Short-Term Reversals and Trading Activity[☆]

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Abstract

We document a pronounced negative interaction between short-term return reversals and prior trading activity for both small-cap and large-cap stocks. Stocks with low prior turnover display a strong monthly reversal effect. In contrast, those with high prior turnover display a monthly continuation effect (short-term momentum). Motivated by existing models of the trading process, we posit that the observed interaction stems from the relation between turnover and news that spurs speculative trading. We investigate this proposition empirically using a simple proxy for the fraction of turnover that is driven by news. The results are consistent with the predictions of our hypothesis.

Keywords: turnover, trading volume, information flow, liquidity, return continuations, momentum, cross-section of expected returns

Declarations of interest: none

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Abstract

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1. Introduction

The short-term reversal effect uncovered by Jegadeesh (1990) and Lehmann (1990) has remained an intriguing puzzle for well over two decades. We show that the likelihood of short-term reversals in monthly stock returns is strongly influenced by prior levels of monthly trading activity. Specifically, the cross-sectional relation between monthly returns and the first lag of monthly returns is highly dependent on prior monthly turnover. Although stocks that have low prior turnover display a pronounced reversal effect, those that have high prior turnover display a continuation effect. In other words, high prior turnover is associated with short-term momentum rather than short-term reversals in monthly stock returns.

What explains these findings? We hypothesize that turnover acts as a proxy for the flow of news that drives trading, and that the negative interaction between monthly return reversals and prior turnover arises from the interplay between short-term price pressure generated by uninformed traders and short-term continuations generated by the actions of speculative traders. To see the intuition, consider a stock that has experienced a low flow of news for a given month. This implies that its return is largely due to short-term price pressure generated by uninformed trading. Hence, there is likely to be a reversal in the following month because expectations of future payoffs remain largely unaffected. Now change the scenario to one in which the flow of news has been relatively high. This implies that the return is largely due to speculative trading. Hence, there is likely to be continuation in the following month provided that the new information has not been fully incorporated into the stock price.

Evidence that stock returns are related to prior trading activity is not new. However, previous studies do not necessarily agree on the direction of the effect. Consider, for example, Cooper (1999) and Avramov et al. (2006). The former, which investigates the profitability of simple filter rules for the top 300 NYSE and AMEX firms by market capitalization, reports that large-cap stocks which have experienced high turnover growth display either weak reversals or continuations in weekly returns. The latter, which studies a much broader sample of NYSE and AMEX firms, reports that stocks which have high prior turnover display stronger reversals in weekly returns than those which have low prior turnover.[1] The conflicting nature of these findings suggests that market capitalization may be an important confounding factor in research on short-term reversals. We employ a broader and longer sample than either Cooper (1999) or Avramov et al. (2006), but pay close attention to the role of market capitalization effects.

Our findings are in line with those of Cooper (1999) in the sense that high turnover predicts continuations in subsequent returns for both small-cap and large-cap stocks. Unlike Cooper (1999), however, we directly address the role of liquidity in determining the short-term autocorelations of returns.[2] We find that the impact of conditioning on prior turnover *increases* with liquidity. Thus high prior turnover predicts stronger short-term momentum for high-liquidity stocks than for low-liquidity stocks. This is broadly consistent with Cooper (1999) because his sample consists of high-liquidity stocks. In contrast, Avramov et al. (2006) report that contrarian trading strategies generate the highest hypothetical profits for high-turnover, low-liquidity stocks. They find, therefore, that such strategies are unlikely to be profitable after accounting for trading costs. Our results give rise to a less pessimistic view concerning the potential profitability of trading on short-term reversals and/or short-term momentum.

To help motivate our information flow hypothesis, we turn to the model of Wang (1994), which assumes that trading occurs for both informational (speculative) and non-informational (hedging) reasons. Under the model, the nature of the relation between returns and prior trading activity is largely determined by the degree of information asymmetry. If information asymmetry is low, then the reversal effect strengthens as trading volume increases. This corresponds to a scenario in which the short-term price pressure mechanism that underpins the Campbell et al. (1993) model is the dominant factor in determining the serial correlation properties of returns. If information asymmetry is high, on the other hand, then the reversal

[1] Interestingly, Avramov et al. (2006) also investigate reversals in monthly returns and find that high-turnover stocks display a weaker reversal effect than low-turnover stocks, which runs counter to their findings using weekly returns. This underscores the extent to which previous findings sometimes disagree.

[2] Cooper (1999) confines his analysis to the top 300 NYSE and AMEX firms by market capitalization to ensure that there is minimal variation in liquidity across stocks.

effect weakens as trading volume increases under suitable parameterizations of the model. This corresponds to a scenario in which the speculative trading activity of privately-informed investors is the dominant factor in determining the serial correlation properties of returns.

We argue that empirical evidence favors the latter scenario. For example, we form a set of 25 value-weighted portfolios by sorting stocks into quintiles using turnover and then sorting the stocks in each turnover quintile into return quintiles. We then construct long-short portfolios using the high- and low-prior-return quintiles. To reduce the influence of firms whose economic importance is debatable, the sample used to construct the portfolios, which extends from July 1963 to December 2018, excludes stocks whose market equity is below the 20th percentile of the NYSE market equity distribution on a month-by-month basis (the "all-but-micro-cap" sample). For stocks in the bottom quintile of prior turnover, the winners-minus-losers (WML) portfolio has an average return of -0.83% per month, which has a t-statistic of -4.87. In contrast, the WML portfolio for stocks in the top quintile of prior turnover has an average return of 0.58% per month, which has a t-statistic of 2.35. Thus the reversal effect, which is quite strong for low-turnover stocks, is nonexistent for high-turnover stocks.

Our empirical investigation of the information flow hypothesis builds on these results. We start from the basic premise that a considerable fraction of monthly trading activity is motivated by either public or private news that changes expectations of future payoffs. This should not be a controversial proposition in view of existing models of speculative trading and the price-discovery process. Under the well-known Tauchen and Pitts (1983) model, for example, squared daily stock returns and daily trading volume share a common factor: the rate at which information that alters stock valuations arrives to market. Thus a key prediction of the model is that the flow of news drives both volume and volatility.

We therefore conduct a simple test to see whether the role of news in generating turnover might explain our findings. If the interaction between return reversals and prior turnover is linked to the flow of unobserved news, then the Tauchen and Pitts (1983) model predicts that there should be a similar interaction between return reversals and prior volatility. We find that this is indeed the case. The interaction between return reversals and prior volatility is both negative and highly statistically significant. This finding lends indirect support to the hypothesis that turnover acts as proxy for the flow of news that drives speculative trading.

Under this hypothesis, the interaction between short-term reversals and prior turnover has a straightforward interpretation. Consider a stock that falls in the lower tail of the cross-sectional distribution of returns for the month. If the turnover for the stock is low, then it has experienced a below-average return over a period in which the flow of news has been relatively low. The data indicate that this below-average return is likely to be followed by an above-average return over the next month (a short-term reversal effect). Conversely, if the turnover for the stock is high, then it has experienced a below-average return over a period in which the flow of news has been relatively high. The data indicate that this below-average return is likely to be followed by a below-average return over the next month (a short-term momentum effect).

Linking short-term return reversals to prices changes that occur in the absence of much news captures the basic spirit of Campbell et al. (1993) model. More broadly, it is consistent with the implications of the Llorente et al. (2002) model, which is closely related to that of Wang (1994). The Llorente et al. (2002) model assumes that there are two basic types of trades: hedging and speculative. Hedging trades convey no signal about future payoffs, so the returns generated by these trades display reversals. Speculative trades, on the other hand, are driven by new information that is only partially incorporated into the stock price in a given trading session. Thus the returns generated by speculative trades display continuations. Because the model implies that the impact of speculative trades is fundamentally different than that of hedging trades, it predicts that cross-sectional differences in the relative importance of speculative trading should help to explain differences in the strength of the reversal effect across firms.

To test this prediction, we need a measure that captures the relative contribution of speculative trading to overall trading activity. Our proxy for the fraction of turnover that is driven by speculative trading is motivated by the extensions of the Tauchen and Pitts (1983) model developed by Andersen (1996) and Li and Wu (2006). Both extensions introduce liquidity traders within the general Tauchen and Pitts (1983) framework. Andersen (1996) assumes at the outset that there is no covariance between squared daily returns and the component of daily trading volume that is generated by liquidity trades. Li and Wu (2006) relax this assumption and show that the estimated covariance is *negative* for a range of individual stocks. Both models therefore imply that the monthly estimated correlation between the squared demeaned daily returns and daily turnover should be a useful proxy for the relative contribution of news-driven trades to monthly turnover figures for individual stocks. In addition, Wang (1994) shows that the correlation between volume and absolute returns increases with information asymmetry. Thus a weakening of the reversal effect as prior turnover increases is more likely to be associated with a high correlation than a low correlation under his model.

Conditioning on the estimated correlations lends further credence to the information-flow hypothesis. For instance, we replicate the portfolio sorts after partitioning the stocks in the all-but-micro-cap sample into two categories on a month-by-month basis: those which have a low fraction of news-driven turnover (estimated correlations below the median value) and those that have a high fraction of news-driven turnover (estimated correlations above the median value). For stocks in the bottom quintile of prior turnover, the WML portfolio has an average return of -1.03% per month for the former category (t-statistic of -6.25) and -0.75% per month for the latter category (t-statistic of -3.84). For stocks in the top quintile of prior turnover, however, the WML portfolio has an average return of -0.35% per month for the former category (t-statistic of -1.32) and 1.06% per month for the latter category (t-statistic of 3.69). Thus the reversal effect is much stronger for stocks with a low fraction of news-driven turnover, which is consistent with the predictions of the Llorente et al. (2002) model. Again, the results are similar for WML portfolios formed from large-cap stocks.

To supplement the evidence produced by the portfolio sorts, we fit a series of cross-sectional regressions that control for other price-related anomalies. In particular, we sort stocks into deciles using monthly turnover, and then regress the returns for the stocks in selected deciles on lagged monthly values of returns, log turnover, log realized volatility, log market equity, and a standard measure of price momentum. For stocks in the bottom decile of prior turnover, the average estimated slope on prior returns is -0.70 with a t-statistic of -10.14. For stocks in the top decile of prior turnover, the average estimated slope on prior returns is 0.13 with a t-statistic of 2.75. Hence, we again find that high prior turnover is associated with short-term momentum rather than short-term reversals in monthly stock returns.

We perform several other tests to assess the robustness of our results. One potential concern with respect to the regression evidence is that our specifications employ a fairly small set of controls. We address this concern by expanding the set of controls to include the book-to-market ratio along with a host of anomaly variables that have been used as mispricing indicators in the recent empirical literature (Stambaugh et al., 2015; Stambaugh and Yuan, 2017). Specifically, we employ variables that capture financial distress, share growth, total accruals, net operating assets, gross profitability, asset growth, return on assets, and investment to assets. Including all of these variables as additional controls in the regressions has only a minor impact on the average estimated slopes on prior monthly stock returns. There are still marked differences in the average estimated slopes across turnover deciles.

The role of microstructure effects in generating short-term reversals is another potential robustness issue. For instance, Ball et al. (1995) and Conrad et al. (1997) report that bid-ask bounce makes a significant spurious contribution to the measured profitability of short-term contrarian strategies using samples that overlap with the early part of our sample period. To assess whether this is a concern in our setting, we replicate our portfolio sorts using the most recent 20 years of data in our sample (January 1999 to December 2018). The average returns for the WML portfolios generally have smaller absolute t-statistics in this case, but this is primarily due to the increase in standard errors associated with the large reduction in the number of monthly return observations. Using the subset of all-but-micro-cap stocks that have a high fraction of news-driven turnover, for example, the WML portfolio for stocks in the top quintile of prior turnover has an average return of 1.28% per month with a t-statistic of 2.00. Given that this is larger than the value of 1.06% per month obtained using data for the whole sample period, it seems unlikely that accounting for bid-ask bounce would undermine our key conclusions.

To gain additional insights, we use the spread-based measure of liquidity proposed by Chung and Zhang (2014) to assess robustness to liquidity effects. We find that linear regressions produce only weak evidence of a relation between liquidity and return reversals. But the portfolio sorts reveal the presence of a marked three-way interaction between liquidity, turnover, and reversals. First, we find that the negative interaction between prior turnover and return reversals is stronger for more liquid stocks. Second, we find that conditioning on the fraction of news driven turnover generates more pronounced changes in the relation between prior turnover and return reversals for more liquid stocks. Third, we find that stocks with high liquidity, high turnover, and a high fraction of news driven turnover display the strongest short-term momentum effect. We conclude, therefore, that our results are not driven by the influence of illiquid stocks.

It is notable that increases in liquidity appear to amplify the impact of conditioning on turnover. The evidence of both short-term reversal and short-term momentum effects for large-cap stocks that have low bid-ask spreads suggests that short-term autocorrelation properties of monthly returns hold substantial economic interest for investors. Furthermore, the strong interaction between the magnitude of reversal effect and the correlation between squared daily returns and daily turnover represents an important new piece of the larger puzzle. Because the nature of the evidence makes it difficult to envision a plausible explanation for this interaction that does not involve some type of information-based story, our findings clearly raise the bar for research that seeks to explain the short-term reversal anomaly.

2. Data Sources, Sample Selection, and Variable Descriptions

We obtain daily and monthly stock returns along with a number of related items, such as stock prices, trading volume, shares outstanding, exchange codes, and share codes, from the Center for Research in Security Prices (CRSP). The sample begins in July 1963, ends in December 2018, and is restricted to ordinary common equity (share code 10 or 11) for NYSE, AMEX, and NASDAQ firms. We also use monthly returns for the four Carhart (1997) factors and the monthly risk-free rate, which are from the Ken French data library, along with annual values of various items from the Compustat annual industrial file. These items are used to construct the book-to-market ratio and a range of anomaly variables.

2.1. Variable descriptions and notation

Let $R_{i,t}$ and $TURN_{i,t}$ denote the return and turnover of stock i for month t. We use portfolio sorts and cross-sectional regressions to assess whether conditioning on $TURN_{i,t-1}$ conveys useful information about the relation between $R_{i,t-1}$ and $R_{i,t}$. To account for the patterns in average returns associated with other price-based anomalies, we employ the market value of equity, monthly realized volatility, and a standard measure of price momentum as controls. These variables are denoted by $ME_{i,t}$, $VOL_{i,t}$, and $MOM_{i,t}$ for stock i in month t. A couple of other variables also feature prominently in our tests: the estimated monthly correlation of daily turnover with daily squared returns and the average monthly value of the daily percentage bid-ask spread. We use $CORR_{i,t}$ and $SPREAD_{i,t}$ to denote these variables for stock i in month t. Finally, we employ a range of standard anomaly variables as part of our robustness checks. The definitions of these variables follow Stambaugh et al. (2015) with minor exceptions. All of the variables are described in more detail in the appendix.

For tests that involve portfolio sorts, we use both average returns and estimates of risk-adjusted expected returns (alphas) to assess portfolio performance. The risk-adjusted expected returns are estimated using the four-factor model of Carhart (1997). Specifically, we use ordinary least squares (OLS) to fit time-series regressions of the form

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p,1}(MKT_t - R_{f,t}) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}UMD_t + \epsilon_{p,t}, \qquad (1)$$

where $R_{p,t}$ denotes the return on portfolio p for month t, $R_{f,t}$ denotes the return on the risk-free asset for month t, and MKT_t, SMB_t, HML_t, and UMD_t denote the returns generated by the market, size, value, and momentum factors for month t.

2.2. Sample selection

Previous research suggests that market capitalization is cross-sectionally correlated with a number of firm characteristics that might play a part in determining the short-term autocorrelations of individual stock returns. To forestall any concerns that our findings are driven by firms whose economic importance is debatable, we exclude stocks whose market capitalization falls below the 20th percentile of the NYSE market equity distribution from the sample used to develop our baseline results. Following Fama and French (2008), we call this the all-but-micro-cap sample. We also report results using large-cap stocks, which are defined as having a market capitalization at or above the 50th percentile of the NYSE market equity distribution. Our discussion of the short-term autocorrelation properties of micro-cap stocks is confined to a section that deals with robustness issues.

3. Portfolio Sorts and Cross-Sectional Regressions

We begin our investigation of the relation between monthly return reversals and trading activity using univariate portfolio sorts. Specifically, we form two sets of quintile portfolios by sorting stocks on prior monthly returns and prior monthly turnover. All of the portfolios are rebalanced monthly and each stock is weighted in proportion to its market equity at the time the portfolio is formed. Table 1 presents a range of descriptive statistics for the portfolios. The statistics in panel A are for the full sample of available NYSE, AMEX, and NASDAQ stocks. Those in panels B and C are for the all-but-micro-cap and large-cap samples that will be used for most of the subsequent analysis.

(Table 1 about here)

The results are similar for all three samples. First, the portfolios formed on prior returns show evidence of the monthly reversal anomaly first documented by Jegadeesh (1990). That is, low-prior-return portfolios outperform high-prior-return portfolios. But the differences in average returns between the high and low quintiles are fairly small. Using the sample that includes all stocks, for example, the WML portfolio has an average return of -0.25% per month and an estimated four-factor alpha of -0.32% per month, which is statistically significant at the 10% level (a t-statistic of -1.72).

