC + PRSTKCC, both set to zero if missing), asset growth (dA/A_{-1}), book-to-market equity ($\log(B/M)$), and *Size* (log of market capitalization). The sample excludes financial firms and firms with negative book equity. Data are at the annual frequency and cover 1963 to 2018.

4. Conclusion

Momentum (the tendency for winners to outperform losers) and reversal (the tendency for losers to outperform winners) coexist with almost equal strengths at the 1-month horizon. While the previous month's low-turnover stocks exhibit a strong short-term reversal effect (−16.9% per annum), the previous month's high-turnover stocks exhibit an almost equally strong continuation effect (+16.4% per annum), which we dub *short-term momentum*. This finding is not limited to the United States but extends to 22 international developed markets. We show that short-term momentum generates significant abnormal returns relative to standard factors; persists for 12 months; is stronger with an implementation lag; survives conservative estimates of transaction costs; and is strongest among the largest, most liquid, and most extensively covered stocks.

Short-term momentum and conventional price momentum share the same basic philosophy: both are a bet on recent winners financed by a bet against recent losers, and both are designed to avoid diluting the continuation effect with short-term reversal. However, while conventional momentum does this by skipping the most recent month, short-term momentum's trading signal *is* the performance over the most recent month, and it instead avoids reversal by conditioning on high share turnover in the most recent month. The two are alike in terms of profitability and persistence and are related in terms of characteristic tilts, portfolio overlap, and time-series correlation. However, there are also noteworthy differences between them. While short-term momentum is strongest among the largest and most extensively covered stocks, Hong, Lim, and Stein (2000) find that "once one moves past the very smallest capitalization stocks (where thin market making capacity does indeed appear to be an issue) the profitability of momentum strategies declines sharply with market capitalization" and "momentum strategies work particularly well among stocks that have low analyst coverage" (p. 267). In addition, short-term momentum exhibits far less crash risk than does conventional momentum and, unlike conventional momentum, does not appear to be spanned or driven by other, well-known momentum effects, such as those in earnings, industry returns, and factor returns. As such, an open question for future research is whether short-term momentum and conventional momentum are the same phenomenon in different guises or related phenomena with important differences.

Theoretically, the existence of a high-turnover continuation effect is postulated by the models of Wang (1994) and Llorente et al. (2002). Still, these models' high-information-asymmetry mechanism is not supported in the data as an explanation for short-term momentum. While high-information-asymmetry stocks should be small, illiquid, and have low analyst coverage, we find the exact opposite for short-term momentum: It is *strongest* among the largest, most liquid, and most extensively covered stocks. Notwithstanding these results, size, liquidity, and analyst coverage may simply be imperfect proxies for information asymmetry. Finding better proxies and retesting the mechanism is certainly an interesting avenue for future research. Alternatively, models that relax the strict rationality assumption and instead allow for underinference from prices by some traders (a mild form of bounded rationality) would predict that short-term momentum should be stronger among stocks where any underinference from prices is not overwhelmed by noninformational trading. We argue that the cross-sectional variation in short-term momentum is broadly consistent with such an explanation: It is stronger among stocks less likely to be affected by temporary price pressure and among stocks more likely to cause disagreement among traders. Refining this argument, including tests of additional predictions and formally discriminating between alternative classes of models, is also an interesting avenue for future research.

Appendix. Tables and figures omitted from the main text

This appendix contains tables and figures omitted from the main text. Additional results can be found in the paper's Internet Appendix.

Table A.1
Portfolio characteristics for double sorts on 1-month returns and turnover

	$r_{1,0}$ deciles									
$TO_{1,0}$ deciles	Low	2	3	4	5	6	7	8	9	High
					Portfolio $r_{1,0}$					
Low	−0.14	−0.07	−0.04	−0.02	0.00	0.02	0.04	0.06	0.09	0.19
2	−0.14	−0.07	−0.04	−0.02	0.00	0.02	0.04	0.06	0.09	0.18
3	−0.14	−0.07	−0.04	−0.02	0.00	0.02	0.04	0.06	0.09	0.17
4	−0.13	−0.07	−0.04	−0.02	0.00	0.02	0.04	0.06	0.09	0.18
5	−0.14	−0.07	−0.04	−0.02	0.00	0.02	0.04	0.06	0.09	0.18
6	−0.14	−0.07	−0.04	−0.02	0.00	0.02	0.04	0.06	0.09	0.18
7	−0.14	−0.07	−0.04	−0.02	0.00	0.02	0.04	0.06	0.10	0.19
8	−0.14	−0.08	−0.04	−0.02	0.00	0.02	0.04	0.06	0.10	0.20
9	−0.16	−0.08	−0.04	−0.02	0.00	0.02	0.04	0.06	0.10	0.22
High	−0.18	−0.08	−0.04	−0.02	0.00	0.02	0.04	0.06	0.10	0.28
					Portfolio $TO_{1,0}$					
Low	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
2	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.05
3	0.06	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.06
4	0.07	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.08
5	0.09	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.10
6	0.11	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.12
7	0.14	0.10	0.09	0.08	0.08	0.08	0.08	0.09	0.10	0.14
8	0.17	0.12	0.10	0.10	0.09	0.09	0.10	0.11	0.12	0.18
9	0.23	0.15	0.13	0.12	0.12	0.12	0.13	0.13	0.16	0.24
High	0.43	0.27	0.24	0.22	0.21	0.21	0.22	0.24	0.28	0.47
					Average market capitalization ($ mio.)					
Low	176	414	803	1,003	985	1,174	1182	1,227	952	364
2	530	1,880	2,957	3,642	4,806	4,167	4,212	3,866	2,789	994
3	711	2,169	3,140	4,219	4,481	4,498	4,439	4,117	3,340	1,290
4	930	2,275	3,262	3,676	3,753	4,009	3,945	3,875	3,116	1,265
5	905	2,376	2,815	3,445	3,753	3,566	3,842	3,550	3,016	1,396
6	934	2,485	2,829	3,485	3,499	3,335	3,391	3,411	2,654	1,284
7	923	2,142	2,488	3,010	3,259	3,347	3,167	2,990	2,389	1,206
8	925	1,886	2,198	2,660	2,811	2,805	2,858	2,565	2,154	1,158
9	855	1,675	1,984	2,079	2,180	2,496	2,364	2,151	1,919	1,132
High	722	1,403	1,589	1,697	1,706	1,756	1,667	1,779	1,511	898
					Average number of stocks					
Low	177	95	83	74	68	66	63	66	72	124
2	78	41	34	30	28	27	27	29	33	59
3	58	32	27	24	23	23	22	24	27	47
4	49	29	24	22	21	21	21	22	24	42
5	44	26	22	21	20	20	20	21	23	39
6	39	24	21	20	19	19	20	20	22	36
7	37	24	21	20	20	19	19	20	22	36
8	36	24	22	20	20	20	20	21	23	37
9	35	24	22	21	21	21	21	22	24	37
High	41	29	27	26	26	26	26	27	29	47

This table shows the time-series averages of portfolio characteristics for the double sorts on the previous month's return ($r_{1,0}$) and turnover ($TO_{1,0}$) in Table 1. Portfolio $r_{1,0}$ is the time-series average of each portfolios' monthly value-weighted $r_{1,0}$, and similarly for portfolio $TO_{1,0}$. Average market capitalization is the time-series average of each portfolio's monthly equal-weighted average market capitalization in millions of dollars. Average number of stocks is the time-series average of each portfolios' monthly number of stocks. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 to December 2018.

