Reversals and the returns to liquidity provision*

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Abstract

Different aspects of liquidity impact the performance of short-run reversals in different ways, consistent with the predictions of microstructure models. Higher volatility is associated with faster, initially stronger reversals, while lower turnover is associated with more persistent, ultimately stronger reversals. These facts also hold outside the US and explain several seemingly disparate results in the literature.

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1. Introduction

Different aspects of stock-level liquidity impact the strength and persistence of reversals in different, predictable ways. Higher volatility is associated with faster, initially stronger reversals, while lower turnover is associated with more persistent, ultimately stronger reversals. These facts are consistent with the intuition that volatility is positively related to liquidity providers' inventory risk while turnover is negatively related to inventory duration. Our cross-sectional results complement Nagel's (2012) evidence connecting the time-series performance of reversal strategies to aggregate market liquidity. They also hold outside the US, and provide a unifying framework for explaining several seemingly disparate results in the literature.

To study the cross-sectional implications of liquidity on reversals, we use a reversal strategy that should better capture price movements driven by liquidity trades. To isolate liquidity-driven effects, we remove components of past performance associated with two important news-related phenomena: the post-earnings-announcement drift of Ball and Brown (1968) and the short-run industry momentum of Moskowitz and Grinblatt (1999). Standard reversals can be decomposed into these news-related effects and announcement-adjusted industry-relative reversals. The latter are less contaminated by news-driven effects, so should provide a more reliable lens through which to study the returns to liquidity provision.

Using these reversals, we study the impact of different aspects of stock-level liquidity on reversal performance. Market-making capacity is positively related to stock size, inventory risk is positively related to volatility, and inventory duration is negatively related to turnover. Reversals should consequently be stronger among smaller and more volatile stocks, and more persistent among stocks with lower turnover. Our empirical analysis yields results consistent with these intuitions. Reversals are stronger among smaller stocks, a fact well-documented in the literature. This is

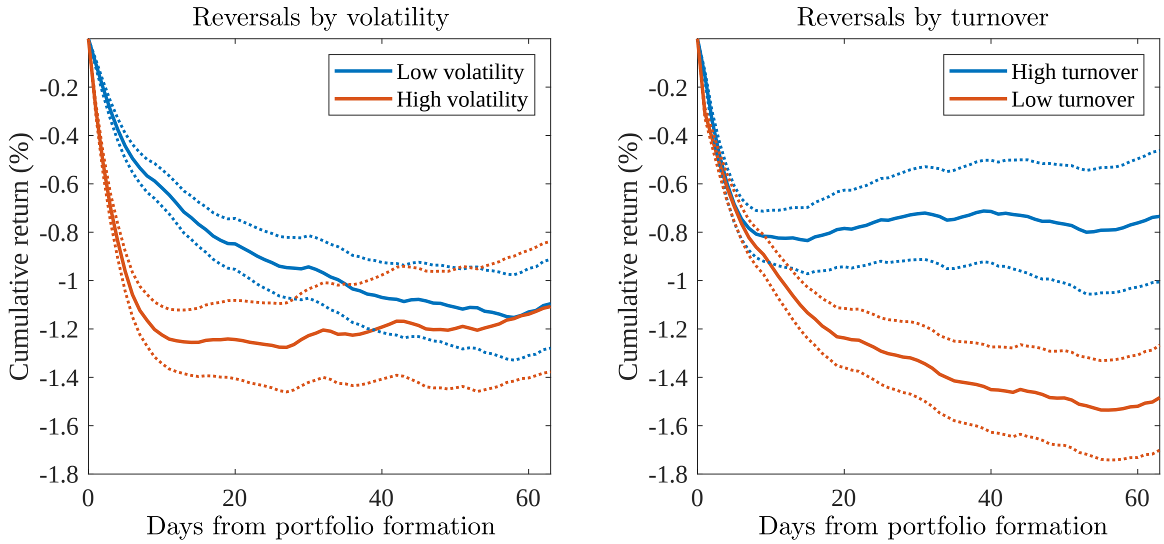


Fig. 1. Announcement-adjusted industry-relative reversals by volatility and turnover. The figure shows cumulative average performance from portfolio formation of reversal strategies within the low and high NYSE volatility quintiles (left panel) and the low and high NYSE turnover quintiles (right panel). The strategies are constructed using an independent quintile sort using NYSE breaks on five days of industry-relative performance, ignoring returns in any three-day earnings-announcement window. Volatility is estimated using the standard deviation of daily returns over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63-day window. Portfolio returns are value weighted. The 95% confidence bounds use Newey-West standard errors calculated with ten lags, twice the length of the past-performance window. The sample covers January 1973 through December 2021.

largely driven by strong first-day effects among microcap stocks, however, and there is surprisingly little variation in the strength of reversals across the top four NYSE size quintiles, which together account for 97% of total market capitalization. In contrast, volatility and turnover have significant impacts on the strength and persistence of reversals across the whole cross-section of these characteristics, which affect stocks of all sizes. Higher volatility is associated with quicker, initially larger reversals, while lower turnover is associated with longer-lived, eventually larger reversals.

Figure 1 shows the dramatic impacts that volatility and turnover have on reversals. Leaving the details of strategy construction for later, the basic picture is clear. The left panel shows the average cumulative value-weighted winner-minus-loser return spread for strategies constructed among high- or low-volatility stocks. The right panel shows the same for reversals constructed among high- or low-turnover stocks. In the left panel, reversals are faster and initially stronger among more volatile stocks, and the differences between the two volatility groups are particularly pronounced over the first two weeks. In the right panel, turnover has little impact on the spread over the first two weeks, but a striking effect on persistence. The reversal is over after only two weeks for high-turnover stocks, but continues to grow for almost three months for low-turnover stocks. These patterns explain and connect several seemingly disparate results in the literature, a fact we explore in greater detail later.[1]

The remainder of the paper is organized as follows. Section 2 decomposes reversals into news-related components and announcement-adjusted industry-relative reversals. Section 3 investigates how different aspects of liquidity impact reversals, and shows that volatility is primarily associated with magnitudes, while turnover is strongly associated with persistence. Section 4 presents international evidence. Section 5 uses our findings to explain results in the literature. Section 6 concludes.

2. Liquidity-driven reversals

We would like to understand how different aspects of stock-level liquidity impact liquidity-driven reversals, but standard short-run reversals correspond poorly to the ones predicted by microstructure models. In these models the price impact of liquidity trades is transitory, generating reversals (Roll, 1984; Glosten and Milgrom, 1985; Grossmann and Miller, 1988).[2] In contrast, the price impact of information-related trades should theoretically be permanent, and empirically price movements associated with news generate continuations (e.g., Chan, 2003; Jiang, Li, and Wang,

[1]Results explained by these patterns include the differential impact of turnover on reversals at different horizons (Avramov, Chordia, and Goyal, 2006); the existence of one-month momentum among high-turnover stocks (Medhat and Schmeling, 2022); the remarkable strength of industry-relative reversals among low-volatility stocks (Novy-Marx and Velikov, 2016); the concentration of momentum among high-volatility stocks (Arena, Haggard, and Yan, 2008); and the difference in strength between short- and intermediate-horizon momentum (Novy-Marx, 2012).

[2]The microstructure hypothesis for reversals dates to the early literature (e.g., Niederhoffer and Osborne, 1966; Fama, 1970). The primary alternative hypothesis is overreaction (Jegadeesh, 1990; Subrahmanyam, 2005). By 1990, however, evidence emerges tending to reject the overreaction hypothesis (Lehmann, 1990; Kaul and Nimalendran, 1990; Lo and MacKinlay, 1990). The recent literature generally supports the hypothesis that liquidity effects primarily drive short-run reversals.

2021). Removing news effects from past performance should consequently strengthen reversals and make them a more reliable lens through which to study liquidity.[3]

2.1. Reversals and post-earnings-announcement drift

Short-run reversals, as commonly constructed, trade against the most important news regularly released about individual firms: their earnings. Earnings announcements are strongly associated with fundamental momentum, i.e., the post-earnings-announcement drift (PEAD) of Ball and Brown (1968), and are significant drivers of price momentum (Chordia and Shivakumar, 2006; Novy-Marx, 2015).

Table 1 shows how this short position in PEAD strongly attenuates the performance of standard reversals. The first row (REV) reports the average monthly returns to a standard reversal strategy. At the end of each month, the strategy buys losers and sells winners, defined as the extreme NYSE quintiles by stock performance over the preceding month. The sample is all US common stocks on NYSE, AMEX, and NASDAQ with available market and accounting data from CRSP and Compustat. The first column reports that over the sample period for which we have high-quality earning announcement data, January 1973 to December 2021, the average monthly value-weighted loser-minus-winner return spread is 31 basis points (bps) per month and only marginally significant (t-statistic of 1.68).

The second and third columns report this spread separately for firms that announced earnings in the prior month (announcers) and for firms that did not (non-announcers). Consistent with results of Hameed and Mian (2015), the reversal is weaker among announcers, an insignificant spread of only 6 bps/month. The strategy trades against firms' earnings surprises here, and this short position in PEAD obscures the reversal. In contrast, the spread among non-announcers is 51 bps/month,

[3] Nagel (2012) argues that "past returns are a noisy proxy for market makers' inventory positions," so news weakens reversal because "the public information component in returns adds noise unrelated to inventory imbalances" (p. 2006). Internet Appendix E.1 provides direct evidence linking past performance to order flow, and thus the inventory-imbalance hypothesis for reversals.

Table 1. Reversal performance and earnings announcements.
This table reports average monthly excess returns to a simple reversal strategy based on prior month's stock returns (REV) and a similarly-constructed, announcement-adjusted reversal strategy based on returns that exclude earnings-announcement returns (REVX). For REVX, prior month's returns are adjusted for any firms that announce earnings by subtracting the three-day cumulative abnormal return (i.e, the return in excess of the market return) around the announcement day. Both strategies are long losers and short winners, defined as the extreme quintiles by prior month's performance using NYSE breaks. Returns are value weighted, and strategies are rebalanced monthly. The first column shows these strategies' average monthly returns. The second column shows the average loser-minus-winner return spread between only those firms in the strategies that announced earnings in the month before portfolio formation, while the last column shows the spread for the non-announcers. The sample covers January 1973 through December 2021.

	Stocks included		
	All	Announcers	Non-announcers
REV	0.31	0.06	0.51
	[1.68]	[0.30]	[2.54]
REVX	0.54	0.54	0.51
	[2.96]	[2.60]	[2.64]

two-thirds higher than the unconditional spread, and significant (t-statistic of 2.54).

The second line of the table (REVX) repeats the exercise, but for reversal strategies based on prior month's announcement-adjusted stock performance. Specifically, we exclude any abnormal announcement returns from prior month's performance by subtracting the cumulative abnormal return (i.e., the return in excess of the market return) realized over the three-day window around any earnings announcement (here the X in REVX signifies this exclusion).[4] Without the PEAD headwind the unconditional average spread is much larger, 54 bps/month, remarkably similar to the spread seen among non-announcers in the standard reversal strategy, and significant (t-statistic of 2.96). There is essentially no difference in strategy performance between announcers and non-announcers.

[4] Da, Liu, and Schaumburg (2015) also attempt to control for the component of past performance driven by fundamental cash-flow news when constructing their residual-return reversals. They subtract an estimate of the return driven by innovations to cash-flow expectations, which they calculate using analyst consensus earnings forecasts from I/B/E/S and the three-stage estimation procedure of Da and Warachka (2011). Our procedure is far simpler, and does not exclude two-thirds of firms, representing a quarter of total market capitalization, due to a lack of analyst coverage.

2.2. Reversals and industry momentum

Standard reversals, in addition to shorting PEAD, short industry momentum. Moskowitz and Grinblatt (1999) document a significant, positive one-month auto-correlation in industry returns. They conjecture 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), and this aggregation helps identify news-related price movements correlated across stocks. Standard reversals buy losers, so tend to hold losing industries, yielding a short exposure to industry momentum that impairs average performance.

This fact is explicitly recognized by Da et al. (2015), who construct reversal strategies within industries and note that these "industry controls, by taking out the industry momentum effect, will mechanically enhance the short-term return reversal." Rather than constructing strategies within industries, Hameed and Mian (2015) argue for "benchmarking stock returns with the returns on peer firms in the industry to better identify short-term return reversals [... which] provides a more natural framework to identify returns to supplying liquidity" (p. 90). They report that doing so significantly increases the magnitude of the observed reversals. Novy-Marx and Velikov (2016) use a similar construction and document average industry-relative reversal spreads more than two and a half times the spread for standard reversals.

2.3. Reversal decomposition

We can decompose reversals into an effect theoretically related to liquidity and short exposures to PEAD and industry momentum. To do so, we consider the performance of five strategies: standard reversals (REV), post-earnings-announcement drift (PEAD), one-month industry momentum (IMOM), industry-relative reversals (IRR), and announcement-adjusted industry-relative reversals (IRRX).

Panel A of Table 2 shows the strategies' average monthly excess returns. Over our

Table 2. Reversal strategy return decomposition.
Strategies considered are reversals (REV); industry-relative reversals (IRR); industry-relative, announcement-adjusted reversals (IRRX); post-earnings-announcement drift (PEAD); and one-month industry momentum (IMOM). The first four strategies trade the extreme quintiles, using NYSE breaks, of stocks sorted on prior month's return (REV); prior month's return in excess of the value-weighted return to a firm's Fama and French 49 industry (IRR); this industry-relative return adjusted by subtracting the three-day cumulative abnormal return around the firm's most recent earnings announcement (IRRX); and this three-day cumulative abnormal announcement-window return (PEAD). IMOM trades the top and bottom ten Fama and French 49 industries based on prior month's value-weighted industry returns. REV, IRR, and IRRX buy losers and short winners, while PEAD and IMOM buy winners and short losers. Portfolio are rebalanced at the end of each month, and returns are value weighted. The sample covers January 1973 through December 2021.

Panel A: Strategy average monthly excess return (%)

REV	PEAD	IMOM	IRR	IRRX
0.31	0.53	0.68	0.74	1.08
[1.68]	[5.45]	[3.57]	[5.40]	[9.35]

Panel B: Results from $\text{REV}_t = \alpha + \beta_{\text{IRRX}}\text{IRRX}_t + \beta_{\text{PEAD}}\text{PEAD}_t + \beta_{\text{IMOM}}\text{IMOM}_t + \epsilon_t$

α	β_{IRRX}	β_{PEAD}	β_{IMOM}	Adj. R^2 (%)
0.13	0.76	-0.54	-0.53	87.0
[1.73]	[27.8]	[-17.4]	[-30.4]	

sample, PEAD and IMOM earn highly significant returns of 53 bps/month ($t = 5.45$) and 68 bps/month ($t = 3.57$). Removing the short position in industry momentum from standard reversals more than doubles its average return (74 bps/month for IRR versus 31 bps/month for REV). IRRX, which additionally removes the short position in PEAD, performs stronger still, earning on average 108 bps/month with a t-statistic of 9.35.[5]

Panel B shows results of regressing the returns to REV onto those of IRRX, IMOM, and PEAD. The REV strategy's large positive exposure to IRRX and large negative exposures to PEAD and IMOM explain 87% of its time-series variation, and

[5]The t-statistic on IRRX is remarkably similar to that reported by Da et al. (2015) on their within-industry, residual-based reversals, a strategy that is similar in spirit to, though far more complicated than, the announcement-adjusted industry-relative reversal strategy considered here. The results they report, however, are for equal-weighted portfolio returns. Equal-weighted strategies dramatically over-weight the smallest stocks, where it is well known that reversals are stronger (French and Roll, 1986; Jegadeesh, 1990; Lo and MacKinlay, 1990). The t-statistic on the average monthly returns to an equal-weighted version of our IRRX strategy exceeds 14.

the remaining abnormal returns are insignificant. Reversals appear weak because they are largely obscured by trading against post-earnings-announcement drift and industry momentum. IRRX, which removes the conflating effects of PEAD and IMOM, should consequently provide a more reliable lens through which to study liquidity, and is the reversal we use in most of our later tests.

Appendix A provides a more detailed exploration of the relations between these strategies. It also shows that our results hold post-decimalization (the last twenty years of our sample), a period over which the market is generally more liquid.[6]

3. Stock-level liquidity's impact on reversals

This section documents how different aspects of stock-level liquidity impact reversals. Kyle (1985) argues that "liquidity is a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets. These include tightness (the cost of turning around a position over a short period of time), depth (the size of an order flow innovation required to change prices a given amount), and resiliency (the speed with which prices recover from a random, uninformative shock)" (p. 1316). Since no single variable comprehensively measures liquidity, our analysis uses three stock-level characteristics commonly associated with different aspects of liquidity: size, volatility, and turnover. Jointly, these three variables explain on average more than 96% of the cross-sectional variation in the popular Amihud (2002) illiquidity measure (see Appendix Table B1). In the following, we provide intuition for how and why these characteristics should impact reversals. We then provide evidence consistent with this intuition.

[6]While market participants refer to this period as "post-decimalization" because the US Securities and Exchange Commission ordered all US markets to quote in decimals rather than fractions starting no later than April 9, 2001, the term is often used more generally to encompass other roughly concurrent market trends that also tended to reduce transaction costs and improve liquidity. These include the spread of electronic trading facilities that enabled direct market access and the increasing prevalence of algorithmic trading.

3.1. Reversals by size, volatility, and turnover: intuition

Reversals arise naturally in models of intermediation to compensate risk-averse market makers for bearing price risk (e.g., Grossmann and Miller, 1988). More volatile stocks are associated with greater inventory risk, so should theoretically experience larger liquidity-driven reversals (Vayanos and Wang, 2012). This suggests that stock-level volatility should be positively related to reversal magnitude.

In contrast, turnover should matter more for the persistence of reversals because it captures inventory duration, i.e., the time it takes a liquidity supplier to unwind her positions. Hendershott and Seasholes (2006) argue that "Market makers may control their inventories differently across stocks. Thus, the speed at which prices reverse may depend on inventory control policies [...which] depend on trading activity, stock volume, and market maker participation rates." (p. 16). Easley, López de Prado, and O'Hara (2012) argue that "trade time, as captured by volume, is a more relevant metric than clock time" for microstructure effects (p. 1458). Stocks with lower turnover, which are associated with longer inventory duration and for which the volume clock runs slower, should thus be associated with more persistent reversals.

Finally, market making is more limited for smaller-capitalization stocks (Merton, 1987; Grossmann and Miller, 1988). Informed traders may also pose liquidity providers a more acute adverse-selection problem, yielding wider spreads and a larger transitory component of price impact (Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987). Reversals should consequently be stronger among smaller stocks, consistent with the evidence of French and Roll (1986) and Jegadeesh (1990).