Second, the portfolios formed on prior turnover show no reliable evidence of differences in performance. The average returns of the high-prior-turnover portfolios exceed those of the low-prior-turnover portfolios by a small margin. However, the estimated alphas of WML portfolios are slightly negative, and all of them are statistically insignificant at the 10% level. As might be anticipated, however, the results indicate that the volatility of the portfolio returns is an increasing function of prior turnover. The volatilities for the high turnover portfolios are almost twice as large as those for the low turnover portfolios for the both the all-but-micro-cap and large-cap samples.

Although we find only weak evidence of monthly return reversals in Table 1, this is because the univariate portfolio sorts fail to capture the strong interaction between prior returns and prior turnover. To illustrate this point, we use the all-but-micro-cap sample to form a set of 25 portfolios that reveal how the monthly reversal effect varies across turnover quintiles. As noted earlier, we exclude micro-cap stocks from the baseline analysis because their economic importance is debatable. These stocks also tend to display a variety of characteristics, such as low prices, low liquidity, and high trading costs, that lead to robustness concerns. By focusing on small- and large-cap stocks at the outset, we minimize any such concerns.

The portfolios are constructed by first sorting stocks into turnover quintiles and then sorting the stocks in each turnover quintile into return quintiles. All of the portfolios are rebalanced monthly, and each stock is weighted in proportion to its market equity at the time the portfolio is formed. Table 2 presents the results. Panel A reports the average monthly excess return and estimated four-factor alpha for each portfolio, with heteroskedasticity-robust t-statistics in parentheses. Panel B reports the average monthly turnover and average monthly realized volatility of the constituent stocks across all stock-month observations. (Table 2 about here)

Table 2 paints a very different picture than Table 1. Stocks contained in the bottom quintile of prior turnover display a strong reversal effect. The average return on the WML portfolio is -0.83% per month with a t-statistic of -4.87, and the estimated four-factor alpha of the portfolio is almost identical: -0.82% per month with a t-statistic of -4.72. Thus the four-factor model explains little, if any, of the monthly reversal effect for low-turnover stocks. The reversal effect diminishes as prior turnover increases. Nonetheless, it remains statistically significant at the 10% level for stocks in the bottom four turnover quintiles. For stocks in the top turnover quintile, however, the average return on the WML portfolio is both *positive* and statistically significant at the 5% level: 0.58% per month with a t-statistic of 2.35. The estimated four-factor alpha of the portfolio is somewhat smaller, but it is still statistically significant at the 10% level.

(Table 3 about here)

Table 3 shows that we obtain similar results if we restrict the analysis to large-cap stocks. We again find that the stocks contained in the bottom quintile of prior turnover display a strong reversal effect. The WML portfolio has an average return of −0.90% per month with a t-statistic of −5.82 and an estimated four-factor alpha of −0.90% per month with a t-statistic of −5.66. For stocks in the top quintile of prior turnover, however, the WML portfolio has an average return of 0.56% per month with a t-statistic of 2.24, and an estimated four-factor alpha of 0.42% per month with a t-statistic of 1.71. Thus the results of the portfolio sorts are insensitive to the presence of small-cap stocks in the sample.

(Figure 1 about here)

Overall the evidence is indicative of a pronounced negative interaction between prior turnover and the likelihood of monthly return reversals. But the results in Tables 2 and 3 do not address the question of whether the nature of the interaction effect has evolved over time. To provide insights in this regard, Figure 1 plots the average returns of the WML portfolios for the bottom and top quintiles of prior turnover using a rolling 10-year window of monthly observations.[3] The top panel is for the WML portfolios formed from all-but-micro-cap stocks and the bottom panel is for those formed from large-cap stocks.

The plots in Figure 1 have several interesting features. First, they highlight the extent to

[3]We compute the rolling average returns for month t by averaging the returns for months $t-59$ to $t+60$. The length of the window is reduced as necessary to account for the lack of observations near the beginning and end of the sample (i.e., for months 1 to 59 and 607 to 666). For example, the average returns for July 1963 are computed using a forward-looking window of 61 observations and those for December 2018 are computed using a backward-looking window of 60 observations. This approach is equivalent to using kernel regression with a uniform kernel to estimate the conditional expected portfolio returns at each point in time. To see why, consider the case in which we specify a fractional time index of the form t/T as the regressor. With a uniform kernel and bandwidth h, the kernel estimator at the point $t = s$ is an equally-weighted average of the returns in the window $s - Th$ to $s + Th$. Because the variance of the regressor converges to 1/12 as T gets large, the Silverman (1986) rule-of-thumb approach for choosing the optimal bandwidth implies that $h = (1.48/\sqrt{12})T^{-1/5}$. This choice of bandwidth for $T = 666$ corresponds to rolling estimation using 13 years of data. Using this bandwidth yields slightly smoother plots than those in Figure 1.

which prior turnover conveys information about the short-term autocorrelations of monthly stock returns. Consider the evidence for WML portfolios formed from all-but-micro-cap stocks. The rolling average return for the high-turnover portfolio exceeds that for the low-turnover portfolio for the entire sample period. The gap between the average returns ranges from a low of 0.30% per month to a high of 3.3% per month. The WML portfolios formed from large-cap stocks also display this property. The gap between the rolling average returns of the WML portfolios ranges from a low of 0.13% per month to a high of 3.3% per month.

Second, the plots do not display any clear time trends. The gap between the average returns for the low- and high-turnover portfolios fluctuates, but not in a systematic way. It narrows in the late 1970s, widens for most of the next two and a half decades, and then narrows again near the end of the sample. The lack of readily identifiable time trends is interesting in view of how the market landscape evolved over the course of our sample period. Some of the notable changes include a large decline in trading costs, price decimalization, a reduction in average trade size, the rise of electronic order execution systems, and the growth in high-frequency trading.

Third, the high-turnover portfolios have positive average returns for most 10-year holding periods. The exceptions occur during the interval between the early 1970s and the early 1980s. The average returns are particularly high from around 1990 to around 2010, and then decline to a much lower level around 2015. Nonetheless, they have largely remained positive in recent years. The plots therefore suggest that the short-term momentum effect for high-turnover stocks has persisted across a wide range of market conditions.

These findings bolster the view that prior turnover has a strong influence on the sign of the first-order autocorrelations of monthly returns. We should point out that Connolly and Stivers (2003) also investigate the relation between turnover and autocorrelations, but find that conditioning on prior turnover has a relatively small effect for weekly large-cap portfolio returns. Although the contrast in findings could be due solely to the choice of data frequency, we suspect that it has more to do with methodological differences. Because we sort individual stocks on prior turnover, we avoid having to construct measures of "abnormal turnover" for portfolios formed on market capitalization. The evidence suggests that our approach amplifies the "signal-to-noise" ratio, thereby producing a clearer picture of the impact of conditioning on prior turnover. Consequently, we regard our results as more economically interesting and more reliable with respect to the strength of the interaction effect. Our analysis also leads to a richer set of insights concerning the likely origins of this effect. We turn now to a discussion of this issue.

3.1. A working hypothesis

Several hypotheses have been put forward to explain the short-term reversal anomaly. Overreaction, for example, is the favored behavioral story for the negative average returns produced by WML portfolios (see, e.g., De Bondt and Thaler, 1985). But this hypothesis doesn't fit the evidence developed thus far. Why would we see overreaction for low-turnover stocks and underreaction for high-turnover stocks? Short-term price pressure that stems from uninformed trading is also a widely-discussed mechanism for generating short-term reversals. But these discussions are usually framed in terms of the Campbell et al. (1993) model. Because the model implies that degree of uninformed trading is positively correlated with the trading volume, it predicts that the reversal effect should be stronger for stocks with high prior trading activity, which is at odds with the evidence from the portfolio sorts.

However, there are a couple of models that offer theoretical support for an inverse relation between the strength of the reversal effect and prior trading activity. Wang (1994) shows that such a relation can arise in a setting in which investors trade for both informational (speculative) and non-informational (hedging) reasons. Under the model, the nature of the relation between returns and prior trading activity is largely determined by the degree of information asymmetry. If information asymmetry is high, then the reversal effect weakens as trading volume increases under suitable parameterizations of the model. This corresponds to a scenario in which the speculative trading activity of privately-informed investors is the dominant factor in determining the serial correlation properties of returns.

Llorente et al. (2002) develop a closely related model with a simpler information structure that provides very sharp predictions about the relation between trading activity and the autocorrelations of subsequent returns. Under the model, price changes are generated in three different ways. The first is through the arrival of public news about future payoffs, the second is through hedging trades that are conducted for non-informational reasons, and the third is through speculative trades that are motivated by private information about future payoffs. The price changes due to public news are completely unpredictable. But those due to hedging and speculative trades generate serial correlation in returns.

Hedging trades convey no information about future payoffs, and thus returns generated by hedging trades display reversal effects. Speculative trades, on the other hand, are driven by information that is only partially incorporated into the stock price in a given period (i.e., the equilibrium is less than fully revealing), and thus returns generated by speculative trades display continuation effects. Because the effects of hedging and speculative trades work in opposite directions, the model implies that the relative importance of speculative trading activity should be a key determinant of the short-term autocorrelation properties of returns.

Accordingly, we hypothesize that the negative interaction between monthly return reversals and prior turnover arises from the interplay between short-term price pressure generated by uninformed traders and short-term continuations generated by the actions of speculative traders. As a first step towards developing measures to test this hypothesis, we consider the implications of the speculative trading model of Tauchen and Pitts (1983). Although the model is much simpler than those of Wang (1994) and Llorente et al. (2002), it has similar implications with respect to the relation between news and trading activity. Under the model, squared daily returns and daily trading volume share a common factor: the rate at which news that alters stock valuations arrives to market.[4] It therefore implies that turnover

[4]More generally, this common-factor structure follows from the mixture-of-distributions hypothesis (MDH). The MDH posits that the daily return R and daily trading volume V are generated by a bivariate mixture model of the form

$$
\begin{aligned}
R &= \sigma_R \sqrt{I} Z_R, \\
V &= \mu_V I + \sqrt{I} Z_V,
\end{aligned}
$$

where I is the daily information flow, Z_R and Z_V are standardized shocks, and I, Z_R and Z_V are mutually independent. Hence, it implies that $R^2 = \sigma_R^2 I + U_R$ and $V = \mu_V I + U_V$, where U_R and U_V are mean-zero innovations with $\mathrm{Cov}(U_R, U_V) = 0$. Andersen (1996) discusses the MDH and its extensions in detail.

and volatility should both have the potential to act as basic proxies for speculative trading activity. This observation suggests an obvious question in light of our findings thus far: Do turnover and volatility conveys similar signals about the likelihood of subsequent return reversals?

3.2. Evidence from cross-sectional regressions

If the negative interaction between reversals and prior turnover is due to the impact of speculative trading, then there should be a similar interaction between reversals and prior volatility. We use a cross-sectional regression approach to investigate whether this is the case. Specifically, we fit monthly cross-sectional regressions of the form

$$R_{i,t} = \delta_0 + \delta_1 R_{i,t-1} + \delta_2 \log TURN_{i,t-1} + \delta_3 \log VOL_{i,t-1} + \delta_4 \log ME_{i,t-1} + \delta_5 MOM_{i,t-1} + u_{i,t} \quad (2)$$

for selected decile groupings of stocks that are formed by conducting month-by-month sorts on either prior turnover or prior realized volatility. This strategy has several noteworthy features. First, we are essentially fitting varying-coefficient models because the coefficient estimates are local to the turnover or volatility neighborhood defined by the decile groupings. Second, we employ log transformations of turnover, realized volatility, and market equity because these variables have highly skewed distributions with long right tails. Third, we use price-based anomaly variables as our principal controls because we view these variables are prime candidates for capturing short-term autocorrelations in individual stock returns. Models that include a much more extensive set of anomaly-based covariates are considered as part of the robustness checks.

Fitting a separate linear regression to each decile of stocks is designed to capture non-linearity without having to specify a nonlinear model. The basic idea is to estimate the marginal effect of each regressor on expected stock returns while holding either turnover (or volatility) *approximately* constant. An alternative strategy would be to fit global cross-sectional regressions that include an appropriate set of pairwise interactions between the main regressors. This approach leads to similar conclusions about the relation between prior turnover and short-term reversals. However, the interpretation of the coefficient estimates is less straightforward.

Table 4 summarizes the regression results. To aid in interpreting the estimates, we demean each of the regressors on a month-by-month basis using its cross-sectional mean for the specific decile under consideration, and then divide each demeaned variable by its monthly cross-sectional standard deviation across all deciles. With this method of standardization, the average estimated intercept for a given decile is the average monthly return on an equally-weighted portfolio of the constituent stocks, and a one unit change in a regressor for a given decile is directly comparable to a one unit change in the regressor for any other another decile (i.e., the estimates are expressed in the same units for every decile).

(Table 4 about here)

Panel A reports the average coefficient estimates for turnover deciles 1, 4, 7, and 10. As anticipated, the average estimated slopes on prior returns are indicative of a strong negative interaction between monthly return reversals and prior turnover. Using all-but-micro-cap stocks, for example, the regressions for decile 1 produce an average estimated slope of −0.70 with a t-statistic of −10.14. In contrast, the average estimated slope for decile 10 is 0.13 with a t-statistic of 2.75. Thus the pattern uncovered via portfolio sorts is still evident after controlling for the explanatory power of volatility, market equity, and momentum. Specifically, stocks with low prior turnover display strong short-term reversals and those with high prior turnover display short-term momentum.

The results for large-cap stocks are similar. The average estimated slope for stocks in the bottom decile of prior turnover is −0.55 with a t-statistic of −7.36, whereas that for stocks in the top decile of prior turnover is 0.06 with a t-statistic of 1.10. Although the latter estimate is not statistically significant, it seems likely that it understates the strength of the short-term momentum effect. We say this because interactions are inherently nonlinear. The regressions are designed to capture nonlinearity via local OLS fits. But our local estimation strategy is not optimized to deliver the best tradeoff between bias and variance.

We also see evidence of the low-volatility anomaly in the results. Using all-but-micro-cap stocks, for example, the average estimated slope on log volatility is negative and statistically significant at the 5% level in every case. In contrast, most of the average estimated slopes for log turnover are statistically insignificant at the 5% level. The only exception is for decile 10, which is also the decile for which log volatility has the strongest effect. For the stocks in decile 10, increases in log volatility and log turnover are associated with statistically significant decreases in average returns. Thus, for stocks that display high levels of turnover, changes in turnover and volatility convey similar signals about expected stock returns, which is consistent with the notion that these variables share a common factor.

But does this result hold more broadly? Panel B, which reports the average coefficient estimates for volatility deciles 1, 4, 7, and 10, addresses this question. As predicted by our information-flow hypothesis, the general pattern of the average estimated slopes on prior returns is similar to that in panel A. Using all-but-micro-cap stocks, for example, the regressions for decile 1 produce an average estimated slope of -0.55 with a t-statistic of -6.62, whereas those for decile 10 produce an average estimated slope of 0.01 with a t-statistic of 0.27. Stocks with low prior volatility display strong short-term reversals. But there is no evidence of a reversal effect for those with high prior volatility.

Interestingly, all but two of the average estimated slopes on log turnover in panel B are positive and statistically significant at the 10% level. At first glance this finding may appear to be at odds with the results reported in panel A. But this is not the case. Note in particular that the average estimated intercept in panel A increases across deciles 1, 4, and 7, which indicates that large increases in turnover are associated with increases in average stock returns. It is only at the highest level of turnover than we see a drop in average returns.

This pattern of estimates points to a nonlinear and potentially non-monotonic relation between prior turnover and expected stock returns. Similarly, the average estimated intercept in panel B increases across deciles 1, 4, and 7, but falls for decile 10. The average estimated slope on log volatility also changes sign as we move across deciles. It is positive and statistically significant for decile 1, but negative and statistically significant for decile 10. These findings point to a nonlinear and non-monotonic relation between volatility and expected stock returns.

Overall the estimates support the hypothesis that volatility and turnover share a common factor that helps to explain differences in the first-order autocorrelations of monthly stock returns across firms. If the factor is news that drives speculative trading, then this casts the relation between monthly return reversals and prior turnover in a new light. Consider a stock that falls in the lower tail of the cross-sectional distribution of returns. If it has low turnover, then it has experienced a below-average return over a period in which the flow of news has been relatively low. The data indicate that this below-average return is likely to be followed by an above-average return over the next month (a short-term reversal effect). Conversely, if the stock has high turnover, then it has experienced a below-average return over a period in which the flow of news has been relatively high. The data indicate that this below-average return is likely to be followed by a below-average return over the next month (a short-term momentum effect).

3.3. A closer look at the relation between turnover and reversals

To investigate further, we extend our empirical tests using a correlation-based measure that is designed to proxy for the fraction of turnover that is driven by news. Wang (1994, p. 129) provides one motivation for considering this measure. Specifically, he notes that his model implies that "trading volume is always positively correlated with absolute price changes and the correlation increases with information asymmetry." Because a sufficient degree of information asymmetry is the key to generating an inverse relation between the strength of the reversal effect and prior trading activity in his framework, the model suggests that the short-term momentum effect should be stronger for stocks that display a high correlation between volume and volatility, all else being equal.[5]

But this is not the primary motivation for our measure. Instead, we look to the models of Andersen (1996) and Li and Wu (2006), which generalize the Tauchen and Pitts (1983) model by introducing liquidity traders within the same general modeling framework. Andersen

[5]Note that this argument focuses on relative rather than absolute information asymmetry. Stocks that fall into the lower end of the cross-sectional distribution of correlations might still have a level of information asymmetry that is high enough to generate an inverse relation between the strength of the reversal effect and prior trading activity.