Table A.2
Independent double sorts on the previous month's return and turnover

	$r_{1,0}$ deciles										$r_{1,0}$ strategies		
	Low	2	3	4	5	6	7	8	9	High	$\mathbb{E}[r^e]$	α_{FF6}	α_q
$TO_{1,0}$ deciles													
					Portfolio excess return								
Low	1.28	1.28	0.83	0.93	0.63	1.01	0.78	0.74	0.38	−0.14	−1.42	−1.53	−1.57
											(−6.11)	(−5.95)	(−6.27)
2	1.71	1.06	1.02	0.95	1.05	0.88	0.75	0.73	0.64	−0.03	−1.74	−1.76	−1.73
											(−5.41)	(−4.61)	(−4.51)
3	1.36	1.27	1.27	1.02	1.16	1.00	0.59	0.75	0.36	0.47	−0.89	−1.05	−1.15
											(−2.54)	(−2.75)	(−3.04)
4	1.62	1.46	1.40	1.36	0.90	1.06	0.82	0.59	0.82	0.09	−1.53	−1.82	−1.73
											(−5.15)	(−5.88)	(−4.90)
5	1.52	1.55	1.38	1.02	1.21	0.86	0.86	0.98	0.61	0.46	−1.06	−1.29	−1.37
											(−3.22)	(−3.00)	(−3.37)
6	1.55	1.10	1.32	1.24	0.82	0.84	0.99	1.07	0.77	0.72	−0.83	−0.96	−0.90
											(−2.59)	(−2.63)	(−2.36)
7	1.13	1.01	1.17	0.95	1.04	1.21	0.92	0.98	0.80	0.49	−0.64	−0.77	−0.67
											(−3.10)	(−2.73)	(−2.39)
8	1.33	1.10	1.14	1.06	1.19	1.18	0.96	0.84	0.88	0.79	−0.55	−0.43	−0.40
											(−2.07)	(−1.39)	(−1.18)
9	0.94	1.10	1.17	1.24	1.14	0.95	1.05	1.26	1.00	0.69	−0.25	−0.31	−0.23
											(−0.91)	(−1.07)	(−0.56)
High	0.12	0.78	0.98	1.00	0.86	0.48	0.89	0.96	0.90	1.12	1.00	0.98	1.06
											(4.02)	(3.40)	(3.31)
$TO_{1,0}$ strategies													
$\mathbb{E}[r^e]$	−1.16	−0.50	0.15	0.08	0.23	−0.53	0.10	0.23	0.52	1.26			
	(−4.63)	(−1.93)	(0.46)	(0.23)	(0.68)	(−1.72)	(0.35)	(0.75)	(1.72)	(5.06)			
α_{FF6}	−1.15	−0.34	0.40	0.07	0.33	−0.35	0.28	0.34	0.74	1.36			
	(−4.47)	(−1.21)	(1.33)	(0.23)	(1.04)	(−1.22)	(1.01)	(1.17)	(2.73)	(5.26)			
α_q	−1.18	−0.16	0.38	0.04	0.31	−0.38	0.23	0.26	0.78	1.46			
	(−4.38)	(−0.59)	(1.14)	(0.11)	(0.87)	(−1.18)	(0.77)	(0.74)	(2.45)	(5.19)			

This table shows portfolios from independent double sorts on the previous month's return ($r_{1,0}$) and turnover ($TO_{1,0}$). We use sorts into deciles based on NYSE breakpoints. Portfolios are value weighted and rebalanced at the end of each month. The table also shows the performance of long-short strategies across the deciles. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Time-series averages of the portfolios' characteristics are provided in Table IA.1 in the Internet Appendix. Data are at the monthly frequency and cover July 1969 to December 2018, where the start date ensures nonempty portfolios as a result of the independent sorts.

Table A.3
Independent quintile double sorts on 1-month returns and turnover excluding end-of-month effects

A. Portfolio excess returns and strategy performance

$TO_{1,0-\text{EOM}}$ quintiles	$r_{1,0-\text{EOM}}$ quintiles Low	2	3	4	High	$r_{1,0-\text{EOM}}$ strategies $\mathbb{E}[r^e]$	α_{FF6}	α_q
	Portfolio excess return							
Low	0.50	0.28	0.47	0.49	0.23	−0.26	−0.30	−0.26
						(−1.57)	(−1.83)	(−1.39)
2	0.75	0.73	0.56	0.35	0.33	−0.42	−0.51	−0.45
						(−2.26)	(−2.61)	(−2.16)
3	0.62	0.76	0.63	0.59	0.51	−0.12	−0.23	−0.10
						(−0.64)	(−1.13)	(−0.41)
4	0.57	0.72	0.68	0.59	0.54	−0.04	0.02	0.09
						(−0.21)	(0.09)	(0.34)
High	0.00	0.81	0.72	0.60	0.74	0.74	0.77	0.86
						(4.21)	(4.03)	(3.37)
$TO_{1,0-\text{EOM}}$ strategies								
$\mathbb{E}[r^e]$	−0.50	0.53	0.25	0.11	0.51			
	(−2.88)	(2.50)	(1.07)	(0.48)	(2.87)			
α_{FF6}	−0.52	0.51	0.34	0.10	0.55			
	(−3.04)	(2.89)	(1.84)	(0.57)	(3.92)			
α_q	−0.52	0.55	0.31	0.02	0.60			
	(−3.04)	(2.85)	(1.62)	(0.07)	(3.29)			

B. Portfolio characteristics

$TO_{1,0-\text{EOM}}$	$r_{1,0-\text{EOM}}$ quintiles Low	2	3	4	High	$r_{1,0-\text{EOM}}$ quintiles Low	2	3	4	High
	Portfolio $r_{1,0-\text{EOM}}$					Portfolio $TO_{1,0-\text{EOM}}$				
Low	−0.10	−0.03	0.00	0.04	0.12	0.02	0.02	0.02	0.02	0.02
2	−0.09	−0.03	0.00	0.04	0.11	0.04	0.04	0.04	0.04	0.04
3	−0.09	−0.03	0.00	0.04	0.11	0.06	0.06	0.06	0.06	0.06
4	−0.10	−0.03	0.00	0.04	0.12	0.09	0.09	0.09	0.09	0.09
High	−0.12	−0.03	0.00	0.04	0.16	0.20	0.18	0.18	0.18	0.21
	Average M ($ mio.)					Average N				
Low	379	1,490	2,082	2,000	732	439	275	246	227	286
2	1,275	3,150	3,850	3,685	1,939	145	106	102	99	116
3	1,367	2,895	3,315	3,261	2,013	126	90	85	89	115
4	1,297	2,334	2,622	2,571	1,719	134	81	74	83	137
High	1,016	1,634	1,800	1,747	1,218	180	70	61	75	222

This table shows portfolios double sorted on the previous month's return and turnover, while skipping the sorting variables' end-of-month values ($r_{1,0-\text{EOM}}$ and $TO_{1,0-\text{EOM}}$) measured at the month's last 3 trading days. We use independent sorts into quintiles based on NYSE breakpoints. Portfolios are value weighted and rebalanced at the end of each month. Panel A shows portfolio excess returns and the performance of long-short strategies across the quintiles. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Panel B shows the time-series averages of the monthly value-weighted average portfolio characteristics as well as the equal-weighted average market capitalization and the number of stocks. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 to December 2018, except for the q-factors, which are available from January 1967.

Table A.4
Short-term momentum's investment allocation and capacity

		A					*B*	
		Average fraction of each $1 investment allocated to each NYSE size quintile (%)					Investment capacity	
Strategy	Leg	Micro	2	3	4	Mega	Average fraction (%)	December 2018 ($B)
Short-term momentum	Long	8.5	12.9	19.2	27.1	32.3	0.69	71.4
	Short	8.8	14.4	21.3	27.1	28.4	0.57	38.7
Short-term reversal*	Long	27.4	14.2	13.8	16.1	28.5	0.88	43.0
	Short	39.2	13.9	12.0	13.7	21.1	0.62	12.1
Short-term momentum (excl. EOM)	Long	8.7	13	19.1	27.1	31.9	0.69	96.4
	Short	8.8	14.1	20.9	27.1	29.1	0.56	53.8
Short-term momentum (5×5, excl. EOM)	Long	5.7	9.1	14.1	23.1	48.1	4.25	387.4
	Short	6.3	9.9	15.2	23.7	45.0	3.10	863.6
Short-term momentum (largecaps, excl. EOM)	Long	0.0	0.0	11.4	32.7	56.0	2.31	353.3
	Short	0.0	0.0	10.7	31.9	57.3	2.21	465.7
Short-term momentum (megacaps, excl. EOM)	Long	0.0	0.0	0.0	0.0	100.0	2.17	587.0
	Short	0.0	0.0	0.0	0.0	100.0	2.07	650.3

This table shows the investment allocation and capacity for the strategies considered in Table 7. Panel A shows, for each strategy, the time-series average of the underlying portfolios' investment allocation to each NYSE size quintile, that is, how each portfolio on average allocates each invested dollar to each NYSE size quintile. Panel B shows, for each strategy, the investment capacity of the underlying portfolios measured in two ways: (1) the time-series average of the portfolio's market capitalization as a percentage of the aggregate market capitalization and (2) the portfolio's market capitalization in billions of dollars at the end of the sample in December 2018.