3.2. Reversals by size, volatility, and turnover: evidence

Figure 2 provides evidence supporting these predictions. It shows the evolution of reversals among stocks of similar liquidity. Specifically, it shows the average cumulative winner-minus-loser spread out to three months for strategies based on announcement-adjusted industry-relative returns among groups of stocks with similar market capitalization (Panel A), volatility (Panel B), and turnover (Panel C). Past performance is measured over the prior single trading day (left column), five trading days (center column), or 21 trading days (right column), where we include the shorter look-back periods because they may correspond better to the inventory management of liquidity suppliers. All strategies are from independent quintile sorts using NYSE breaks, and portfolio returns are value weighted.[7] Volatility is the standard deviation of daily returns over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63-day window, each requiring a minimum of 42 observations. We adjust NASDAQ volume prior to 2004 following Gao and Ritter (2010) (see Internet Appendix E.2).

Panel A shows reversals by size. Its striking feature is that while reversals are much larger among microcap stocks (bottom NYSE size quintile), there are almost no differences across the other size quintiles, which together account for 97% of market capitalization. This is true for all three past-performance horizons, and the larger microcap spreads are primarily driven by strong first-day effects.

Panel B shows considerable dispersion in the magnitude and speed of reversals across all volatility quintiles. For a single day of past performance (left column), there is a large, monotonic difference in magnitudes, with faster, stronger reversals among more volatile stocks. For five days of past performance (middle column), there is a similar, monotonic spread in magnitudes, but primarily driven by the speed at which the reversals occur. Two weeks after formation, the spread is more than twice as large for high-volatility stocks as it is for low-volatility stocks, but the spreads converge after two months. This difference in persistence yields a very different

[7]The independent sorts yield more similar average pre-formation past performance across the winner and loser portfolios, but occasionally portfolios with relatively few holdings. The Internet Appendix (Table E4) shows results using sequential double sorts, which guarantee a nearly equal number of NYSE stocks in both sides of each reversal strategy, but exhibit more variation in pre-formation past performance across winners and losers. Results are almost indistinguishable.

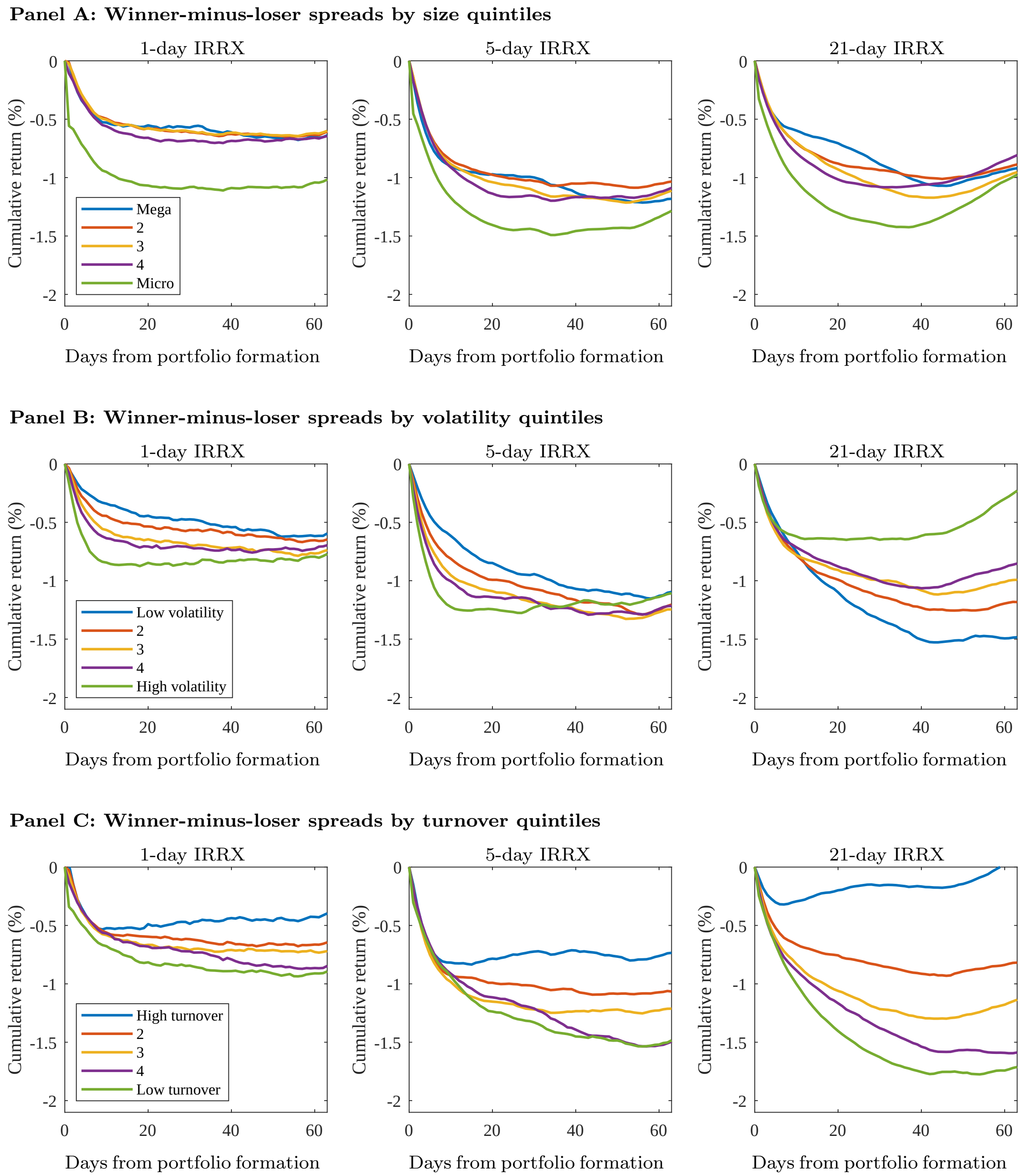


Fig. 2. IRRX performance from formation by size, volatility, and turnover. The figure shows cumulative average performance from portfolio formation of announcement-adjusted industry-relative reversal strategies (IRRX) within size, volatility, and turnover quintiles constructed using NYSE breaks (Panels A to C, respectively). The IRRX strategies are based on industry-relative returns adjusted for earnings announcement by ignoring returns in any three-day earnings announcement window, measured over the previous one, five, and 21 days (left to right, respectively). Volatility is estimated using the standard deviation of daily returns over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63-day window, each requiring a minimum of 42 daily observations. Portfolio returns are value weighted. The sample covers January 1973 through December 2021.

pattern for 21 days of past performance (right column). Here, past performance only predicts reversals out to two weeks among high-volatility stocks, but out to almost three months among low-volatility stocks. This yields a larger low-volatility reversal.

Panel C similarly exhibits substantial dispersion across all turnover quintiles. For one day of past performance (left column) there are almost no differences over the first two weeks post-formation, except for a large first-day effect for the most illiquid, low-turnover stocks. Two weeks after formation, however, the reversal is over for high-turnover stocks, but persists for stocks that trade less. This is perhaps clearest for five days of past performance (middle column). Here, the spreads are nearly indistinguishable for two weeks but then diverge, because the reversal ends for high-turnover stocks but continues growing for almost three months in the low-turnover quintile. These extreme differences in persistence yield dramatic differences in magnitudes using 21 days of past performance (right column). Among high-turnover stocks, where reversals are highly transitory, there is almost no reversal. Among low-turnover stocks, where reversals are highly persistent, we see the largest eventual spread observed across all specifications.[8]

3.3. Isolating the effects of volatility and turnover

The results in Figures 1 and 2 are extremely suggestive. Higher volatility is clearly associated with faster and initially stronger reversals, while lower turnover is associated with longer-lived and eventually stronger reversals. These results, however, do not account for correlations between different aspects of liquidity. Higher volatility is directly associated with less liquidity, but more volatile stocks tend to trade more and this tends to mitigate volatility's direct impact on liquidity. Similarly, while higher turnover is associated with more liquidity, actively traded stocks tend to be

[8]The Internet Appendix shows similar results for the weaker reversals common in the literature, those based on unadjusted stock returns (Figure E5). Here momentum sets in more quickly, especially when using longer past-performance evaluation periods over which more firms announce earnings, but the basic patterns shown in Figure 2 hold.

more volatile, which is associated with less liquidity.[9]

To evaluate how volatility and turnover directly impact reversals in isolation, we employ the propensity-matched sorting technique introduced by Novy-Marx (2015) and used by Novy-Marx and Velikov (2022). To additionally control for market capitalization, we construct these portfolios within each of three size universes, defined following Fama and French (2016) as large (above NYSE median), micro (bottom NYSE quintile), and small (the rest). Specifically, within each size universe, we construct three portfolios with similar turnover but dispersion in volatility by selecting groups of three stocks with almost identical turnover, then assign these to different portfolios on the basis of volatility. Similarly, we construct three portfolios with similar volatility but dispersion in turnover using the same propensity-matched sorting procedure. Within each of these portfolios, the top and bottom third by five-day announcement-adjusted industry-relative returns are assigned to winner and loser portfolios. Portfolio returns are value weighted. Table E2 in the Internet Appendix shows that this procedure yields portfolios that are well-matched on two of our three aspects of liquidity, but have significant dispersion in the third.

Figure 3 shows results that confirm the simple associations seen in Figures 1 and 2, but with a clearer separation of effects. The left panel shows, in all three size universes, that after controlling for turnover higher volatility is associated with stronger reversals for two weeks, but nearly parallel performance thereafter. In contrast, the right panel shows remarkable similarity in performance at short horizons, but differences over longer horizons. With the exception of the nearly 80 bps first-day effect seen on the highly illiquid low-turnover microcaps, reversals are nearly identical across turnover groups for the first two weeks, but then diverge because the effect is more persistent among stocks with lower turnover.

[9] Appendix B provides a detailed analysis of liquidity variable correlations. The Internet Appendix also documents the specific correlation discussed above; Table E1 shows that high-volatility portfolios tend to hold stocks that trade more than those held in low-volatility portfolios, and high-turnover portfolios tend to hold more volatile stocks than those held by low-turnover portfolios.

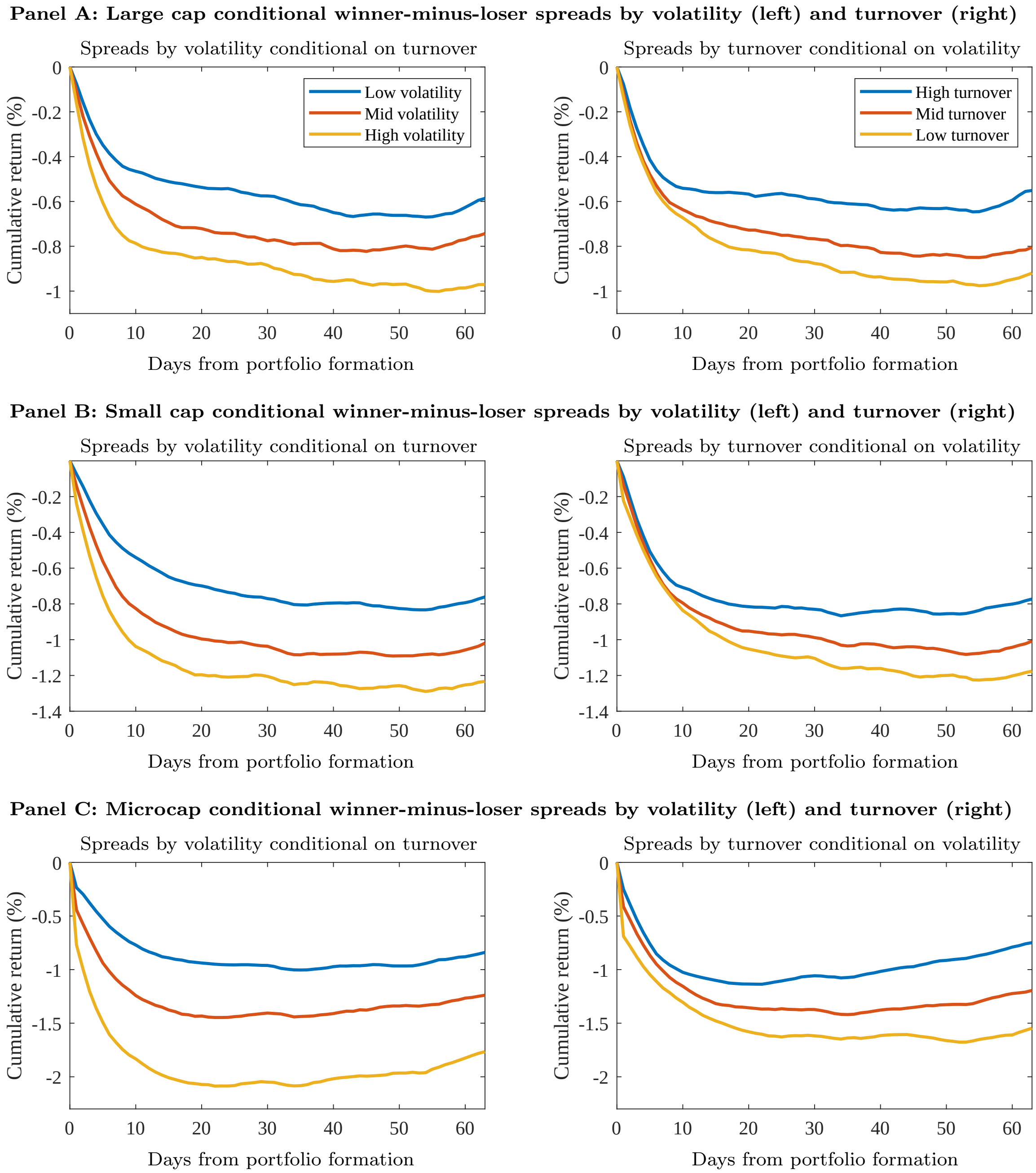


Fig. 3. Conditional IRRX performance from portfolio formation by volatility and turnover. The figure shows cumulative average performance from portfolio formation of reversal strategies by volatility controlling for turnover (left side), and by turnover controlling for volatility (right side), within the large, small, and microcap universes (Panels A to C, respectively, where large is above NYSE median market capitalization, micro is the bottom NYSE quintile, and small is the rest). Within each size universe, three portfolios are constructed with similar turnover but dispersion in volatility by selecting groups of three stocks with almost identical turnover, and then assigning these to different portfolios on the basis of volatility. Three portfolios with similar volatility but dispersion in turnover are also constructed using the same propensity-matched sorting procedure. Within each of these portfolios the top and bottom third by past performance are assigned to winner and loser portfolios, where past performance is industry-relative returns, ignoring returns in any three-day announcement window, measured over the previous five days. Volatility is estimated using the standard deviation of daily returns over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63 day window. Portfolio returns are value weighted. The sample covers January 1973 through December 2021.

These results are consistent with the idea that volatility matters more for reversal magnitudes, because it captures inventory risk associated with alleviating order imbalances and thus the compensation demanded for supplying liquidity, while turnover matters more for reversal persistence, because it captures inventory duration and thus the time it takes liquidity suppliers to unwind the positions they accrue.

4. International evidence

While our main analysis focuses on the US, which has the longest sample and most well-populated cross sections, our results also hold outside the US.

Table 3 replicates the reversal decomposition of Table 2 using data from non-US developed markets and emerging markets. Panel A reports the average monthly returns of five strategies: reversals (REV), post-earnings announcement drift (PEAD), industry momentum (IMOM), industry-relative reversals (IRR), and announcement-adjusted industry-relative reversals (IRRX). In both regions, REV is insignificant while IMOM and PEAD are significant (marginally so for IMOM in non-US developed markets). IRR earns roughly 35 bps/month with t-statistics exceeding 2.6 in both regions. IRRX is even stronger, with an average return near 80 bps/month and t-statistics exceeding 5.0. Panel B shows results of time-series regressions of REV returns on IRRX, PEAD, and IMOM returns by region. Consistent with the US results shown in Table 2, in both regions REV is long IRRX and short IMOM and PEAD, and the abnormal returns are insignificant. Appendix Table C1 provides a more detailed exploration of the relations between these strategies.

Figure 4 shows the average performance of IRRX strategies based on five days of past performance among stocks with similar size, volatility, or turnover, in non-US developed markets (Panel A) and emerging markets (Panel B). Results for volatility (middle column) and turnover (right column) agree with the US results shown in

Table 3. International reversal strategy return decomposition.
Strategies considered are reversals (REV); industry-relative reversals (IRR); announcement-adjusted industry-relative reversals (IRRX); post-earnings announcement drift (PEAD); and industry momentum (IMOM). The first four strategies trade the extreme quintiles of stocks sorted on prior month's return (REV); this return in excess of the return to a firm's industry (IRR); this industry-relative return adjusted by subtracting the three-day cumulative abnormal return (in excess of the country's value-weighted market return) around the firm's most recent earnings announcement within three months (IRRX); and this cumulative abnormal announcement-window return (PEAD). Quintiles use country-specific, free-float adjusted market-cap breakpoints. IMOM trades stocks in the top and bottom four industries within a country based on the prior month's industry returns. There are 12 industries in total, corresponding to the 2-digit Global Industry Classification Standard (GICS) plus a group for a missing classification, and industry returns are country specific and value weighted. REV, IRR, and IRRX buy losers and short winners, while PEAD and IMOM buy winners and short losers. Portfolios are rebalanced at the end of each month and portfolio returns are value weighted using free-float-adjusted market cap. We use US dollar returns and market-cap values. Developed markets excluding the US include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom. Emerging markets include Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey. The developed and emerging market samples start in January 1996 and January 1999, respectively, with start dates determined by earnings-announcement availability, and run through December 2021.