(1996) assumes at the outset that there is no covariance between squared daily returns and the component of daily trading volume that is generated by liquidity trades. Under this assumption, the *overall* covariance between squared daily returns and daily trading volume rises as the contribution of liquidity trades to volume falls, all else being equal.

Li and Wu (2006) relax the zero-covariance assumption of Andersen (1996) and show that the estimated covariance between squared daily returns and the component of daily trading volume that is generated by liquidity trades is *negative* for a range of individual stocks. This finding supports the view that the overall covariance between squared daily returns and daily turnover rises as the contribution of liquidity trades to volume falls. Hence, both the theory and empirical evidence suggest that the monthly estimated correlation between squared daily returns and daily turnover should be a useful proxy for the relative contribution of news-driven trades to monthly turnover for individual stocks.

This simple measure is appealing for our purposes because it is easy to estimate and has clear theoretical underpinnings. However, we acknowledge that the subsequent results are best interpreted as providing an indirect test of the information flow hypothesis. One could argue, for instance, that many factors could potentially generate cross-sectional variation in the correlation between volume and volatility. But suppose for the sake of counterargument that conditioning on this correlation helps to explain the relation between return reversals and trading activity. The most straightforward explanation for such a finding would be one suggested by the Andersen (1996) and Li and Wu (2006) models. To attribute it to some other factor, there would have to be a plausible argument for linking the factor in question to the relation between return reversals and trading activity. In our view, such a finding would be difficult to explain without invoking some type of information-based story.

We begin by considering a simple extension of cross-sectional regressions considered in panel A of Table 4. First, we partition the set of available stocks for each month into two groups: those which have a low fraction of news-driven turnover (estimated correlations below the median value for the month) and those that have a high fraction of news-driven turnover (estimated correlations above the median value for the month). Second, we sort the stocks in each group into turnover deciles and examine the regression evidence. The motivation for this approach is straightforward. Under our information-flow hypothesis, stocks with a low fraction news-driven turnover should display a more pronounced reversal effect than those with a high fraction news-driven turnover. Table 5 summarizes the regression results. (Table 5 about here)

Panel A reports the results obtained using all-but-micro-cap stocks. First consider the evidence for stocks that have a low fraction of news-driven turnover. The average estimated slopes on prior returns for deciles 1, 4, and 7 are -0.58, -0.68, and -0.59 with t-statistics of -8.49, -9.38, and -8.56, respectively. Thus we see little indication that the reversal effect weakens with increasing turnover from these results. The regressions for decile 10, however, produce an average estimated slope of -0.06 with a t-statistic of -0.98, which suggests that the estimated reversal effect is substantially weaker for stocks in the highest turnover category. Still, we see no evidence of a short-term momentum effect.

Now consider the evidence for stocks that have a high fraction of news-driven turnover. The average estimated slopes on prior returns for deciles 1, 4, and 7 are -0.66, -0.48, and -0.22 with t-statistics of -6.94, -5.52, and -2.54. Hence, they point to a weakening of the reversal effect as turnover increases. More notably, the regressions for decile 10 produce an average estimated slope of 0.22 with a t-statistic of 3.60, indicating that high-turnover display a statistically-significant momentum effect. Thus the results for all-but-micro-cap stocks line up quite well with the predictions of the Llorente et al. (2002) model.

Panel B reports the results obtained using large-cap stocks. In general, they display the same basic patterns as those in panel A. The reversal effect weakens with increasing turnover. However, the changes in the average estimated slope on prior returns are more pronounced for stocks that have a high fraction of news-driven turnover. For example, the regressions for decile 10 produce an average estimated slope of -0.09 with a t-statistic of -1.45 for stocks that have a low fraction of news-driven turnover, and 0.11 with a t-statistic of 1.64 for stocks that have a high fraction of news-driven turnover. So we again conclude that the evidence is in line with the predictions of the Llorente et al. (2002) model.

Table 6 shows how conditioning on the fraction of news-driven turnover affects the results of the portfolio sorts. Panel A is for portfolios formed from all-but-micro-cap stocks. For stocks in the bottom quintile of prior turnover, the WML portfolio has an average return of -1.03% per month (a t-statistic of -6.25) for stocks with a low fraction of news-driven turnover and -0.75% per month (a t-statistic of -3.84) for stocks with a high fraction of news-driven turnover. Thus the reversal effect appears to be somewhat weaker in the latter case. For stocks in the top quintile of prior turnover, the WML portfolio has an average return of -0.35% per month (a t-statistic of -1.32) for stocks with a low fraction of news-driven turnover and 1.06% per month (a t-statistic of 3.69) for stocks with a high fraction of news-driven turnover. (Table 6 about here)

The key takeaway from these results is that conditioning on our proxy for the fraction of news-driven turnover clearly matters. Indeed, the results point to a stronger conditioning effect than those of the regressions. This may be because portfolio sorts are fully non-parametric. All of the evidence thus far is indicative of a strong interaction between prior turnover and monthly return reversals. Although our regressions are designed to highlight this interaction, they may not capture it to the same extent as the portfolio sorts.

Panel B shows that repeating the portfolio sorts for large-cap stocks produces almost identical findings. For stocks in the top quintile of prior turnover, for instance, the WML portfolio has an average return of -0.35% per month (a t-statistic of -1.34) for stocks with a low fraction of news-driven turnover and 1.06% per month (a t-statistic of 3.72) for stocks with a high fraction of news-driven turnover. Of course it is important to bear in mind that the portfolio sorts do not control for potential confounding anomalies. Subject to this caveat, however, the results are fully consistent with our information flow hypothesis. (Figure 2 about here)

Figure 2 shows how conditioning on the fraction of new-driven turnover affects the rolling 10-year average returns on the WML portfolios formed from all-but-micro-cap stocks. The top and bottom panels are for the low and high categories, respectively. In general, the portfolios formed from stocks with a low fraction of news driven turnover have negative average returns, regardless of the level of prior turnover. We see little evidence of short-term momentum for this category of stocks. The average return on the high-prior-turnover portfolio turns positive around 2010 and stays positive through the end of 2018, but it never rises very far above zero.

In contrast, the high-prior-turnover portfolio formed from stocks with a high fraction of news driven turnover has a positive average return for most of the sample period. The value is as high as 3.3% per month during the mid-1990s. So short-term momentum is readily evident for this category of stocks. In addition, the gap between average returns for the low- and high-prior-turnover portfolios is quite wide for much of the sample period, reaching a maximum value of 4.4% per month. The sharp contrast between the plots in the top and bottom panels is consistent with the presence of a strong interaction between the level of turnover, the fraction of turnover driven by news, and monthly return reversals.

As noted earlier, the average return on the high-prior-turnover portfolio increase towards the end of the sample period for stocks with a low fraction of news-driven turnover. Although this is suggestive of some weakening in the reversal effect in the last decade, the evidence is far from definitive. In the bottom panel, for example, the gap between average returns for the low- and high-prior-turnover portfolios widens over the last few years of the sample period. On the whole we can discern little in the way of readily-identifiable time trends. (Figure 3 about here)

Figure 3 replicates the plots in Figure 2 using large-cap stocks. Excluding small-cap stocks from the WML portfolios produces only minor changes in the results. We see the same general patterns as in Figure 2. Specifically, the portfolios formed from stocks that have a low fraction of news driven turnover generally have negative average returns, regardless of the level of prior turnover, and the high-prior-turnover portfolio formed from stocks that have a high fraction of news driven turnover has a positive average return for most of the sample period. In short, the rolling average returns for the portfolios formed from large-cap stocks are similar to those of the portfolios that include both small- and large-cap stocks.

3.4. Alternative explanations for short-term momentum

The short-term momentum effect for stocks with high prior turnover is one of the most intriguing aspects of our findings. Recall that the Llorente et al. (2002) model implies that short-term momentum arises from the reaction of rational traders to the arrival of new information that alters conditional expectations of future payoffs. The evidence that stocks with a high fraction of news-driven turnover display the strongest momentum is consistent with this feature of the model. But it is important to point out that there may be other mechanisms for generating momentum that could give rise to the same result.

Underreaction to news is one possibility that comes to mind. Not only does an underreaction story have the potential to explain why short-term momentum is concentrated in stocks that have a high fraction of news-driven turnover, it also meshes fairly well with our other findings. Suppose, for example, that speculative traders underreact to news and uninformed traders generate short-term price pressure that leads to price concessions. Under these circumstances, the reversal effect should dominate for stocks with low information flow. But this effect should weaken as we move to stocks with higher information flow, especially those that have a high fraction of news-driven turnover. Thus the net result might be a strong negative interaction between turnover and short-term reversals in conjunction with a short-term momentum effect for stocks that display a sufficiently high level of turnover.

Regardless of how short-term momentum arises, however, it is apparent that our findings raise the bar for research that seeks to explain the short-term autocorrelation properties of monthly stock returns. Any proposed explanation for the short-term reversal anomaly must contend with both the negative interaction between prior turnover and monthly return reversals and the evidence that the prior monthly correlation between squared daily returns and daily turnover conveys substantial information about the likelihood of monthly return reversals. Because it is difficult to envision a plausible explanation for the latter finding that does not entail some type of information-based story, it may be worthwhile to revisit at least some of the empirical results reported by previous studies in the short-term reversal literature.

4. Robustness Checks and Further Analysis

The short-term reversal anomaly has attracted its fair share of attention since it was first uncovered by the Jegadeesh (1990) and Lehmann (1990). In a number of cases, prior research identifies methodological or robustness issues that could potentially play a role in our findings. We therefore investigate whether any of the issues or concerns that appear to be most relevant to our analysis have a meaningful impact on our main results.

4.1. Regressions using an expanded set of controls

Our baseline regressions control for several price-based anomalies that have been widely studied in the literature. We focus on priced-based anomalies because they seem most likely to be associated with short-term reversals. But there is always a possibility that using a broader set of controls would materially alter our findings. To address this issue, we expand the set of covariates to include the book-to-market ratio along with a wide range of anomaly variables that are used as mispricing indicators in the recent literature (Stambaugh et al., 2015; Stambaugh and Yuan, 2017). The anomaly variable include measures of financial distress, share growth, accruals, net operating assets, gross profitability, asset growth, return on assets, and investment to assets.[6] Table 7 summarizes the results of this robustness check.[7] (Table 7 about here)

Expanding the set of controls has only a minor impact on our findings. Using all-but-micro-cap stocks, for example, the average estimated slopes for prior monthly returns are -0.71, -0.64, -0.42, and 0.05 with t-statistics of -7.49,-8.03,-5.78, and 0.88. Thus there are still marked differences in the estimated slopes across turnover deciles. The most notable change from the results in Table 4 is that the average estimated slope for the top turnover decile is no longer statistically significant. This is due to both a decrease in the magnitude of the estimate and an increase in its standard error, which suggests that the controls may explain part of the short-term momentum effect for high turnover stocks. But the evidence

[6]Specifically, we use the estimated probability of bankruptcy from Ohlson (1980), the annual growth rate of the split-adjusted shares outstanding, the annual change in non-cash working capital minus depreciation expense (as a fraction of average total assets for the year), operating assets minus operating liabilities (as a fraction of beginning-of-year total assets), revenues minus cost of goods sold (as a fraction of end-of-year total assets), the annual growth rate of total assets, the ratio of annual earnings to beginning-of-year total assets, and the annual change in gross property, plant, and equipment plus the annual change in inventories (as a fraction of beginning-of-year total assets). Our definitions of these variables match those of Stambaugh et al. (2015) with one minor exception: the return on assets is computed using annual rather than quarterly data. See the appendix for details.

[7]Firms are required to have non-missing values of all regressors to be included in a given monthly regression. This requirement substantially reduces the number of available observations for months in the early part of our sample period. We therefore use data for January 1973 to December 2018 for the analysis. Because CRSP expanded its coverage to NASDAQ stocks in 1973, this ensures that we have an adequate sample size for each regression.

is not conclusive.

For instance, the regression for the top turnover decile of large-cap stocks produces an average estimated slope on prior returns of 0.05, which is very close to the value of 0.06 reported in Table 4. Thus it is unclear whether the decrease in the average estimated slope for all-but-micro-cap stocks is due to a weaker short-term momentum, or whether it is largely due to the change in sample composition that results from requiring firms to have non-missing values of all the regressors to be included in the regressions. Even if the former effect predominates, however, the basic message of Table 7 is consistent with that of Table 4. That is, high levels of prior turnover are associated with a dramatic weakening of the short-term reversal effect.

4.2. Liquidity effects

Liquidity could potentially play a confounding role in our findings. For example, Avramov et al. (2006) report that return reversals are more pronounced for less liquid stocks at both the weekly and monthly horizon. They conduct their analysis using the price-impact criterion of Amihud (2002), which is one of the most widely used proxies for liquidity in empirical research. However, the recent study of Lou and Shu (2017) reports that the cross-sectional explanatory power of the Amihud (2002) criterion for individual stock returns is almost entirely attributable to its dependence on dollar trading volume. This makes the criterion ill suited to our purposes because dollar trading volume is very highly correlated with turnover for most stocks.

Following the recommendations of Fong et al. (2017), we use the monthly average of the daily proportional bid-ask spread to investigate liquidity effects. Its value for stock i in month t is denoted by $SPREAD_{i,t}$. Fong et al. (2017) report that, in general, $SPREAD_{i,t}$ is the most accurate low-frequency proxy for liquidity. This is consistent with the results of Chung and Zhang (2014), who use data for 1993 to 2007 to investigate the performance of a wide range of different liquidity proxies (including the Amihud (2002) criterion) and find that $SPREAD_{i,t}$ has the highest correlation with the daily time-weighted average quoted spread from the Trade and Quote files of the NYSE. (Table 8 about here)

Table 8 shows how conditioning on liquidity affects the results of the portfolio sorts. We form the portfolios in two steps. First, we partition the set of available stocks into two categories for each month t: those with low liquidity ($SRREAD_{i,t}$ above the median value for month t) and those with high liquidity ($SPREAD_{i,t}$ below the median value for month t). Second, we construct low- and high-liquidity versions of the portfolios considered in Table 2 for each category of stocks. Due to the limited availability of bid and ask prices in the CRSP daily stock file, the sample period is January 1993 to December 2018.

Panel A reports the results for all-but-micro-cap stocks. To assess the overall effect of liquidity, we look at the mean values of the average portfolio returns across turnover quintiles. The values for the low- and high prior-return portfolios are 0.82 and 0.28 for low-liquidity stocks and 0.62 and 0.39 for high-liquidity stocks. So these statistics suggest that the reversal effect becomes weaker as liquidity increases. But we also find evidence of three-way interaction between liquidity, turnover, and reversals. The WML portfolios formed from low- and high-prior-turnover stocks with high liquidity have average returns of −1.25 and 1.18 with t-statistics of −4.55 and 2.64, whereas those formed for stocks with low liquidity have average returns of −0.86 and 0.06 with t-statistics of −3.23 and 0.13. Thus prior turnover becomes more informative about the likelihood of short-term reversals as liquidity increases.

Using large-cap stocks for the portfolio sorts yields similar results. The WML portfolios formed from low- and high-prior-turnover stocks with high liquidity have average returns of −0.93 and 1.09 with t-statistics of −3.61 and 2.24, whereas the values for stocks with low liquidity are −0.78 and 0.41 with t-statistics of −2.85 and 0.90. Hence, the tendency for high-turnover stocks to display short-term momentum increases with liquidity, and the effect of conditioning on prior turnover becomes more pronounced as liquidity increases. (Table 9 about here)

Table 9 uses cross-sectional regressions to provide additional evidence on liquidity effects. The results in panel A, which are for selected turnover deciles that are formed from either low-liquidity or high-liquidity stocks, are consistent with the evidence from the portfolio sorts. The average estimated slope on prior monthly returns displays marked differences across turnover deciles for both low- and high-liquidity stocks. Specifically, it ranges from -0.65 for decile one (t-statistic of -4.15) to 0.01 for decile ten (t-statistics of -0.15) in the case of low-liquidity stocks, and from -0.69 for decile one (t-statistic of -4.84) to 0.16 for decile 10 (t-statistics of 1.94) in the case of high-liquidity stocks. The short-term reversal effect weakens as turnover increases, but the interaction with turnover is stronger for high-liquidity stocks. For these stocks we see a statistically-significant short-term momentum effect for decile ten.

The results in panel B are for selected liquidity deciles that are formed from either low-turnover or high-turnover stocks. The estimates suggest that the overall relation between liquidity and short-term reversals is relatively weak, which is again consistent with the evidence from the portfolio sorts. The average estimated slope on prior monthly returns ranges from -0.45 to -0.25 for low-turnover stocks and from -0.15 to 0.02 for high-turnover stocks. At first glance, therefore, cross-sectional differences in liquidity do not appear to be very informative about the likelihood of subsequent return reversals.