Table A.5
Short-term momentum and industry adjustments

	A			*B* Decomposition of benchmark strategy performance into an industry-hedged ("within-industry") component and the industry hedge								
	Strategies from sorts on industry-demeaned variables			Benchmark strategies			Industry-hedged strategies			The industry hedges		
Turnover decile	$\mathbb{E}[r^e]$	α_{FF6}	α_q	$\mathbb{E}[r^e]$	α_{FF6}	α_q	$\mathbb{E}[r^e]$	α_{FF6}	α_q	$\mathbb{E}[r^e]$	α_{FF6}	α_q
Low	−2.00	−2.12	−2.07	−1.41	−1.45	−1.43	−1.73	−1.74	−1.73	0.32	0.29	0.30
	(−10.25)	(−8.51)	(−7.25)	(−7.13)	(−6.19)	(−5.95)	(−8.41)	(−8.26)	(−7.52)	(3.68)	(3.27)	(3.00)
2	−1.73	−1.94	−1.84	−1.19	−1.31	−1.34	−1.62	−1.78	−1.76	0.43	0.47	0.42
	(−7.57)	(−6.61)	(−4.87)	(−4.61)	(−4.04)	(−4.21)	(−7.00)	(−5.93)	(−6.62)	(3.74)	(4.26)	(3.04)
3	−1.75	−1.95	−1.93	−1.34	−1.62	−1.66	−1.65	−1.83	−1.87	0.30	0.21	0.22
	(−7.79)	(−6.43)	(−4.83)	(−5.02)	(−5.61)	(−4.87)	(−7.32)	(−7.37)	(−6.50)	(2.57)	(1.57)	(1.52)
4	−2.08	−2.23	−2.32	−0.85	−1.02	−0.91	−1.22	−1.33	−1.21	0.37	0.31	0.31
	(−7.75)	(−8.63)	(−9.15)	(−3.63)	(−4.15)	(−2.92)	(−5.84)	(−6.08)	(−5.25)	(3.21)	(2.53)	(2.20)
5	−1.09	−1.28	−1.08	−0.45	−0.63	−0.51	−0.96	−1.08	−0.96	0.51	0.46	0.44
	(−4.37)	(−4.58)	(−3.72)	(−1.94)	(−2.29)	(−1.54)	(−4.63)	(−4.71)	(−3.57)	(4.50)	(3.85)	(3.14)
6	−0.96	−0.97	−1.02	−0.59	−0.60	−0.41	−0.94	−1.05	−0.97	0.35	0.45	0.56
	(−3.95)	(−3.53)	(−3.27)	(−2.50)	(−2.35)	(−1.20)	(−4.88)	(−4.52)	(−3.56)	(2.74)	(3.35)	(3.08)
7	−0.89	−0.91	−0.92	−0.67	−0.85	−0.96	−0.94	−1.09	−1.19	0.27	0.23	0.23
	(−3.32)	(−2.85)	(−2.61)	(−2.52)	(−2.55)	(−2.37)	(−4.13)	(−3.77)	(−3.85)	(2.31)	(1.56)	(1.36)
8	−0.33	−0.44	−0.42	0.23	0.13	0.21	−0.19	−0.22	−0.19	0.42	0.35	0.40
	(−1.24)	(−1.75)	(−1.38)	(0.85)	(0.47)	(0.60)	(−0.81)	(−1.00)	(−0.69)	(4.01)	(2.96)	(2.98)
9	−0.04	−0.21	−0.10	0.05	0.00	0.19	−0.12	−0.25	−0.12	0.17	0.26	0.31
	(−0.17)	(−0.67)	(−0.29)	(0.21)	(0.01)	(0.55)	(−0.58)	(−0.98)	(−0.43)	(1.56)	(2.31)	(2.17)
High	1.18	0.95	1.16	1.37	1.37	1.65	0.89	0.86	1.06	0.48	0.51	0.59
	(4.08)	(2.78)	(2.94)	(4.74)	(4.22)	(4.47)	(3.35)	(2.87)	(3.31)	(5.65)	(5.11)	(4.68)

This table shows the performance of winner-minus-loser strategies similar to those in Table 1, except that we consider industry-adjusted signals or performance. We use conditional sorts into deciles based on NYSE breakpoints, first on returns and then on turnover. Portfolios are value weighted and rebalanced at the end of each month. Panel A shows strategies from sorts where the sorting variables are demeaned by their value-weighted average industry values. Panel B shows a decomposition of the benchmark strategies (from sorts on unadjusted variables) into an industry-hedged ("within-industry") component and the industry hedge. The industry-hedged strategies are from sorts on unadjusted variables, but each stock's position is combined with an offsetting position of equal size in the corresponding value-weighted industry portfolio. The industry hedges are these offsetting positions in the value-weighted industry portfolios. The industries are the Fama and French 49 industries. Test statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover January 1963 to December 2018.

Table A.6
Short-term momentum and crash risk

A. Higher-order moments and downside beta

Statistic	Market excess return	Short-term momentum	Conventional momentum
Skew	−0.55	−0.48	−5.74
	(−7.08)	(−6.24)	(−29.72)
Kurtosis	9.87	7.55	74.05
	(12.73)	(10.94)	(20.65)
Co-skewness		0.47	−1.87
		(1.60)	(−8.05)
Down-side β		0.07	−0.71
		(0.52)	(−6.35)

B. Regression results

Intercepts, slopes, and test-statistics (in parentheses) from time-series regressions of strategy returns

		Short-term momentum			Conventional momentum		
Coefficient	Variable	(1)	(2)	(3)	(4)	(5)	(6)
α_0	1	1.15	1.50	1.50	1.33	1.22	1.22
		(4.33)	(5.02)	(5.04)	(6.20)	(5.30)	(5.35)
α_B	$1_{B,t-1}$		−1.65	−3.29		−0.63	1.45
			(−2.55)	(−3.78)		(−1.28)	(2.19)
β_0	r^e_{mt}	−0.20	−0.22	−0.22	−0.27	0.19	0.19
		(−4.09)	(−3.15)	(−3.16)	(−6.70)	(3.58)	(3.61)
β_B	$1_{B,t-1} \times r^e_{mt}$		0.03	−0.29		−0.94	−0.53
			(0.34)	(−1.92)		(−12.53)	(−4.59)
$\beta_{B,U}$	$1_{B,t-1} \times 1_{U,t} \times r^e_{mt}$			0.56			−0.72
				(2.80)			(−4.66)
Adj. R^2		1.4%	1.9%	2.5%	3.8%	16.7%	18.2%

This table shows downside and crash risk measures for the short-term momentum strategy. For comparison, it also shows the corresponding measures for the market excess return and/or a conventional momentum strategy from decile sorts on prior 12-2 month performance using NYSE breakpoints.

Panel A shows, for each strategy, the skewness and kurtosis of $\log(1+r^e_t+r_{ft})$, where r^e_t is the strategy's monthly excess return and r_{ft} is the monthly risk-free rate. The corresponding test statistics (in parentheses) are for the null of normally distributed returns. Panel A also shows the two momentum strategies' coskewness with the market, computed as the slope coefficient from a univariate regression of $\varepsilon_t(r^e)$ on $(r^e_{mt})^2$, where the latter is the squared excess market return and where $\varepsilon_t(r^e)$ is the residual from a univariate regression of r^e_t on r^e_{mt}. Finally, panel A shows the two momentum strategies' downside β, computed as the coefficient β_D from the regression $r^e_t = \alpha + \beta r^e_{mt} + \beta_D \max\{0, -r^e_{mt}\} + \epsilon_t$.

Panel B shows results from Daniel and Moskowitz's (2016) regressions, where the most general form is $r^e_t = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + (\beta_B + \beta_{B,U} I_{U,t}) I_{B,t-1}) r^e_{mt} + \epsilon_t$. Here, $I_{B,t-1}$ is an ex ante "bear market" indicator that equals one if the cumulative market excess return over the previous 24 months is negative and is otherwise zero, and $I_{U,t}$ is a contemporaneous "up-market" indicator that equals one if the market excess return is positive in month t and is otherwise zero. The intercepts, α_0 and α_B, are multiplied by 100 and are thus stated in % per month.