Panel A: Strategy average monthly excess return (%)

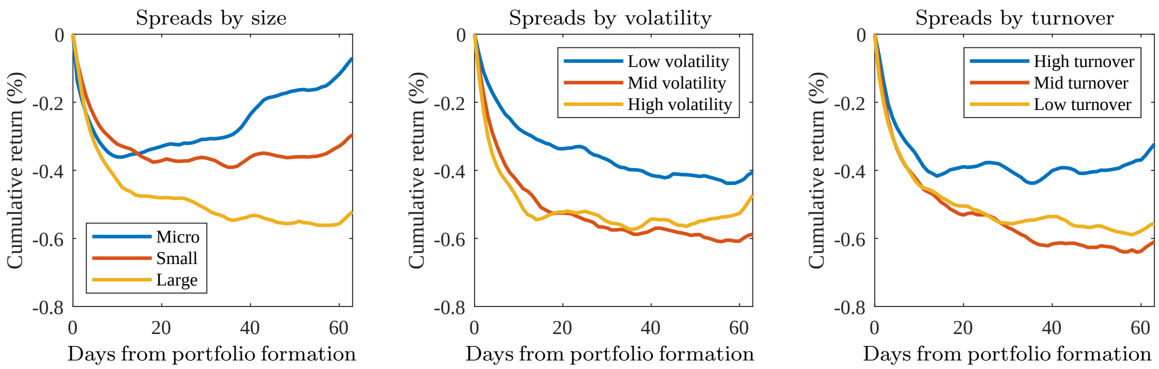
	REV	PEAD	IMOM	IRR	IRRX
Developed	0.13	0.55	0.31	0.40	0.83
	[0.62]	[4.31]	[1.97]	[3.10]	[6.75]
Emerging	-0.18	0.74	0.59	0.35	0.80
	[-1.03]	[5.94]	[3.79]	[2.67]	[5.07]

Panel B: Results from $\text{REV}_t = \alpha + \beta_{\text{IRRX}}\text{IRRX}_t + \beta_{\text{PEAD}}\text{PEAD}_t + \beta_{\text{IMOM}}\text{IMOM}_t + \epsilon_t$

	α	β_{IRRX}	β_{PEAD}	β_{IMOM}	Adj. R^2 (%)
Developed	0.00	0.61	-0.22	-0.84	85.4
	[0.03]	[14.5]	[-5.78]	[-24.3]	
Emerging	0.00	0.32	-0.05	-0.32	50.6
	[0.01]	[6.45]	[-0.88]	[-13.6]	

Figure 2. Higher volatility is generally associated with faster, initially stronger reversals, while lower turnover is associated with more persistent, ultimately stronger reversals. Results by size (left column) look different than in the US. The largest stocks surprisingly exhibit the strongest reversals, especially in emerging markets, because reversals are transient among small stocks. While we adjust returns to account for news, these adjustments are imperfect and news-driven continuations may be stronger among smaller stocks in these markets. Better understanding why small-cap reversals are so transient outside the US is a subject for future research.

Panel A: Developed ex-US winner-minus-loser spreads by size, volatility, and turnover



Panel B: Emerging market winner-minus-loser spreads by size, volatility, and turnover

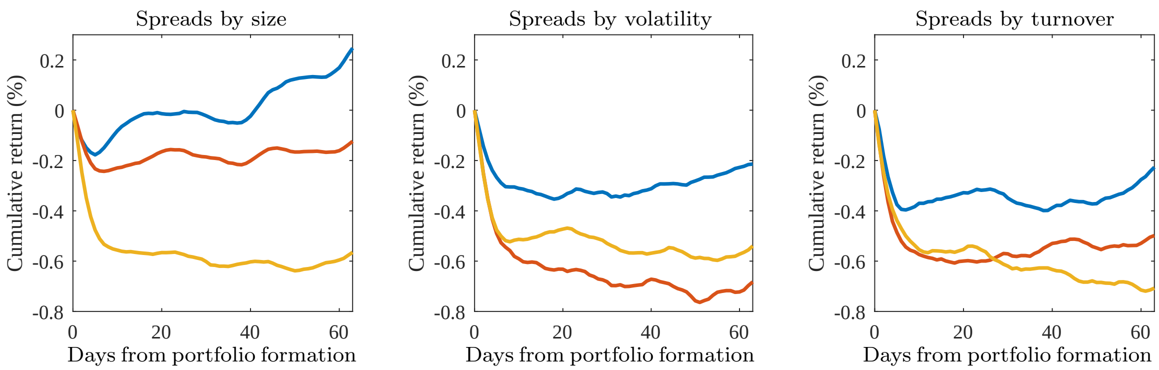


Fig. 4. International IRRX returns from formation by size, volatility, and turnover. The figure shows cumulative average performance from portfolio formation of announcement-adjusted industry-relative reversal strategies (IRRX) within size, volatility, and turnover groups in developed-ex US markets (Panel A) and in emerging markets (Panel B). Size is total (not free-float adjusted) market capitalization and the size groups use country-specific, free-float adjusted market-cap breakpoints. Micro caps are the smallest 5%, small caps are the next 15%, and large caps are the remaining 80%. The volatility and turnover groups are based on terciles using country-specific, free-float adjusted market-cap breakpoints, such that each tercile contains approximately one third of a country's total free-float adjusted market cap. Volatility is estimated using the standard deviation of daily returns over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63 day window, each requiring a minimum of 42 daily observations over the estimation window. The IRRX strategies are constructed using independent tercile sorts, again using country-specific, free-float adjusted market-cap breakpoints, on industry-relative performance measured over the previous five days. There are 12 industries in total, corresponding to the 2-digit Global Industry Classification Standard (GICS) plus a group for a missing classification, and industry returns are country specific and value weighted. Portfolio returns are value weighted using free-float adjusted market-cap. We use US dollar returns and market-cap values. Developed-ex US markets include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom. The sample period covers January 1996 through December 2021. Emerging markets include Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey. The sample period covers January 1999 through December 2021.

5. Implications

Collectively, the findings presented thus far explain and connect several seemingly disparate results previously reported in the literature.

5.1. Explaining short-term momentum

Medhat and Schmeling (2022) show that low-turnover stocks exhibit strong one-month reversals, while high-turnover stocks exhibit "short-term momentum" over the same horizon. While this short-run momentum is surprising in light of the antecedent literature, it is wholly expected given our results on the transitory nature of reversals among high-turnover stocks.

Figure 5 explains the main results of Medhat and Schmeling (2022) while providing additional nuance. It shows the average cumulative winner-minus-loser spread for reversal strategies constructed from extreme NYSE stock return quintiles, using all stocks and separately for stocks in the lowest and highest NYSE turnover quintiles. In the left panel, strategies are based on prior month's stock return. Here, one-month reversals are strongest among low-turnover stocks because the effect is more persistent. The panel shows, however, that there are also reversals among high-turnover stocks, but they are highly transitory. They end after a single week and are well into the short-run momentum of Medhat and Schmeling (2022) at the monthly horizon.

The right panel repeats the exercise using strategies based on prior week's stock return. After one week, the reversal is actually stronger among high-turnover stocks. After one month, however, the reversal appears stronger among low-turnover stocks, again driven by its greater persistence.

5.2. Explaining reversal strength by Amihud illiquidity and turnover

These same facts explain results of Avramov et al. (2006). They find that "reversal profitability declines with turnover at the monthly frequency," but that "Illiq-

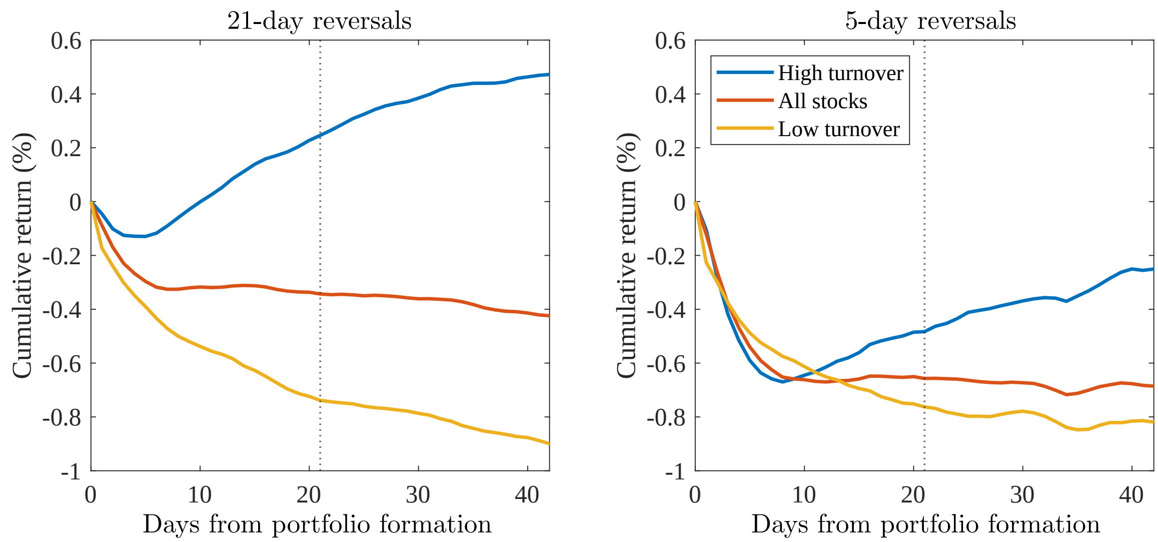


Fig. 5. Coexistence of reversal and momentum in one-month returns. The figure shows the average cumulative performance from portfolio formation to winner-minus-loser strategies based on past (unadjusted) stock performance. In the left panel, past performance is measured over the month preceding portfolio formation (21 trading days), while, in the right panel, past performance is measured over the week preceding portfolio formation (5 trading days). Strategies are constructed using all stocks or separately for low- and high-turnover stocks by intersecting the extreme NYSE quintiles based on past performance with the extreme NYSE quintiles based on turnover (independent sorts). Turnover is estimated as the fraction of shares outstanding traded over the 63-day window preceding portfolio formation, requiring a minimum of 42 observations. Portfolios are formed daily, and returns are value weighted. The sample covers January 1973 through December 2021.

uidity has a larger impact on reversals than turnover" (p. 2379-82). In Figure 5, differences in reversal persistence explain why reversal profitability declines with turnover.[10] The measure they use for illiquidity explains why they find illiquidity has a larger impact on reversals magnitude than turnover. They use Amihud's measure, which Appendix Table B1 shows basically proxies for size. The table reports an average correlation between Amihud illiquidity and market capitalization of -93%, sufficiently large that studying the impact of Amihud illiquidity on reversals provides little information beyond that from studying the impact of size. Figure 2 documents

[10] Avramov et al. (2006) also find that "High turnover and high illiquidity stocks observe more reversals than low turnover and low illiquidity stocks" at the weekly frequency (p. 2379). This surprising finding that reversals are stronger among the more liquid high-turnover stocks is largely driven by skipping a day between observing past performance and forming portfolios. They consequently ignore first-day effects, which Figure 5 shows are larger and more important for the less liquid low-turnover stocks. Skipping a day prior to formation may be appropriate when considering the practicality of trading reversal strategies, but ignoring the large first-day effects observed for the least liquid stocks is misleading when studying liquidity.

that reversals are strong among microcap stocks.

5.3. Explaining the strength of low-volatility, industry-relative reversals

The remarkable strength of industry-relative reversals among stocks with below-NYSE-median volatility documented by Novy-Marx and Velikov (2016) can be understood similarly. Kozak, Nagel, and Santosh (2020) report that the strategy is the single largest component of the stochastic discount factor (SDF) they construct using 50 anomaly portfolios. These facts have left the impression that industry-relative reversals are stronger among stocks with lower volatility. This is not the case. Industry-relative reversals are stronger among high-volatility stocks, but highly transient, and consequently look weak when measured at the monthly frequency that is more appropriate for trading the strategy among low-volatility stocks.

This can be seen in Figure 6, which shows the cumulative average winner-minus-loser return spread for industry-relative reversals constructed among stocks with either above or below NYSE median volatility. In the left panel, strategies are based on 21-days of industry-relative performance. One month after formation, the spread is much larger among low-volatility stocks (106 vs. 39 bps), because among high-volatility stocks the reversal ends and momentum sets after just two weeks. For these stocks, where the reversal is transient, the monthly frequency is too low. The right panel shows the performance of strategies based on five days of industry-relative performance. Here, the reversal is much stronger among high-volatility stocks. In fact, the average spread among high-volatility stocks in the right panel after just two weeks is already larger than that among low-volatility stocks in the left panel after a full month (116 vs 106 bps). Although the literature has focused on the strength of monthly low-volatility industry-relative reversals, their performance is actually weaker than that of high-volatility industry-relative reversals constructed at higher frequencies.

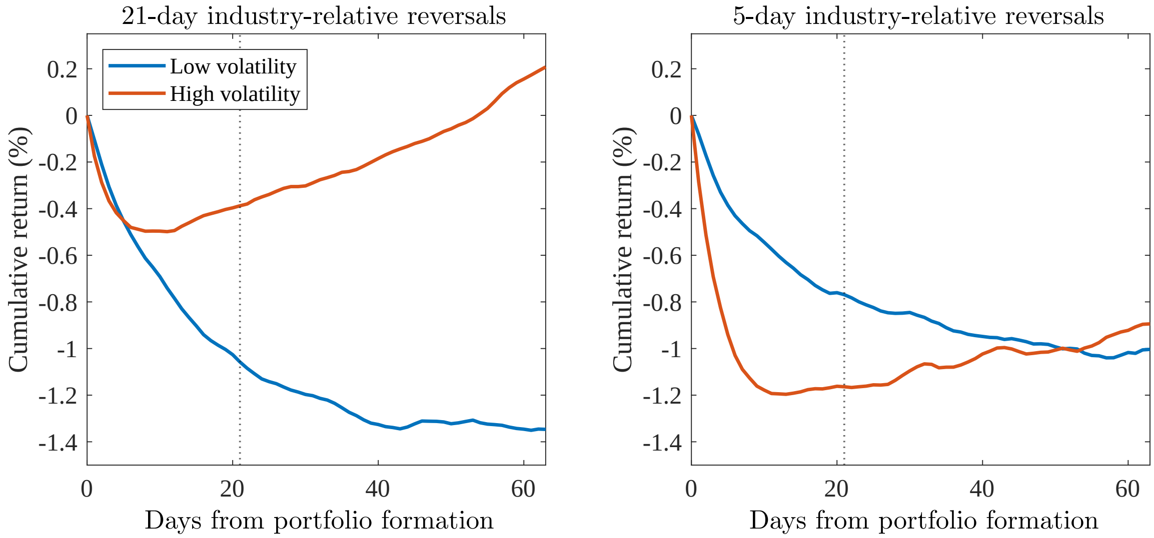


Fig. 6. IRR performance from portfolio formation, high- vs. low-volatility stocks. The figure shows the average cumulative performance from portfolio formation for winner-minus-loser strategies based on past industry-relative stock performance. In the left panel, past performance is measured over the month preceding portfolio formation (21 trading days), while, in the right panel, past performance is measured over the week preceding portfolio formation (5 trading days). In both cases, strategies are constructed for low- and high-volatility stocks, by intersecting the extreme NYSE quintiles based on past performance with the extreme NYSE quintiles based on volatility. Volatility is estimated from the standard deviation of daily returns over 63-day window preceding portfolio formation, requiring a minimum of 42 observations. Portfolios are formed daily, and returns are value weighted. The sample covers January 1973 through December 2021.

5.4. Explaining the differences in short- and intermediate-horizon momentum

Novy-Marx (2012) documents that "momentum is primarily driven by firms' performance 12 to seven months prior to portfolio formation, not by a tendency of rising and falling stocks to keep rising and falling" (p. 429). We have previously seen that high volatility is associated with large but transient reversals, while low volatility is associated with more persistent reversals. This same channel explains the difference in strength between short- and intermediate-horizon momentum, because volatility also predicts the horizon over which momentum operates. This fact also explains the finding of Arena et al. (2008) that "returns to momentum investing are higher among high idiosyncratic volatility (IVol) stocks" (p. 159).

Figure 7 shows the link between volatility and the onset of momentum. It plots

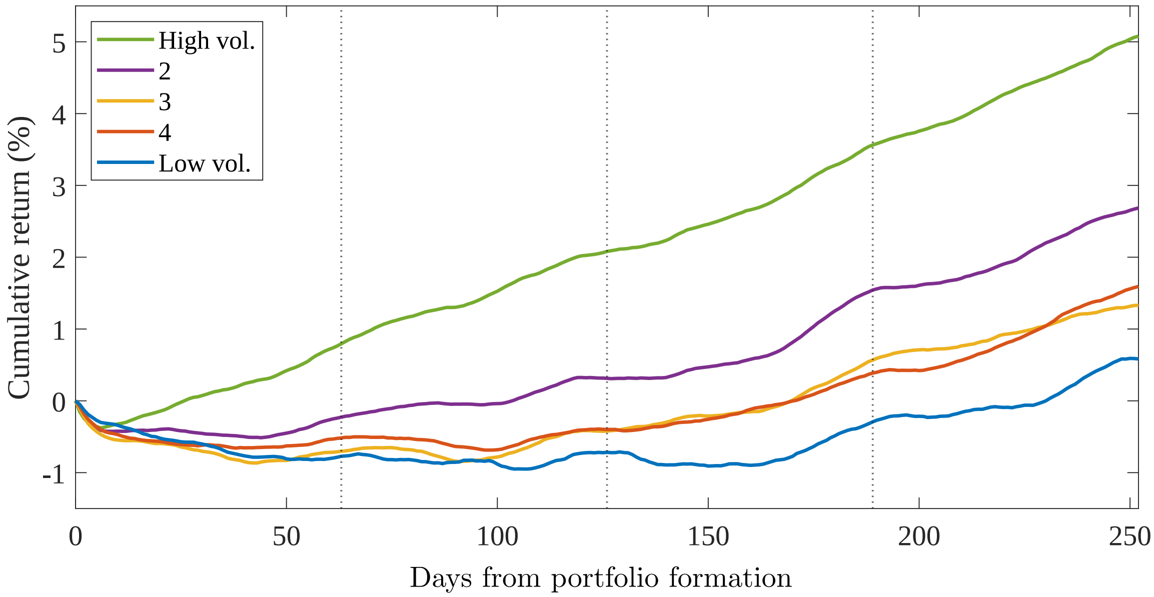


Fig. 7. Long-run average winner-minus-loser spread by volatility quintiles. This figure shows cumulative average performance for four quarters after portfolio formation of winner-minus-loser strategies, based on simple stock performance over the single month prior to portfolio formation, constructed within volatility portfolios. Strategies are constructed using independent quintile sorts, using NYSE breaks, on stock returns realized over the previous 21 trading days, and volatility estimated from the standard deviation of daily returns over the preceding 63 trading days (42 observations minimum). Portfolio returns are value weighted. The sample covers January 1973 through December 2021.

the average cumulative winner-minus-loser spreads out to one year (252 trading days) for strategies based on prior month's stock performance constructed within NYSE volatility quintiles. Momentum sets in far more quickly for more volatile stocks. In the high-volatility quintile, momentum sets in after just two weeks, while no momentum is observed for eight months in the low-volatility quintile.[11] This suggests a refined prediction that connects the results of Arena et al. (2008) and Novy-Marx (2012): the disparity in strength between short- and intermediate-horizon momentum should be concentrated in, and stronger among, low-volatility stocks.

[11] Appendix Figure D3 expands on these results by decomposing momentum into long-run IRRX, IMOM, and PEAD, and showing these components by size, volatility, and turnover. Size is the strongest determinant of the long-run strength of PEAD and IMOM, but has almost no power predicting differences in the strength of the component of momentum driven by IRRX. Both volatility and turnover do; the IRRX component of momentum is strong for high-volatility and high-turnover stocks, but essentially absent among low-volatility and low-turnover stocks.