To complete our analysis of liquidity effects, we investigate whether conditioning on liquidity alters our conclusions regarding the relation between return reversals and the prior monthly correlation between squared daily returns and daily turnover. Specifically, we replicate the portfolio sorts described in Table 6 for the low- and high-liquidity categories of all-but-micro-cap stocks. The results are summarized in Table 10. (Table 10 about here)

Panel A shows that low-liquidity stocks with a low fraction of news-driven turnover display a reversal effect for every quintile of prior turnover, although it is not statistically significant for the top quintile. The average returns for the WML portfolios range from -1.55% to -0.52% per month. In comparison, the range is -0.50% to 0.27% per month for low-liquidity stocks with a high fraction of news-driven turnover. This points to a substantial weakening of the reversal effect as the fraction of news-driven turnover increases.

Panel B shows that high-liquidity stocks also display ample evidence of return reversals. But the reversal effect is more pronounced among the subset of stocks that have a low fraction of news-driven turnover. For stocks with a high fraction of news-driven turnover, the WML portfolio for the top prior turnover quintile has an average return of 1.63% per month with a t-statistic of 3.11. This is considerably higher than the average return on the corresponding portfolio formed from low-liquidity stocks. Hence, the evidence indicates that stocks with high liquidity, high turnover, and a high fraction of news driven turnover display a stronger short-term momentum effect than stocks with low liquidity, high turnover, and a high fraction of news driven turnover.

These findings highlight the importance of accounting for nonlinear phenomena. Although the regression estimates in panel B of Table 9 provide only weak evidence of a linear relation between liquidity and return reversals, the average portfolio returns in Table 10 point to strong nonlinear effects in the data. In particular, they are indicative of a marked three-way interaction between liquidity, turnover, and reversals. Because the effect of conditioning on the fraction of new-driven turnover becomes more pronounced as liquidity increases, it is apparent that our conclusions are not driven by low liquidity stocks.

4.3. Portfolio sorts for a low-trading-cost sample period

Several studies raise concerns about the role of bid-ask spreads in generating short-term reversals. For instance, Ball et al. (1995) and Conrad et al. (1997) report that bid-ask bounce makes a significant spurious contribution to the measured profitability of short-term contrarian trading strategies. If bid-ask bounce influences our results, then research on trading costs suggests that its impact is likely to be of most concern for the early part of our sample period. Jones (2002), for example, estimates that quoted proportional spreads for Dow Jones stocks declined from around 0.60% in the 1980s to around 0.20% at the end of the 20th century. To see if the relation between reversals and prior turnover during the early part of the sample period drives our findings, we replicate the portfolio sorts described in Table 6 using the most recent 20 years of data. The results, which are shown in Table 11, are consistent with those for the full sample period. (Table 11 about here)

Using all-but-micro-cap stocks, for example, the WML portfolio for stocks in the bottom quintile of prior turnover has an average return of -0.91% per month (a t-statistic of -2.76) for stocks with a low fraction of news-driven turnover and -0.74% per month (a t-statistic of -1.89) for stocks with a high fraction of news-driven turnover. In comparison, the WML portfolio for stocks in the top quintile of prior turnover has an average return of 0.11% per month (a t-statistic of 0.20) for stocks with a low fraction of news-driven turnover and 1.28% per month (a t-statistic of 2.00) for stocks with a high fraction of news-driven turnover.

The t-statistics in Table 11 are generally smaller in magnitude than those in Table 6. However, this is mainly due to the reduction in the number of observations. The shorter sample period is roughly one-third as long as the full sample period. Despite the relatively large standard errors of the average returns in Table 11, we still find that the portfolios formed from stocks with a high-fraction of news driven turnover produce clear evidence of a strong interaction between prior turnover and return reversals. It seems unlikely, therefore, that the sensitivity of measured WML returns to bid-ask bounce is more than a minor concern.

4.4. Short-term reversals among micro-cap stocks

The evidence indicates that sensitivity to liquidity effects is not a concern in our setting. But they might be a key robustness issue for studies that include micro-cap stocks in the analysis. These stocks, which have been excluded from consideration thus far, account for almost 60% of the available firm-year observations for our 1963-to-2018 sample period. In general, we would expect micro-cap stocks to be much less liquid than small- and large-cap stocks, making them prime candidates for strong return reversals. This may be one of the reasons that the short-term momentum effect for small- and large-cap stocks has gone undetected in prior research. If micro-cap stocks display strong return reversals, then including them in the analysis could mask the evidence of short-term momentum for high-turnover stocks. (Table 12 about here)

Consider the results in Table 12, which uses portfolio sorts to illustrate the relation between prior turnover and short-term reversals for micro-cap stocks. As anticipated, the reversal effect is particularly pronounced for these stocks, both in terms of magnitude and statistical significance. The WML portfolios for the bottom four quintiles of prior turnover have average returns that range from -1.48% to -1.84% per month, and the smallest unsigned t-statistic is 8.01. The reversal effect is weaker for micro-cap stocks in the top quintile of prior turnover, but there is no evidence whatsoever of short-term momentum. The WML portfolio has an average return of -0.68 with a t-statistic of -2.50.

Because micro-cap stocks are of questionable importance from a capital markets perspective, the presence of such a strong short-term reversal effect among these stocks would raise robustness concerns in many applications. However, this is clearly not the case with respect to the documented interaction between prior turnover and return reversals. Not only does the interaction appear to be more pronounced for small- and large-cap stocks than for micro-cap stocks, it is also more pronounced for high-liquidity stocks than for low-liquidity stocks. The evidence in this regard should allay any concerns about the economic significance of our findings.

5. Conclusions

The likelihood of short-term return reversals is strongly linked to prior trading activity for both small- and large-cap stocks. Stocks with low prior turnover have the strongest tendency to display monthly return reversals. Those with high prior turnover display short-term momentum. We posit that these findings arise from the interplay between short-term price pressure generated by uninformed traders and short-term continuations generated by the actions of speculative traders. By conditioning on a proxy for the fraction of turnover that is driven by news, we show that the predictions of our hypothesis are consistent with the observed negative interaction between prior turnover and reversals in monthly stock returns.

The pronounced reversal effect in monthly returns for liquid, low-turnover, large-cap stocks is an intriguing phenomenon that belies the view that short-term reversals are of little economic significance. In addition, the link between the strength of reversal effect and the correlation between squared daily returns and daily turnover is a telling finding. Because the nature of the evidence makes it difficult to envision a plausible explanation for this interaction that does not involve some type of information-based story, our findings clearly raise the bar for research that seeks to explain the short-term reversal anomaly.

More broadly, the evidence suggests that market capitalization probably plays an important confounding role in research on short-term reversals. Our analysis reveals that the reversal effect is particularly strong for micro-cap stocks, which account for almost 60% of the available firm-year observations for our sample period. Hence, the presence of these stocks in the dataset tends to mask evidence of short-term momentum. This may be one of the reasons why the short-term momentum effect for high-turnover stocks has gone largely undetected in prior research. Without adequate controls for the influence of market capitalization, studies of the short-term reversal anomaly are likely to produce incomplete and potentially misleading findings with respect to the autocorrelation properties of individual stock returns.

Appendix A. Variable Definitions

The variables used for the analysis are described in detail below. They are constructed using data from CRSP (daily and monthly stock files) and Compustat (annual industrial file).

A.1. Variables used for the baseline analysis

All of the data items used to construct these variables are from CRSP. The CRSP items names are shown in roman capital letters.

1. $R_{i,t}$: Denotes the return for stock i in month t. It is RET from the monthly stock file.

2. $TURN_{i,t}$: Denotes turnover for stock i in month t. $TURN = \text{VOL}/(10 \times \text{SHROUT})$, where VOL and SHROUT are trading volume and shares outstanding from the monthly stock file.

3. $ME_{i,t}$: Denotes the market equity of firm i in month t. $ME = |\text{PRC}| \times (\text{SHROUT}/1000)$, where PRC is the stock price from the monthly stock file.

4. $VOL_{i,t}$: Denotes the realized volatility for stock i in month t. We compute this variable as

$$VOL_{i,t} = \left(\sum_{n=1}^{N_{i,t}} (R_{i,t_n} - \hat{m}_t(R_{i,t_n}))^2 \right)^{1/2},$$

where R_{i,t_n} is the stock return for day n of month t (RET from the daily stock file), $N_{i,t}$ is the number of days with non-missing daily returns for stock i in month t, and $\hat{m}_t(R_{i,t_n}) = (1/N_{i,t}) \sum_{n=1}^{N_{i,t}} R_{i,t_n}$. We treat $VOL_{i,t}$ as missing if $N_{i,t} < 11$.

5. $MOM_{i,t}$: Denotes the momentum for stock i in month t, which is measured using the stock return over the first 11 months of the prior year. That is, $MOM_{i,t} = (\prod_{n=1}^{11}(1 + R_{i,t-n})) - 1$.

6. $CORR_{i,t}$: Denotes the correlation between squared demeaned daily stock returns and daily turnover for stock i in month t. We compute this variable as

$$CORR_{i,t} = \frac{\sum_{n=1}^{N_{i,t}}(TURN_{i,t_n} - \hat{m}_t(TURN_{i,t_n}))(S_{i,t_n} - \hat{m}_t(S_{i,t_n}))}{(\sum_{n=1}^{N_{i,t}}(TURN_{i,t_n} - \hat{m}_t(TURN_{i,t_n}))^2)^{1/2}(\sum_{n=1}^{N_{i,t}}(S_{i,t_n} - \hat{m}_t(S_{i,t_n}))^2)^{1/2}},$$

where $\hat{m}_t(TURN_{i,t_n}) = (1/N_{i,t})\sum_{n=1}^{N_{i,t}} TURN_{i,t_n}$, $\hat{m}_t(S_{i,t_n}) = (1/N_{i,t})\sum_{n=1}^{N_{i,t}} S_{i,t_n}$, and $S_{i,t_n} = (R_{i,t_n} - \hat{m}_t(R_{i,t_n}))^2$. We treat $CORR_{i,t}$ as missing if $N_{i,t} < 11$.

A.2. Additional variables used for the robustness checks

Most of these variables are constructed using one or more annual Compustat data items.[8] To account for the delay between the end of a firm's fiscal year and the date its annual report is disseminated, we match Compustat information for firms whose fiscal years end in month $t-16$ with stock returns for months $t-11$ to t. Because this methodology implies that all annual data items are lagged by at least four months with respect to the interval covered by returns, a t subscript for a Compustat-based variable indicates that it is constructed using financial statements for fiscal years that end in month $t-5$ or earlier. Compustat mnemonics are shown in roman capital letters, and lag($\cdot$) is used to denote the first annual lag of the argument.

1. $BTM_{i,t}$: Denotes the book-to-market equity ratio for stock i in month t. Market equity is $ME_{i,t}$. Book equity is derived from Compustat. Following Fama and French (1992), it is defined as shareholders equity (SEQ), plus balance-sheet deferred taxes and investment tax credit (TXDITC), if available, minus the book value of preferred stock, which is either its redemption value (PSTKRV), liquidation value (PSTKL), or par value (PSTK), in this order of preference. If the value of SEQ is missing, we substitute common equity plus preferred stock (CEQ plus PSTK), if available, or assets minus liabilities (AT minus LT), if available, in this order of preference. We treat book equity as missing if it is less than zero.

2. $AG_{i,t}$: Denotes asset growth for firm i in month t. The continuously-compounded growth rate of firm assets over the prior fiscal year (log(AT/lag(AT))).

3. $ROA_{i,t}$: Denotes the return on assets for firm i in month t. The ratio of income before

[8] We exclude firms with less than two years of Compustat data to mitigate the well-known biases that arise from the way in which firms are added to the file.

extraordinary items to beginning-of-year assets for the prior fiscal year (IB divided by lag(AT)).

4. $GP_{i,t}$: Denotes gross profitability for firm i in month t. The ratio of revenue minus cost of goods sold to assets for the prior fiscal year (REV minus COGS as a fraction of AT).

5. $NOA_{i,t}$: Denotes net operating assets for firm i in month t. The ratio of operating assets minus operating liabilities for the prior fiscal year to beginning-of-year total assets. Operating assets are assets (AT) minus cash and short-term investments (CHE). Operating liabilities are assets (AT), minus debt in current liabilities (DLC), minus long-term debt (DLTT), minus minority interest (MIB), minus par value of preferred stock (PSTK), minus common equity (CEQ). Missing values of MIB and PSTK are set to zero.

6. $ITA_{i,t}$: Denotes the investment-to-assets ratio for firm i in month t. Investment is the change in gross property, plant, and equipment over the prior fiscal year (PPEGT minus lag(PPEGT)) plus the change in inventories over the prior fiscal year (INVT minus lag(INVT)). Assets are the beginning-of-year assets (lag(AT)).

7. $ACC_{i,t}$: Denotes total accruals for firm i in month t. The ratio of the change in non-cash working capital over the prior fiscal year minus the depreciation expense (DP) for the year to the average value of assets for the year (the average of AT and lag(AT)). Non-cash working capital is current assets (ACT), minus cash and short-term investments (CHE), minus current liabilities (LCT), plus debt in current liabilities (DLC), plus taxes payable (TXP). Missing values of DLC and TXP are set to zero.

8. $NNS_{i,t}$: Denotes share growth for firm i in month t. The continuously-compounded growth rate of split-adjusted shares outstanding (AJEX times CSHO) over the prior fiscal year.

9. $OSC_{i,t}$: Denotes the O-score (estimated bankruptcy probability) for firm i in month t.

The formula is

$$
\begin{aligned}
OSC \quad = \quad & -1.32 - 0.407 \log(\mathrm{AT}) + 6.03 \left(\frac{\mathrm{DLC} + \mathrm{DLTT}}{\mathrm{AT}} \right) - 1.43 \left(\frac{\mathrm{ACT} - \mathrm{LCT}}{\mathrm{AT}} \right) + \\
& 0.076 \left(\frac{\mathrm{LCT}}{\mathrm{ACT}} \right) - 1.72 \times 1_{(\mathrm{LT} > \mathrm{AT})} - 2.37 \left(\frac{\mathrm{NI}}{\mathrm{AT}} \right) - 1.83 \left(\frac{\mathrm{PI}}{\mathrm{LT}} \right) + \\
& 0.285 \times 1_{(\mathrm{NI} < 0 \ \& \ \mathrm{lag}(\mathrm{NI}) < 0)} - 0.521 \left(\frac{\mathrm{NI} - \mathrm{lag}(\mathrm{NI})}{|\mathrm{NI}| + |\mathrm{lag}(\mathrm{NI})|} \right),
\end{aligned}
$$

where NI is net income, PI is pre-tax income, and $1_{(\cdot)}$ denotes the indicator function.

10. $SPREAD_{i,t}$: Denotes the average proportional bid-ask spread for firm i in month t. We compute this variable as

$$SPREAD_{i,t} = \frac{1}{N_{i,t}} \sum_{n=1}^{N_{i,t}} 2 \left(\frac{A_{i,t_n} - B_{i,t_n}}{A_{i,t_n} + B_{i,t_n}} \right),$$

where A_{i,t_n} and B_{i,t_n} denote the closing bid and ask prices for day n of month t (ASK and BID from the daily stock file). Following Chung and Zhang (2014), we treat the summand for day t_n as missing if $A_{i,t_n} = B_{i,t_n} = 0$ or if $A_{i,t_n} - B_{i,t_n} > (A_{i,t_n} + B_{i,t_n})/4$.

