The Review of Financial Studies

Comomentum: Inferring Arbitrage Activity from Return Correlations

Dong Lou
London School of Economics

Christopher Polk
London School of Economics

We propose a novel measure of arbitrage activity to examine whether arbitrageurs can have a destabilizing effect on the stock market. We focus on stock price momentum, a classic example of a positive-feedback strategy that our theory predicts can be destabilizing. Our measure, dubbed comomentum, is the high-frequency abnormal return correlation among stocks on which a typical momentum strategy would speculate. When comomentum is low, momentum strategies are stabilizing, reflecting an underreaction phenomenon that arbitrageurs correct. When comomentum is high, the returns on momentum stocks strongly revert, reflecting prior overreaction from crowded momentum trading that pushes prices away from fundamentals. (*JEL* G02, G12, G23)

Received July 21, 2020; editorial decision March 25, 2021 by Editor Tarun Ramadorai. Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

Arbitrageurs play a key role in financial markets, yet their impact on prices is not well understood. Indeed, the debate about whether arbitrage activity

We are grateful to Malcolm Baker, Joe Chen, Lauren Cohen, Josh Coval, Kent Daniel, Karl Diether, Andrea Frazzini, Ken French, George Gao, Clifton Green, Byoung Hwang, Petri Jylha, Augustin Landier, Jon Lewellen, Marc Lipson, Chris Malloy, Toby Moskowitz, Abhiroop Mukherjee, Robert Novy-Marx, Monika Piazzesi, Tarun Ramadorai, Clemens Sialm, Erik Stafford, Sheridan Titman, Dimitri Vayanos, and Tuomo Vuolteenaho and seminar participants at Boston College, Brandeis University, Dartmouth College, Edinburgh University, Emory University, London Business School, London School of Economics, University of Paris Dauphine, Shanghai Advanced Institute of Finance, University of Southern California, the 2012 Paul Woolley Research Initiative Workshop, the First Annual Duisenberg Workshop in Behavioral Finance, the 2012 NBER Asset Pricing Fall Meeting, the 2012 Miami Behavioral Finance Conference, 2013 American Finance Association Annual Meetings, the 2013 Adam Smith Asset Pricing Conference, the 2013 Napa Conference on Financial Market Research, the 2013 Paul Woolley Centre Conference, the 2013 Western Finance Association Meetings, the 2013 Oxford Asset Pricing Retreat, the 2013 SIFR Conference on Re-thinking Beta, the 2013 European Finance Association Meetings, the 2014 4Nations Cup, the 2014 Inquire Europe/UK Joint Seminar, the 2014 AQR Capital Management Insight Award Conference for the Best Paper in Asset Management, the 2015 Mizuho Bank Annual Conference, the 2016 UBS Quant Conference, the 2016 Citigroup Quant Research Conference, and the 2016 London Quant Group Meeting for comments. We thank Andrea Frazzini and Ken French for providing the data used in our analysis and M. L. Cooper for copy editing. Financial support from Inquire Europe, the Q group, and the Paul Woolley Centre at the LSE is gratefully acknowledged. Supplementary data can be found on *The Review of Financial Studies* web site. Send correspondence to Christopher Polk, c.polk@lse.ac.uk.

The Review of Financial Studies 35 (2022) 3272–3302

doi: 10.1093/rfs/hhab117 Advance Access publication October 27, 2021

is stabilizing or destabilizing goes back to at least Keynes (1936) and Hayek (1945). In many asset pricing models, arbitrageurs are the sole force that ensures market efficiency; thus, the extent to which the market is efficient depends crucially on the amount of arbitrage activity (e.g., Friedman 1953). An opposing view argues that arbitrage activity can at times become crowded; thus, too much arbitrage trading can destabilize prices.[1]

Arbitrage activity, however, is extremely difficult to measure at any given point in time. For one thing, the exact composition of arbitrageurs in financial markets is unknown. Additionally, for a significant fraction of institutional investors, typically perceived as the "smart money" in the market, accurate high-frequency data on capital under management is unavailable. Moreover, many arbitrageurs use leverage, short-selling, and derivatives contracts to amplify returns as well as to hedge against risks; yet information about these activities is simply unobservable to researchers.[2] Finally, the effect of arbitrage activity on prices critically depends on the liquidity of the traded assets, which may vary cross-sectionally and through time. In sum, existing proxies for arbitrage activity suffer from *poor measurement* of a *portion of the inputs* to the arbitrage process, for *a subset of arbitrageurs*.