Table 4. Short and intermediate horizon momentum by volatility quintiles. This table shows average monthly return spreads for short- and intermediate-horizon momentum strategies. These strategies, as in Novy-Marx (2012), buy winners and sell losers based on stock performance over the first five months of the preceding half year ($MOM_{6,2}$) and stock performance over the first half of the preceding year ($MOM_{12,7}$). The first column shows returns for all stocks, where winners and losers are the top and bottom NYSE quintiles of the corresponding past performance measure. The next five columns show performance of the momentum strategies by NYSE volatility quintiles, constructed using independent sorts on volatility and past performance. The last column shows the average difference between the momentum strategies' performances in the top and bottom volatility quintiles. Volatility is estimated using the standard deviation of daily returns over the preceding 63 trading days and requires a minimum of 42 observations. Portfolio returns are value weighted, and portfolios are rebalanced at the end of each calendar month. The sample covers January 1973 through December 2021.

		NYSE volatility quintile					
	All	Low	2	3	4	High	H−L
$MOM_{12,7}$	0.87	0.68	0.77	0.73	1.01	0.96	0.28
	[4.57]	[3.54]	[4.01]	[3.68]	[4.32]	[4.59]	[1.16]
$MOM_{6,2}$	0.22	-0.30	-0.25	0.14	0.49	1.17	1.48
	[1.03]	[-1.10]	[-1.18]	[0.57]	[2.01]	[5.07]	[4.66]
Diff.	0.65	0.98	1.02	0.60	0.53	-0.21	-1.20
	[2.86]	[3.06]	[3.80]	[2.11]	[1.92]	[-0.89]	[-3.27]

Table 4 tests this prediction. It shows that short-horizon momentum is completely absent from low volatility stocks but strong among high volatility stocks. There is little difference in the strength of intermediate-horizon momentum across volatility quintiles, however, and as a result the disparity in performance between short- and intermediate-horizon momentum strategies decreases strongly with volatility.[12]

[12] Goyal and Wahal (2015) explicitly note that the Novy-Marx (2012) result "appears to be driven largely by a carryover of short-term reversals from month -2" (p. 1237). While reversals that extend into the second month contribute to the disparity in performance between short- and intermediate-horizon momentum, they only explain a small fraction of the difference (see Appendix Table E3). The Goyal and Wahal (2015) explanation fails to recognize that reversals persist more than two months for many stocks, and that for low-volatility stocks there is a long lag, extending more than half a year, before momentum sets in.

6. Conclusion

Different aspects of stock-level liquidity have different, predictable impacts on the strength and persistence of short-run reversals. More volatile stocks are associated with faster, initially stronger reversals, while stocks with lower turnover are associated with more persistent, ultimately stronger reversals. These facts are consistent with the intuition that volatility is positively related to liquidity providers' inventory risk, while turnover is negatively related to their inventory duration. Our cross-sectional results complement the time-series evidence provided by Nagel (2005) linking the performance of reversal strategies to aggregate market liquidity.

The impact of turnover on reversal persistence that we document is particularly remarkable: reversals last only days among the highest turnover stocks but extend several months for those with the lowest turnover. While the latter may seem implausibly long for a liquidity-driven phenomenon, Hendershott and Menkveld (2014) present evidence "of active intermediation across days as inventory management is not a strictly intra-day phenomenon in which intermediaries go home flat" and "significant first-order autocorrelation in inventories, showing that these positions can last for multiple days" (p. 410). Moreover, the time it takes a liquidity provider to offload inventories only represents a lower bound on the persistence of liquidity effects. When unwinding positions, liquidity providers often trade with other short-term buyers fulfilling a market-making function. Stocks may need to trade several times before finding their eventual homes. Better understanding the nature and behavior of secondary (and tertiary) liquidity providers, and how liquidity providers trade amongst themselves, is a promising subject for future research, and one that would shed additional light on the processes generating the observed reversal persistence.

Our findings also explain several seemingly disparate results in the literature. The negative relation between turnover and reversal persistence helps explain the differential impact of turnover on reversals at the weekly and monthly horizons documented by Avramov et al. (2006), and the Medhat and Schmeling (2022) finding that high-turnover stocks exhibit one-month momentum. The positive relation between volatility and reversal magnitudes at short horizons provides an explanation for the large returns to one-month low-volatility industry-relative reversals at the monthly horizon documented by Novy-Marx and Velikov (2016), the difference in strength between short- and intermediate-horizon momentum found by Novy-Marx (2012), and the Arena et al. (2008) finding that momentum is concentrated among high-volatility stocks. Collectively, these facts highlight the importance of studying market phenomena at the appropriate frequency.

Finally, our results have implications for practitioners. Better understanding the details of liquidity provision can improve execution. Accounting for the cross-sectional differences in the magnitude and persistence of reversals when trading can potentially reduce the cost of demanding liquidity and increase the compensation for providing it. While this is critical to anyone playing a market-making role, it is more broadly important to anyone who trades. The gross returns to providing liquidity can be high, as evidenced by the extremely attractive performance of our proxy for liquidity-driven reversals. Actively exploiting these reversals is certainly less profitable, as even liquidity providers incur transaction costs, but investors can benefit from incorporating short-run reversals into their rebalancing process. For example, employing a reversal screen, which uses the results of this paper to help inform how and when to execute trades, can improve expected returns without incurring additional turnover and trading costs. Conceptually, it does so by delaying trades that demand high-cost liquidity until the liquidity is cheaper, but delaying these trades no longer than necessary (Novy-Marx and Velikov, 2016, 2019). For broadly diversified strategies that can hold many substitutes, such a screen can add value by improving execution with minimal impact on the strategy's long-term focus.

A. Appendix: Detailed reversal decomposition

This appendix provides more details on the decomposition of standard reversals into news-related effects and announcement-adjusted industry-relative reversals provided in Section 2.3. Figure A1 shows the performance of \$1, net of financing costs charged at the risk-free rate, invested since the beginning of 1973 into each of five strategies: reversals (REV); post-earnings-announcement drift (PEAD); one-month industry momentum (IMOM); industry-relative reversals (IRR); and announcement-adjusted industry-relative reversals (IRRX).[13] Most strikingly, the figure shows that trading IRRX was far more profitable than trading REV, and that there is an apparent, strong negative correlation between REV and IMOM.

Table A1 reports results of time-series regressions employing the returns to the five strategies. Panel A reports the strategies' average monthly returns. Panel B regresses the returns of REV onto the returns of the other strategies. The first three columns show, not surprisingly, that REV is long IRR, but short PEAD and IMOM. The fourth specification shows that IRR and IMOM jointly do a good job pricing REV. The fifth specification shows that adding PEAD provides almost no new information because IRR, just like REV, is significantly short PEAD. The last specification fully decomposes the three effects, showing that REV has a large positive exposure to IRRX (industry-relative reversals designed to avoid PEAD), but large negative exposures to PEAD and IMOM.

Panel C performs spanning tests of IRR and IRRX. The first three specifications

[13] The figure shows $\prod_{s=0}^{t}(1 + r_{L,s} - r_{S,s})$, where $r_{L,s}$ and $r_{S,s}$ are the monthly returns to the portfolios held long and short, respectively, and t ranges from January 1973 to December 2021. This is the cumulative performance of a strategy that initially buys \$1 of the portfolio held long and short-sells \$1 of the portfolio held short, and, motivated by Regulation T, posts cash collateral equal to 50% of the total equity exposure in a non-interest bearing margin account each month. Alternatively, this may be conceptualized as the performance of the book of a trader following the strategy when the trader's margin account earns the risk-free rate but her firm charges her for the use of their capital at that same rate. Daniel and Moskowitz (2016) instead add the risk-free rate to the return spread, i.e., they use cumulative simple returns. We prefer the cumulated monthly excess returns, similar to those used by Detzel, Novy-Marx, and Velikov (2022), because they more accurately reflect economic profitability and are not arbitrarily rewarded by high inflation.

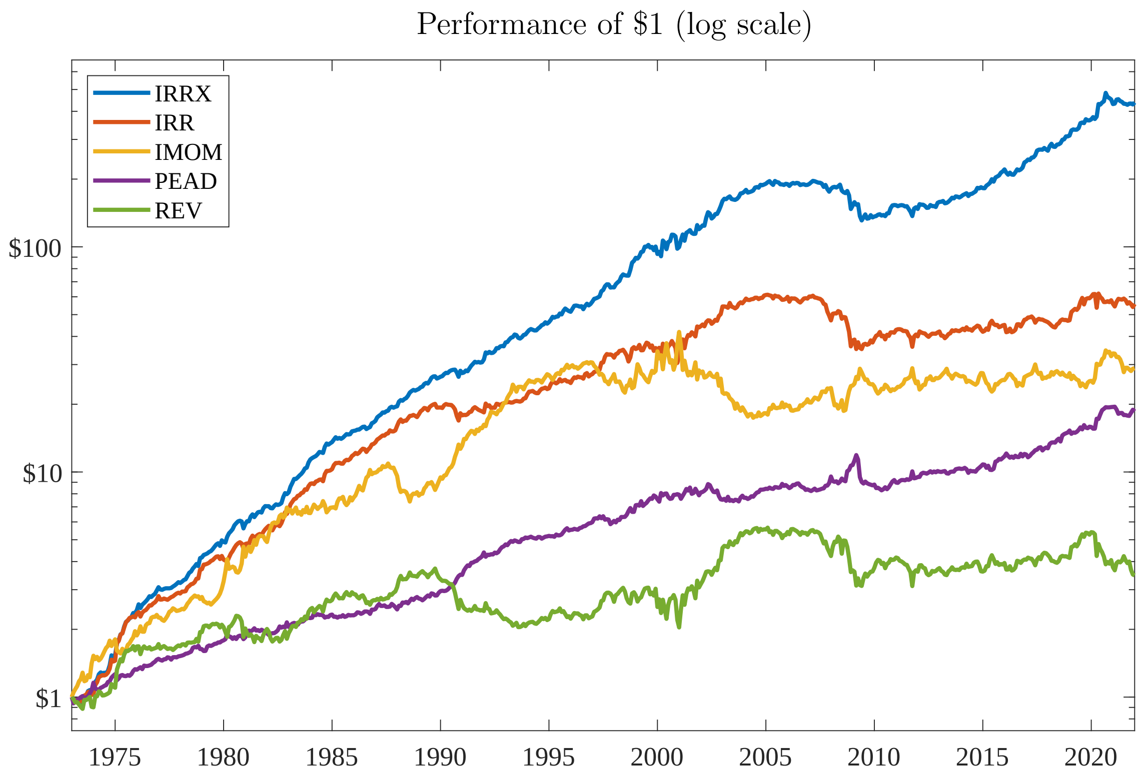


Fig. A1. Strategy performance over time. The figure shows the performance of $1, net of financing costs charged at the risk-free rate, invested in each of reversals (REV); one-month industry momentum (IMOM); post-earnings-announcement drift (PEAD); industry-relative reversals (IRR); and announcement-adjusted industry-relative reversals (IRRX). IMOM trades in the top and bottom ten Fama and French (1997) 49 industry portfolios based on the prior month's value-weighted industry return. The other strategies trade the extreme quintiles, using NYSE breaks, of stocks sorted on prior month's stock return (REV); prior month's return in excess of the returns to a firm's Fama and French 49 value-weighted industry portfolio (IRR); this industry-adjusted return further adjusted by subtracting the three-day cumulative abnormal return (in excess of the value-weighted market return) around a firm's most recent earnings announcement, provided the announcement was in the latest quarter (IRRX); and this cumulative abnormal announcement-window return (PEAD). REV, IRR, and IRRX buy losers and short winners, while PEAD and IMOM buy winners and short losers. Portfolios are value weighted and rebalanced at the end of each month. The sample covers January 1973 through December 2021.

show that IRR has a significant negative alpha relative to IRRX and a large positive alpha relative to PEAD, but that IRR is inside the joint span of IRRX and PEAD. In contrast, the last three specifications show that IRRX is outside the span of IRR and PEAD, whether individually or together. The large positive loading of IRRX on PEAD in the last specification does not reflect a long exposure of IRRX to PEAD, but hedges the short exposure the IRRX-replicating portfolio would otherwise get through its large, positive loading on IRR.

Table A1. Reversal strategy return decomposition.
The table reports results from time-series regressions of the form:

$$y = \alpha + \beta_{\mathbf{x}}\mathbf{x} + \epsilon.$$

Strategies considered are reversals (REV); industry-relative reversals (IRR); industry-relative, announcement-adjusted reversals (IRRX); post-earnings-announcement drift (PEAD); and one-month industry momentum (IMOM). The first four strategies trade the extreme quintiles, using NYSE breaks, of stocks sorted on prior month's return (REV); prior month's return in excess of the value-weighted return to a firm's Fama and French 49 industry (IRR); this industry-relative return adjusted by subtracting the three-day cumulative abnormal return around the firm's most recent earnings announcement, provided the announcement was in the latest quarter (IRRX); and this three-day cumulative abnormal announcement-window return (PEAD). IMOM trades the top and bottom ten Fama and French 49 industries based on prior month's value-weighted industry returns. REV, IRR, and IRRX buy losers and short winners, while PEAD and IMOM buy winners and short losers. Portfolio returns are value weighted, and portfolios are rebalanced at the end of each month. The sample covers January 1973 through December 2021.

Panel A: Average monthly excess return (%)

Strategy	REV	PEAD	IMOM	IRR	IRRX
	0.31	0.53	0.68	0.74	1.08
	[1.68]	[5.45]	[3.57]	[5.40]	[9.35]

Panel B: Determinants of reversal performance

	y = REV					
α	-0.54	0.86	0.73	0.07	0.12	0.13
	[-5.32]	[7.84]	[4.18]	[1.10]	[1.78]	[1.73]
IRR	1.16			0.79	0.77	
	[38.7]			[36.6]	[34.1]	
IMOM		-0.80		-0.50	-0.49	-0.53
		[-34.1]		[-32.2]	[-32.0]	[-30.4]
PEAD			-0.80		-0.07	-0.54
			[-10.7]		[-2.49]	[-17.4]
IRRX						0.76
						[27.8]
Adj. R^2 (%)	71.8	66.5	16.6	89.8	89.9	87.0

Panel C: Spanning tests employing IRRX, IRR, and PEAD

	y = IRR			y = IRRX		
α	-0.25	1.05	0.06	0.60	1.05	0.22
	[-2.71]	[8.16]	[0.81]	[7.97]	[8.91]	[3.48]
IRRX	0.92		0.94			
	[29.6]		[42.2]			
IRR				0.65		0.80
				[29.6]		[42.2]
PEAD		-0.58	-0.63		0.05	0.51
		[-10.9]	[-23.6]		[0.97]	[19.1]
Adj. R^2 (%)	59.8	16.7	79.4	59.8	-0.0	75.2

A.1. Post-decimalization results

Table A2 replicates the results of Table A1 starting from May 2001, the first full month after decimalization. While reversals are weaker post-decimalization, our main conclusions are unchanged. The REV strategy, which trades against PEAD and IMOM, is weak, generating average monthly excess returns of only 18 bps/month (t-statistic of 0.18). The IRRX strategy remains significant, generating average monthly excess returns of 58 bps/month (t-statistic of 3.29). In the post-decimalization sample, the difference in average returns is primarily driven by the IRRX strategy avoiding the short position in PEAD as, consistent with Figure A1, the returns to IMOM are negligible post-decimalization. However, even in the late sample controlling for industry momentum continues to improve the precision with which we can identify the compensation for providing liquidity.

Figure A2 replicates Figure 1, breaking the sample at April 9, 2001, the introduction of decimalization. It shows the average winner-minus-loser spread from formation for strategies based on five days of announcement-adjusted industry-relative returns constructed using only high- or low-volatility stocks or only high- or low-turnover stocks. The figure shows that the patterns we document for the impacts of volatility and turnover hold in both sub-samples. Overall, reversals are weaker in the post-decimalization sample, which is associated with greater average market liquidity, and the confidence bands are wider due to the shorter sample, but the results are qualitatively consistent across the two sub-samples.

Table A2. Reversals decomposition post-decimalization
The table reports result from time-series regressions of the form:

$$y = \alpha + \beta_{\mathbf{x}}\mathbf{x} + \epsilon.$$

Strategies considered are reversals (REV), industry-relative reversals (IRR), industry-relative announcement-adjusted reversals (IRRX), post-earnings announcement drift (PEAD), and one-month industry momentum (IMOM). The first four strategies are long/short the extreme quintiles, using NYSE breaks, of stocks sorted on prior month's return (REV), prior month's return in excess of the return to a firm's Fama and French 49 value-weighted industry (IRR), this same industry-relative return adjusted by subtracting the three-day cumulative abnormal return around the firm's most recent earnings announcement (IRRX), and the three-day cumulative abnormal return around the firm's most recent earnings announcement (PEAD). IMOM is long/short stocks in the top and bottom 10 Fama and French 49 industries on the basis of the prior month's industry returns. Portfolio returns are value weighted, and portfolios are rebalanced at the end of each month. The post-decimalization sample covers May 2001 through December 2021.