The sample excludes financial firms. Data are at the monthly frequency and cover January 1927 to December 2018.

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Short-term Momentum — Internet Appendix

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Appendix IA. Additional results

This internet appendix contains additional tables and figures omitted from the main paper.

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Table IA.1
Portfolio characteristics for independent double sorts on the previous month's return and turnover

	$r_{1,0}$ deciles									
$TO_{1,0}$ deciles	Low	2	3	4	5	6	7	8	9	High
	Portfolio $r_{1,0}$									
Low	−0.15	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.20
2	−0.14	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.19
3	−0.14	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.19
4	−0.14	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.18
5	−0.14	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.18
6	−0.14	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.18
7	−0.14	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.18
8	−0.14	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.18
9	−0.15	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.19
High	−0.17	−0.08	−0.05	−0.02	0.00	0.02	0.04	0.06	0.10	0.24
	Portfolio $TO_{1,0}$									
Low	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
2	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
3	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
4	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
5	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
6	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
7	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
8	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
9	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
High	0.34	0.30	0.30	0.29	0.30	0.29	0.30	0.29	0.30	0.36
	Average market capitalization ($ mio.)									
Low	126	352	690	1,058	999	1,160	1,201	1,014	667	276
2	444	1,911	3,381	4,306	5,005	4,795	4,405	4,069	2,919	830
3	627	2,308	3,544	4,099	4,487	4,361	4,337	4,241	3,338	969
4	744	2,493	3,300	3,803	4,023	4,108	4,207	4,098	3,281	1,200
5	842	2,534	3,106	3,716	3,762	3,556	3,748	3,888	3,292	1,288
6	925	2,508	2,782	3,300	3,655	3,714	3,536	3,453	2,858	1,428
7	959	2,355	2,649	2,869	2,963	3,107	3,121	3,110	2,672	1,421
8	988	2,119	2,326	2,481	2,514	2,879	2,746	2,483	2,314	1,353
9	1,032	1,741	1,898	2,070	2,055	2,272	2,224	2,294	2,064	1,232
High	875	1,523	1,772	1,691	1,661	1,716	1,730	1,805	1,693	1,090
	Average number of stocks									
Low	179	107	96	87	79	75	68	68	67	96
2	68	42	38	35	34	33	32	32	32	46
3	49	32	29	29	28	27	27	27	27	37
4	42	28	26	25	25	25	24	25	25	34
5	39	26	24	23	23	23	23	24	25	34
6	38	26	23	22	21	21	22	23	25	36
7	40	26	22	20	20	20	20	23	26	40
8	44	26	21	19	18	18	19	22	27	48
9	52	27	20	18	16	17	18	21	29	60
High	81	26	18	15	14	14	16	20	29	101

This table shows the time-series averages of the portfolio characteristics for the independent double sorts on the previous month's return ($r_{1,0}$) and turnover ($TO_{1,0}$), as shown in Table A.2 in the main text. Portfolio $r_{1,0}$ is the time-series average of each portfolios' monthly value weighted $r_{1,0}$, and similarly for portfolio $TO_{1,0}$. Average market capitalization is the time-series average of each portfolio's monthly equal-weighted average market capitalization in millions of dollars. Average number of stocks is the time-series average of each portfolios' monthly number of stocks. Data are at the monthly frequency and cover July 1969 to December 2018, where the start date is to ensure non-empty portfolios as a result of the independent sorts.

Table IA.2
Short-term momentum and size: Robustness checks

A Performance of $r_{1,0}$ strategies within $TO_{1,0} \perp M$ deciles				*B* Performance of $r_{1,0}$ strategies within size deciles			
$TO_{1,0} \perp M$ decile	$\mathbb{E}[r^e]$	α_{FF6}	α_q	Size decile	$\mathbb{E}[r^e]$	α_{FF6}	α_q
Low	−1.88	−1.98	−1.98	Smallest	−2.08	−2.37	−2.35
	(−9.40)	(−9.11)	(−6.82)		(−7.85)	(−7.71)	(−6.31)
2	−1.62	−1.65	−1.55	2	−1.04	−1.26	−1.28
	(−7.47)	(−7.34)	(−5.46)		(−4.57)	(−4.48)	(−3.63)
3	−1.38	−1.44	−1.44	3	−0.81	−1.08	−1.06
	(−5.57)	(−5.81)	(−4.97)		(−3.48)	(−3.50)	(−2.66)
4	−1.21	−1.36	−1.43	4	−0.66	−0.85	−0.89
	(−5.43)	(−4.92)	(−4.17)		(−2.66)	(−2.47)	(−1.98)
5	−0.88	−1.07	−1.00	5	−0.82	−1.04	−1.03
	(−3.46)	(−4.06)	(−3.26)		(−3.60)	(−4.19)	(−3.44)
6	−1.01	−1.12	−1.03	6	−0.90	−0.98	−0.90
	(−3.58)	(−3.44)	(−2.77)		(−3.95)	(−3.21)	(−2.51)
7	−0.11	−0.24	−0.22	7	−0.98	−1.04	−0.91
	(−0.43)	(−0.80)	(−0.68)		(−4.41)	(−4.34)	(−2.87)
8	0.11	0.08	0.04	8	−0.61	−0.59	−0.42
	(0.44)	(0.29)	(0.13)		(−2.40)	(−2.09)	(−1.25)
9	0.22	0.07	0.24	9	−0.40	−0.40	−0.28
	(0.87)	(0.27)	(0.74)		(−1.71)	(−1.42)	(−0.95)
High	1.27	1.26	1.54	Largest	−0.03	−0.15	−0.04
	(4.36)	(3.78)	(3.99)		(−0.17)	(−0.73)	(−0.14)

This table shows the performance of winner-minus-loser strategies based on the previous month's return within deciles of the previous month's 'residual turnover' relative to size ($TO_{1,0} \perp M$; panel A) and size (market capitalization from CRSP, M; panel B). Portfolios are from double sorts on the previous month's return ($r_{1,0}$) and either $TO_{1,0} \perp M$ or size. We use conditional sorts into deciles based on NYSE breakpoints, first on $r_{1,0}$ and then on either $TO_{1,0} \perp M$ or size. Portfolios are value weighted and rebalanced at the end of each month. $TO_{1,0} \perp M$ is the residual from cross-sectional regression of $TO_{1,0}$ on $\log(M)$, estimated using WLS with market capitalization as weight. Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 to December 2018, except when applying the q-factors, which are available from January 1967.