We propose a new way to measure arbitrage activity. Our innovation is to measure the *outcome* of the arbitrage process. In particular, we measure the past degree of *abnormal* return correlations among those stocks on which an arbitrageur would speculate. The basic premise of our approach is that when arbitrageurs take positions in assets, their trades can have *simultaneous* price impacts on those assets and thus cause return comovement.[3]

We use this insight to provide new evidence on the long-standing debate over the impact of arbitrageurs on prices. We argue that the phenomenon of stock price momentum is a natural candidate for our analysis. Jegadeesh and Titman (1993) show that when portfolios are formed based on short-run stock performance (e.g., returns over the last year), past losers tend to be future losers, and past winners tend to be future winners. Despite the profitability of such a strategy and its vast popularity among active institutional investors, there exists no compelling risk-based explanation for this effect. Indeed, Fama and French (1996) acknowledge that momentum is "the main embarrassment of the three-factor model." Competing behavioral models ultimately attribute price momentum to either an underreaction or overreaction phenomenon, but these models also struggle, as even this basic characteristic of abnormal

---

[1] Stein (1987) models the way the introduction of imperfectly informed rational speculators can destabilize markets. See DeLong et al. (1990) for a model in which an increase in the number of rational speculators can be destabilizing.

[2] A notable exception is Hanson and Sunderam (2014), who exploit time variation in the cross-section of short interest to infer the amount of arbitrage capital in quantitative trading strategies.

[3] Our approach builds on the ideas in Barberis and Shleifer (2003) and Barberis, Shleifer, and Wurgler (2005), who argue that institutional features may play an important role in the movement of stocks' discount rates, causing returns to comove above and beyond that implied by their fundamentals.

momentum profits (underreaction vs. overreaction) has been difficult to pin down (Jegadeesh and Titman 2001).[4]

We focus on momentum not only because of the failure of rational models to explain these stylized facts but also because momentum is a classic example of a positive-feedback strategy. For this class of trading strategies, arbitrageurs do not base their demand on an independent estimate of fundamental value. Instead, their demand for an asset is an increasing function in lagged asset returns. Because momentum trading exacerbates the initial return signal, from the perspective of an individual arbitrageur, it is difficult, if not impossible, to gauge the amount of capital that has already been deployed in the strategy. A positive-feedback trading strategy like momentum is thus the most likely place where arbitrage activity can be destabilizing when trading becomes too crowded.[5]

Guided by this intuition, we study the empirical relation between crowded trading and arbitrage returns. Our notion of arbitrage activity is a broad one that potentially includes both arbitrageurs who face limits to arbitrage when trading momentum signals and other investors who follow a naive positive-feedback strategy. Indeed, we include in our definition any trader whose investment activity resembles a quantitative momentum strategy.

We first identify the size of the momentum crowd by the relative degree of abnormal return correlations, controlling for common risk factors, among momentum stocks measured in a relatively long ranking period (e.g., 12 months).[6] This choice is motivated by the view that momentum traders trade different flavors of the momentum strategy (e.g., use signals based on returns from the past 3 to 12 months) and thus would generate excess comovement throughout our formation period as they put on their trades. Our approach of measuring abnormal return correlations in a relatively long formation period allows us to avoid having to choose a particular flavor of price momentum and to focus instead on the total arbitrage activity in the momentum strategy. We dub this measure *comomentum*.