Panel A: Average monthly return (%)

Strategy	REV	PEAD	IMOM	IRR	IRRX
	0.18	0.36	0.09	0.20	0.58
	[0.62]	[2.09]	[0.34]	[0.94]	[3.29]

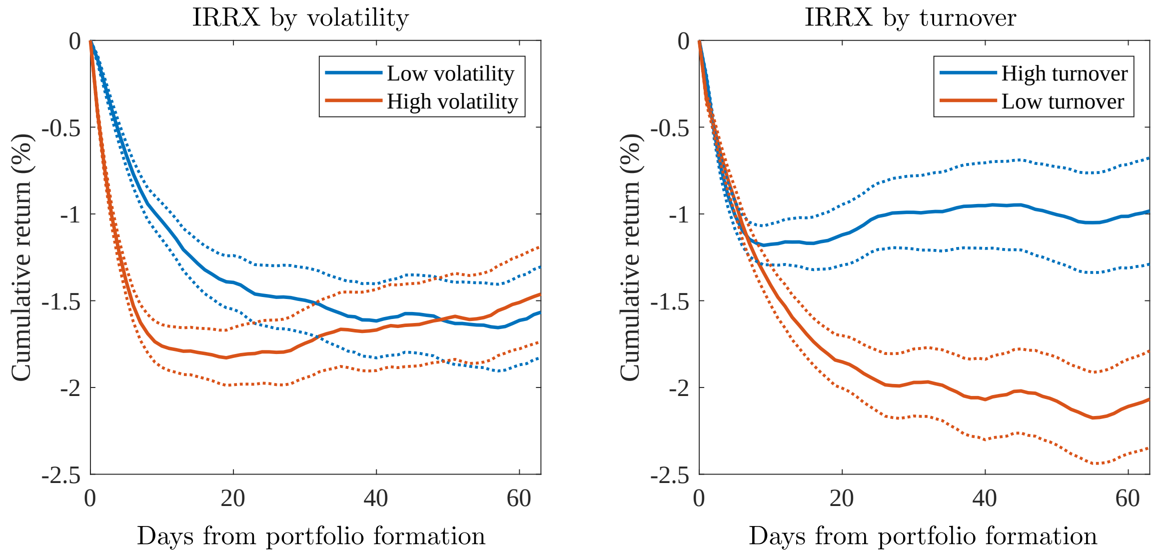
Panel B: Determinants of reversal performance

	y = REV					
α	-0.06	0.26	0.46	0.06	0.08	0.01
	[-0.41]	[1.52]	[1.74]	[0.62]	[0.87]	[0.10]
IRR	1.20			0.83	0.82	
	[28.0]			[24.2]	[22.7]	
IMOM		-0.91		-0.51	-0.50	-0.64
		[-21.5]		[-18.0]	[-17.6]	[-19.6]
PEAD			-0.77		-0.06	-0.55
			[-7.92]		[-1.55]	[-11.4]
IRRX						0.73
						[16.0]
Adj. R^2 (%)	76.1	65.1	20.0	89.6	89.7	84.4

Panel C: Spanning tests employing IRRX, IRR, and PEAD

	y = IRR			y = IRRX		
α	-0.27	0.39	-0.08	0.47	0.52	0.23
	[-1.65]	[2.02]	[-0.74]	[3.56]	[2.96]	[2.26]
IRRX	0.81		0.92			
	[14.1]		[23.1]			
IRR				0.55		0.75
				[14.1]		[23.1]
PEAD		-0.54	-0.69		0.16	0.57
		[-7.49]	[-16.8]		[2.52]	[14.0]
Adj. R^2 (%)	44.6	18.2	74.2	44.6	2.1	69.1

Panel A: Winner-minus-loser spreads by volatility and turnover, pre-decimalization



Panel B: Winner-minus-loser spreads by volatility and turnover, post-decimalization

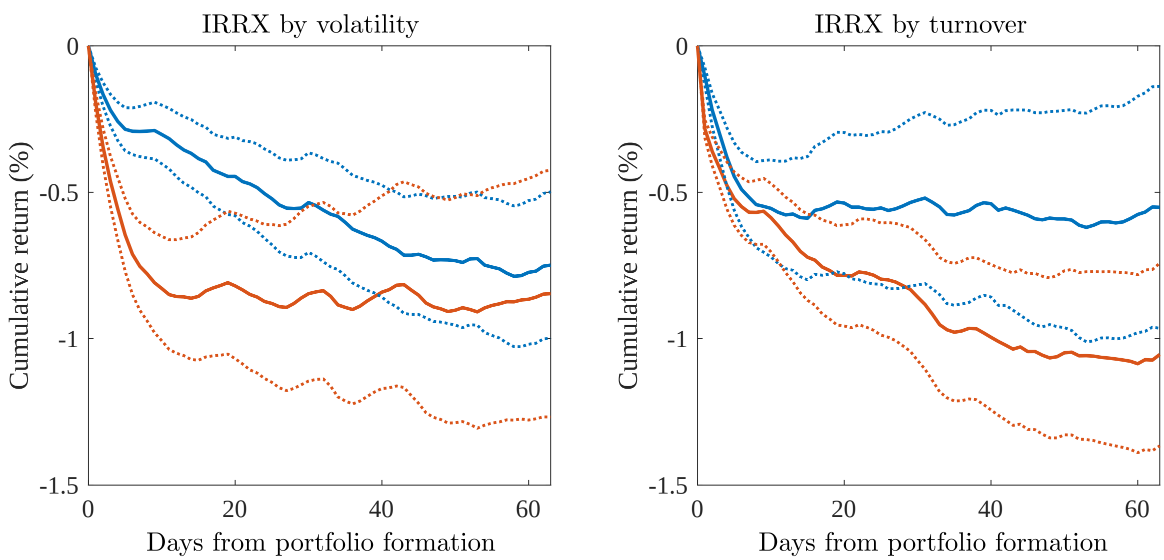


Fig. A2. Five-day IRRX by volatility and turnover, pre- and post-decimalization. The figure shows cumulative average performance from portfolio formation of industry-relative reversal strategies within the low and high NYSE volatility quintiles (left panel) and the low and high NYSE turnover quintiles (right panel). The IRRX strategies are constructed using an independent quintile sort, again using NYSE breaks, on previous industry-relative performance, ignoring returns in any three-day earnings announcement window, measured over the previous five days. Volatility is estimated using the standard deviation of daily returns over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63 day window. Portfolio returns are value weighted. The 95% confidence bounds are based off Newey-West standard errors calculated using ten lags, twice the length of the past performance window. The pre-decimalization sample covers January 1973 through April 8, 2001; the post-decimalization sample covers April 9, 2001 through December 2021.

B. Liquidity-variable correlations

Inspired by Kyle's (1985) "lambda" measure of price impact, the Amihud (2002) illiquidity measure is an estimate of the semi-elasticity of a stock's price to the value of the stock traded. The T-day estimate of the measure for stock i on day t is

$$\text{Amihud}_{i,t,T} \equiv \frac{1}{T}\sum_{s=1}^{T}\frac{|r_{i,t-s}|}{P_{i,t-s}\cdot\text{Volume}_{i,t-s}} = \frac{1}{T}\sum_{s=1}^{T}\frac{|r_{i,t-s}|}{\text{ME}_{i,t-s}\cdot\text{TO}_{i,t-s}},$$

where $P_{i,t-s}$ and $\text{Volume}_{i,t-s}$ are firm i's share price and the number of the firm's shares that trade on day $t-s$, $\text{ME}_{i,t-s}$ is market equity, and $\text{TO}_{i,t-s}$ is turnover measured as the fraction of shares outstanding that trade on day $t-s$.

Replacing the average ratio on the right-hand side of the previous equation with the ratio of averages yields our approximation

$$\text{Amihud}_{i,t,T} \approx \frac{\frac{1}{T}\sum_{s=1}^{T}|r_{i,t-s}|}{\frac{1}{T}\sum_{s=1}^{T}\text{ME}_{i,t-s}\cdot\text{TO}_{i,t-s}} \approx \frac{\sqrt{2/\pi}\;\sigma_{i,t,T}}{\text{ME}_{i,t}\cdot\text{TO}_{i,t,T}}, \tag{B1}$$

where $\sigma_{i,t,T}$ is the standard deviation of daily returns over the previous T days, $\text{TO}_{i,t,T} \equiv \frac{1}{T}\sum_{s=1}^{T}\text{TO}_{i,t-s}$ is the average daily fraction of shares traded over the preceding T days, and $\sqrt{2/\pi}$ is the ratio of the mean absolute deviation to the standard deviation of a normal random variable.

Figure B1 shows daily correlations between the Amihud measure and our approximation as well as its components. The figure shows a stable, near-perfect correlation between the directly-estimated Amihud measure and our simple approximation. This is driven by the Amihud measure's relatively high positive correlation with volatility, fairly large negative correlation with turnover, and extremely large negative correlation with size.

Panel A of Table B1 provides average correlations between the liquidity variables. The table shows a striking -0.93 correlation between the Amihud measure and size.

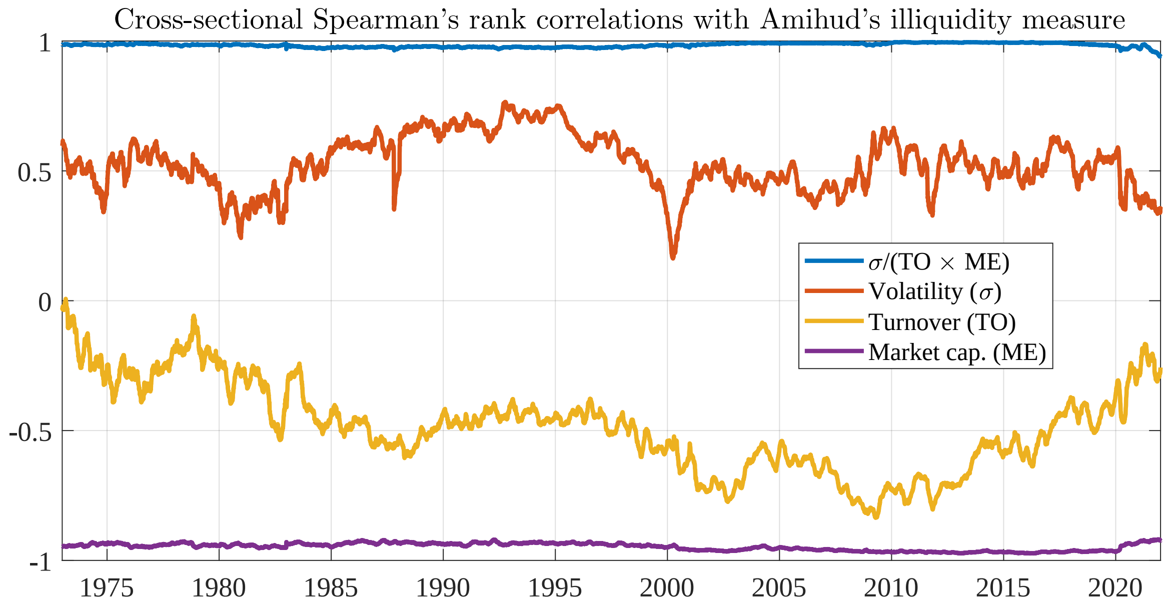


Fig. B1. Cross-sectional correlations with Amihud illiqudity measure. This figure shows the daily cross-sectional Spearman's rank correlations between the directly estimated Amihud illiquidity measure and its approximation,

$$\text{Amihud} \;\; \underset{\sim}{\propto} \;\; \frac{\sigma}{\text{ME} \cdot \text{TO}},$$

where σ is volatility, TO is turnover, and ME is market capitalization. It also shows the correlations between the Amihud measure and the individual components used to construct the approximation: volatility, turnover, and market capitalization. Volatility, turnover, and the Amihud measure are each estimated over the preceding 63 days, where these estimations require a minimum of 42 daily observations and we excluded zero-turnover days when estimating Amihud. The sample covers January 2, 1973 through December 31, 2021.

Because size has far more cross-sectional variability than volatility or proportional turnover, it drives most of the variation in the Amihud measure. The magnitude of this correlation is sufficiently large to suggests caution when interpreting results employing the Amihud measure, because it basically just proxies for size. Panel A also shows that larger stocks are more liquid because, in addition to just being bigger, they tend to be less volatile and turn over more. In contrast, the positive average correlation between volatility and turnover tends to complicate the direct interpretation of these variables' relation to liquidity. While higher volatility is directly associated with less liquidity, more volatile stocks tend to trade more, which

Table B1. Liquidity-variable correlations and FMB regressions.
Panel A of this table shows time-series average daily cross-sectional Spearman's rank between the directly estimated Amihud illiquidity measure and its approximation,

$$\text{Amihud} \quad \underset{\sim}{\propto} \quad \frac{\sigma}{\text{ME} \cdot \text{TO}},$$

where σ is volatility, TO is turnover, and ME is market capitalization. It also shows the correlations between Amihud and the components of this approximation. Panel B presents results of Fama and Macbeth (1973) regressions using the log-variables, motivated by the approximation

$$\ln(\text{Amihud}) \quad \approx \quad \ln \sigma - \ln \text{TO} - \ln \text{ME} + c.$$

The regression t-statistics are calculated using Newey-West standard errors estimated using one year (252 trading days) of daily lags. Volatility, turnover, and Amihud illiquidity are all estimated over the preceding 63 days, where these estimations require a minimum of 42 non-zero daily observations. The sample covers January 1973 through December 2021.

Panel A: Illiquidity variables' average correlations

	Turnover	Size	$\frac{\sigma}{\text{TO} \cdot \text{ME}}$	Amihud
Volatility	0.23	-0.55	0.51	0.49
Turnover		0.30	-0.52	-0.52
Size			-0.95	-0.93
$\frac{\sigma}{\text{TO} \cdot \text{ME}}$				0.98

Panel B: Fama-MacBeth regressions explaining Amihud illiquidity

	(1)	(2)	(3)	(4)
Volatility	2.65			0.88
	[31.2]			[41.9]
Turnover		-1.56		-1.13
		[-23.3]		[-78.0]
Size			-1.41	-1.13
			[-72.6]	[-173.3]
Mean-R^2 (%)	25.6	28.2	86.0	96.4

somewhat mitigates volatility's direct impact. Similarly, while higher turnover is associated with more liquidity, actively traded stocks tend to be more volatile, which is associated with less liquidity.

Motivated by the approximate log-linear relation

$$\ln(\text{Amihud}) \quad \approx \quad \ln \sigma - \ln \text{TO} - \ln \text{ME} + c, \tag{B2}$$

Panel B of Table B1 reports results of Fama and Macbeth (1973) regressions of the Amihud measure onto the three components of our Amihud approximation. Individually, each of the variables is highly significant, explaining on average 25.6, 28.2, and 86.0% of the cross-sectional variation in the logged Amihud measure, respectively. In the multiple regression, the coefficient estimates for volatility, turnover, and size are close to the approximate predicted values of one, negative one, and negative one suggested by equation (B2). On average the three variables jointly explain 96.4% of the cross-sectional variation in Amihud illiquidity. Including all three as explanatory variables also greatly increases the significance of each.

C. Additional international evidence

C.1. Reversal decomposition: international evidence

Figure C1 shows the performance of $1, net of financing costs charged at the risk-free rate, invested into reversals (REV), post-earnings-announcement drift (PEAD), industry momentum (IMOM), industry-relative reversals (IRR), and announcement-adjusted industry-relative reversals (IRRX). Portfolios are from country-specific sorts and are rebalanced at the end of each month. Portfolio returns are value weighted using US-dollar returns and market-capitalizations. The left panel shows results for developed markets excluding the US over the sample January 1996 through December 2021, while the right panel shows results for emerging markets over the sample January 1999 through December 2021, where the start dates are determined by the availability of earning-announcement dates. Data are from Bloomberg. Similar to the US results (Figure A1), Figure C1 shows a much higher profitability for IRRX than for REV, and a negative correlation between REV and IMOM. This is true both in non-US developed markets and in emerging markets.

Table C1 reports results of time-series regressions employing returns to the five

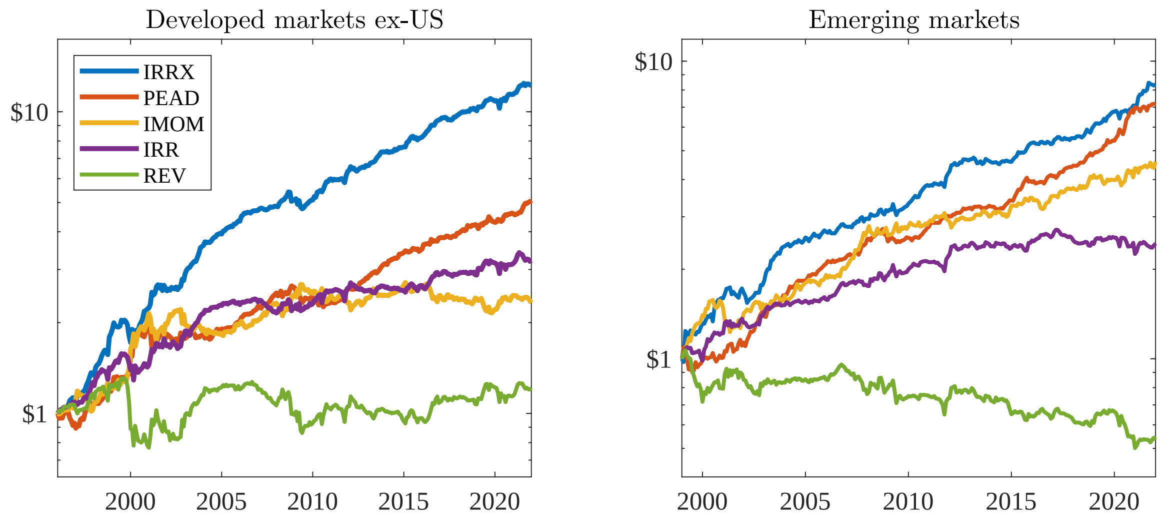


Fig. C1. International strategy performance over time. The figure shows the performance of $1, net of financing costs charged at the risk-free rate, invested into reversals (REV); industry-relative reversals (IRR); announcement-adjusted industry-relative reversals (IRRX); post-earnings-announcement drift (PEAD); and industry momentum (IMOM). The first four strategies trade the extreme quintiles of stocks sorted on prior month's return (REV); this return in excess of the return to a firm's industry (IRR); this industry-relative return adjusted by subtracting the three-day cumulative abnormal return (in excess of the country's value-weighted market return) around the firm's most recent earnings announcement within three months (IRRX); and this cumulative abnormal announcement-window return (PEAD), respectively, using country-specific, market-cap breakpoints. IMOM trades stocks in the top and bottom four industries within a country on the basis of the prior month's industry returns. There are 12 industries in total, corresponding to the 2-digit Global Industry Classification Standard (GICS) plus a group for a missing classification, and industry returns are country specific and value weighted. REV, IRR, and IRRX buy losers and short winners, while PEAD and IMOM buy winners and short losers. Portfolios are rebalanced at the end of each month and portfolio returns are value weighted using free-float-adjusted market cap. We use US dollar returns and market-cap values. Developed markets excluding the US (left panel) include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom. Emerging markets (right panel) include Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey. The developed and emerging market samples start in January 1996 and January 1999, respectively, determined by earnings-announcement dates availability, and run through December 2021.

strategies, which are consistent with the US results presented in Table A1. Panel A reports the strategies' average monthly returns. Panels B1 and B2 show that in both regions REV is long IRR, but short IMOM and PEAD significantly impairing its performance. In both regions IMOM, PEAD, and IRRX jointly explain all of standard reversals average returns. Panels C1 and C2 show spanning tests for IRR and IRRX. IRR is long IRRX but short PEAD and is within their joint span in either region. Conversely, IRRX is outside the span of IRR and PEAD in both regions.

Table C1. International reversal strategy return decomposition.
The table reports results from time-series regressions of the form:

$$y = \alpha + \beta_{\mathbf{x}}\mathbf{x} + \epsilon.$$

Strategies considered are reversals (REV); industry-relative reversals (IRR); announcement-adjusted industry-relative reversals (IRRX); post-earnings announcement drift (PEAD); and industry momentum (IMOM). The first four strategies trade the extreme quintiles of stocks sorted on prior month's return (REV); this return in excess of the return to a firm's industry (IRR); this industry-relative return adjusted by subtracting the three-day cumulative abnormal return (in excess of the country's value-weighted market return) around the firm's most recent earnings announcement within three months (IRRX); and this cumulative abnormal announcement-window return (PEAD). Quintiles use country-specific, free-float adjusted market-cap breakpoints. IMOM trades stocks in the top and bottom four industries within a country based on the prior month's industry returns. There are 12 industries in total, corresponding to the 2-digit Global Industry Classification Standard (GICS) plus a group for a missing classification, and industry returns are country specific and value weighted. REV, IRR, and IRRX buy losers and short winners, while PEAD and IMOM buy winners and short losers. Portfolios are rebalanced at the end of each month and portfolio returns are value weighted using free-float-adjusted market cap. We use US dollar returns and market-cap values. Developed markets excluding the US include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom. Emerging markets include Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey. The developed and emerging market samples start in January 1996 and January 1999, respectively, with the start dates determined by earnings-announcement dates availability, and run through December 2021.