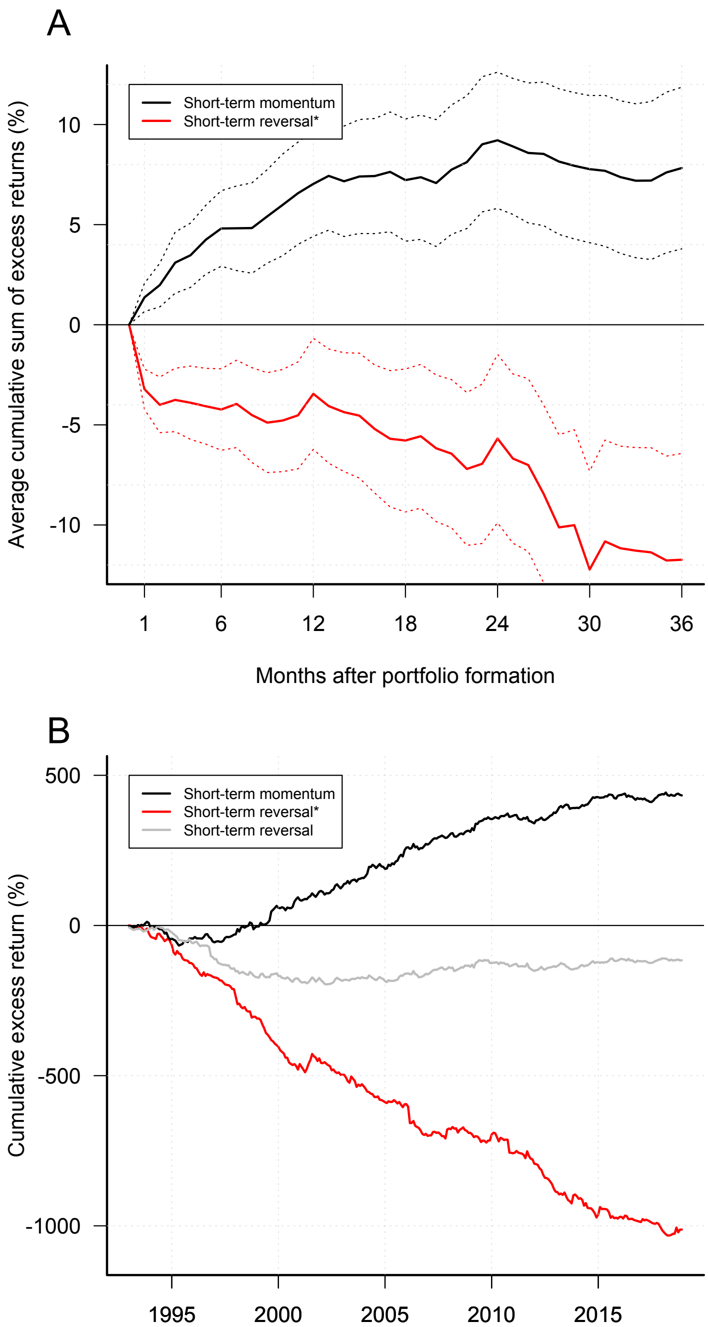

Figure IA.1
International short-term momentum returns: Persistence and historical performance Panel A shows the average cumulative sums of post-formation excess returns to each of the international short-term momentum (STMOM) and international short-term reversal* (STREV*) strategies along with 95% confidence bands. Panel B shows a time-series plot of cumulative sums of excess returns to the international STMOM and STREV* strategies as well as a conventional short-term reversal strategy. Data are at the monthly frequency and cover January 1993 to December 2018.

Table IA.3
Short-term momentum controlling for size: International evidence

Size group	Short-term momentum [WML, high turnover] controlling for size $\mathbb{E}[r^e]$	α_{DMFF6}	Short-term reversal* [WML, low turnover] controlling for size $\mathbb{E}[r^e]$	α_{DMFF6}
A: Size breakpoint is median				
Small	0.52	0.57	−3.15	−2.84
	(1.24)	(1.22)	(−8.64)	(−8.31)
Large	0.99	1.03	−1.67	−1.49
	(3.50)	(3.55)	(−4.73)	(−4.12)
B: Size breakpoints are quintiles				
Small	−0.23	−0.15	−3.45	−3.55
	(−0.36)	(−0.18)	(−3.54)	(−4.68)
2	0.55	0.69	−2.68	−2.34
	(1.16)	(1.38)	(−7.78)	(−6.84)
3	0.71	0.85	−2.40	−2.11
	(1.90)	(2.16)	(−6.51)	(−4.41)
4	0.65	0.83	−1.85	−1.77
	(1.45)	(1.81)	(−4.00)	(−3.80)
Large	1.12	1.14	−1.50	−1.06
	(4.01)	(3.88)	(−3.12)	(−2.31)
C: Largest 100 stocks per country				
Largest 100	0.62	0.46	0.44	0.68
per country	(3.25)	(2.68)	(1.45)	(1.99)

This table shows the performance of international short-term momentum and short-term reversal* strategies constructed with a control for size (market capitalization). In panels A and B, the strategies are from $N \times 3 \times 3$ conditional sorts on size and the previous month's return and turnover, in that order, where the breakpoints for returns and turnover are the 20th and 80th percentiles. In panel A, $N = 2$ and the size breakpoint is the median; in panel B, $N = 5$ and the size breakpoints quintiles. In panel C, the strategies are from 2×2 independent sorts on returns and turnover among the 100 largest stocks by monthly market capitalization within each country, where the breakpoints for returns and turnover are the 50th rank. We use independent double sorts to form country-specific portfolios that are value weighted and rebalanced at the end of each month. We then weight each country's portfolio by the country's total market capitalization for the previous month to form each international portfolio. All returns and market values are in U.S. dollars and excess returns are above the monthly U.S. T-bill rate. Abnormal returns are relative to Fama and French's (2017) developed markets five-factor model including the momentum factor (DMFF6). Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are at the monthly frequency and cover January 1993 to December 2018.

Table IA.4
Short-term momentum and end-of-month effects: International evidence

A Performance of $r_{1,0-\mathrm{EOM}}$ strategies within $TO_{1,0-\mathrm{EOM}}$ deciles			*B* Performance of r_{EOM} strategies within TO_{EOM} deciles		
$TO_{1,0-\mathrm{EOM}}$ decile	$\mathbb{E}[r^e]$	α_{DMFF6}	TO_{EOM} deciles	$\mathbb{E}[r^e]$	α_{DMFF6}
Low	−1.35	−0.98	Low	−3.29	−3.46
	(−2.82)	(−1.88)		(−7.97)	(−7.06)
2	−0.91	0.16	2	−2.11	−2.16
	(−1.88)	(0.28)		(−3.22)	(−3.76)
3	−0.78	−0.61	3	−2.06	−2.13
	(−1.50)	(−1.06)		(−4.83)	(−5.03)
4	0.30	0.89	4	−2.47	−2.77
	(0.81)	(1.93)		(−6.09)	(−6.38)
5	−0.19	−0.06	5	−2.42	−2.32
	(−0.49)	(−0.12)		(−4.72)	(−4.94)
6	−0.04	−0.25	6	−2.09	−1.85
	(−0.09)	(−0.63)		(−4.68)	(−3.72)
7	0.62	0.56	7	−1.76	−2.00
	(1.68)	(1.48)		(−4.79)	(−4.67)
8	0.48	0.66	8	−1.13	−1.47
	(1.23)	(1.69)		(−2.62)	(−3.49)
9	0.98	1.08	9	−0.88	−0.97
	(3.83)	(3.43)		(−2.46)	(−2.32)
High	1.66	1.71	High	−0.42	−0.25
	(3.96)	(3.78)		(−1.06)	(−0.71)

This table shows the average excess returns and the abnormal returns to international winner-minus-loser strategies among stocks with different values for the previous month's share turnover. In panel A, the sorting variables exclude their end-of-month values ($r_{1,0-\mathrm{EOM}}$ and $TO_{1,0-\mathrm{EOM}}$) measured at the month's last three trading days. In panel B, the sorting sorting variables are just the end-of-month values (r_{EOM} and TO_{EOM}) measured at the month's last three trading days. The underlying portfolios are from double sorts on the previous month's return and turnover. We use independent double sorts to form country-specific portfolios that are value weighted and rebalanced at the end of each month. We then weight each country's portfolio by the country's total market capitalization for the previous month to form each international portfolio. All returns and market values are in U.S. dollars and excess returns are above the monthly U.S. T-bill rate. Abnormal returns are relative to Fama and French's (2017) developed markets five-factor model including the momentum factor (DMFF6). Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are at the monthly frequency and cover January 1993 to December 2018.

Table IA.5
Short-term momentum and other stock-level momentum strategies: Additional results

A: Characteristic tilts

	Time-series average of long-short difference in monthly portfolio characteristics and equal-weighted market capitalization				
Strategy	B/M	GP/A_{-1}	COP/A_{-1}	dA/A_{-1}	MC
STMOM	6.38	−4.62	−1.44	−5.42	177
	(3.74)	(−4.73)	(−2.53)	(−1.65)	(3.32)
MOM	−17.40	3.19	2.96	−4.52	583
	(−4.40)	(1.78)	(2.21)	(−1.27)	(2.38)
CAR_3	−0.89	1.77	0.70	−0.77	203
	(−0.91)	(2.73)	(1.69)	(−0.44)	(3.85)
SUE	−26.20	9.62	6.15	−3.28	1,090
	(−10.85)	(6.81)	(5.90)	(−0.83)	(4.02)
ROE	−59.69	33.16	21.87	−27.67	4,237
	(−3.75)	(18.77)	(19.83)	(−1.67)	(0.96)

B: Overlap among winners

	MOM	CAR_3	SUE	ROE
STMOM	0.34	0.28	0.16	0.16
	(28.94)	(42.82)	(24.30)	(17.08)
MOM		0.24	0.30	0.27
		(32.51)	(22.52)	(21.97)
CAR_3			0.22	0.21
			(45.82)	(36.15)
SUE				0.30
				(36.00)