At each point in time, we measure the abnormal comovement for the long and short sides separately and then average the results together to form our

---

4 Tests differentiating between underreaction and overreaction interpretations of momentum profits are based on the examination of long-horizon, post-holding-period abnormal returns with the aim of determining whether momentum profits eventually revert. Previous tests, such as the ones in Jegadeesh and Titman (2001), have been inconclusive as results tend to be sample specific, not consistent across subsets of stocks, and sensitive to the benchmark model. In stark contrast, after conditioning on whether arbitrage activity is relatively low or high, our analysis reveals that momentum is an underreaction phenomenon when arbitrage activity is low and an overreaction phenomenon when arbitrage activity is high. Therefore, one additional contribution of our work is to argue that a key reason for the inconclusiveness of previous tests, such as those in Jegadeesh and Titman (2001), is that arbitrage activity varies through time.

5 DeLong et al. (1990) argue that positive-feedback trading strategies are prone to destabilizing behavior. Stein (2009) highlights the coordination problem often implicit in arbitrage strategies, such as momentum.

6 Controlling for common risk factors, such as industry, size, and value, helps reduce the extent to which common news about intrinsic value may be driving the correlation we measure. Nevertheless, we show that our results are robust to not using these controls.

comomentum measure. We argue that it is natural to separately measure the abnormal correlations within the long and short legs of the momentum strategy, as some market participants face binding short-sell constraints (e.g., mutual funds, who are known to be momentum traders). Moreover, even long-short investors, such as hedge funds, may choose to bet on only one side of the momentum strategy in certain periods. If we were to incorporate the correlations between the winner and loser portfolios, such an approach would implicitly assume that all momentum traders take simultaneous long-short momentum bets. Measuring these components separately, on the other hand, allows us to pick up the impact of both long-only and long-short momentum bets.[7]

We then link both the profitability and any subsequent reversal of momentum strategy returns to our comomentum variable. Intuition predicts that when comomentum is relatively low, that is, momentum strategies are not crowded, abnormal returns to a standard momentum strategy should be positive and not revert. In this case, arbitrage activity is stabilizing, as the underreaction phenomenon is being eliminated. However, when comomentum is relatively high, momentum strategies may become crowded. If so, arbitrage activity actually may be destabilizing, resulting in prices overshooting the fundamental value. Put differently, the underreaction or overreaction characteristic of momentum, that is, whether momentum profits revert in the long run, is time varying and crucially depends on the size of the momentum crowd.[8]

Our comomentum measure of the momentum crowd is a success based on several empirical findings. First, comomentum is significantly correlated with existing variables plausibly linked to the size of arbitrage activity in this market. These proxies include not only well-known variables, such as institutional ownership of the winner decile and hedge fund assets under management, but also more refined novel measures, such as the net arbitrage trading (NAT) variable of Chen, Da, and Huang (2019) that measures the difference between quarterly abnormal hedge fund holdings and abnormal short interest. Second, when comomentum is relatively high, the *long-run* buy-and-hold returns to a momentum strategy are predictably negative. This finding is consistent with relatively high amounts of arbitrage activity having pushed prices further away from fundamentals during the formation period. Third, comomentum forecasts relatively high holding-period return volatility and relatively more negative holding-period return skewness for the momentum strategy.

These findings are economically large and robust. For the 20% of the sample period that is associated with the highest values of comomentum, a typical momentum strategy yields 12.7% lower returns over the first year, relative

[7] That said, we show that our results were robust to measuring comomentum as the abnormal correlation of a composite portfolio that pools winners and losers together (with a negative sign in front of the returns of the latter), thus taking all potential sources of abnormal covariance into account.

[8] Our proposed crowded-trading mechanism does not have a clear prediction for momentum profits in the short run. In fact, momentum strategies could be possibly more profitable with higher arbitrage trading as underreaction evolves into overreaction.

to its performance during the 20% of the sample period associated with low comomentum. In the second year after formation, the momentum strategy continues to lose 13% (again, relative to the low comomentum subsample). Thus, the 2-year cumulative return on a typical momentum stock is more than 25 percentage points lower when comomentum is relatively high. These estimates are both individually and jointly strongly statistically significant (t-statistic of -3.35 for the joint test).