Panel A: Average monthly return (%)

Strategy	REV	PEAD	IMOM	IRR	IRRX
Developed markets	0.13	0.55	0.31	0.40	0.83
	[0.62]	[4.31]	[1.97]	[3.10]	[6.75]
Emerging markets	-0.18	0.74	0.59	0.35	0.80
	[-1.03]	[5.94]	[3.79]	[2.67]	[5.07]

Panel B1: Determinants of reversal performance, developed markets

	y = REV					
α	-0.45	0.48	0.52	-0.06	-0.01	0.00
	[-4.91]	[4.47]	[2.74]	[-1.05]	[-0.19]	[0.03]
IRR	1.44			0.95	0.92	
	[36.5]			[28.4]	[27.4]	
IMOM		-1.14		-0.61	-0.60	-0.84
		[-29.4]		[-22.2]	[-21.8]	[-24.3]
PEAD			-0.72		-0.08	-0.22
			[-8.71]		[-3.05]	[-5.78]
IRRX						0.61
						[14.5]
Adj. R^2 (%)	81.1	73.6	19.7	92.7	92.9	85.4

Table C1 continued.

Panel B2: Determinants of reversal performance, emerging markets

	y = REV					
α	-0.59	0.27	-0.05	-0.27	-0.30	0.00
	[-6.14]	[1.96]	[-0.27]	[-3.35]	[-3.44]	[0.01]
IRR	1.16			0.94	0.95	
	[26.6]			[23.9]	[23.8]	
IMOM		-0.77		-0.41	-0.41	-0.68
		[-14.8]		[-12.3]	[-12.3]	[-13.6]
PEAD			-0.18		0.03	-0.05
			[-2.10]		[0.87]	[-0.88]
IRRX						0.32
						[6.45]
Adj. R^2 (%)	72.1	44.4	1.6	81.9	81.9	51.6

Panel C1: Spanning tests employing IRRX, IRR, and PEAD, developed markets

	y = IRR			y = IRRX		
α	-0.25	0.62	-0.06	0.55	0.94	0.49
	[-2.65]	[5.07]	[-0.68]	[6.52]	[7.63]	[5.52]
IRRX	0.78		0.73			
	[19.4]		[18.8]			
IRR				0.70		0.74
				[19.4]		[18.8]
PEAD		-0.40	-0.25		-0.21	0.09
		[-7.58]	[-6.75]		[-3.91]	[2.20]
Adj. R^2 (%)	54.9	15.7	60.5	54.9	4.7	55.3

Panel C2: Spanning tests employing IRRX, IRR, and PEAD, emerging markets

	y = IRR			y = IRRX		
α	0.04	0.47	0.14	0.61	0.91	0.65
	[0.33]	[3.48]	[1.06]	[4.27]	[5.45]	[4.24]
IRRX	0.38		0.37			
	[8.71]		[8.46]			
IRR				0.57		0.56
				[8.71]		[8.46]
PEAD		-0.17	-0.12		-0.15	-0.05
		[-2.79]	[-2.13]		[-1.94]	[-0.74]
Adj. R^2 (%)	21.7	2.8	22.4	21.7	1.4	21.3

C.2. Liquidity-variable correlations: international evidence

Figure C2 shows, for non-US developed markets (left) and emerging markets (right), the daily cross-sectional correlations between direct estimates of the Amihud illiquidity measure and our simple approximation from section B, Amihud $\stackrel{\propto}{\sim} \frac{\sigma}{\text{ME}\cdot\text{TO}}$, and the components of this approximation. Each correlation is calculated separately for each country, then weighted-averaged across countries using free-float-adjusted market cap. Volatility, turnover, and Amihud are estimated over the preceding 63 days (minimum of 42 days) and we exclude zero-turnover days for Amihud.

While correlations shown in the figure are somewhat noisier than those for the US (Figure B1) they tell the same basic story. In both markets, the Amihud measure has a stable, near-perfect correlation with its approximation. This is driven by a considerable albeit noisy positive correlation with volatility, a fairly large negative correlation with turnover, and a very large negative correlation with size.

Table C2 shows time-series averages of cross-sectional Sperman's rank correlations between the liquidity variables for both non-US developed markets (Panel A) and emerging markets (Panel B). The table confirms the Amihud measure has a near-perfect correlation with its approximation, a positive correlation with volatility, a relatively large and negative correlation with turnover, and a very large negative correlation with size. In general, the correlations between the variables in non-US markets are qualitatively similar to those for the US (Table B1). The only exception is the observed positive correlation between turnover and size, which is considerably smaller in emerging markets compared to developed markets.

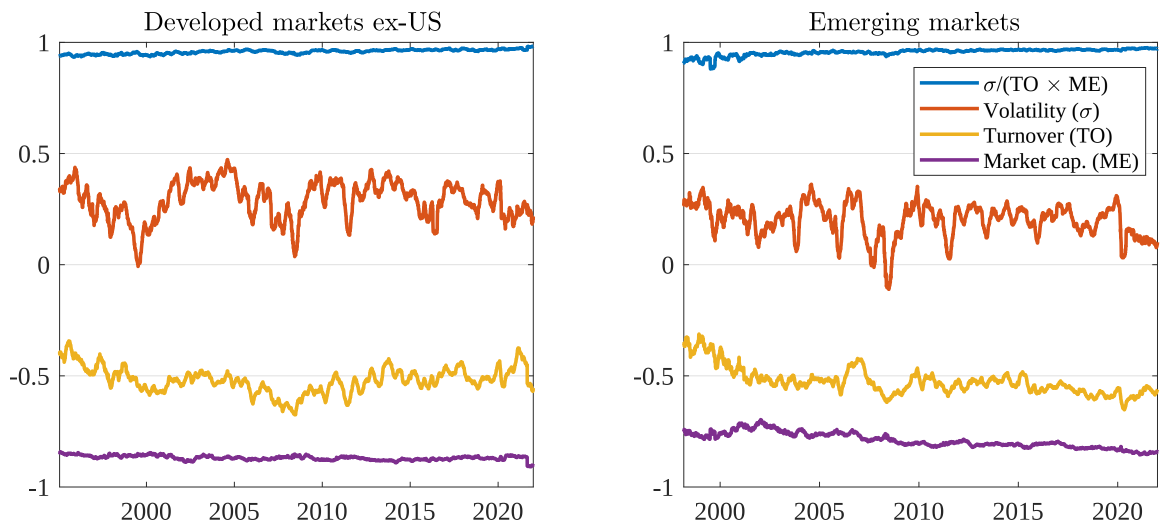


Fig. C2. International cross-sectional correlations with Amihud illiquidity. This Figure shows the daily cross-sectional Spearman's rank correlations between the directly estimated Amihud illiquidity measure and its approximation,

$$\text{Amihud} \;\underset{\sim}{\propto}\; \frac{\sigma}{\text{ME} \cdot \text{TO}},$$

where σ is volatility, TO is turnover, and ME is total (not free-float adjusted) market capitalization, in both developed markets excluding the US (left panel) and in emerging markets (right panel). It also shows the correlations between Amihud and the components of this approximation. Each day, each correlation is calculated separately for each country, then weighted-averaged across countries by country-level, free-float-adjusted market cap. Volatility, turnover, and Amihud are all estimated over the preceding 63 days, where these estimations require a minimum of 42 daily observations, and we exclude zero turnover days from the Amihud estimation. Developed markets excluding the US (left panel) include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom. The sample period covers January 1996 through December 2021. Emerging markets (right panel) include Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey. The sample period covers January 1999 through December 2021.

Table C2. International liquidity-variable correlations.
This table shows time-series average daily cross-sectional Spearman's rank between the directly estimated Amihud illiquidity measure and its approximation,

$$\text{Amihud} \underset{\sim}{\propto} \frac{\sigma}{\text{ME} \cdot \text{TO}},$$

where σ is volatility, TO is turnover, and ME is total (not free-float adjusted) market capitalization. It shows these correlations both in developed markets excluding the US (Panel A) and in emerging markets (Panel B). Volatility, turnover, and Amihud are all estimated over the preceding 63 days, where these estimations require a minimum of 42 daily observations, and we exclude zero turnover days from the Amihud estimation. Each day, each correlation is calculated separately for each country, then weighted-averaged across countries by country-level, free-float-adjusted market cap. Developed markets excluding the US (top panel) include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom. The sample period covers January 1996 through December 2021. Emerging markets (bottom panel) include Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey. The sample period covers January 1999 through December 2021.

	Turnover	Size	$\frac{\sigma}{\text{TO} \cdot \text{ME}}$	Amihud
Panel A: Developed markets excluding the US				
Volatility	0.30	-0.42	0.35	0.29
Turnover		0.19	-0.52	-0.52
Size			-0.90	-0.87
$\frac{\sigma}{\text{TO} \cdot \text{ME}}$				0.96
Panel B: Emerging markets				
Volatility	0.31	-0.33	0.21	0.20
Turnover		0.08	-0.55	-0.52
Size			-0.81	-0.79
$\frac{\sigma}{\text{TO} \cdot \text{ME}}$				0.96

D. Momentum components by aspects of liquidity

Figure 7 in Subsection 5.4 shows the average cumulative winner-minus-loser spreads out to one year (252 trading days) after portfolio formation for strategies based on prior month's stock performance constructed within volatility quintiles. Figure D3 expands on these results, decomposing the performance of momentum into long-run IRRX, IMOM, and PEAD, and shows these by size, volatility, and turnover.

The figure shows that size is the strongest determinant of the long-run strength of industry momentum and post-earnings-announcement drift, with both effects far stronger among smaller stocks, consistent with the results Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989), and Hou (2007). Size has almost no power, however, to predict differences in the strength of the component of momentum driven by announcement-adjusted industry-relative returns, while both volatility and turnover do. The IRRX component of momentum is strong for high-volatility and high-turnover stocks, but essentially absent among low-volatility and low-turnover stocks.

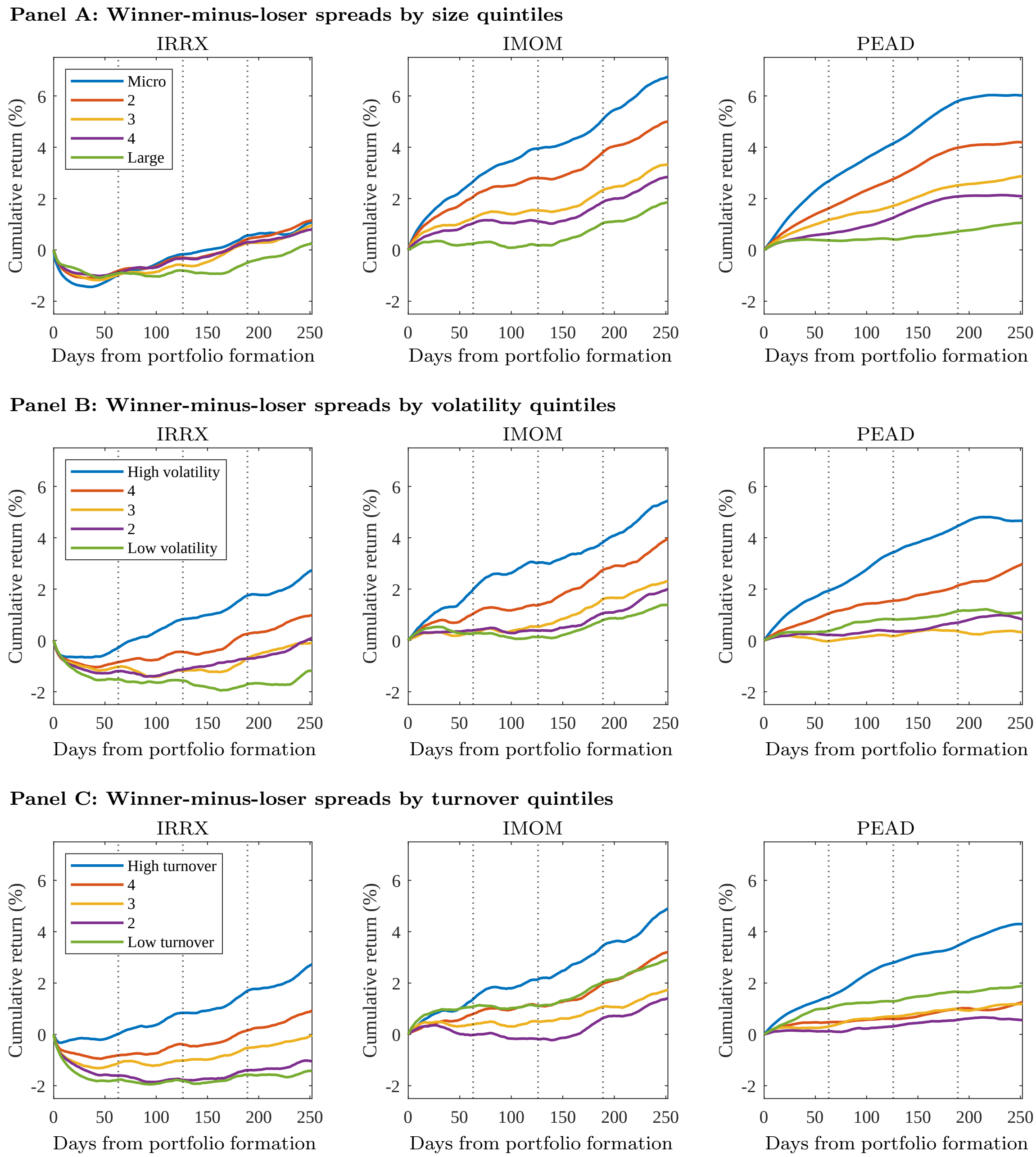


Fig. D3. Long-run IRRX, IMOM, and PEAD performance by size, volatility, and turnover. The figure shows long-run cumulative average performance from portfolio formation of announcement-adjusted industry-relative reversal strategies (left), industry-momentum strategies (center), and post-earnings-announcement drift strategies. It shows each of these within size, volatility, and turnover quintiles constructed using NYSE breaks (Panels A to C, respectively). IRRX and PEAD strategies are constructed using independent quintile sorts, again using NYSE breaks, on prior 21-day announcement-adjusted industry-relative performance and three-day cumulative abnormal returns around any earnings announcements in the preceding 63 days, respectively. IMOM is long (short) stocks from the 10 best (worst) performing Fama and French 49 industry portfolios over the 21 days prior to portfolio formation. Volatility is estimated using the standard deviation of daily returns over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63 day window, both requiring a minimum of 42 daily observations. Portfolio returns are value weighted. The sample covers January 1973 through December 2021.

E. Internet Appendix

E.1. Past performance as a proxy for order imbalance

Figure E1 provides direct evidence for Nagel's (2012) claim that "lagged returns [...] proxy for unobserved market-maker inventory imbalances" (p. 2006). It shows time-series means of value-weighted average abnormal order imbalance around portfolio formation for winners and losers, controlling for size (Panel A), volatility (Panel B), and turnover (Panel C). Winners and losers are based on five days of announcement-adjusted, industry relative returns, and the underlying portfolios, which are formed daily, are from independent quintile sorts using NYSE breakpoints. Each stock's order imbalance is the difference in buyer- and seller-initiated trading volume on a given day, as identified by the Lee and Ready (1991) algorithm, scaled by the stock's total volume for the day.

The figure shows that, in the week leading up to formation, winners see an excess of buyer-initiated trades representing roughly 10-20% of cumulative average daily trading volume. Conversely, losers see an abnormal excess of seller-initiated trades of a similar magnitude. Abnormal imbalance builds up gradually in the week preceding formation, peaks on the day of formation, and unwinds within a week. Size and turnover produce much more dispersion in imbalance compared to volatility, with smaller and less-traded stocks seeing greater buy and sell imbalance (Panels A and C). These results are consistent with Nagel's model, in which past performance is a noisy proxy for the inventory imbalances of risk-averse liquidity suppliers. Our results further show that these imbalances are particularly pronounced among smaller and less-traded stocks, which are also less liquid. This adds to the cross-sectional evidence by Hendershott and Seasholes (2006, 2007) and the recent time-series evidence by Boyarchenko, Larsen, and Whelan (2022) on the link between order imbalances and subsequent price reversals.