C: Overlap among losers

	MOM	CAR_3	SUE	ROE
STMOM	0.20	0.32	0.15	0.26
	(15.17)	(33.40)	(34.06)	(16.89)
MOM		0.27	0.33	0.40
		(33.01)	(32.00)	(23.60)
CAR_3			0.25	0.34
			(41.76)	(36.50)
SUE				0.51
				(39.85)

This table complements Table 8 in the main text with additional characteristic tilts (panel A) for the short-term momentum strategy and the four other stock-level momentum strategies. It also shows time-series averages of monthly overlap of stocks for the strategies' winner and loser portfolios (panels B and C), where the overlap of two sets, X and Y, is given by $|X \cap Y|/\min\{|X|,|Y|\}$. In panel A, all accounting variables are annual. B/M is book-to-market equity, where M is as of prior December from CRSP, and where the lagging is to avoid taking unintentional positions in conventional momentum. GP/A_{-1} is gross profits relative to 1-year lagged total asset. COP/A_{-1} is cash-based operating profits-to-lagged total assets. dA/A_{-1} is the year-over-year relative change in total assets. MC is monthly market capitalization from CRSP in \$million. Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 to December 2018 for short-term momentum and conventional momentum, but the PEAD and ROE strategies start from January 1972 due to data availability in Compustat.

Table IA.6
Short-term momentum excluding earnings announcements

A: Performance of $r_{1,0}$ strategies within $TO_{1,0}$ deciles excluding earnings announcers				*B*: Performance of $r_{[1,0]\backslash \text{EAD}}$ strategies within $TO_{[1,0]\backslash \text{EAD}}$ deciles			
$TO_{1,0}$ decile	$\mathbb{E}[r^e]$	α_{FF6}	α_q	$TO_{[1,0]\backslash \text{EAD}}$ decile	$\mathbb{E}[r^e]$	α_{FF6}	α_q
Low	−1.82	−1.89	−1.94	Low	−1.80	−1.85	−1.92
	(−5.99)	(−5.18)	(−5.64)		(−7.32)	(−6.71)	(−7.87)
2	−1.77	−1.90	−1.90	2	−1.44	−1.62	−1.63
	(−5.28)	(−5.70)	(−5.10)		(−5.02)	(−4.58)	(−4.98)
3	−1.40	−1.50	−1.41	3	−1.58	−1.79	−1.76
	(−4.08)	(−3.58)	(−3.62)		(−5.51)	(−5.91)	(−5.39)
4	−1.05	−1.27	−1.18	4	−1.06	−1.16	−1.01
	(−3.10)	(−3.80)	(−2.87)		(−3.90)	(−4.46)	(−3.23)
5	−0.95	−0.94	−0.83	5	−0.84	−0.97	−0.83
	(−2.65)	(−2.26)	(−2.00)		(−3.21)	(−3.22)	(−2.19)
6	−0.16	−0.13	−0.02	6	−0.57	−0.46	−0.34
	(−0.40)	(−0.31)	(−0.04)		(−2.27)	(−1.73)	(−0.93)
7	−0.40	−0.56	−0.37	7	−0.97	−1.04	−1.06
	(−1.22)	(−1.56)	(−0.76)		(−3.40)	(−3.10)	(−2.89)
8	−0.58	−0.72	−0.72	8	−0.49	−0.69	−0.72
	(−1.61)	(−1.71)	(−1.69)		(−1.89)	(−2.16)	(−1.91)
9	0.04	−0.13	0.08	9	0.05	−0.05	0.12
	(0.10)	(−0.30)	(0.14)		(0.18)	(−0.13)	(0.32)
High	1.31	1.30	1.44	High	1.16	1.19	1.40
	(2.75)	(2.49)	(3.05)		(3.30)	(3.00)	(3.46)

This table shows the performance of long-short strategies that buy the previous month's winners and sell the previous month's losers among stocks with different share turnover in the previous month. In panel A, the sorts exclude earnings announcers, i.e., excluding firms whose most recent earnings announcement date (Compustat's RDQ) fell in the previous month. In panel B, the sorting variables exclude their values for the three days around earnings announcement dates ($r_{[1,0]\backslash \text{EAD}}$ and $TO_{[1,0]\backslash \text{EAD}}$). Portfolios are from conditional sorts into deciles based on NYSE breakpoints, first on returns and then on turnover, and are value weighted and rebalanced at the end of each month. Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover January 1972 to December 2018, where the start date is determined by the availability of data on quarterly earnings announcement dates in Compustat.

Table IA.7
Short-term momentum and industry momentum

	Intercepts, slopes, and test-statistics (in parentheses) from time-series regressions of the form $y_t = \alpha + \boldsymbol{\beta}' \mathbf{X}_t + \epsilon_t$						
	Short-term momentum [WML, high turnover]			Industry momentum			
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A: Controls are the FF6 factors							
Intercept	1.37	0.79	0.92	0.98	0.84	0.63	0.52
	(4.74)	(2.73)	(3.01)	(4.59)	(3.48)	(2.94)	(2.32)
IMOM		0.59	0.53				
		(7.74)	(7.89)				
STMOM						0.26	0.23
						(6.93)	(5.57)
MKT			−0.31		−0.07		0.01
			(−3.82)		(−1.05)		(0.13)
SMB			0.07		−0.14		−0.13
			(0.51)		(−1.62)		(−1.67)
HML			−0.02		0.08		0.07
			(−0.09)		(0.81)		(0.75)
RMW			−0.30		−0.19		−0.09
			(−1.52)		(−1.33)		(−0.66)
CMA			0.15		0.04		0.00
			(0.62)		(0.26)		(0.01)
MOM			0.15		0.33		0.25
			(1.07)		(4.17)		(3.59)
Adj. R^2		15.1%	18.3%		6.8%	15.1%	18.3%
B: Controls are the q-factors							
Intercept	1.42	0.86	1.15	0.95	0.88	0.58	0.46
	(4.74)	(2.88)	(3.67)	(4.24)	(3.42)	(2.60)	(1.66)
IMOM		0.59	0.57				
		(7.40)	(7.17)				
STMOM						0.26	0.26
						(6.65)	(5.91)
MKT			−0.33		−0.10		0.00
			(−3.78)		(−1.30)		(0.00)
ME			0.07		−0.06		−0.07
			(0.39)		(−0.49)		(−0.91)
ROE			−0.30		0.19		0.24
			(−1.72)		(1.22)		(1.91)
I/A			0.13		0.08		0.03
			(0.62)		(0.35)		(0.20)
Adj. R^2		15.0%	18.2%		1.8%	15.0%	16.1%

This table shows time-series regression results for the short-term momentum (STMOM) strategy and for Moskowitz and Grinblatt's (1999) one-month industry momentum (IMOM) strategy. We sort the 49 industries from Fama and French (1997), excluding financials, on their previous month's value-weighted average return and form a 'winner' and a 'loser' industry portfolio each containing 5 industries. These portfolios are value weighted and rebalanced at the end of each month. The IMOM strategy is long the winner- and short the loser industry portfolio. In panel A, the additional controls are the FF6 factors. In panel B, the additional controls are the q-factors. Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 (panel A) or January 1967 (panel B) to December 2018, where the start date in panel B is determined by the availability of the q-factors.

Table IA.8
Short-term momentum and factor momentum

	Intercepts, slopes, and test-statistics (in parentheses) from time-series regressions of the form $y_t = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t$							
	Short-term momentum [WML, high turnover]				Conventional momentum			
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.95	1.01	0.98	1.31	0.18	0.37	0.24	0.27
	(2.89)	(3.23)	(3.00)	(4.31)	(0.78)	(1.76)	(1.15)	(2.35)
FMOM^{TS}	1.31		0.24	−0.18	3.10		1.05	0.27
	(3.33)		(0.44)	(−0.30)	(12.65)		(3.48)	(1.21)
FMOM^{XS}		1.81	1.55	1.64		4.08	3.00	0.14
		(3.53)	(2.17)	(2.32)		(12.93)	(7.66)	(0.52)
MKT				−0.35				0.05
				(−4.19)				(1.60)
SMB				−0.07				0.00
				(−0.59)				(0.03)
HML				−0.05				0.04
				(−0.25)				(0.59)
RMW				−0.34				−0.20
				(−1.44)				(−2.11)
CMA				0.18				−0.18
				(0.64)				(−1.75)
MOM				0.07				1.34
				(0.32)				(19.19)
Adj. R^2	3.9%	5.0%	4.9%	8.3%	36.8%	42.2%	43.4%	81.6%

This table shows time-series regression results for the short-term momentum strategy from Table 1 in the main text. The explanatory variables are Ehsani and Linnainmaa's (2020) time-series factor momentum strategy (FMOM^{TS}) and cross-sectional factor momentum strategy (FMOM^{XS}). Additional controls are the factors from Fama and French's (2015) five-factor model in addition to the momentum factor (MOM). The table also shows the corresponding results for a conventional 12-2 month momentum strategy from decile sorts using NYSE breakpoints.