These striking results are complemented by a long list of additional empirical findings.[9] We highlight three placebo/difference-in-differences tests. First, it is well-known that institutional ownership was low before the late 1960s. For example, Blume and Keim (2014) document that institutions held less than 5% of equity during most of this time. Since the sort of professional arbitrageurs we are interested in are mostly institutional money managers who trade a portfolio of stocks, arbitrage activity of that sort was simply not prevalent before 1965.[10] Consistent with our crowded-trade hypothesis, we find that comomentum does not forecast time variation in expected holding and post-holding returns of momentum stocks in the 1927–1964 data.

Second, we split the post-1980 sample into low and high institutional ownership subsets. We find that the relation between comomentum and the long-run reversal of returns to stocks in the momentum strategy is much stronger for stocks with higher institutional ownership. The t-statistic on the associated difference-in-differences test is -3.91.

Our third test measures a placebo version of comomentum for the set of momentum stocks in question in the period prior to our actual comomentum measurement period. This version holds the momentum portfolio constant but calculates a placebo comomentum measure in the year prior to portfolio ranking. We confirm that this placebo comomentum has no incremental information about subsequent expected returns on momentum stocks. Moreover, controlling for placebo comomentum increases the absolute magnitude of the t-statistic on our key finding by more than 40%. This increase indicates that this particular difference-in-differences approach is also a useful way to control for any potential risk factors omitted in our construction of comomentum.[11]

---

9 We also perform a bevy of robustness checks of our main empirical finding. The underperformance we link to comomentum is robust to implementing a variety of factor adjustments, measuring across different subsamples (including subsamples that exclude the financial crisis where momentum underperformed), controlling for existing variables known to forecast momentum returns, and constructing comomentum in a variety of ways. Furthermore, the Internet Appendix provides a variety of supplementary evidence at the firm, fund, and international levels that further confirms the sensibility of our approach to measuring arbitrage activity. All of our findings are consistent with our model's view of the potentially destabilizing effect of arbitrage activity on positive-feedback strategies.

10 Indeed, the first hedge fund, run by Alfred Jones, did not grab public attention until an article published in *Fortune* (Loomis 1966).

11 We do not claim that our findings are proof that markets are inefficient as we cannot rule out that some future neoclassical model of risk may justify the patterns we find. Nevertheless, we do think that the time-varying

We confirm the intuition motivating our empirical analysis in a simple stylized model following Hong and Stein (1999) in the Internet Appendix. In particular, we study an economy where in the absence of arbitrageurs, information is gradually incorporated into prices, a classic underreaction phenomenon. We add to this basic setup both momentum and value traders who optimally trade those signals. We consider a baseline version of the model where separate groups of momentum and value traders optimize on individual signals, as well as an extended version where a single group of arbitrageurs trade on both signals simultaneously in an optimal fashion. In contrast to Hong and Stein (1999), who keep the amount of arbitrage capital fixed, we allow it to vary stochastically through time, with both observable and unobservable components; arbitrageurs then condition their trading intensity on the observable component of aggregate arbitrage capital.

Our theoretical results confirm that when the momentum crowd is relatively large, momentum strategies are more destabilizing, with a stronger reversal in the long run. The destabilizing aspect of momentum trading is exacerbated when those traders condition on a relatively more noisy signal of the amount of capital in the strategy. Interestingly, even when momentum traders know the amount of momentum capital with certainty in each period, we still show that their composite activity is destabilizing, as arbitrageurs do not adjust their trading intensity to fully offset the exogenous fluctuation in arbitrage capital.

Our theory not only confirms the intuition driving our key empirical analysis but also motivates an important comparison. In particular, we construct a similar comovement measure for the value strategy, *covalue*, and study its relation with expected returns of value stocks. Our model predicts that relatively higher arbitrage activity by value investors should be associated with relatively higher (rather than lower, as in the case of momentum) expected long-horizon returns for the value strategy. This predicted difference in how arbitrage activity affects the long-horizon returns on momentum versus value stocks arises because the former is a positive-feedback strategy and the latter is a negative-feedback strategy. More specifically, although value traders' demand is a linear function of the value signal (just like momentum traders' demand is a linear function of the momentum signal), the resultant value demand shrinks the value signal. This fact has two implications: (1) The equilibrium value signal is a positive predictor of future value strategy returns (in contrast, the momentum signal can be a negative predictor of future returns). (2) High value activity is accompanied by a relatively large value signal, which in turn indicates high expected returns to the value strategy.