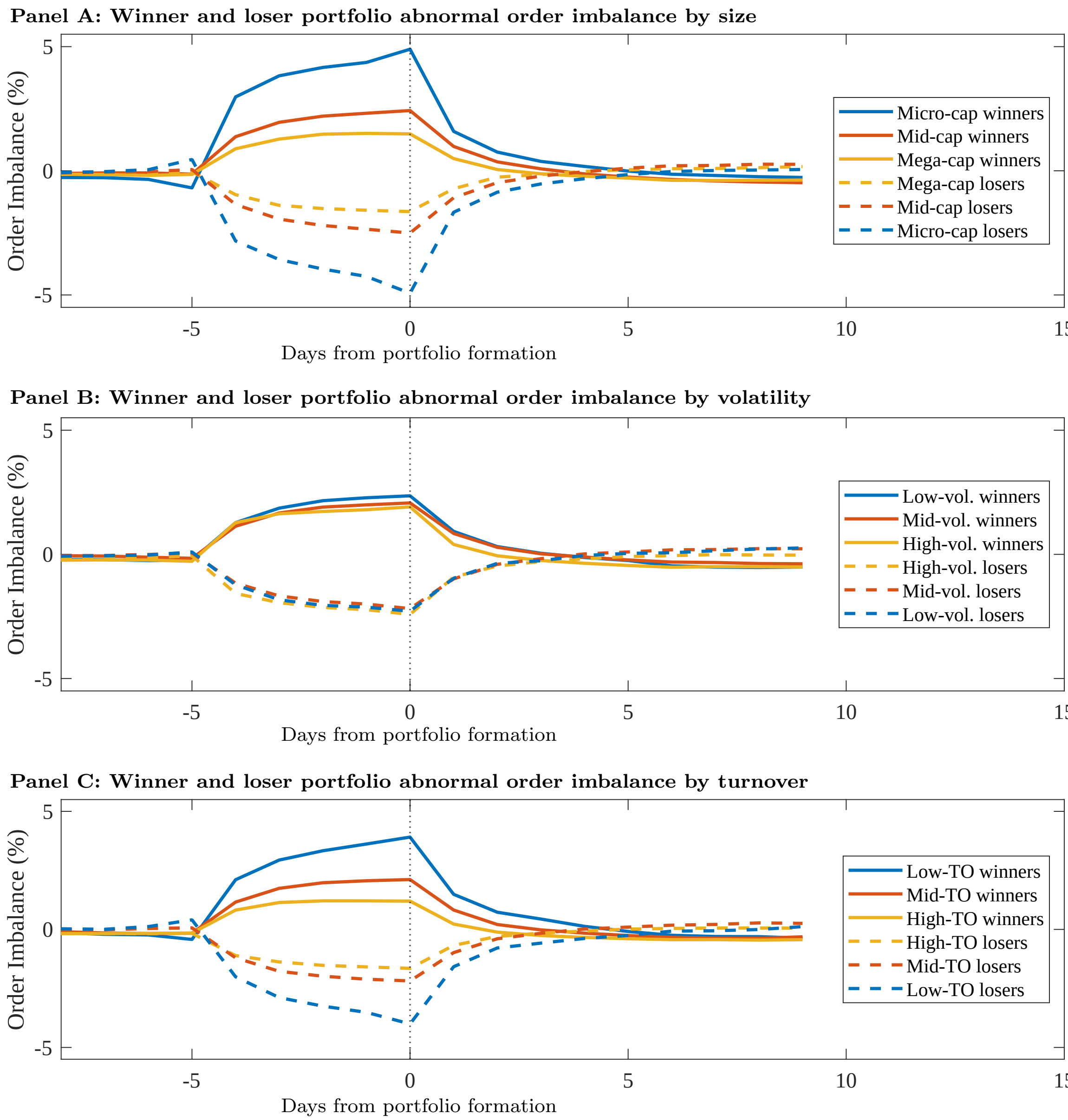


Fig. E1. Order imbalance around reversal-strategy formation by size, volatility, and turnover. This figure shows abnormal order imbalance for winner and loser portfolios around portfolio formation. Portfolios are constructed daily, using independent double quintile sorts, employing NYSE breaks, on five-day announcement-adjusted industry-relative returns (IRRX) and either size, volatility, or turnover (Panels A through C, respectively). Size is market capitalization; volatility is estimated from the standard deviation of daily returns in the 63 days before portfolio formation (minimum of 42 observations); and turnover is the average fraction of shares traded each day in the same 63 day window (minimum of 42 observations). Order imbalance is defined as OI = (BuyVolume − SellVolume)/(BuyVolume + SellVolume), and abnormal order imbalance is OI minus its trailing average over the 63 days that end with the day before IRRX signal is measured (i.e., days 68-6 relative to portfolio formation, with a mininum of 42 observations). The figure plots time-series means of daily value-weighted average abnormal order imbalance for the IRRX winners and losers in the low, middle, high quintile portfolios of the conditioning variable. Buy- and sell-volume is from the NYSE Daily Trade and Quote (TAQ) database and based on the Lee and Ready (1991) algorithm. The sample covers October 2003 through December 2021, with the start date determined by the availability of the TAQ data used for buy- and sell-volume.

Appendix Figure E2 provides further evidence linking reversals to liquidity. It reproduces Figure 1 from Nagel (2012), which shows that the profitability of reversal strategies closely tracks the level of market volatility, which is strongly associated with the cost of trading. Following Nagel (2012), the figure shows strategies constructed as the average of five underlying reversal strategies, each based on a single day of past performance measured on one of the five days preceding portfolio construction. We consider a straight reversal strategy (REV) and an announcement-adjusted industry-relative reversal strategy (IRRX). Portfolio weights for these strategies are, as in Lehmann (1990), given by

$$w_{i,t}^{j} \quad = \quad -\frac{r_{i,t-j} - r_{m,t-j}^{\mathrm{EW}}}{\frac{1}{2}\sum_{i=1}^{N}\left|r_{i,t-j} - r_{m,t-j}^{\mathrm{EW}}\right|}, \tag{E3}$$

where $r_{i,t-j}$ is either the return to stock i (REV) or the stock's announcement-adjusted industry-relative return (IRRX) j days prior to formation for $j \in \{1, 2, ..., 5\}$, and $r_{m,t-j}^{\mathrm{EW}}$ is the equal-weighted market return on the same day. The resulting strategies are hedged of their conditional market exposure. Reversal strategies have time-varying conditional market loadings because winner portfolios tend to over-weight high-beta stocks when formed following market up-days, but under-weight these stocks following down days, while loser portfolios do the opposite. Reversal strategies consequently tend to have negative conditional market betas when formed following market up-days, but positive conditional market betas following down days. For each of the five underlying strategies we consequently subtract off the market's value-weighted excess return, MKT_t, times the strategy's conditional market loading, $\beta_1^j + \beta_2^j \,\mathrm{sgn}(\mathrm{MKT}_{t-j})$, where the β_1^j and β_2^j are estimated from the regression

$$R_t^j \quad = \quad \beta_0^j + \beta_1^j \,\mathrm{MKT}_t + \beta_2^j \,\mathrm{sgn}\left(\mathrm{MKT}_{t-j}\right) \mathrm{MKT}_t + \epsilon_t^j, \tag{E4}$$

where R_t is the excess return to the unhedged strategy based on performance realized j days prior to formation (either REV or IRRX). The final reversal strategies are equal-weighted averages of the five underlying, hedged, return-weighted sub-strategies. The figure shows that the correlation between reversal strategy profitability and market volatility documented by Nagel has persisted, and also holds for our announcement-adjusted industry-relative reversal strategies.

Figure E3 shows similar results for simpler reversal strategies. To a first-order approximation, the portfolio returns of the strategies considered by Nagel are weighted by the sum of stocks' returns over the previous five days, which is roughly their five-day cumulative return. Novy-Marx and Velikov (2022) show that rank-weighted strategies are nearly indistinguishable from equal-weighted strategies, and similar to signal-weighted strategies, because these weighting schemes ignore capitalization. We should consequently expect the strategies considered by Nagel to be quite similar to equal-weighted strategies sorted on the basis of five-day past performance. Figure E3 shows three-month moving averages of VIX and three-month moving averages of daily returns to equal-weighted REV and IRRX strategies based on the extreme NYSE quintiles from sorts on five-day past performance. The figure shows an even tighter relation between strategy performance and VIX than that in Figure E2.

The captions of Figures E2 and E3 also report results from predictive regressions that forecast a strategy's daily excess return using the level of VIX observed the preceding day. Lagged VIX has more power explaining the return variation of the equal-weighted strategies than the return variation of the return-weighted strategies. The R^2 from the regressions for the equal-weighted strategies, 13.3 and 14.1%, are nearly twice as high as the 8.0 and 6.8% from the regressions for the return-weighted strategies favored by Nagel. Given that VIX averages 20.4% over the sample, the regressions suggest that providing liquidity is profitable on average provided market volatility exceeds 7-8%.

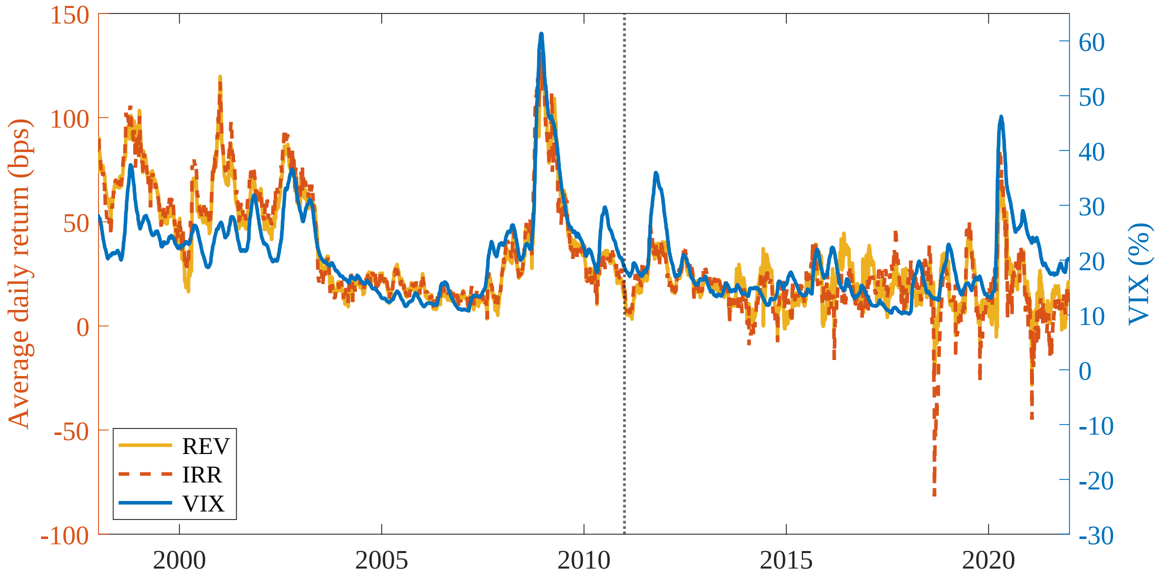


Fig. E2. Moving averages of VIX and return-weighted REV and IRRX. This figure replicates and extends Figure 1 of Nagel (2012). It shows three-month moving averages of the daily returns to a reversal strategy (REV); the daily returns to an announcement-adjusted industry-relative reversal strategy (IRRX); and the daily CBOE volatility index (VIX). The strong association between market volatility and reversal strategy profitability is evident in the Nagel sample, January 1998 through December 2010, and persists through the end of our sample, December 2021.

Strategy construction follows Nagel (2012). REV and IRRX are both constructed as the average of five reversal strategies each based on a single day of past performance, measured on each of the five days preceding portfolio construction. The underlying portfolios are return-weighted by the past performance measure used for strategy construction in excess of the equal-weighted market return (see equation (E3)). REV is based on simple daily stock returns, and IRRX is based on industry-relative stock returns ignoring any returns in the three day window around any earnings announcement. Both strategies are hedged against conditional market-factor exposure (see equation (E4))

Time-series regressions of the daily returns to the two reversal strategies' onto the level of VIX the previous day yield the following results:

$$100 \times \text{REV}_t = \underset{[20.2]}{32.6} + \underset{[14.2]}{2.35} \left(\text{VIX}_{t-1} - \overline{\text{VIX}}\right) + \epsilon_t$$

$$100 \times \text{IRRX}_t = \underset{[18.6]}{32.8} + \underset{[13.9]}{2.48} \left(\text{VIX}_{t-1} - \overline{\text{VIX}}\right) + \epsilon_t.$$

The t-statistics are calculated using Newey and West (1987) standard errors estimated with 63 daily lags. VIX is demeaned ($\overline{\text{VIX}} = 20.4\%$), so the intercepts suggests that on average the strategies earn almost 33 bps per day. The slope coefficients on VIX imply that a one percentage point increase in VIX is associated with a 2.35 bps higher expected daily REV return and a 2.48 bps higher expected daily IRRX return. The regressions' R^2 values are 8.0% and 6.8%, respectively.

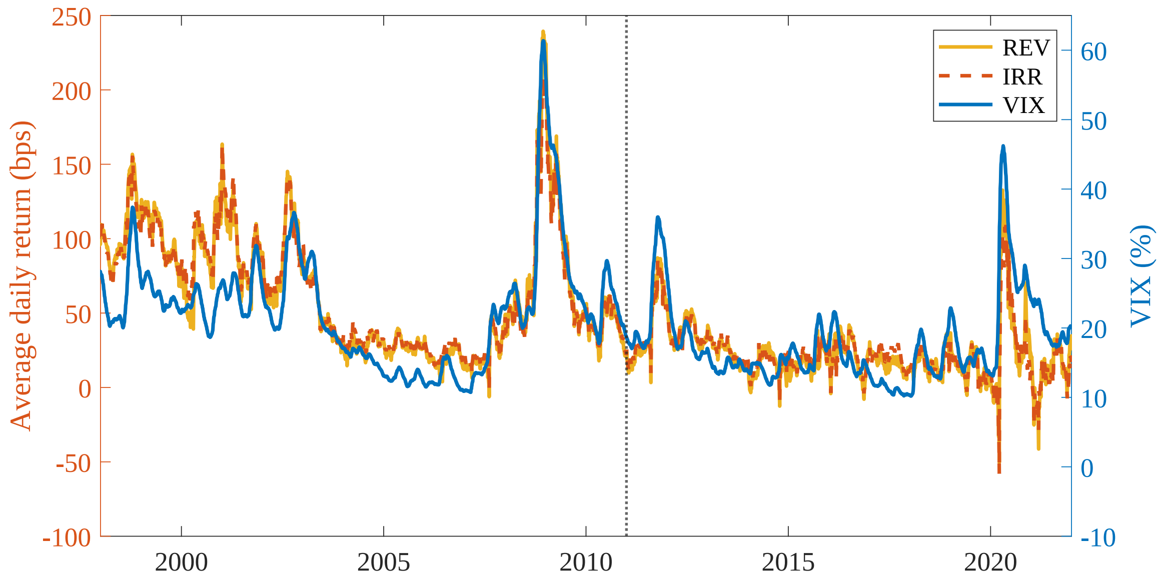


Fig. E3. Moving averages of VIX and equal-weighted REV and IRRX. This figure highlights the close connection between the return-weighted strategies used in Nagel (2012) and simple equal-weighted strategies. It shows three-month moving averages of the daily returns to a reversal strategy (REV); the daily returns to an announcement-adjusted industry-relative reversal strategy (IRRX); and the daily CBOE volatility index (VIX). The strong association between market volatility and reversal strategy profitability is evident in the Nagel sample, January 1998 through December 2010, and persists through the end of our sample, December 2021.

Strategies trade the extreme quintiles of five-day past performance (long losers and short winners), measured as simple five-day stock returns (REV) or as five-day industry-relative stock returns ignoring any returns in the three day window around any earnings announcement (IRRX). This yields strategies similar to those in Nagel (2012), which are formed as equal-weighted average of five return-weighted strategies each based on a single day of past performance measured one to five days prior to formation. To keep these strategies as simple as possible, they are not hedge.

Time-series regressions of the daily returns to the two reversal strategies' onto the level of VIX the previous day yield the following results:

$$100 \times \mathrm{REV}_t = \underset{[20.3]}{46.2} + \underset{[19.6]}{4.38} \left(\mathrm{VIX}_{t-1} - \overline{\mathrm{VIX}}\right) + \epsilon_t$$

$$100 \times \mathrm{IRRX}_t = \underset{[20.1]}{46.4} + \underset{[16.3]}{3.89} \left(\mathrm{VIX}_{t-1} - \overline{\mathrm{VIX}}\right) + \epsilon_t.$$

The t-statistics are calculated using Newey and West (1987) standard errors estimated with 63 daily lags. VIX is demeaned ($\overline{\mathrm{VIX}} = 20.4\%$), so the intercepts suggests that on average the strategies earn more than 46 bps per day. The slope coefficients on VIX imply that a one percentage point increase in VIX is associated with a 4.38 bps higher expected daily REV return and a 3.89 bps higher expected daily IRR return. The R^2 values are 13.3% and 14.1%.

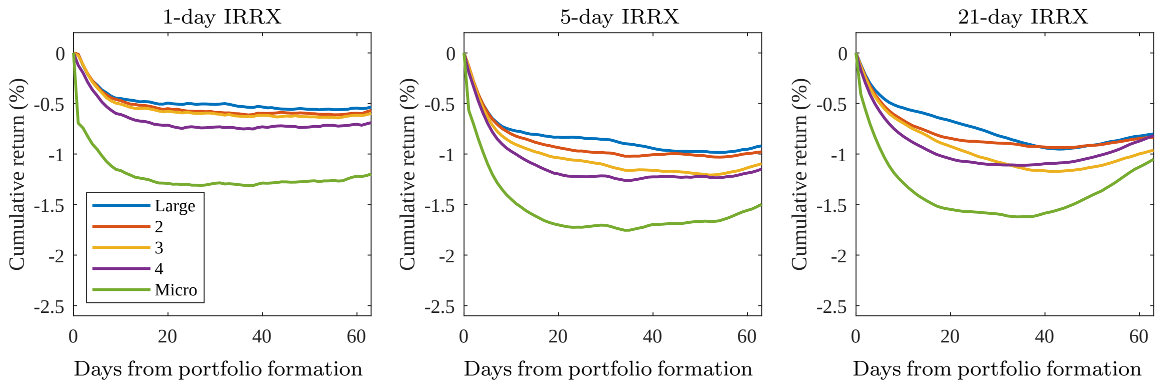
E.2. Gao and Ritter (2010) adjustment to pre-2004 NASDAQ volume

Following Gao and Ritter (2010), and much of the subsequent literature, we adjust NASDAQ trading volume prior to 2004 to account for "institutional features of the way that Nasdaq and NYSE-Amex volume are computed" (p. 51). Specifically, prior to February 1, 2001, we divide NASDAQ volume by 2.0; from February 1, 2001 to December 31, 2001, we divide by 1.8; and from January 1, 2002 to December 31, 2003, we divide by 1.6. No adjustment is made after January 1, 2004.