FMOM^{TS} is long factors with a positive return and short factors with negative return over the prior 12-1 months. FMOM^{XS} is long factors with an above-median return and short factors with a below-median return over the prior 12-1 months. The FMOM strategies' long and short legs are weighted by the number of factors in each leg relative to the total number of factors and are rebalanced at the end of each month.

Underlying the FMOM strategies are 14 U.S. factors and 6 develop market factors. The U.S. factors are size (SMB), value (HML), profitability (RMW), asset growth (CMA), short-term reversal, long-term reversal, accruals, cash flow-to-price, earnings-to-price, net share issues, residual variance, Pástor and Stambaugh's (2003) traded liquidity factor, Frazzini and Pedersen's (2014) betting-against-beta (BAB), and Asness, Frazzini, and Pedersen's (2019) quality-minus-junk (QMJ). The developed market factors are SMB, HML, RMW, CMA, BAB, and QMJ. The accruals, cash flow-to-price, earnings-to-price, net share issues, and residual variance factors are long and short the top and bottom 30% of stocks based on univariate sorts using data from Ken French's website. The BAB and QMJ factors are from AQR's website.

Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are at the monthly frequency and cover July 1964 to December 2018, where the start date is due to the availability of the FMOM strategies.

Table IA.9
Short-term momentum and longer formation periods

	Intercepts, slopes, and test-statistics (in parentheses) from time-series regressions of the form $y_t = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t$									
	2 months formation		3 months formation		4 months formation		5 months formation		6 months formation	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A: Dependent variable is alternative short-term momentum return										
Intercept	0.99	0.02	1.00	0.15	1.06	0.38	1.24	0.64	1.19	0.62
	(2.95)	(0.08)	(3.11)	(0.57)	(3.16)	(1.36)	(3.78)	(1.93)	(3.25)	(1.80)
STMOM		0.71		0.62		0.50		0.45		0.42
		(15.12)		(13.70)		(13.38)		(9.50)		(7.35)
Adj. R^2		46.5%		34.0%		21.5%		17.3%		14.9%
B: Dependent variable is alternative short-term reversal return*										
Intercept	−1.07	−0.13	−0.88	−0.02	−0.49	0.33	−0.48	0.27	−0.49	0.24
	(−4.70)	(−0.60)	(−3.78)	(−0.07)	(−2.05)	(1.46)	(−1.87)	(1.10)	(−1.84)	(0.94)
STREV*		0.67		0.61		0.58		0.53		0.51
		(12.74)		(11.21)		(10.02)		(9.20)		(6.86)
Adj. R^2		36.1%		28.4%		23.9%		18.9%		16.1%

This table shows time-series regression results for alternative short-term momentum and short-term reversal* strategies constructed using longer formation periods. The strategies are constructed similar to their one-month counterparts in Table 1 in the main text, except that the sorting variables are cumulative return and average monthly share turnover for the previous 2,...,6 months. The explanatory variables are the benchmark STMOM and STREV* strategies from Table 1 in the main text based on a one-month formation period. Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover January 1963 to December 2018.

Table IA.10
Short-term momentum and volatility: Robustness checks

A				*B*			
Performance of $r_{1,0}$ strategies within $TO_{1,0} \perp \sigma_{1,0}$ deciles				Performance of $r_{1,0}$ strategies within $\sigma_{1,0}$ deciles			
$TO_{1,0} \perp \sigma_{1,0}$ decile	$\mathbb{E}[r^e]$	α_{FF6}	α_q	$\sigma_{1,0}$ decile	$\mathbb{E}[r^e]$	α_{FF6}	α_q
Low	−1.54	−1.59	−1.57	Low	−2.36	−2.45	−2.56
	(−5.55)	(−5.97)	(−5.13)		(−11.51)	(−11.13)	(−11.59)
2	−0.77	−0.97	−0.87	2	−1.72	−1.80	−1.81
	(−3.07)	(−3.31)	(−2.21)		(−7.12)	(−6.61)	(−6.55)
3	−0.91	−0.96	−1.02	3	−1.73	−1.90	−2.04
	(−3.37)	(−3.28)	(−2.82)		(−6.17)	(−6.96)	(−6.55)
4	−1.38	−1.36	−1.45	4	−1.66	−1.75	−1.77
	(−5.13)	(−5.06)	(−4.80)		(−6.06)	(−5.60)	(−5.64)
5	−0.63	−0.75	−0.64	5	−1.72	−1.99	−1.92
	(−2.42)	(−2.86)	(−2.18)		(−6.78)	(−6.75)	(−6.77)
6	−0.72	−0.89	−0.75	6	−1.86	−1.97	−2.06
	(−3.00)	(−3.09)	(−2.24)		(−7.45)	(−7.00)	(−7.56)
7	−0.49	−0.59	−0.44	7	−1.16	−1.17	−1.20
	(−1.95)	(−2.03)	(−1.17)		(−4.86)	(−4.54)	(−4.42)
8	−0.15	−0.32	−0.27	8	−1.67	−1.72	−1.79
	(−0.54)	(−0.89)	(−0.69)		(−5.60)	(−5.01)	(−4.58)
9	−0.06	−0.11	0.06	9	−1.16	−1.29	−1.29
	(−0.26)	(−0.46)	(0.16)		(−4.74)	(−4.91)	(−4.41)
High	1.06	0.96	1.21	High	−0.65	−0.86	−0.87
	(3.86)	(3.07)	(3.47)		(−2.25)	(−2.63)	(−2.41)

This table shows the performance of winner-minus-loser strategies based on the previous month's return within deciles of the previous month's 'residual turnover' relative to volatility ($TO_{1,0} \perp \sigma_{1,0}$; panel A) or volatility ($\sigma_{1,0}$; panel B). Portfolios are from double sorts on the previous month's return ($r_{1,0}$) and either $TO_{1,0} \perp \sigma_{1,0}$ or $\sigma_{1,0}$. We use conditional sorts into deciles based on NYSE breakpoints, first on $r_{1,0}$ and then on either $TO_{1,0} \perp \sigma_{1,0}$ or $\sigma_{1,0}$. Portfolios are value weighted and rebalanced at the end of each month. $TO_{1,0} \perp \sigma_{1,0}$ is the residual from cross-sectional regression of the previous month's share turnover on $\sigma_{1,0}$, estimated using WLS with market capitalization as weight, and $\sigma_{1,0}$ is the standard deviation of the previous month's daily stock returns using a minimum of 15 daily observations. Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 to December 2018, except when applying the q-factors, which are available from January 1967.