---

patterns that we document raise the bar even further than that set by Fama and French (1996), who cannot explain the unconditional momentum premium. In particular, a risk explanation will be challenging as it will require either betas or risk premiums to vary in a remarkable way: momentum traders must choose to collectively increase their momentum bets when the momentum stocks in question have lower expected returns, higher volatility, and more negative skewness. Nevertheless, we grant that as-of-yet-unknown hedging demands could rationalize these surprising patterns.

Thus, when arbitrage activity is relatively high, momentum becomes an overreaction phenomenon. In contrast, value trading, which dampens the value signal, never results in overreaction. We confirm that, consistent with our theory, covalue does forecast subsequent long-horizon returns to the value strategy with a positive sign.

1. Data and Methodology

The challenge to econometricians in testing our model's predictions is the same one faced by individual arbitrageurs in the market: to come up with a reasonable measure of aggregate arbitrage activity for a strategy. A key contribution of this paper is to take up this challenge directly by proposing one such measure.

Our measure is motivated by the observation that arbitrageurs tend to buy or sell a diversified portfolio of stocks at the same time; for example, in the case of the momentum strategy, arbitrageurs usually buy a portfolio of winner stocks and sell a portfolio of loser stocks simultaneously. To the extent that arbitrageurs' trading can move stock prices in the short run, we can then infer the amount of arbitrage activity in a strategy by examining high-frequency (i.e., daily or weekly) return correlations, over and beyond common risk factors, among the portfolio of stocks that are likely to be bought or sold simultaneously by arbitrageurs.[12] For example, for the momentum strategy, we can extract information about arbitrage activity in the strategy by looking at the return correlation among stocks in the winner and/or loser portfolios.[13]

An alternative approach to measuring the amount of arbitrage activity in a strategy would be to exploit the correlation of the strategy's returns with respect to a proxy for intermediary capital; Cho (2020) is an example of that technique.[14] However, several potential issues crop up with this approach in our context. First, one needs to take a stand on how to measure intermediary capital. Second, proxies for intermediary capital may not reflect the concerns of the arbitrageurs trading the anomaly in question (e.g., momentum). Finally, measures of intermediary capital are typically not available at high frequencies.

At the end of each month, we sort all stocks into deciles based on their previous 12-month returns (skipping the most recent month). We then compute

---

12 For example, Anton and Polk (2014) and Lou (2012) find that mutual funds tend to expand or shrink their existing holdings in response to capital flows, and that such flow-induced trading can lead to excess comovement among stocks collectively held by mutual funds.

13 Frazzini, Israel, and Moskowitz (2020) show that a single hedge fund can rebalance its momentum portfolio within a day. Our analysis focuses on the aggregate quantitative momentum trader (i.e., the sum of all momentum traders); one could reasonably expect that the rebalancing by this aggregate investor takes place over a longer window.

14 Two additional methods for measuring arbitrage activity include using hedge fund holdings (Brunnermeier and Nagel 2004; Griffin and Xu 2009; Cao et al. 2018) or exploiting information in short-selling activity (Boehmer, Jones, and Zhang 2008; Yan 2014; Hanson and Sunderam 2014; Hwang, Liu, and Xu 2019). In Table 2, we compare our comomentum measure to the approach of Chen, Da, and Huang (2019), who propose a net arbitrage trading measure that combines these two techniques.

pairwise abnormal correlations using 52 weekly (Friday-to-Friday) returns for all stocks in each decile *in the portfolio ranking period*. (Our results are robust to calculating abnormal correlations using daily returns in the past year.) One concern is that arbitrageurs begin trading only after the momentum characteristic is observed. That concern is mitigated by the fact that we measure the momentum characteristic based on a relatively long ranking period of one year. Indeed, Jegadeesh and Titman (1993) consider ranking periods as short as 3 months. Presumably many momentum traders are trading many different flavors of the momentum strategy during our formation period and thus would be generating excess comovement throughout our 1-year ranking period.[15]