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Table 1
Portfolios Formed on Returns and on Turnover

Panel A: All stocks

	Portfolios formed on prior returns						Portfolios formed on prior turnover					
Quintile	Mean	Vol	Avg ME	ME Share	4-Fac Alpha	t-stat	Mean	Vol	Avg ME	ME Share	4-Fac Alpha	t-stat
Low (L)	0.59	6.70	0.78	8.86	0.07	0.64	0.44	3.64	0.27	3.09	0.01	0.07
2	0.73	5.07	1.89	21.53	0.23	3.30	0.46	4.18	0.96	11.02	−0.07	−1.06
3	0.55	4.33	2.39	27.28	0.05	1.23	0.55	4.24	2.84	32.42	0.03	0.61
4	0.51	4.29	2.42	27.65	0.01	0.12	0.59	4.86	2.84	32.38	−0.02	−0.45
High (H)	0.33	5.17	1.28	14.67	−0.25	−2.54	0.56	6.44	1.85	21.09	−0.17	−2.07
H−L	−0.25				−0.32	−1.72	0.11				−0.17	−1.35

Panel B: All-but-micro-cap stocks

Decile	Mean	Vol	Avg ME	ME Share	4-Fac Alpha	t-stat	Mean	Vol	Avg ME	ME Share	4-Fac Alpha	t-stat
Low (L)	0.62	6.13	3.02	14.68	0.11	1.08	0.42	3.71	3.67	17.83	−0.03	−0.50
2	0.64	4.64	4.63	22.48	0.12	2.08	0.51	3.95	6.27	30.46	0.04	0.74
3	0.56	4.27	4.97	24.12	0.05	1.29	0.58	4.56	4.76	23.13	0.05	1.34
4	0.45	4.27	4.85	23.55	−0.04	−0.77	0.56	5.25	3.52	17.10	−0.04	−0.92
High (H)	0.33	5.05	3.12	15.16	−0.24	−2.50	0.57	6.98	2.36	11.48	−0.13	−1.27
H−L	−0.30				−0.34	−1.98	0.15				−0.10	−0.69

Panel C: Large-cap stocks

Decile	Mean	Vol	Avg ME	ME Share	4-Fac Alpha	t-stat	Mean	Vol	Avg ME	ME Share	4-Fac Alpha	t-stat
Low (L)	0.62	5.79	6.48	16.90	0.11	1.20	0.42	3.62	12.02	31.34	−0.02	−0.38
2	0.65	4.49	8.43	21.98	0.15	2.87	0.57	4.14	10.02	26.13	0.10	2.41
3	0.50	4.22	8.61	22.46	0.02	0.37	0.57	4.57	7.04	18.35	0.10	2.46
4	0.43	4.20	8.42	21.97	−0.05	−0.98	0.53	5.26	5.33	13.91	−0.05	−0.97
High (H)	0.32	4.87	6.40	16.69	−0.22	−2.43	0.52	6.95	3.94	10.27	−0.14	−1.26
H−L	−0.30				−0.33	−1.99	0.10				−0.12	−0.81

Each panel reports descriptive statistics for two sets of value-weighted quintile portfolios. The statistics are the average excess percentage return (Mean), the volatility of the excess percentage return (Vol), the average market equity of the stocks in the portfolio across all stock-month observations (Avg ME) in billions of dollars, the percentage of total market equity across all stock-month observations that is attributable to the stocks in the portfolio (ME share), the intercept produced by a time series regression the excess percentage returns on the four Carhart (1997) factors (4-Fac Alpha), and the heteroskedasticity-robust t-statistic of the intercept (t-stat). To estimate the alpha of a portfolio, we use ordinary least squares to fit a time-series regression of its monthly excess return on the monthly realizations of the four Carhart (1997) factors. The returns for month $t+1$ are for portfolios formed in month t. We form the first set of portfolios by sorting stocks into return quintiles, and the second set of portfolios by sorting stocks into turnover quintiles. Each stock is weighted in proportion to its market equity at the time the portfolios are formed. The sample used to form the portfolios in a given month is either all available NYSE, AMEX, and NASDAQ stocks (all stocks), the subset of stocks whose market equity is equal to or larger than the 20th percentile of the NYSE market-equity distribution (all-but-micro-cap stocks), or the subset of stocks whose market equity is equal to or larger than the 50th percentile of the NYSE market-equity distribution (large-cap stocks). The sample period is July 1963 to December 2018.

Table 2
Portfolios Formed on Returns After Sorting on Turnover Using All-But-Micro-Cap Stocks

Panel A: Average excess portfolio returns and estimated four-factor alphas

	Prior return quintile						Prior return quintile					
	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Prior turnover quintile	Average excess return						Estimated four-factor alpha					
Low (L)	0.85	0.60	0.43	0.39	0.02	−0.83	0.37	0.11	−0.04	−0.07	−0.45	−0.82
	(4.17)	(3.66)	(2.65)	(2.47)	(0.12)	(−4.87)	(3.17)	(1.11)	(−0.39)	(−0.73)	(−3.88)	(−4.72)
2	0.93	0.76	0.56	0.29	0.06	−0.87	0.46	0.27	0.09	−0.18	−0.39	−0.85
	(4.55)	(4.45)	(3.51)	(1.81)	(0.35)	(−5.31)	(3.99)	(3.17)	(1.09)	(−2.31)	(−4.15)	(−5.13)
3	0.94	0.81	0.50	0.46	0.32	−0.61	0.40	0.27	−0.05	−0.06	−0.19	−0.59
	(4.01)	(4.08)	(2.77)	(2.68)	(1.69)	(−3.42)	(3.50)	(3.19)	(−0.69)	(−0.81)	(−1.85)	(−3.28)
4	0.70	0.61	0.63	0.59	0.33	−0.37	0.09	−0.00	0.04	−0.04	−0.31	−0.40
	(2.74)	(2.78)	(3.02)	(2.81)	(1.51)	(−1.83)	(0.73)	(−0.05)	(0.45)	(−0.47)	(−2.54)	(−2.02)
High (H)	0.12	0.53	0.73	0.73	0.71	0.58	−0.49	−0.19	−0.03	0.05	−0.08	0.41
	(0.38)	(1.80)	(2.58)	(2.65)	(2.40)	(2.35)	(−2.98)	(−1.39)	(−0.23)	(0.37)	(−0.46)	(1.71)
Average	0.71	0.66	0.57	0.49	0.29		0.16	0.09	0.00	−0.06	−0.28	
	(3.14)	(3.49)	(3.20)	(2.80)	(1.53)		(1.97)	(2.00)	(0.03)	(−1.29)	(−3.56)	

Panel B: Turnover and volatility characteristics

	Average monthly turnover of stocks (%)					Average monthly volatility of stocks (%)				
L (Low)	2.13	2.07	2.08	2.12	2.15	9.38	7.47	7.23	7.58	9.85
2	4.56	4.56	4.55	4.56	4.58	9.66	7.67	7.44	7.80	10.22
3	6.96	6.91	6.90	6.91	6.97	10.56	8.43	8.15	8.53	11.11
4	10.60	10.45	10.41	10.46	10.61	12.13	9.90	9.62	10.01	12.80
H (High)	26.11	21.57	21.22	21.82	26.95	16.91	13.11	12.75	13.42	18.23

Each panel reports descriptive statistics for a set of 25 value-weighted portfolios. Panel A reports the average monthly excess return and estimated alpha for each portfolio, with heteroskedasticity-robust t-statistics shown in parentheses. To estimate the alpha of a portfolio, we use ordinary least squares to fit a time-series regression of its monthly excess return on the monthly realizations of the four Carhart (1997) factors. Panel B reports the average monthly turnover and average monthly realized volatility of the constituent stocks across all stock-month observations. The portfolio returns for month $t+1$ are for portfolios formed on stock returns and turnover in month t. First, we sort stocks into turnover quintiles. Second, we sort the stocks contained in each turnover quintile into return quintiles. Third, we weight the month $t+1$ excess returns of the stocks in each of the 25 groups in proportion to the stock's month-end market equity for month t. The sorts and portfolios exclude stocks whose market equity is smaller than the 20th percentile of the NYSE market-equity distribution for month t. The sample period is July 1963 to December 2018.

Table 3
Portfolios Formed on Returns After Sorting on Turnover Using Large-Cap Stocks

Panel A: Average excess portfolio returns and estimated four-factor alphas

	Prior return quintile						Prior return quintile					
	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Prior turnover quintile	Average excess return						Estimated four-factor alpha					
Low (L)	0.87	0.58	0.41	0.26	−0.03	−0.90	0.41	0.11	−0.04	−0.17	−0.48	−0.90
	(4.63)	(3.57)	(2.70)	(1.68)	(−0.18)	(−5.82)	(3.66)	(1.15)	(−0.43)	(−1.84)	(−4.93)	(−5.66)
2	0.96	0.70	0.61	0.41	0.18	−0.78	0.45	0.25	0.13	−0.07	−0.26	−0.71
	(4.87)	(3.86)	(3.62)	(2.47)	(1.08)	(−5.07)	(4.22)	(2.97)	(1.69)	(−0.83)	(−2.92)	(−4.55)
3	0.80	0.81	0.56	0.48	0.25	−0.55	0.36	0.29	0.05	−0.01	−0.24	−0.60
	(3.55)	(4.17)	(2.99)	(2.74)	(1.36)	(−3.08)	(3.19)	(3.27)	(0.58)	(−0.08)	(−2.38)	(−3.40)
4	0.68	0.61	0.59	0.54	0.36	−0.32	0.12	0.04	−0.01	−0.07	−0.27	−0.39
	(2.77)	(2.78)	(2.83)	(2.51)	(1.63)	(−1.65)	(1.07)	(0.40)	(−0.12)	(−0.71)	(−2.20)	(−2.04)
High (H)	0.04	0.50	0.64	0.80	0.60	0.56	−0.54	−0.15	−0.02	0.15	−0.13	0.42
	(0.14)	(1.71)	(2.33)	(2.90)	(2.09)	(2.24)	(−3.23)	(−1.09)	(−0.18)	(0.98)	(−0.71)	(1.71)
Average	0.67	0.64	0.56	0.50	0.27		0.16	0.11	0.02	−0.03	−0.28	
	(3.13)	(3.39)	(3.18)	(2.83)	(1.48)		(2.07)	(2.35)	(0.54)	(−0.68)	(−3.48)	

Panel B: Turnover and volatility characteristics

	Average monthly turnover of stocks (%)						Average monthly volatility of stocks (%)					
L (Low)	2.92	2.96	2.97	2.96	2.95		7.61	6.37	6.23	6.46	8.07	
2	5.41	5.36	5.36	5.38	5.41		7.94	6.81	6.67	6.89	8.34	
3	7.59	7.54	7.52	7.55	7.61		8.84	7.59	7.46	7.68	9.25	
4	10.97	10.79	10.79	10.82	10.97		10.29	8.86	8.68	8.96	10.83	
H (High)	24.83	21.04	20.77	21.26	26.11		14.47	11.74	11.50	11.91	15.59	

Each panel reports descriptive statistics for a set of 25 value-weighted portfolios. Panel A reports the average monthly excess return and estimated alpha for each portfolio, with heteroskedasticity-robust t-statistics shown in parentheses. To estimate the alpha of a portfolio, we use ordinary least squares to fit a time-series regression of its monthly excess return on the monthly realizations of the four Carhart (1997) factors. Panel B reports the average monthly turnover and average monthly realized volatility of the constituent stocks across all stock-month observations. The portfolio returns for month $t+1$ are for portfolios formed on stock returns and turnover in month t. First, we sort stocks into turnover quintiles. Second, we sort the stocks contained in each turnover quintile into return quintiles. Third, we weight the month $t+1$ excess returns of the stocks in each of the 25 groups in proportion to the stock's month-end market equity for month t. The sorts and portfolios exclude stocks whose market equity is smaller than the 50th percentile of the NYSE market-equity distribution for month t. The sample period is July 1963 to December 2018.

Table 4
Average Regression Estimates for Turnover and Volatility Deciles

Panel A: Regressions estimated by turnover decile

Regressors in month t	Prior turnover decile using all-but-micro-cap stocks				Prior turnover decile using large-cap stocks			
	1	4	7	10	1	4	7	10
Intercept	0.92	1.06	1.17	0.92	0.89	1.02	1.04	0.90
	(5.67)	(5.68)	(5.22)	(2.87)	(5.70)	(5.96)	(5.10)	(2.98)
R_{t-1}	−0.70	−0.59	−0.35	0.13	−0.55	−0.60	−0.33	0.06
	(−10.14)	(−8.64)	(−5.49)	(2.75)	(−7.36)	(−8.36)	(−5.20)	(1.10)
$\log TURN_{t-1}$	0.04	0.64	−0.01	−0.50	0.07	−0.86	−0.46	−0.40
	(0.91)	(1.64)	(−0.03)	(−3.28)	(1.69)	(−1.87)	(−0.90)	(−2.36)
$\log VOL_{t-1}$	−0.12	−0.14	−0.20	−0.55	−0.14	0.00	−0.19	−0.41
	(−2.40)	(−2.03)	(−2.60)	(−5.84)	(−2.60)	(0.03)	(−2.62)	(−4.29)
$\log ME_{t-1}$	−0.10	−0.13	−0.21	−0.21	−0.06	−0.08	−0.12	−0.07
	(−2.12)	(−2.85)	(−4.07)	(−2.62)	(−1.45)	(−1.98)	(−2.37)	(−0.85)
MOM_{t-1}	0.28	0.37	0.38	0.26	0.19	0.22	0.37	0.29
	(2.91)	(4.33)	(4.58)	(4.38)	(1.85)	(2.22)	(4.40)	(4.85)
R-squared	0.086	0.099	0.088	0.086	0.132	0.131	0.123	0.132

Panel B: Regressions estimated by volatility decile

	Prior volatility decile using all-but-micro-cap stocks				Prior volatility decile using large-cap stocks			
Intercept	0.95	1.21	1.23	0.45	0.90	1.10	1.13	0.54
	(7.31)	(6.64)	(5.36)	(1.27)	(6.90)	(6.42)	(5.38)	(1.66)
R_{t-1}	−0.55	−0.67	−0.32	0.01	−0.53	−0.64	−0.44	0.00
	(−6.62)	(−9.87)	(−5.22)	(0.27)	(−6.32)	(−9.81)	(−6.85)	(0.02)
$\log TURN_{t-1}$	0.08	0.09	0.13	0.02	0.06	0.15	0.22	−0.06
	(2.75)	(1.94)	(2.19)	(0.27)	(1.68)	(2.97)	(3.70)	(−0.78)
$\log VOL_{t-1}$	0.21	−0.07	−0.57	−0.91	0.14	−0.14	−0.08	−0.64
	(4.31)	(−0.21)	(−1.39)	(−6.27)	(2.48)	(−0.34)	(−0.18)	(−4.00)
$\log ME_{t-1}$	−0.07	−0.20	−0.22	−0.21	−0.04	−0.13	−0.18	−0.04
	(−1.97)	(−4.43)	(−3.99)	(−2.20)	(−1.16)	(−3.20)	(−3.83)	(−0.48)
MOM_{t-1}	0.14	0.37	0.32	0.27	0.03	0.23	0.40	0.36
	(1.63)	(4.06)	(3.95)	(3.98)	(0.29)	(2.44)	(4.50)	(5.18)
R-squared	0.085	0.081	0.078	0.075	0.120	0.108	0.112	0.120

We fit the regressions for each month between Jul 1963 and Dec 2018 using selected decile groupings of stocks (1, 4, 7, and 10). The deciles are formed by sorting stocks on either turnover (panel A) or realized volatility (panel B). The dependent variable is the percentage stock return for month t. We use R_{t-1} to denote the stock return for month $t-1$, $\log TURN_{t-1}$ to denote the log turnover for month $t-1$, $\log VOL_{t-1}$ to denote the log realized volatility for month $t-1$, $\log ME_{t-1}$ to denote the log market equity at the end of month $t-1$, and MOM_{t-1} to denote the stock return for the 11-month interval from $t-12$ to $t-2$. Each regressor is standardized on a month-by-month basis (i.e., each variable has a mean of zero and a variance of one in every cross section). The regression for month t excludes stocks for which ME_{t-1} is smaller than either the 20th percentile (all-but-micro-caps) or the 50th percentile (large-caps) of the NYSE market-equity distribution for month $t-1$. We report the average values of the estimated coefficients, Fama and MacBeth (1973) t-statistics (in parentheses), and the average R-squared statistic.

Table 5
Average Regression Estimates for Turnover Deciles by Proportion of News-Driven Turnover

Panel A: Using all-but-micro-cap stocks

Regressors in month t	Prior turnover decile for stocks in low-proportion category 1	4	7	10	Prior turnover decile for stocks in high-proportion category 1	4	7	10
Intercept	0.97	1.08	1.18	1.13	0.89	1.11	1.08	0.76
	(6.01)	(5.88)	(5.61)	(3.67)	(5.28)	(5.63)	(4.53)	(2.27)
R_{t-1}	−0.58	−0.68	−0.59	−0.06	−0.66	−0.48	−0.22	0.22
	(−8.49)	(−9.38)	(−8.56)	(−0.98)	(−6.94)	(−5.52)	(−2.54)	(3.60)
$\log TURN_{t-1}$	0.04	0.62	−0.38	−0.20	0.04	0.30	0.42	−0.52
	(0.82)	(1.18)	(−0.63)	(−1.10)	(0.76)	(0.53)	(0.59)	(−2.26)
$\log VOL_{t-1}$	−0.06	−0.14	−0.13	−0.36	−0.13	−0.17	−0.33	−0.68
	(−1.16)	(−2.16)	(−1.58)	(−3.04)	(−2.05)	(−2.13)	(−3.37)	(−5.72)
$\log ME_{t-1}$	−0.13	−0.13	−0.15	−0.19	−0.08	−0.18	−0.22	−0.26
	(−2.19)	(−2.51)	(−2.73)	(−2.20)	(−1.38)	(−3.65)	(−3.38)	(−2.42)
MOM_{t-1}	0.21	0.29	0.28	0.20	0.39	0.43	0.41	0.31
	(2.05)	(3.00)	(3.32)	(2.84)	(3.06)	(3.71)	(4.14)	(4.39)
R-squared	0.125	0.132	0.130	0.132	0.125	0.129	0.121	0.123

Panel B: Using large-cap stocks

Regressors in month t	Low-proportion 1	4	7	10	High-proportion 1	4	7	10
Intercept	0.93	1.07	1.13	1.05	0.85	0.98	1.01	0.78
	(5.82)	(6.25)	(5.76)	(3.60)	(5.41)	(5.43)	(4.71)	(2.47)
R_{t-1}	−0.47	−0.55	−0.37	−0.09	−0.54	−0.56	−0.18	0.11
	(−5.85)	(−6.56)	(−4.77)	(−1.45)	(−5.18)	(−5.91)	(−2.11)	(1.64)
$\log TURN_{t-1}$	0.10	0.12	−0.85	−0.08	0.08	0.65	1.23	−0.54
	(1.75)	(0.18)	(−1.10)	(−0.42)	(1.21)	(0.89)	(1.59)	(−2.13)
$\log VOL_{t-1}$	−0.13	−0.06	−0.02	−0.30	−0.08	0.03	−0.32	−0.62
	(−1.95)	(−0.74)	(−0.28)	(−2.49)	(−1.19)	(0.39)	(−3.14)	(−4.87)
$\log ME_{t-1}$	−0.02	−0.15	−0.05	−0.15	−0.11	−0.09	−0.17	−0.09
	(−0.35)	(−3.13)	(−0.79)	(−1.62)	(−1.96)	(−1.68)	(−2.46)	(−0.74)
MOM_{t-1}	0.02	0.24	0.21	0.18	0.28	0.16	0.44	0.39
	(0.18)	(1.93)	(2.00)	(2.43)	(1.83)	(1.20)	(4.06)	(4.97)
R-squared	0.203	0.204	0.195	0.197	0.200	0.191	0.187	0.193

We fit the regressions for each month between Jul 1963 and Dec 2018 using selected decile groupings of stocks (1, 4, 7, and 10). The deciles are formed by sorting stocks on turnover. We form two different sets of deciles for each month t: one using stocks for which the estimated correlation between squared demeaned daily returns and daily turnover for month $t-1$ is less than or equal to the median estimated correlation (stocks with a low fraction of news-driven turnover), and one using stocks for which the estimated correlation is greater than the median estimated correlation (stocks with a high fraction of news-driven turnover). The dependent variable is the percentage stock return for month t. We use R_{t-1} to denote the stock return for month $t-1$, $\log TURN_{t-1}$ to denote the log turnover for month $t-1$, $\log VOL_{t-1}$ to denote the log realized volatility for month $t-1$, $\log ME_{t-1}$ to denote the log market equity at the end of month $t-1$, and MOM_{t-1} to denote the stock return for the 11-month interval from $t-12$ to $t-2$. Each regressor is standardized on a month-by-month basis (i.e., each variable has a mean of zero and a variance of one in every cross section). The regression for month t excludes stocks for which ME_{t-1} is smaller than either the 20th percentile (all-but-micro-caps) or the 50th percentile (large-caps) of the NYSE market-equity distribution for month $t-1$. We report the average values of the estimated coefficients, Fama and MacBeth (1973) t-statistics (in parentheses), and the average R-squared statistic.