Table IA.11
Short-term momentum in the pre-1963 era and across sample splits

	Intercepts, slopes, and test-statistics (in parentheses) from time-series regressions of the form $y_t = \alpha + \boldsymbol{\beta}' \mathbf{X}_t + \epsilon_t$							
	1926/7 - 2018/12		1926/7 - 1963/6		1963/7 - 1991/6		1991/7 - 2018/12	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Dependent variable is short-term momentum								
Intercept	1.02	2.16	0.60	2.01	0.71	1.50	2.03	2.31
	(4.23)	(9.03)	(1.61)	(5.89)	(1.92)	(4.73)	(4.80)	(6.18)
MKT		−0.07		0.13		−0.27		0.06
		(−1.12)		(1.94)		(−4.15)		(0.55)
SMB		0.24		−0.02		0.30		−0.11
		(1.90)		(−0.13)		(3.52)		(−0.67)
HML		0.07		−0.15		0.09		−0.18
		(0.65)		(−0.82)		(0.79)		(−0.94)
MOM		−0.07		−0.09		0.13		0.00
		(−0.75)		(−0.87)		(1.31)		(−0.02)
STREV		−1.47		−1.23		−1.34		−1.62
		(−13.73)		(−10.60)		(−9.39)		(−9.23)
LTREV		−0.09		−0.01		0.15		0.73
		(−0.43)		(−0.09)		(1.14)		(3.25)
Adj. R^2		33.6%		26.3%		30.4%		37.2%
*B: Dependent variable is short-term reversal**								
Intercept	−2.82	−1.80	−3.96	−1.99	−1.67	−0.89	−1.15	−1.06
	(−5.40)	(−6.83)	(−6.28)	(−3.57)	(−7.12)	(−3.30)	(−3.72)	(−3.47)
MKT		0.13		−0.07		−0.08		0.10
		(1.25)		(−0.52)		(−1.33)		(1.05)
SMB		−0.25		−0.52		−0.15		−0.19
		(−1.15)		(−1.99)		(−1.30)		(−2.15)
HML		0.00		0.06		0.11		0.03
		(−0.03)		(0.23)		(0.83)		(0.34)
MOM		0.11		−0.05		0.05		0.15
		(1.02)		(−0.34)		(0.61)		(2.28)
STREV		−1.33		−1.55		−1.00		−0.96
		(−7.40)		(−5.64)		(−8.57)		(−8.24)
LTREV		0.01		−0.02		−0.33		0.06
		(0.08)		(−0.05)		(−2.84)		(0.46)
Adj. R^2		26.3%		31.0%		36.6%		33.2%

This table shows time-series regression results for the short-term momentum strategy starting from July 1926. The table also shows the corresponding results for the short-term reversal* strategy. The strategies are constructed as in Table 1 of the main text but using the extended CRSP sample. The explanatory variables are the three Fama-French factors (MKT, SMB, and HML) in addition to the momentum factor (MOM) and the two reversal factors (STREV and LTREV). Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are at the monthly frequency and the sample periods are indicated above the specification numbers. The MOM factor is available from January 1927 while the LTREV factor is available from January 1931.

Table IA.12
Short-term momentum and volatility risk

	Intercepts, slopes, and test-statistics (in parentheses) from time-series regressions of the form $y_t = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \epsilon_t$							
	Short-term momentum [WML, high turnover] controlling for size				Short-term reversal* [WML, low turnover] controlling for size			
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Large-caps (above NYSE median)								
Intercept	0.91	1.48	0.89	1.05	−0.76	0.66	−0.75	−0.66
	(2.86)	(1.82)	(3.05)	(3.56)	(−3.45)	(0.80)	(−3.42)	(−2.63)
VIX_{-1}		−0.03				−0.07		
		(−0.68)				(−1.61)		
ΔVIX			0.30	0.13			0.27	0.17
			(3.61)	(0.95)			(3.25)	(1.56)
MKT				−0.24				−0.15
				(−1.48)				(−1.29)
Adj. R^2		−0.2%	3.6%	4.5%		1.1%	5.9%	6.5%
B: Micro- and small-caps (below NYSE median)								
Intercept	0.65	2.21	0.64	0.83	−1.03	0.72	−1.03	−0.86
	(1.97)	(2.21)	(1.99)	(2.68)	(−4.92)	(0.94)	(−5.34)	(−2.99)
VIX_{-1}		−0.08				−0.09		
		(−1.46)				(−2.13)		
ΔVIX			0.26	0.05			0.25	0.06
			(2.97)	(0.42)			(5.50)	(1.06)
MKT				−0.30				−0.26
				(−2.89)				(−3.75)
Adj. R^2		0.6%	2.7%	4.4%		2.3%	5.6%	8.7%

This table shows time-series regression results for short-term momentum (STMOM) and short-term reversal* (STREV*) strategies constructed among large-caps and all-but-large-caps. The strategies are from $2 \times 2 \times 2$ conditional sorts on size, the previous month's return, and the previous month's share turnover, in that order. The breakpoint for size is the median for NYSE stocks, while the breakpoints for returns and turnover are the 20th and 80th percentiles for NYSE stocks. Portfolios are value weighted and rebalanced at the end of each month. See Table **??** for more on these strategies. The explanatory variables are the one-month lagged CBOE Volatility Index (VIX_{-1}), the contemporaneous monthly change in the implied volatility index ($\Delta\text{VIX} = \text{VIX} - \text{VIX}_{-1}$), and the contemporaneous market return (MKT). The slopes on VIX_{-1} and ΔVIX are multiplied by 100. Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. Data are at the monthly frequency and cover January 1990 to December 2018, where the start date is determined by the availability of the VIX.

Table IA.13
Short-term momentum and illiquidity: Robustness checks

A: Performance of $r_{1,0}$ strategies within $TO_{1,0} \perp \text{Illiq}_{1,0}$ deciles				B: Performance of $r_{1,0}$ strategies within $\text{Illiq}_{1,0}$ deciles			
$TO_{1,0} \perp \text{Illiq}_{1,0}$ decile	$\mathbb{E}[r^e]$	α_{FF6}	α_q	$\text{Illiq}_{1,0}$ decile	$\mathbb{E}[r^e]$	α_{FF6}	α_q
Low	−1.20	−1.29	−1.25	Low	0.26	0.15	0.27
	(−5.28)	(−4.71)	(−4.73)		(1.33)	(0.73)	(1.00)
2	−1.23	−1.38	−1.44	2	−0.55	−0.51	−0.42
	(−4.68)	(−5.00)	(−4.27)		(−2.12)	(−1.72)	(−1.22)
3	−1.14	−1.38	−1.36	3	−0.62	−0.70	−0.66
	(−4.51)	(−5.06)	(−4.05)		(−2.56)	(−2.39)	(−2.09)
4	−0.74	−0.91	−0.84	4	−0.82	−0.90	−0.84
	(−3.32)	(−3.49)	(−2.61)		(−3.63)	(−3.56)	(−2.70)
5	−0.68	−0.80	−0.58	5	−0.87	−1.02	−0.95
	(−2.62)	(−2.53)	(−1.61)		(−3.55)	(−3.58)	(−3.07)
6	−0.42	−0.43	−0.56	6	−0.78	−0.89	−0.78
	(−1.40)	(−1.37)	(−1.55)		(−3.01)	(−2.74)	(−1.95)
7	−0.75	−0.77	−0.81	7	−0.94	−1.18	−1.14
	(−3.06)	(−2.38)	(−2.10)		(−3.82)	(−3.94)	(−2.81)
8	0.12	−0.03	0.05	8	−1.12	−1.23	−1.17
	(0.41)	(−0.10)	(0.14)		(−4.91)	(−4.33)	(−3.29)
9	0.17	0.15	0.31	9	−0.92	−1.02	−0.98
	(0.68)	(0.57)	(0.90)		(−4.14)	(−4.06)	(−3.21)
High	1.37	1.37	1.65	High	−2.05	−2.33	−2.36
	(4.49)	(4.14)	(4.40)		(−7.65)	(−7.59)	(−5.53)

This table shows the performance of winner-minus-loser strategies based on the previous month's return within deciles of the previous month's 'residual turnover' relative to illiquidity ($TO_{1,0} \perp \text{Illiq}_{1,0}$; panel A) and illiquidity ($\text{Illiq}_{1,0}$; panel B). Portfolios are from double sorts on the previous month's return ($r_{1,0}$) and either $TO_{1,0} \perp \text{Illiq}_{1,0}$ or $\text{Illiq}_{1,0}$. We use conditional sorts into deciles based on NYSE breakpoints, first on $r_{1,0}$ and then on either $TO_{1,0} \perp \text{Illiq}_{1,0}$ or $\text{Illiq}_{1,0}$. Portfolios are value weighted and rebalanced at the end of each month. $TO_{1,0} \perp \text{Illiq}_{1,0}$ is the residual from cross-sectional regression of the previous month's share turnover on $\text{Illiq}_{1,0}$, estimated using WLS with market capitalization as weight, and $\text{Illiq}_{1,0}$ is the average absolute return relative to the dollar trading volume using a minimum of 15 daily observations. Test-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelation. The sample excludes financial firms. Data are at the monthly frequency and cover July 1963 to December 2018, except when applying the q-factors, which are available from January 1967.

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