Of course, stocks may move together because of common news about intrinsic value. Therefore, we industry-adjust all returns using the Fama-French 30 industry portfolios as well as control for the Fama-French three factors when computing these abnormal correlations to purge out any comovement in stock returns in the same momentum decile induced by known risk factors. Since this approach may also remove nonfundamental return variation in industry or factor returns, we are careful to confirm that our results are robust to not using these controls. Note that we do not assume that stocks have constant Fama-French betas. Such an approach might result in a high value of comomentum simply reflecting an increase in the Fama-French loadings of the stocks in the momentum portfolio at a point in time. Instead, following Lewellen and Nagel (2006), we allow betas to vary by estimating rolling-window regressions using weekly returns for each stock in each year. Like Lewellen and Nagel (2006), we assume that betas are relatively stable only within the regression window. So, if in a particular year, momentum stocks happen to be small stocks, our short-window regression will remove the extent to which momentum stocks covary with SMB in that year.

Though our approach measures comomentum over a 1-year ranking period, our results continue to hold if we measure comomentum over months $t-7:t-2$ in the formation period. Since it is even more unlikely that conditional betas change substantially over a 6-month window, this test further confirms that conditional betas are unlikely to be driving time-series variation in comomentum. Furthermore, that result shows more broadly that our findings are not sensitive to the length of the comomentum estimation window.

Our primary comomentum measure, $CoMOM$, is a simple average of loser comomentum ($CoMOM^L$) and winner comomentum ($CoMOM^W$), which are the average pairwise abnormal correlation for the loser and winner deciles, respectively. We operationalize this calculation by measuring the average

15 Nevertheless, if we instead measure comomentum in the post-ranking period, all of our results continue to hold. Of course, in this case, we are careful to study momentum trading strategies that only begin after comomentum is measured so that comomentum remains a legitimate predictor of any long-run reversal.

correlation of the three-factor residual of every stock in a particular decile with the decile in question,

$$CoMOM^{L} = \frac{1}{N^{L}}\sum_{i=1}^{N^{L}} Corr(ret_{i}^{L},\ ret_{-i}^{L} \mid rmrf, smb, hml) \tag{1}$$

$$CoMOM^{W} = \frac{1}{N^{W}}\sum_{i=1}^{N^{W}} Corr(ret_{i}^{W},\ ret_{-i}^{W} \mid rmrf, smb, hml) \tag{2}$$

$$CoMOM = .5*(CoMOM^{W} + CoMOM^{L}) \tag{3}$$

where ret_i^L (ret_i^W) is the weekly industry-adjusted return of stock i in the extreme loser (winner) decile, ret_{-i}^L (ret_{-i}^W) is the weekly industry-adjusted return of the equal-weight extreme loser (winner) decile excluding stock i, and N^L (N^W) is the number of stocks in the extreme loser (winner) decile.[16] Note that Table 4 documents that our key result is robust to many variations in our methodology. These variations include examining different subperiods and subsamples, computing comomentum in a variety of ways, controlling for a variety of potentially relevant time-series variables, implementing a variety of performance adjustments, and measuring performance in a strictly out-of-sample fashion as in Goyal and Welch (2008).

The main data set used in this study is the stock return data from the Center for Research in Security Prices (CRSP). To mitigate the impact of microstructure issues, we exclude stocks with prices below $5 a share and/or that are in the bottom NYSE size decile from the sample. We then augment the stock return data with institutional ownership in individual stocks provided by Thomson Financial. We further obtain information on assets under management of active mutual funds and long-short equity hedge funds from Thomson Reuters and Lipper's Trading Advisor Selection System (TASS), respectively. Since the assets managed by mutual funds and hedge funds grow substantially in our sample period, both variables are detrended. Finally, we obtain monthly returns of actively managed equity mutual funds and long-short equity hedge funds from the CRSP survivorship-bias-free mutual fund database and the Lipper TASS database, respectively.