Table 6
Portfolios Formed on Returns After Sorting on Turnover for Stocks Grouped by Proportion of News-Driven Turnover

Panel A: Average excess portfolios returns using all-but-micro-cap stocks

Prior	Prior return quintile for stocks with a low proportion of news-driven turnover						Prior return quintile for stocks with a high proportion of news-driven turnover					
turnover quintile	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Low (L)	0.98	0.72	0.62	0.41	−0.05	−1.03	0.79	0.45	0.48	0.37	0.03	−0.75
	(4.71)	(4.09)	(3.79)	(2.50)	(−0.28)	(−6.25)	(3.52)	(2.64)	(2.83)	(2.10)	(0.17)	(−3.84)
2	1.06	0.84	0.49	0.28	−0.03	−1.09	0.82	0.83	0.57	0.49	0.12	−0.70
	(4.86)	(4.59)	(2.86)	(1.67)	(−0.16)	(−5.89)	(3.52)	(4.45)	(3.30)	(2.91)	(0.62)	(−3.36)
3	1.14	0.80	0.58	0.28	0.01	−1.13	0.81	0.66	0.75	0.49	0.47	−0.34
	(4.96)	(4.21)	(3.25)	(1.57)	(0.07)	(−6.19)	(3.18)	(3.20)	(3.60)	(2.54)	(2.12)	(−1.51)
4	0.87	0.91	0.63	0.70	0.25	−0.62	0.52	0.75	0.71	0.64	0.31	−0.21
	(3.28)	(4.14)	(3.14)	(3.43)	(1.16)	(−2.81)	(1.85)	(2.96)	(2.96)	(2.64)	(1.31)	(−0.93)
High (H)	0.84	0.97	0.61	0.57	0.49	−0.35	−0.21	0.15	0.55	0.74	0.86	1.06
	(2.56)	(3.54)	(2.27)	(2.23)	(1.79)	(−1.32)	(−0.59)	(0.48)	(1.80)	(2.37)	(2.67)	(3.69)
Average	0.98	0.85	0.59	0.45	0.13		0.55	0.57	0.61	0.55	0.36	
	(4.32)	(4.60)	(3.42)	(2.63)	(0.75)		(2.28)	(2.87)	(3.19)	(2.88)	(1.79)	

Panel B: Average excess portfolios returns using large-cap stocks

Prior	Prior return quintile for stocks with a low proportion of news-driven turnover						Prior return quintile for stocks with a high proportion of news-driven turnover					
turnover quintile	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Low (L)	1.16	0.62	0.57	0.27	−0.02	−1.18	0.68	0.49	0.49	0.42	−0.01	−0.70
	(5.79)	(3.41)	(3.36)	(1.69)	(−0.10)	(−6.61)	(3.36)	(2.82)	(2.95)	(2.48)	(−0.08)	(−3.68)
2	1.06	0.69	0.58	0.17	−0.01	−1.06	0.79	0.65	0.60	0.51	0.31	−0.48
	(5.19)	(3.81)	(3.33)	(0.96)	(−0.03)	(−6.53)	(3.61)	(3.35)	(3.25)	(2.83)	(1.61)	(−2.49)
3	1.05	0.77	0.67	0.38	−0.00	−1.05	0.80	0.73	0.53	0.60	0.44	−0.36
	(4.62)	(3.82)	(3.59)	(2.06)	(−0.02)	(−5.66)	(3.31)	(3.36)	(2.52)	(3.10)	(2.04)	(−1.67)
4	0.84	0.80	0.64	0.59	0.27	−0.56	0.36	0.68	0.63	0.57	0.33	−0.03
	(3.26)	(3.67)	(3.15)	(2.90)	(1.26)	(−2.59)	(1.29)	(2.82)	(2.64)	(2.27)	(1.35)	(−0.13)
High (H)	0.84	0.79	0.59	0.57	0.49	−0.35	−0.12	0.25	0.50	0.72	0.94	1.06
	(2.59)	(2.85)	(2.15)	(2.15)	(1.78)	(−1.34)	(−0.35)	(0.79)	(1.65)	(2.36)	(3.00)	(3.72)
Average	0.99	0.73	0.61	0.40	0.15		0.50	0.56	0.55	0.56	0.40	
	(4.56)	(4.01)	(3.55)	(2.33)	(0.82)		(2.23)	(2.82)	(2.88)	(3.01)	(2.05)	

Each panel reports average excess returns for two sets of 25 value-weighted portfolios. The portfolio returns for month $t+1$ are for portfolios formed on stock returns and turnover in month t. First, we use the estimated correlation between squared demeaned daily returns and daily turnover for month t to partition stocks into two categories: those which have an estimated correlation that is less than or equal to the median estimated correlation (stocks with a low fraction of news-driven turnover) and those that have an estimated correlation that is greater than the median estimated correlation (stocks with a high fraction of news-driven turnover). Second, we sort stocks contained in each category into turnover quintiles. Third, we sort the stocks contained in each turnover quintile into return quintiles. Fourth, we weight the month $t+1$ excess returns of the stocks in each of the two sets of 25 groups in proportion to the stock's month-end market equity for month t. The sorts and portfolios exclude stocks whose market equity is smaller than either the 20th percentile (panel A) or the 50th percentile (panel B) of the NYSE market-equity distribution for month t. The sample period is July 1963 to December 2018.

Table 7
Average Regressions Estimates by Turnover Decile Using Anomaly Variables as Controls

Regressors	Prior turnover decile using all-but-micro-cap stocks				Prior turnover decile using large-cap stocks			
in month t	1	4	7	10	1	4	7	10
Intercept	0.91	1.08	1.18	0.93	0.87	1.05	1.05	0.91
	(4.61)	(5.14)	(4.77)	(2.63)	(4.44)	(5.43)	(4.61)	(2.70)
R_{t-1}	−0.71	−0.64	−0.42	0.05	−0.68	−0.65	−0.39	0.05
	(−7.49)	(−8.03)	(−5.78)	(0.88)	(−6.94)	(−7.11)	(−4.75)	(0.75)
$\log TURN_{t-1}$	0.01	0.01	−0.14	−0.52	0.03	−1.39	0.37	−0.21
	(0.23)	(0.01)	(−0.28)	(−2.90)	(0.41)	(−2.41)	(0.59)	(−1.04)
$\log VOL_{t-1}$	−0.00	−0.08	−0.20	−0.41	−0.12	−0.01	−0.11	−0.38
	(−0.02)	(−1.09)	(−2.31)	(−4.11)	(−1.57)	(−0.17)	(−1.40)	(−3.65)
$\log ME_{t-1}$	−0.00	−0.09	−0.19	−0.18	−0.09	−0.06	−0.10	−0.18
	(−0.06)	(−1.60)	(−3.12)	(−2.11)	(−1.56)	(−1.21)	(−1.60)	(−1.98)
MOM_{t-1}	0.29	0.31	0.35	0.23	0.12	0.14	0.31	0.25
	(2.16)	(3.29)	(3.84)	(3.77)	(0.85)	(1.25)	(2.79)	(3.79)
BTM_{t-1}	0.22	0.28	0.13	0.21	0.29	0.14	0.11	0.30
	(4.09)	(3.50)	(1.53)	(2.03)	(3.29)	(1.64)	(1.41)	(2.41)
AG_{t-1}	−0.03	−0.16	0.08	−0.08	0.03	0.05	0.14	−0.12
	(−0.21)	(−1.60)	(0.86)	(−0.88)	(0.19)	(0.41)	(1.16)	(−1.08)
ROA_{t-1}	0.60	0.25	−0.12	0.17	−0.10	0.10	0.08	0.11
	(3.01)	(1.76)	(−0.89)	(1.80)	(−0.24)	(0.38)	(0.46)	(1.06)
GP_{t-1}	0.11	0.10	0.09	0.01	0.14	0.01	0.13	−0.00
	(2.02)	(1.71)	(1.28)	(0.11)	(2.05)	(0.10)	(1.66)	(−0.02)
NOA_{t-1}	−0.13	−0.18	−0.25	−0.19	0.02	−0.13	−0.19	−0.04
	(−1.25)	(−1.69)	(−2.51)	(−2.09)	(0.10)	(−0.96)	(−1.55)	(−0.36)
ITA_{t-1}	−0.06	0.12	−0.03	−0.09	−0.06	0.01	−0.20	0.02
	(−0.59)	(1.36)	(−0.33)	(−1.14)	(−0.44)	(0.09)	(−1.89)	(0.23)
ACC_{t-1}	−0.13	−0.10	−0.05	−0.17	−0.14	−0.04	−0.01	−0.16
	(−2.09)	(−1.78)	(−0.92)	(−3.22)	(−1.85)	(−0.58)	(−0.22)	(−2.44)
NNS_{t-1}	−0.07	−0.01	−0.06	−0.06	0.25	0.01	−0.04	−0.11
	(−0.66)	(−0.16)	(−0.75)	(−0.82)	(1.64)	(0.08)	(−0.43)	(−1.11)
OSC_{t-1}	0.08	0.03	−0.00	−0.10	0.05	−0.13	0.12	−0.07
	(1.00)	(0.33)	(−0.04)	(−1.00)	(0.55)	(−1.20)	(1.10)	(−0.61)
R-squared	0.229	0.215	0.198	0.193	0.362	0.329	0.302	0.307

We fit the regressions for each month between Jan 1973 and Dec 2018 using selected decile groupings of stocks (1, 4, 7, and 10). The deciles are formed by sorting stocks on turnover. The dependent variable is the percentage stock return for month t. We use R_{t-1} to denote the stock return for month $t-1$, $\log TURN_{t-1}$ to denote the log turnover for month $t-1$, $\log VOL_{t-1}$ to denote the log realized volatility for month $t-1$, $\log ME_{t-1}$to denote the log market equity at the end of month $t-1$, MOM_{t-1} to denote the stock return for the 11-month interval from $t-12$ to $t-2$, $BTM_{t-1}$to denote the book-to-market equity ratio for month $t-1$, AG_{t-1} to denote the annual growth rate of total assets for month $t-1$, ROA_{t-1} to denote the ratio of annual earnings to beginning-of-year total assets for month $t-1$, GP_{t-1} to denote revenues minus cost of goods sold (as a fraction of end-of-year total assets) for month $t-1$, NOA_{t-1} to denote operating assets minus operating liabilities (as a fraction of beginning-of-year total assets) for month $t-1$, ITA_{t-1} to denote the annual change in gross property, plant, and equipment plus the annual change in inventories (as a fraction of beginning-of-year total assets) for month $t-1$, ACC_{t-1} to denote the annual change in non-cash working capital minus depreciation expense (as a fraction of average total assets for the year) for month $t-1$, NNS_{t-1} to denote the annual growth rate of the split-adjusted shares outstanding for month $t-1$, and OSC_{t-1} to denote the estimated probability of bankruptcy from Ohlson (1980). Each regressor is standardized on a month-by-month basis (i.e., each variable has a mean of zero and a variance of one in every cross section). The regression for month t excludes stocks for which ME_{t-1} is smaller than either the 20th percentile (all-but-micro-caps) or the 50th percentile (large-caps) of the NYSE market-equity distribution for month $t-1$. We report the average values of the estimated coefficients, Fama and MacBeth (1973) t-statistics (in parentheses), and the average R-squared statistic.

Table 8
Portfolios Formed on Returns After Sorting on Turnover for Stocks Grouped by Liquidity

Panel A: Average excess portfolios returns using all-but-micro-cap stocks

Prior	Prior return quintile for low-liquidity stocks						Prior return quintile for high-liquidity stocks					
turnover quintile	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Low (L)	0.87	0.71	0.60	0.36	0.01	−0.86	1.16	0.87	0.62	0.45	−0.09	−1.25
	(2.61)	(2.85)	(2.58)	(1.54)	(0.04)	(−3.23)	(4.19)	(3.76)	(2.83)	(2.09)	(−0.36)	(−4.55)
2	1.02	1.06	0.57	0.64	0.05	−0.97	0.82	0.90	0.57	0.48	0.43	−0.39
	(2.77)	(3.84)	(2.08)	(2.38)	(0.16)	(−3.33)	(2.33)	(3.07)	(2.41)	(2.11)	(1.75)	(−1.27)
3	0.88	0.92	0.68	0.52	0.06	−0.82	0.78	0.83	0.60	0.55	0.47	−0.32
	(2.35)	(2.77)	(2.33)	(1.75)	(0.19)	(−2.59)	(1.96)	(2.70)	(2.00)	(2.00)	(1.34)	(−0.84)
4	0.81	0.94	0.88	0.44	0.71	−0.09	0.66	0.85	0.95	0.65	0.33	−0.33
	(1.95)	(2.71)	(2.84)	(1.36)	(2.08)	(−0.28)	(1.53)	(2.30)	(2.70)	(1.81)	(0.90)	(−0.88)
High (H)	0.51	0.58	0.53	0.42	0.58	0.06	−0.35	0.28	0.85	0.92	0.84	1.18
	(0.94)	(1.28)	(1.23)	(1.04)	(1.19)	(0.13)	(−0.65)	(0.55)	(1.68)	(1.81)	(1.71)	(2.64)
Average	0.82	0.84	0.65	0.48	0.28		0.62	0.74	0.72	0.61	0.39	
	(2.21)	(2.86)	(2.41)	(1.77)	(0.93)		(1.74)	(2.52)	(2.63)	(2.23)	(1.35)	

Panel B: Average excess portfolios returns using large-cap stocks

Prior	Prior return quintile for low-liquidity stocks						Prior return quintile for high-liquidity stocks					
turnover quintile	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Low (L)	0.99	0.86	0.50	0.30	0.21	−0.78	0.91	0.89	0.52	0.31	−0.02	−0.93
	(3.31)	(3.42)	(1.92)	(1.19)	(0.73)	(−2.85)	(3.24)	(3.82)	(2.45)	(1.47)	(−0.09)	(−3.61)
2	1.22	0.80	0.77	0.51	0.01	−1.22	0.91	0.85	0.66	0.24	0.62	−0.29
	(3.98)	(2.79)	(2.84)	(1.91)	(0.02)	(−4.77)	(2.66)	(2.85)	(2.54)	(0.91)	(2.39)	(−0.97)
3	0.97	0.76	0.93	0.83	0.24	−0.74	0.78	0.78	0.63	0.50	0.25	−0.53
	(2.79)	(2.35)	(3.25)	(2.82)	(0.80)	(−2.65)	(2.01)	(2.27)	(2.06)	(1.74)	(0.68)	(−1.45)
4	0.47	0.52	0.53	0.58	0.33	−0.14	0.78	1.04	1.08	0.55	0.50	−0.28
	(1.16)	(1.45)	(1.64)	(1.69)	(0.92)	(−0.41)	(1.84)	(2.79)	(2.66)	(1.48)	(1.28)	(−0.73)
High (H)	0.27	0.82	0.48	0.80	0.68	0.41	−0.21	0.52	0.89	0.58	0.88	1.09
	(0.54)	(1.80)	(1.13)	(2.15)	(1.52)	(0.90)	(−0.38)	(0.98)	(1.75)	(1.08)	(1.69)	(2.24)
Average	0.79	0.75	0.64	0.61	0.29		0.63	0.82	0.75	0.44	0.45	
	(2.41)	(2.59)	(2.43)	(2.30)	(1.03)		(1.83)	(2.71)	(2.63)	(1.54)	(1.48)	

Each panel reports average excess returns for two sets of 25 value-weighted portfolios. The portfolio returns for month $t+1$ are for portfolios formed on stock returns and turnover in month t. First, we use the number of daily returns that are zero for month t to partition stocks into two categories: those for which the monthly average of the daily proportional bid-ask spread is less than or equal to its median value for the month (high-liquidity stocks) and those for which the monthly average of the daily proportional bid-ask spread is greater than its median value for the month (low-liquidity stocks). Second, we sort stocks contained in each category into turnover quintiles. Third, we sort the stocks contained in each turnover quintile into return quintiles. Fourth, we weight the month $t+1$ excess returns of the stocks in each of the two sets of 25 groups in proportion to the stock's month-end market equity for month t. The sorts and portfolios exclude stocks whose market equity is smaller than either the 20th percentile (panel A) or the 50th percentile (panel B) of the NYSE market-equity distribution for month t. The sample period is January 1993 to December 2018.