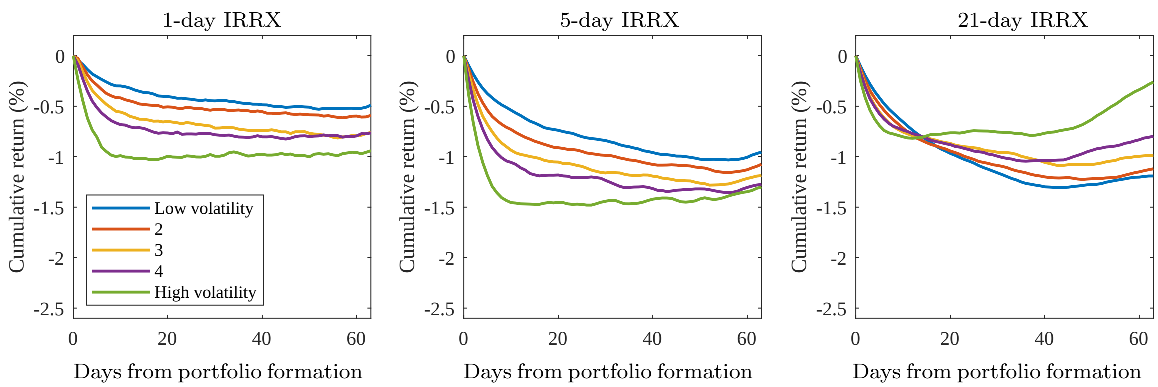
E.3. Reversal returns by size, volatility, and turnover; sequential sorts

Figure 2 shows the performance of announcement-adjusted industry-relative reversals among stocks with similar size, volatility, or turnover. These strategies are constructed using independent sorts on past announcement-adjusted industry-relative stock performance and the conditioning variable (size, volatility, or turnover). The independent sorts have the advantage of yielding more similar average pre-formation past performance across the winner and loser portfolios for different levels of the conditioning variables. They have the disadvantage, however, of occasionally yielding portfolios with relatively few holdings. Table E4 shows results similar to those presented in Figure 2, but for strategies constructed using sequential double sorts. This guarantees a nearly equal number of NYSE stocks in the long and short sides of each reversal strategy, at the cost of exhibiting more variation in pre-formation past performance across winners and losers. That is, the figure shows cumulative average performance from portfolio formation of announcement-adjusted industry-relative reversal strategies (IRRX) within size, volatility, and turnover quintiles (Panels A to C, respectively). The IRRX strategies are constructed using sequential quintile sorts, using NYSE breaks, on the illiquidity variable and then past stock performance, measured over the previous one, five, and 21 days (left to right, respectively). Volatility is estimated using the standard deviation of daily returns

Panel A: Winner-minus-loser spreads by size quintiles



Panel B: Winner-minus-loser spreads by volatility quintiles



Panel C: Winner-minus-loser spreads by turnover quintiles

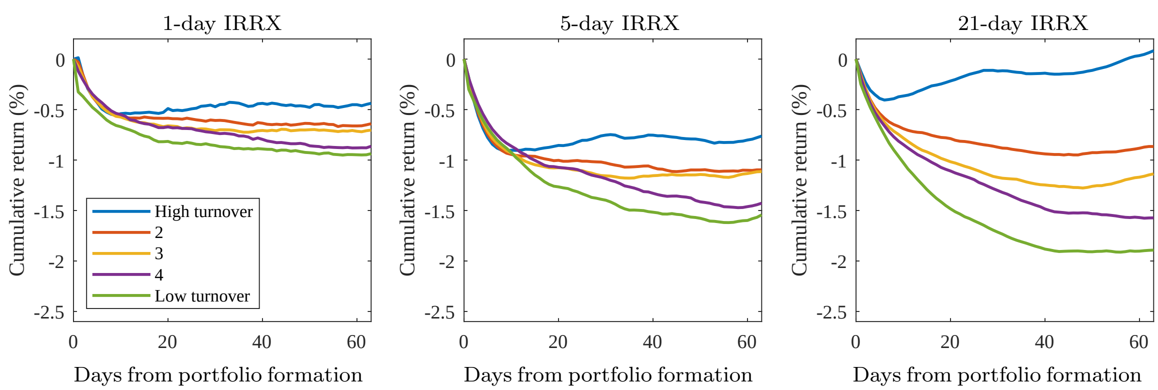


Fig. E4. IRRX performance from formation by size, volatility, and turnover; sequential sorts. The figure shows cumulative average performance from portfolio formation of announcement-adjusted industry-relative reversal strategies (IRRX) within size, volatility, and turnover quintiles constructed using NYSE breaks (Panels A to C, respectively). The IRRX strategies are constructed using sequential quintile sorts, using NYSE breaks, on the illiquidity variable and then past stock performance, measured over the previous one, five, and 21 days (left to right, respectively). The sequential sorts guarantee that roughly the same number of NYSE stocks are in the long and short sides of each reversal strategy. Volatility is estimated using the standard deviation of daily returns over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63 day window, requiring a minimum of 42 daily observations over the estimation window. Portfolio returns are value weighted. The sample covers January 1973 through December 2021.

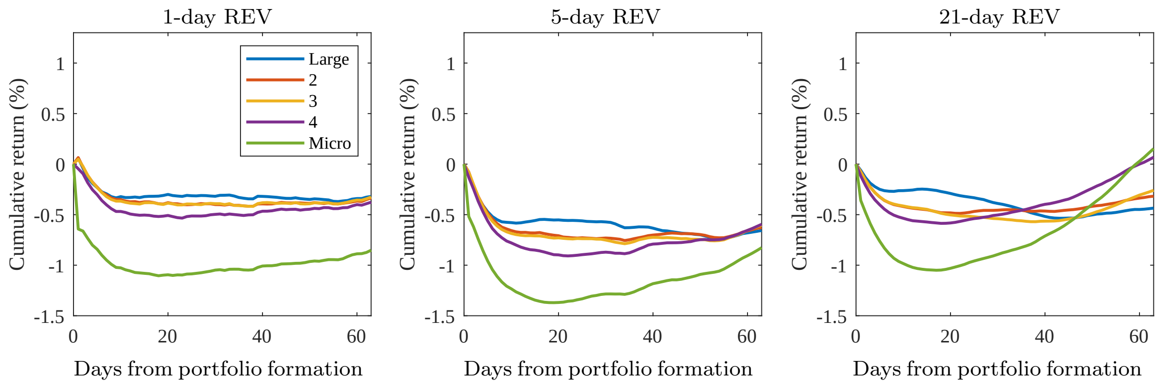
over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63 day window, requiring a minimum of 42 daily observations over the estimation window. Portfolio returns are value weighted. The sample covers January 1973 through December 2021.

The patterns shown in this figure are almost indistinguishable to those seen in Figure 2, which constructed similar strategies using independent double sorts. Panel A shows strong microcap reversals, but little variation in reversal strength across the other size portfolios regardless of the horizon over which past performance is measured. Panel B shows stronger, faster reversals among higher volatility stocks for shorter past-performance windows, but the relatively transient nature of the reversal among high-volatility stocks means that among these stocks the reversal ends quickly for the longer past performance window. Panel C shows little variation in the initial speed of reversals based on relatively short-horizon past performance when constructed using stocks with different levels of turnover, but dramatic differences in reversal persistence. This yields large differences in the eventual magnitude of the reversals, especially for the strategies based on a full month of past performance, where momentum sets in after a matter of days for the high-turnover stocks, but the reversal persist for months for the lowest turnover stocks.

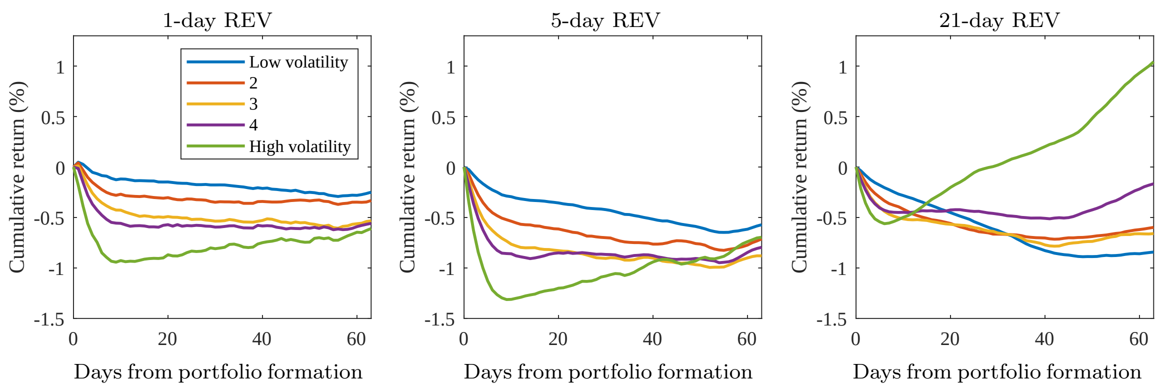
Figure E5 shows qualitatively similar results for the weaker reversals commonly studied in the literature, those based on unadjusted stock returns. These strategies are constructed identically to those shown in Figure E4, but with past performance measured using simple stock returns, not announcement-adjusted industry-relative returns.[14] Here, reversals are weaker because momentum sets in quicker, driven by the long positions in industry momentum and PEAD. This is especially the case for the strategies based on the longer past-performance evaluation periods, over which

[14]Using the sequential sort is necessary here, as industry co-movement present in past stock returns largely removed from announcement-adjusted industry-relative returns, means the independent sorts can yield wildly unbalanced portfolios, which are occasionally even empty.

Panel A: Winner-minus-loser spreads by size quintiles



Panel B: Winner-minus-loser spreads by volatility quintiles



Panel C: Winner-minus-loser spreads by turnover quintiles

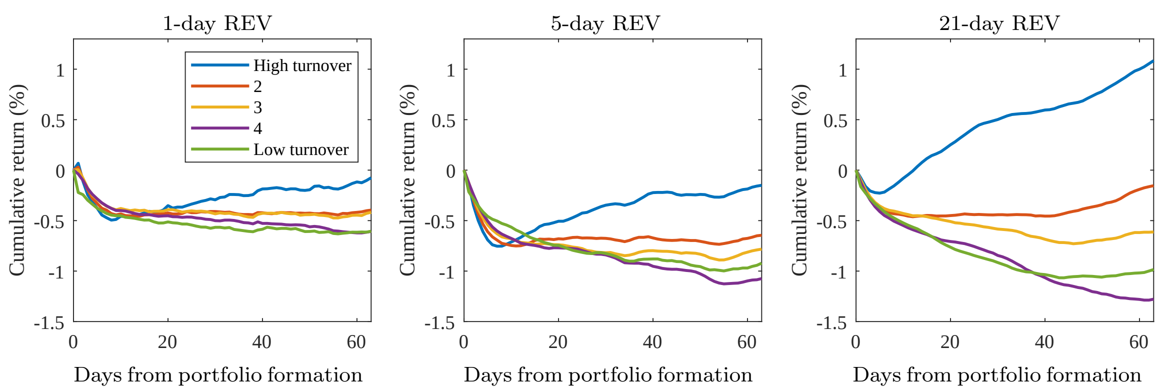


Fig. E5. REV performance from formation by size, volatility, and turnover, sequential sorts. The figure shows cumulative average performance from portfolio formation of straight reversal strategies (REV) within size, volatility, and turnover quintiles constructed using NYSE breaks (Panels A to C, respectively). The REV strategies are constructed using sequential quintile sorts, using NYSE breaks, on the illiquidity variable and then past stock performance, measured over the previous one, five, and 21 days (left to right, respectively). The sequential sorts guarantee that roughly the same number of NYSE stocks are in the long and short sides of each reversal strategy. Volatility is estimated using the standard deviation of daily returns over the preceding 63 days, while turnover is the average percent of shares outstanding traded each day over the same 63 day window, requiring a minimum of 42 daily observations over the estimation window. Portfolio returns are value weighted. The sample covers January 1973 through December 2021.

more firms have announced earnings. Even so, the same basic patterns hold: strong microcap reversals but little variation in performance associated with size across the other four market capitalization quintiles; higher volatility associated with stronger, faster reversals over the first two weeks after portfolio formation; and lower turnover strongly associated with slower, more persistent reversals.

E.4. Characteristics of portfolios sorted on size, volatility, and turnover

Subsection 3.2 investigates the performance of reversal strategies constructed within portfolios sorted on size, volatility, and turnover. Subsection 3.3 notes that, consistent with the liquidity-variable correlations in Table B1, high-volatility portfolios tend to hold stocks that trade more than those held in low-volatility portfolios, and high-turnover portfolios tend to hold more volatile stocks than those held by low-turnover portfolios. High-volatility portfolios also tend to hold smaller stocks, while high-turnover portfolios tend to hold larger stocks.

We can quantify these interactions using the average size, volatility, and turnover ranks for portfolios sorted on the same characteristics. Each day, we parameterize the cross-sectional size, volatility, and turnover ranks across the full market from zero to one. For each portfolio, we calculate the average rank of each characteristic as the time-series mean of the portfolio's average cross-sectional rank. A value below 0.5 indicates that a portfolio tends to hold stocks below the median of the relevant characteristic. Table E1 reports the average size, volatility, and turnover ranks for portfolios from NYSE quintile sorts on these three characteristics, i.e., the portfolios within which we construct the reversal strategies shown in Figures 1 and 2.

The table shows the biases in the portfolio characteristics discussed above. For the low- and high-volatility quintiles, the average volatility ranks are 0.06 and 0.79, reflecting the intended large dispersion in volatility. Their average turnover ranks, however, are 0.38 and 0.59, reflecting a more modest, but still meaningful, unintended

Table E1. Simple portfolio average size, volatility, and turnover ranks.
This table shows the time-series average of the average cross-sectional size, volatility, and turnover ranks for NYSE quintile portfolios sorted directly on the same three characteristics, size (Panel A), volatility (Panel B), and turnover (Panel C). Size is market equity. Volatility and average daily turnover as a fraction of shares outstanding are estimated over the preceding 63 days, where these estimations require a minimum of 42 daily observations. The sample covers January 1973 through December 2021.

Portfolio	Low	2	3	4	High
Panel A: NYSE size quintiles					
Average size rank	0.30	0.68	0.80	0.89	0.97
Average volatility rank	0.64	0.47	0.38	0.31	0.23
Average turnover rank	0.43	0.56	0.60	0.62	0.60
Panel B: NYSE volatility quintiles					
Average size rank	0.76	0.74	0.69	0.61	0.44
Average volatility rank	0.06	0.18	0.32	0.48	0.79
Average turnover rank	0.38	0.46	0.50	0.54	0.59
Panel C: NYSE turnover quintiles					
Average size rank	0.44	0.58	0.63	0.65	0.64
Average volatility rank	0.44	0.42	0.44	0.50	0.65
Average turnover rank	0.17	0.43	0.60	0.75	0.91

dispersion in turnover. Similarly, for the low- and high-turnover quintiles, the average turnover ranks are 0.17 and 0.91, as intended, but the volatility ranks are 0.44 and 0.65, reflecting considerable unintended dispersion in volatility. In both cases, the sorts on volatility and turnover also generate unintended dispersion in size, with the high-volatility and low-turnover portfolios biased toward smaller stocks.

Table E2 reports similar statistics for the propensity-matched portfolios used in Figure 3. Panel A reports the time-series average of the cross-sectional volatility and turnover ranks for the portfolios constructed by sorting on volatility among stocks propensity-matched on turnover in each size universe. Panel B shows the same for the portfolios constructed by sorting on turnover among stocks propensity-matched on volatility. The procedure does a great job of controlling for the matching characteristic while allowing for dispersion in the primary sorting characteristic.

Table E2. Propensity-matched portfolio average volatility and turnover ranks. This table shows the time-series average of the average cross-sectional volatility and turnover ranks (left and right sides, respectively) for portfolios sorted on volatility after propensity matching on turnover (Panel A), and for portfolios sorted on turnover after propensity matching on volatility (Panel B). It shows these ranks for these portfolios constructed in each of the size universes, large (above NYSE median market capitalization), micro (bottom NYSE quintile), and small (the rest). Volatility and average daily turnover as a fraction of shares outstanding are estimated over the preceding 63 days, where these estimations require a minimum of 42 daily observations. The sample covers January 1973 through December 2021.

	Average volatility rank			Average turnover rank		
Portfolio	Low	Mid	High	Low	Mid	High
Panel A: Volatility-sorted portfolios propensity-matched on turnover						
Micro	0.43	0.65	0.83	0.46	0.46	0.46
Small	0.28	0.44	0.62	0.58	0.58	0.58
Large	0.16	0.28	0.43	0.61	0.61	0.61
Panel B: Turnover-sorted portfolios propensity-matched on volatility						
Micro	0.64	0.64	0.64	0.24	0.45	0.68
Small	0.45	0.45	0.45	0.38	0.59	0.77
Large	0.29	0.29	0.29	0.45	0.63	0.76

Panel A shows that there is essentially no variation in turnover across the volatility-sorted portfolios constructed using stocks matched on turnover. There is somewhat lower average turnover across all the microcap portfolios, but within each size universe the volatility-sorted portfolios exhibit almost identical turnover. At the same time, the procedure generates significant dispersion in the volatility of the stocks in the underlying portfolios, though with only three portfolios and the control for turnover there is less variation in volatility across these portfolios than in the simple quintile sort. Panel B shows similar results for portfolios propensity-matched on volatility and sorted on turnover within size universes. It again shows differences in volatility across size universes, with the microcap stocks on average having far higher volatility ranks than large-cap stocks, but essentially no variation in average volatility rank across turnover-sorted portfolios within a given size universe.

Table E3. Short and intermediate horizon momentum by volatility quintiles. This table replicates Table 4 using the conventions of Goyal and Wahal (2015) instead of those of Novy-Marx (2012). It shows average monthly return spread for short- and intermediate-horizon momentum strategies, where these strategies, as in Goyal and Wahal (2015), buy winners and sell losers based on stock performance over the first five months of starting seven months and ending two month prior to portfolio formation ($\text{MOM}_{7,3}$) and stock performance over the first five months of the preceding year ($\text{MOM}_{12,8}$). The first column shows returns for all stocks, where winners and losers are the top and bottom NYSE quintiles of the corresponding past performance measure. The next five columns show performance of the momentum strategies by NYSE volatility quintiles, constructed using independent sorts on volatility and past performance. The last column shows the average difference between the momentum strategies' performances in the top and bottom volatility quintiles. Volatility is estimated using the standard deviation of daily returns over the preceding 63 trading days, and requires a minimum of 42 observations. Portfolio returns are value weighted, and portfolios are rebalanced at the end of each calendar month. The sample covers January 1973 through December 2021.

		NYSE volatility quintile					
	All	Low	2	3	4	High	H−L
$\text{MOM}_{12,8}$	0.79	0.42	0.74	0.75	0.88	0.92	0.50
	[4.26]	[2.44]	[3.95]	[3.89]	[3.76]	[4.48]	[2.16]
$\text{MOM}_{7,3}$	0.31	0.04	-0.23	0.38	0.56	1.07	1.03
	[1.53]	[0.17]	[-1.02]	[1.90]	[2.43]	[4.66]	[3.62]
Diff.	0.48	0.38	0.97	0.37	0.32	-0.15	-0.53
	[2.04]	[1.31]	[3.50]	[1.51]	[1.18]	[-0.60]	[-1.56]

E.5. Robustness tests for short- vs. intermediate-horizon momentum

Goyal and Wahal (2015) claim the disparity in the strength of short- and intermediate-horizon momentum documented by Novy-Marx (2012) "appears to be driven largely by a carryover of short-term reversals from month -2" (p. 1237). They consequently suggest an alternative construction of the strategies. While Novy-Marx (2012) uses stock performance over the first five months of the preceding half year ($r_{6,2}$) and over the first half of the preceding year ($r_{12,7}$), Goyal and Wahal (2015) use performance over the five months starting seven months and ending two months prior to formation ($r_{7,3}$) and over the first five months of the preceding year ($r_{12,8}$).

Table E3 replicates Table 4 using these alternative definitions. The table shows results that are similar to, though slightly weaker than, those presented in Table 4.

The difference in the unconditional performance of short- and intermediate horizon momentum is still significant. Short-horizon momentum is completely absent for lower-volatility stocks, where momentum is slow to set in, but strong even at short horizons for the highest-volatility stocks, where it sets in quickly. As a result, the disparity in the difference between the performance of short- and intermediate-horizon momentum is concentrated among lower volatility stocks. Overall, it does not appear that the "carryover of short-term reversals from month -2" fully explain the disparity in the strength of the short- and intermediate-horizon momentum strategies.

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Robert Novy-Marx provides consulting services to Dimensional Fund Advisors LP.

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