2. Main Results

We first document simple characteristics of our comomentum measure. Table 1, panel A, indicates that comomentum varies significantly through time. We primarily focus on the period from 1965 to 2011, as institutional investing of

[16] We measure comomentum as the average correlation of stock i and the decile portfolio that excludes stock i. However, this approach is not critical. If we instead use the average pairwise correlations between all the stocks in a decile, the correlation between comomentum measures constructed in these slightly two different ways is extremely high, at 0.98.

Table 1
Summary statistics

A. Summary statistics

Variable	N	Mean	SD	Min	Max
CoMOM	564	0.092	0.029	0.037	0.241
$CoMOM^L$	564	0.098	0.038	0.012	0.250
$CoMOM^W$	564	0.086	0.030	0.022	0.270
$MRET$	564	0.231	0.259	−0.453	0.970
$MVOL$	564	0.043	0.014	0.018	0.075

B. Correlation

	CoMOM	$CoMOM^L$	$CoMOM^W$	*MRET*	*MVOL*
CoMOM	1.000				
$CoMOM^L$	0.889	1.000			
$CoMOM^W$	0.820	0.467	1.000		
$MRET$	−0.368	−0.303	−0.331	1.000	
$MVOL$	0.278	0.211	0.273	−0.358	1.000

C. Autocorrelation

	$CoMOM_t$	$CoMOM_t^L$	$CoMOM_t^W$	$CoMOM_{t+1}$	$CoMOM_{t+1}^L$	$CoMOM_{t+1}^W$
$CoMOM_t$	1.000					
$CoMOM_t^L$	0.889	1.000				
$CoMOM_t^W$	0.820	0.467	1.000			
$CoMOM_{t+1}$	0.483	0.468	0.347	1.000		
$CoMOM_{t+1}^L$	0.399	0.390	0.282	0.892	1.000	
$CoMOM_{t+1}^W$	0.436	0.418	0.319	0.819	0.471	1.000

This table provides key characteristics of "comomentum," which we measure as the formation-period excess comovement of the momentum strategy over the period 1965 to 2015. At the end of each month, we sort all stocks into deciles based on their lagged 11-month cumulative returns (skipping the most recent month). We compute pairwise abnormal return correlations (after controlling for the Fama-French three factors) for all stocks in both the bottom and top deciles using weekly Fama-and-French 30-industry-adjusted stock returns in the previous 12 months. To mitigate the impact of microstructure issues, we exclude stocks with prices below \$5 a share and/or that are in the bottom NYSE size decile from the sample. $CoMOM^L$ (loser comomentum) is the average pairwise abnormal return correlation in the loser decile in year t, while $CoMOM^W$ (winner comomentum) is the average pairwise abnormal return correlation in the winner decile. $CoMOM$ is the simple average of $CoMOM^L$ and $CoMOM^W$. $MRET$ is the 2-year return on the CRSP market portfolio from year t-1 to t, and $MVOL$ is the monthly return volatility of the CRSP market portfolio in years t-1 to t. Panel A reports the summary statistics of these variables. Panel B reports the time-series correlations among the key variables for the entire sample period. Panel C reports the autocorrelation coefficients for $CoMOM$, $CoMOM^L$, and $CoMOM^W$, where $CoMOM_t$ and $CoMOM_{t+1}$ (and similarly for $CoMOM_t^L$ and $CoMOM_{t+1}^L$, $CoMOM_t^W$ and $CoMOM_{t+1}^W$) are computed in nonoverlapping 12-month windows.

the sort in which we are interested was relatively small pre-1965, a fact we exploit in one of our placebo tests. (Since we examine momentum and value strategy returns in the 4 years following portfolio formation, our return data end in 2015.)

During this period, momentum stocks have an economically large average abnormal return correlation of 0.092 during the formation period across the 47-year sample. However, this abnormal correlation can be as low as 0.037 and as high as 0.241. As one would expect, and Table 1, panel B shows, the components of *CoMOM* are highly correlated (correlation of 0.467). Furthermore, *CoMOM* and its components are highly autocorrelated and cross-autocorrelated (Table 1, panel C).