Table 9
Average Regression Estimates for Turnover and Spread-Based Liquidity Deciles

Panel A: Regressions by turnover decile

Regressors in month t	Prior turnover decile using low-liquidity stocks				Prior turnover decile using high-liquidity stocks			
	1	4	7	10	1	4	7	10
Intercept	0.82	0.99	1.10	0.92	1.00	0.96	0.93	0.76
	(3.50)	(3.47)	(3.36)	(1.92)	(4.80)	(3.92)	(2.87)	(1.43)
R_{t-1}	−0.65	−0.34	−0.23	−0.01	−0.69	−0.37	−0.21	0.16
	(−4.15)	(−2.39)	(−1.58)	(−0.15)	(−4.84)	(−3.09)	(−1.96)	(1.94)
$TURN_{t-1}$	−0.14	−1.80	−0.35	−0.59	0.09	0.03	−0.61	−0.55
	(−1.52)	(−2.00)	(−0.32)	(−1.56)	(0.99)	(0.04)	(−0.69)	(−2.00)
$SPREAD_{t-1}$	−0.07	0.02	0.58	−0.20	0.12	0.03	0.06	−0.18
	(−1.34)	(0.16)	(1.95)	(−0.79)	(2.15)	(0.49)	(0.75)	(−1.47)
$\log VOL_{t-1}$	−0.22	−0.23	−0.39	−0.31	−0.17	−0.25	−0.19	−0.35
	(−2.43)	(−1.89)	(−2.99)	(−1.79)	(−2.03)	(−1.80)	(−1.27)	(−1.98)
$\log ME_{t-1}$	−0.16	−0.18	−0.21	−0.06	−0.04	−0.09	−0.13	−0.21
	(−1.61)	(−2.32)	(−2.65)	(−0.53)	(−0.55)	(−1.31)	(−1.40)	(−1.41)
MOM_{t-1}	0.20	0.20	−0.00	0.08	0.06	0.28	0.24	0.15
	(1.07)	(1.31)	(−0.01)	(0.63)	(0.30)	(1.70)	(1.68)	(1.36)
R-squared	0.132	0.113	0.119	0.128	0.129	0.130	0.126	0.127

Panel B: Regressions by spread-based liquidity decile

	Prior liquidity decile using low-turnover stocks				Prior liquidity decile using high-turnover stocks			
Intercept	0.88	1.07	0.98	0.81	0.97	1.01	0.98	1.04
	(4.32)	(4.32)	(3.52)	(2.79)	(2.44)	(2.77)	(2.71)	(2.25)
R_{t-1}	−0.45	−0.32	−0.25	−0.29	0.01	−0.08	−0.15	0.02
	(−4.32)	(−3.59)	(−2.60)	(−3.38)	(0.06)	(−0.60)	(−1.15)	(0.15)
$TURN_{t-1}$	0.14	0.20	0.13	0.00	−0.20	−0.27	0.05	0.04
	(1.59)	(2.47)	(1.61)	(0.03)	(−1.76)	(−2.61)	(0.44)	(0.31)
$SPREAD_{t-1}$	0.93	2.80	0.18	−0.06	−3.58	0.21	−1.13	0.07
	(0.78)	(1.37)	(0.13)	(−0.98)	(−2.50)	(0.10)	(−0.89)	(0.71)
$\log VOL_{t-1}$	−0.04	−0.13	−0.20	−0.24	−0.10	−0.23	−0.32	−0.42
	(−0.45)	(−1.27)	(−1.66)	(−2.10)	(−0.73)	(−1.49)	(−2.14)	(−2.47)
$\log ME_{t-1}$	−0.03	−0.11	−0.26	−0.25	−0.21	−0.31	−0.19	−0.02
	(−0.41)	(−1.29)	(−2.11)	(−1.56)	(−1.83)	(−2.80)	(−1.55)	(−0.14)
MOM_{t-1}	0.16	0.20	0.16	0.02	0.35	0.37	0.52	0.36
	(1.48)	(1.67)	(1.39)	(0.13)	(1.99)	(2.34)	(2.85)	(1.58)
R-squared	0.140	0.123	0.114	0.118	0.154	0.134	0.123	0.123

We fit the regressions for each month between Jan 1993 and Dec 2018 using selected decile groupings of stocks (1, 4, 7, and 10). The deciles are formed by sorting stocks on either turnover (panel A) or a spread-based liquidity proxy (panel B). In each case, we form two different sets of deciles for each month t: one using stocks for which the alternative sorting characteristic (the spread in panel A and turnover in panel B) is less than or equal to its median value, and one using stocks for which this characteristic is above its median value. The dependent variable is the percentage stock return for month t. We use R_{t-1} to denote the stock return for month $t-1$, $SPREAD_{t-1}$ to denote the average value of the daily percentage bid-ask spread for month $t-1$, $\log TURN_{t-1}$ to denote the log turnover for month $t-1$, $\log VOL_{t-1}$ to denote the log realized volatility for month $t-1$, $\log ME_{t-1}$ to denote the log market equity at the end of month $t-1$, and MOM_{t-1} to denote the stock return for the 11-month interval from $t-12$ to $t-2$. Each regressor is standardized on a month-by-month basis (i.e., each variable has a mean of zero and a variance of one in every cross section). The regression for month t excludes stocks for which ME_{t-1} is smaller than the 20th percentile of the NYSE market-equity distribution for month $t-1$. We report the average values of the estimated coefficients, Fama and MacBeth (1973) t-statistics (in parentheses), and the average R-squared statistic.

Table 10

Portfolios Formed on Returns After Sorting on Turnover For Stocks Grouped by Liquidity and Proportion of News-Driven Turnover

Panel A: Average excess portfolios returns using low-liquidity stocks

Prior	Prior return quintile for stocks with a low proportion of news-driven turnover						Prior return quintile for stocks with a high proportion of news-driven turnover					
turnover quintile	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Low (L)	0.76	0.84	0.61	0.42	−0.02	−0.78	0.64	0.52	0.39	0.49	0.21	−0.42
	(2.19)	(3.11)	(2.50)	(1.73)	(−0.07)	(−2.59)	(1.64)	(1.89)	(1.50)	(1.84)	(0.64)	(−1.23)
2	1.11	1.12	0.70	0.63	−0.08	−1.19	0.59	0.73	0.77	0.49	0.12	−0.47
	(2.88)	(3.97)	(2.67)	(2.26)	(−0.25)	(−3.67)	(1.49)	(2.21)	(2.49)	(1.58)	(0.33)	(−1.36)
3	1.24	0.76	0.89	0.47	−0.32	−1.55	0.70	1.09	0.61	0.98	0.55	−0.14
	(3.21)	(2.39)	(3.10)	(1.57)	(−0.93)	(−4.60)	(1.69)	(2.87)	(1.76)	(2.91)	(1.58)	(−0.38)
4	1.08	0.60	0.96	0.49	0.31	−0.77	0.89	0.92	0.38	0.12	0.40	−0.50
	(2.62)	(1.75)	(2.94)	(1.55)	(0.87)	(−2.17)	(1.79)	(2.34)	(1.02)	(0.32)	(1.03)	(−1.14)
High (H)	1.18	0.68	0.81	0.66	0.66	−0.52	0.57	−0.10	0.32	0.79	0.83	0.27
	(2.10)	(1.61)	(2.12)	(1.60)	(1.45)	(−1.10)	(0.96)	(−0.21)	(0.65)	(1.70)	(1.53)	(0.48)
Average	1.07	0.80	0.79	0.54	0.11		0.68	0.63	0.49	0.57	0.42	
	(2.91)	(2.84)	(3.11)	(2.04)	(0.37)		(1.71)	(1.94)	(1.65)	(1.98)	(1.29)	

Panel B: Average excess portfolios returns using high-liquidity stocks

Prior turnover quintile	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Low (L)	1.30	0.69	0.68	0.64	−0.01	−1.31	0.78	0.57	0.60	0.49	0.12	−0.66
	(4.42)	(2.66)	(2.82)	(2.41)	(−0.03)	(−4.26)	(2.30)	(2.29)	(2.59)	(2.15)	(0.47)	(−1.85)
2	1.20	0.76	0.52	0.18	−0.03	−1.23	0.81	0.82	0.62	0.52	0.71	−0.09
	(3.48)	(2.93)	(2.10)	(0.65)	(−0.11)	(−4.14)	(2.05)	(2.67)	(2.10)	(2.04)	(2.22)	(−0.24)
3	1.39	1.07	0.80	0.55	0.06	−1.33	0.54	0.67	0.70	0.59	0.22	−0.32
	(3.59)	(3.08)	(2.98)	(1.98)	(0.20)	(−3.52)	(1.21)	(1.95)	(2.07)	(1.86)	(0.59)	(−0.76)
4	1.03	0.93	0.89	0.57	0.22	−0.81	0.33	0.95	1.18	0.87	0.49	0.17
	(2.40)	(2.74)	(2.76)	(1.71)	(0.66)	(−2.02)	(0.69)	(2.22)	(2.71)	(2.17)	(1.27)	(0.40)
High (H)	0.54	1.20	0.56	0.42	0.67	0.13	−0.50	0.01	0.72	0.73	1.13	1.63
	(0.95)	(2.54)	(1.17)	(0.96)	(1.39)	(0.29)	(−0.89)	(0.01)	(1.29)	(1.21)	(2.10)	(3.11)
Average	1.09	0.93	0.69	0.47	0.18		0.39	0.60	0.76	0.64	0.54	
	(3.09)	(3.35)	(2.75)	(1.83)	(0.67)		(1.02)	(1.92)	(2.47)	(2.14)	(1.68)	

Each panel reports average excess returns for two sets of 25 value-weighted portfolios. The portfolio returns for month $t+1$ are for portfolios formed on stock returns and turnover in month t. First, we use the estimated correlation between squared demeaned daily returns and daily turnover for month t to partition stocks into two categories: those which have an estimated correlation that is less than or equal to the median estimated correlation (stocks with a low fraction of news-driven turnover) and those that have an estimated correlation that is greater than the median estimated correlation (stocks with a high fraction of news-driven turnover). Second, we sort stocks contained in each category into turnover quintiles. Third, we sort the stocks contained in each turnover quintile into return quintiles. Fourth, we weight the month $t+1$ excess returns of the stocks in each of the two sets of 25 groups in proportion to the stock's month-end market equity for month t. The sorts and portfolios exclude stocks whose market equity is smaller than either the 20th percentile (panel A) or the 50th percentile (panel B) of the NYSE market-equity distribution for month t. The sample period is July 1963 to December 2018.

Table 11
Portfolios Formed on Returns After Sorting on Turnover for the 1999 to 2018 Sample Period

Panel A: Average excess portfolios returns using all-but-micro-cap stocks

Prior turnover quintile	Prior return quintile for stocks with a low proportion of news-driven turnover						Prior return quintile for stocks with a high proportion of news-driven turnover					
	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Low (L)	0.86	0.89	0.81	0.63	−0.05	−0.91	0.72	0.67	0.30	0.31	−0.01	−0.74
	(2.24)	(2.88)	(2.72)	(2.23)	(−0.16)	(−2.76)	(1.69)	(2.43)	(1.06)	(1.07)	(−0.04)	(−1.89)
2	1.06	0.89	0.39	0.21	−0.15	−1.21	0.45	0.74	0.43	0.52	0.08	−0.37
	(2.68)	(3.03)	(1.39)	(0.74)	(−0.43)	(−3.12)	(1.08)	(2.36)	(1.58)	(2.00)	(0.24)	(−0.88)
3	0.95	0.77	0.63	0.16	0.17	−0.79	0.67	0.67	0.57	0.63	0.62	−0.05
	(2.47)	(2.48)	(2.31)	(0.53)	(0.50)	(−2.22)	(1.52)	(1.95)	(1.69)	(2.01)	(1.48)	(−0.10)
4	0.52	0.99	0.81	0.41	0.02	−0.51	0.44	0.61	0.83	0.71	0.33	−0.11
	(1.07)	(2.54)	(2.50)	(1.22)	(0.05)	(−1.09)	(0.83)	(1.43)	(2.05)	(1.60)	(0.78)	(−0.22)
High (H)	0.68	0.72	0.18	0.32	0.58	−0.11	−0.26	−0.48	0.30	0.86	1.02	1.28
	(1.08)	(1.44)	(0.36)	(0.68)	(1.13)	(−0.20)	(−0.40)	(−0.84)	(0.55)	(1.43)	(1.61)	(2.00)
Average	0.82	0.85	0.56	0.35	0.11		0.40	0.44	0.49	0.61	0.41	
	(1.99)	(2.80)	(2.04)	(1.23)	(0.35)		(0.92)	(1.35)	(1.57)	(1.90)	(1.13)	

Panel B: Average excess portfolios returns using large-cap stocks

Prior turnover quintile	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Low (L)	1.02	0.47	0.61	0.34	−0.07	−1.09	0.59	0.38	0.44	0.31	−0.07	−0.66
	(3.05)	(1.59)	(2.10)	(1.26)	(−0.24)	(−3.25)	(1.78)	(1.38)	(1.58)	(1.20)	(−0.23)	(−1.99)
2	1.10	0.72	0.88	−0.16	−0.17	−1.27	0.70	0.70	0.33	0.72	0.57	−0.13
	(3.26)	(2.54)	(3.20)	(−0.50)	(−0.56)	(−4.21)	(1.87)	(2.02)	(1.07)	(2.54)	(1.84)	(−0.35)
3	0.85	0.77	0.71	0.56	0.03	−0.82	0.41	0.71	0.28	0.76	0.32	−0.09
	(2.19)	(2.16)	(2.18)	(1.76)	(0.08)	(−2.24)	(0.94)	(1.98)	(0.79)	(2.32)	(0.79)	(−0.20)
4	0.35	0.70	0.84	0.41	−0.09	−0.44	0.09	0.44	0.68	0.75	0.33	0.25
	(0.74)	(1.88)	(2.47)	(1.11)	(−0.22)	(−0.98)	(0.16)	(1.05)	(1.65)	(1.51)	(0.73)	(0.49)
High (H)	0.49	0.80	0.31	0.25	0.56	0.07	−0.41	−0.24	0.34	0.93	1.09	1.50
	(0.76)	(1.48)	(0.59)	(0.50)	(1.05)	(0.12)	(−0.65)	(−0.38)	(0.61)	(1.57)	(1.76)	(2.41)
Average	0.76	0.69	0.67	0.28	0.05		0.27	0.40	0.41	0.69	0.45	
	(1.98)	(2.28)	(2.34)	(0.97)	(0.16)		(0.68)	(1.16)	(1.30)	(2.17)	(1.29)	

Each panel reports average excess returns for two sets of 25 value-weighted portfolios. The portfolio returns for month $t+1$ are for portfolios formed on stock returns and turnover in month t. First, we use the estimated correlation between squared demeaned daily returns and daily turnover for month t to partition stocks into two categories: those which have an estimated correlation that is less than or equal to the median estimated correlation (stocks with a low fraction of news-driven turnover) and those that have an estimated correlation that is greater than the median estimated correlation (stocks with a high fraction of news-driven turnover). Second, we sort stocks contained in each category into turnover quintiles. Third, we sort the stocks contained in each turnover quintile into return quintiles. Fourth, we weight the month $t+1$ excess returns of the stocks in each of the two sets of 25 groups in proportion to the stock's month-end market equity for month t. The sorts and portfolios exclude stocks whose market equity is smaller than either the 20th percentile (panel A) or the 50th percentile (panel B) of the NYSE market-equity distribution for month t. The sample period is January 1999 to December 2018.

Table 12
Portfolios Formed on Returns After Sorting on Turnover Using Micro-Cap Stocks

Panel A: Average excess portfolio returns and estimated four-factor alphas

	Prior return quintile						Prior return quintile					
	L	2	3	4	H	H−L	L	2	3	4	H	H−L
Prior turnover quintile	Average excess return						Estimated four-factor alpha					
Low (L)	1.21	0.58	0.47	0.47	−0.27	−1.48	0.60	−0.01	−0.05	−0.06	−0.85	−1.45
	(4.77)	(3.06)	(2.81)	(2.92)	(−1.52)	(−8.85)	(4.17)	(−0.14)	(−0.52)	(−0.64)	(−7.95)	(−9.25)
2	1.55	0.98	0.79	0.68	−0.25	−1.80	0.88	0.30	0.11	−0.02	−0.93	−1.81
	(5.37)	(4.17)	(3.74)	(3.31)	(−1.18)	(−10.07)	(5.94)	(2.72)	(1.04)	(−0.19)	(−8.40)	(−10.45)
3	1.54	1.09	0.82	0.65	−0.31	−1.84	0.86	0.35	0.06	−0.10	−1.03	−1.89
	(4.68)	(3.97)	(3.35)	(2.78)	(−1.26)	(−9.28)	(5.21)	(3.08)	(0.62)	(−0.98)	(−9.22)	(−10.01)
4	1.66	1.06	0.91	0.65	−0.05	−1.71	1.02	0.32	0.17	−0.14	−0.75	−1.77
	(4.52)	(3.39)	(3.24)	(2.47)	(−0.19)	(−8.01)	(6.00)	(2.38)	(1.57)	(−1.47)	(−6.07)	(−8.59)
High (H)	1.05	0.87	0.83	0.59	0.37	−0.68	0.46	0.13	0.01	−0.24	−0.40	−0.85
	(2.48)	(2.39)	(2.45)	(1.76)	(1.09)	(−2.50)	(2.16)	(0.81)	(0.09)	(−1.72)	(−2.31)	(−3.27)
Average	1.40	0.91	0.77	0.61	−0.10		0.76	0.22	0.06	−0.11	−0.79	
	(4.45)	(3.51)	(3.25)	(2.71)	(−0.44)		(5.87)	(2.40)	(0.76)	(−1.65)	(−9.24)	

Panel B: Turnover and size characteristics

	Average monthly turnover of stocks (%)						Average market equity of stocks ($ billions)				
Low (L)	0.49	0.45	0.41	0.45	0.48		0.03	0.05	0.04	0.05	0.05
2	1.34	1.32	1.31	1.33	1.35		0.04	0.06	0.07	0.07	0.06
3	2.59	2.56	2.56	2.57	2.60		0.05	0.07	0.08	0.08	0.07
4	4.81	4.75	4.74	4.76	4.86		0.06	0.09	0.10	0.10	0.08
High (H)	18.72	13.56	13.23	14.03	21.22		0.08	0.10	0.11	0.11	0.09

The table reports descriptive statistics for a set of 25 value-weighted portfolios. Panel A reports the average monthly excess return and estimated four-factor alpha for each portfolio, with heteroskedasticity-robust t-statistics shown in parentheses. To estimate the alpha of a portfolio, we use ordinary least squares to fit a time-series regression of its monthly excess return on the monthly realizations of the four Carhart (1997) factors. Panel B reports the average monthly turnover and average market equity of the constituent stocks across all stock-month observations. The portfolio returns for month $t+1$ are for portfolios formed on stock returns and turnover in month t. First, we sort stocks into turnover quintiles. Second, we sort the stocks contained in each turnover quintile into return quintiles. Third, we weight the month $t+1$ excess returns of the stocks in each of the 25 groups in proportion to the stock's month-end market equity for month t. The sorts and portfolios only include stocks whose market equity is smaller than the 20th percentile of the NYSE market-equity distribution for month t. The sample period is July 1963 to December 2018.

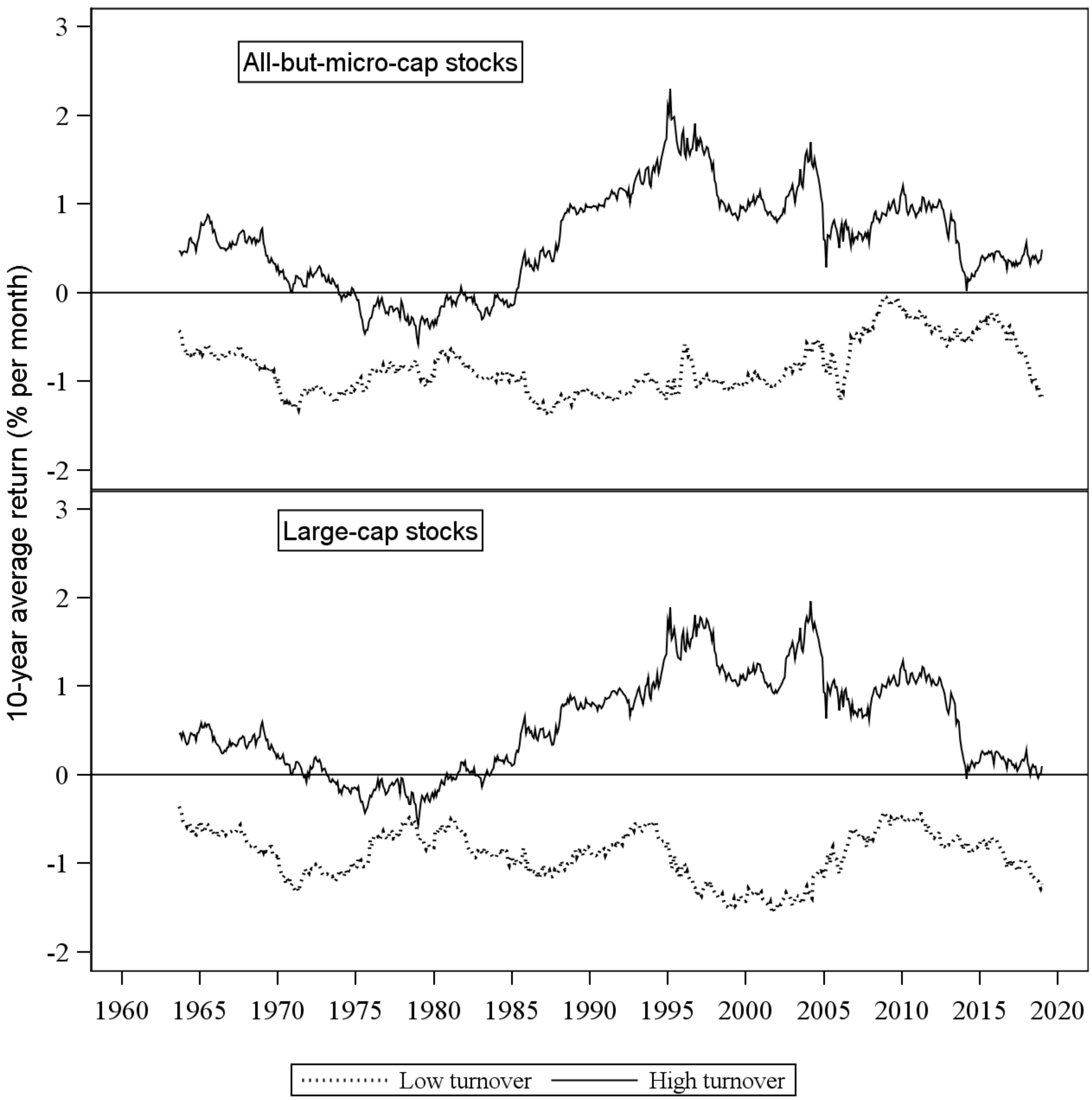

Figure 1. Rolling average returns for WML portfolios
The figure plots rolling 10-year average returns for winners-minus-losers (WML) portfolios that are formed using stocks that fall into the bottom and top quintiles of prior turnover. The sample period is July 1963 to December 2018. We compute the rolling average returns for month t by averaging the returns for months $t-59$ to $t+60$. The length of the window is reduced as necessary to account for the lack of observations near the beginning and end of the sample (i.e., for months 1 to 59 and 607 to 666). For example, the average returns for July 1963 are computed using a forward-looking window of 61 observations and those for December 2018 are computed using a backward-looking window of 60 observations. The top panel is for all-but-micro-cap stocks (market equity equal to or greater than the 20th percentile of the NYSE market equity distribution) and the bottom panel is for large-cap stocks (market equity equal to or greater than the 50th percentile of the NYSE market equity distribution).

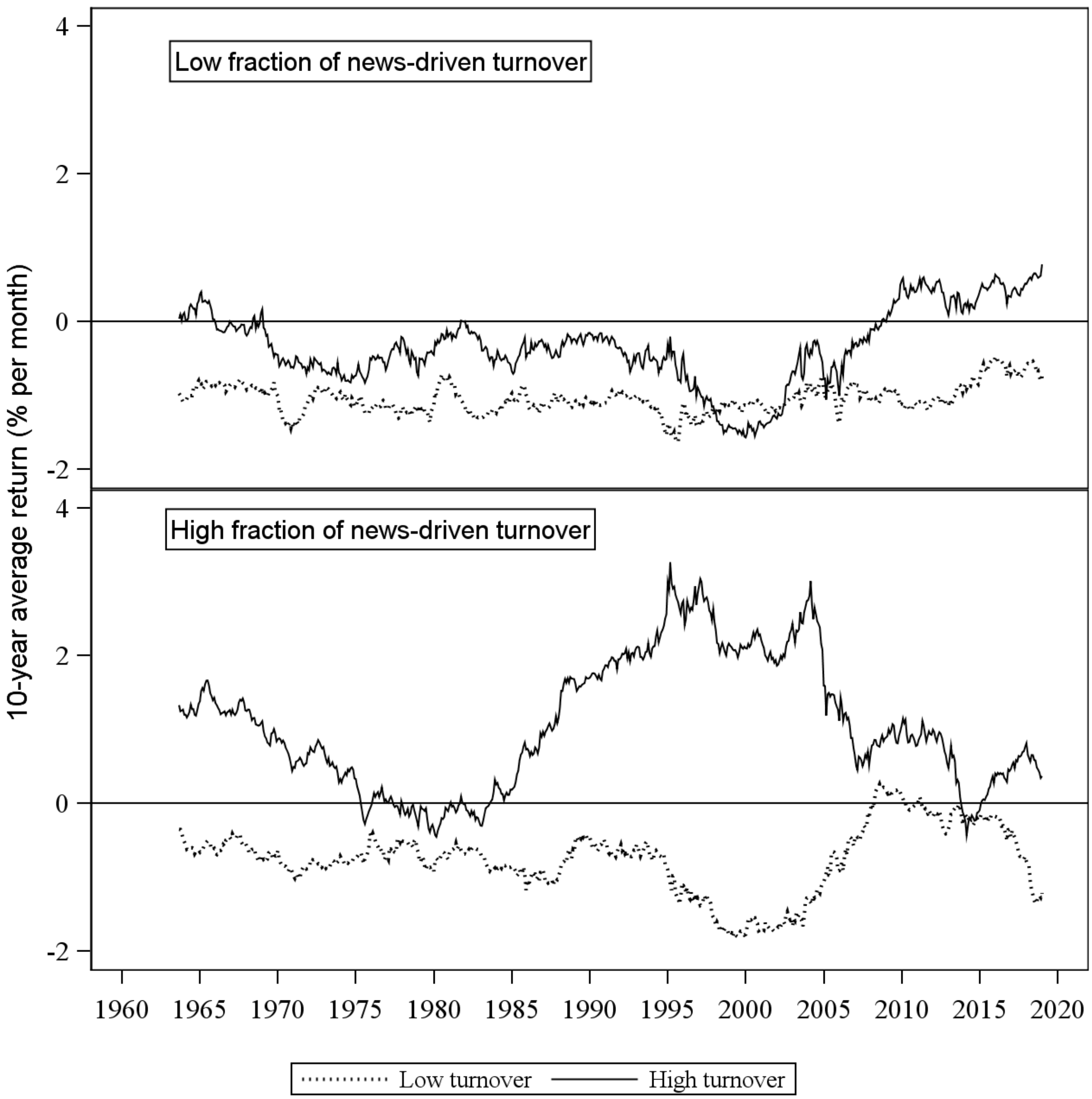

Figure 2. Rolling average returns for WML portfolios formed from all-but-micro-cap stocks
The figure plots rolling 10-year average returns for winners-minus-losers (WML) portfolios that are formed using "all-but-micro-cap" stocks (market equity equal to or larger than the 20th percentile of the NYSE market equity distribution) that fall into the bottom and top quintiles of prior turnover. The sample period is July 1963 to December 2018. We compute the rolling average returns for month t by averaging the returns for months $t-59$ to $t+60$. The length of the window is reduced as necessary to account for the lack of observations near the beginning and end of the sample (i.e., for months 1 to 59 and 607 to 666). For example, the average returns for July 1963 are computed using a forward-looking window of 61 observations and those for December 2018 are computed using a backward-looking window of 60 observations. The top panel is for stocks with a low fraction of news-driven turnover (monthly correlation between squared demeaned daily returns and daily turnover less than its median value) and the bottom panel is for stocks with a high fraction of news-driven turnover (monthly correlation between squared demeaned daily returns and daily turnover greater than its median value).

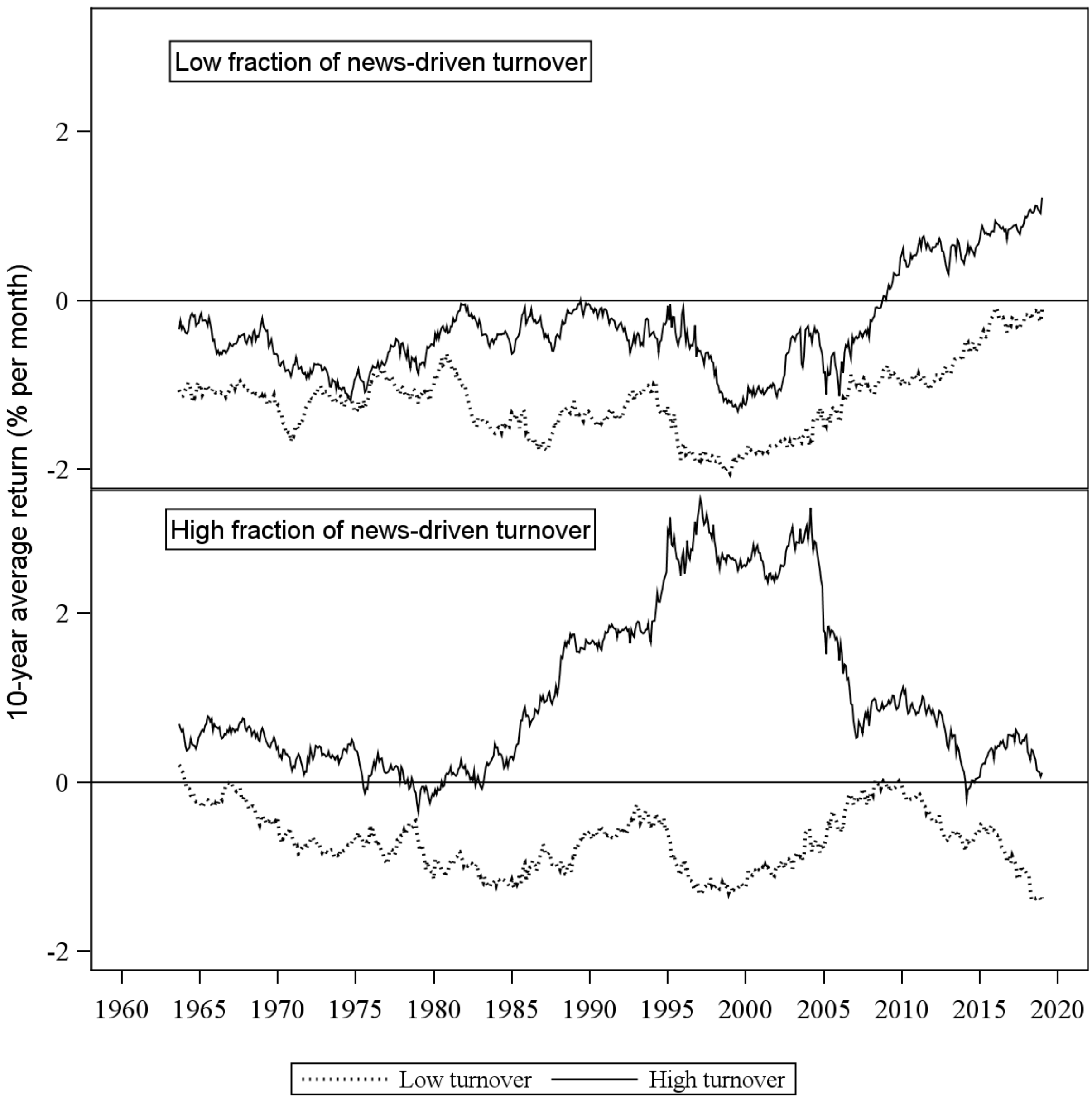

Figure 3. Rolling average returns for WML portfolios formed from large-cap stocks
The figure plots rolling 10-year average returns for winners-minus-losers (WML) portfolios that are formed using large stocks (market equity equal to or larger than the 50th percentile of the NYSE market equity distribution) that fall into the bottom and top quintiles of prior turnover. The sample period is July 1963 to December 2018. We compute the rolling average returns for month t by averaging the returns for months $t-59$ to $t+60$. The length of the window is reduced as necessary to account for the lack of observations near the beginning and end of the sample (i.e., for months 1 to 59 and 607 to 666). For example, the average returns for July 1963 are computed using a forward-looking window of 61 observations and those for December 2018 are computed using a backward-looking window of 60 observations. The top panel is for stocks with a low fraction of news-driven turnover (monthly correlation between squared demeaned daily returns and daily turnover less than its median value) and the bottom panel is for stocks with a high fraction of news-driven turnover (monthly correlation between squared demeaned daily returns and daily turnover greater than its median value).