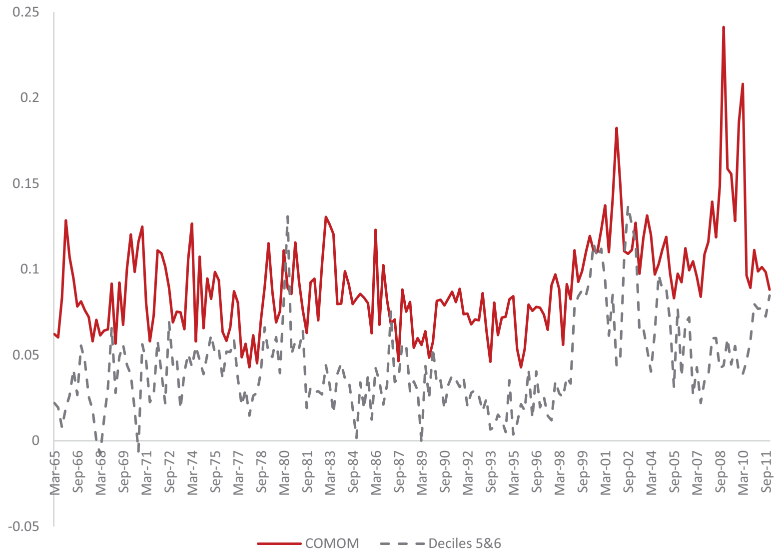


Figure 1
Time series of the comomentum measure
At the end of each month, we sort all stocks into decile portfolios based on their lagged 11-month cumulative returns (skipping the most recent month). We compute pairwise abnormal return correlations (after controlling for the Fama-French three factors) for all stocks in both the bottom and top deciles using weekly Fama-and-French 30-industry-adjusted stock returns in the previous 12 months. To mitigate the impact of microstructure issues, we exclude stocks with prices below $5 a share and/or that are in the bottom NYSE size decile of the sample. $CoMOM$ is the average of $CoMOM^L$ and $CoMOM^W$. $CoMOM^L$ (loser comomentum) is the average pairwise abnormal return correlation in the loser decile in year t, while $CoMOM^W$ (winner comomentum) is the average pairwise abnormal return correlation in the winner decile. Deciles 5&6 is the average of the average pairwise abnormal return correlation in deciles 5 and 6, measured in the same period as $CoMOM$.

Figure 1 plots our comomentum measure. For comparison, we also plot the average excess correlation for a momentum-neutral portfolio (deciles 5 and 6 in our momentum sort). The figure makes it clear that variation in comomentum is distinct from variation in the average excess correlation of the typical stock. Moreover, the figure confirms that comomentum is persistent. The serial correlation in the time series of comomentum is 0.48, while the serial correlation of deciles 5 and 6 is a significantly smaller 0.26.[17]

Figure 1 shows that comomentum was high during the tech boom when momentum strategies were popular. There was also an increase in comomentum in the 2008 financial crisis, which may seem surprising at first. However, a more careful analysis reveals that financial stocks were initially hit with bad news in mid-2008; investors then sold even more financial stocks in late 2008, for many reasons (e.g., binding risk or portfolio constraints). This is indeed a form of momentum trading, on the short side, and is correctly picked up

[17] Note that we calculate this serial correlation for annual observations of comomentum so that each comomentum value corresponds to a nonoverlapping formation period.

by our comomentum measure. As we show in robustness checks, our main result—that comomentum predicts lower momentum returns and stronger long-run reversals—is virtually unchanged even if we exclude 2008–2009 from our sample.

We confirm that comomentum is also persistent in event time. In particular, the average excess correlation in year 1 is more than half of its year 0 value. Moreover, the correlation between year 0 and year 1 comomentum is 0.48, and even year 2 remains quite correlated with the year 0 value (around 0.40). Figure 2 shows this event-time evolution of comomentum. The plot documents that the abnormal comovement among momentum stocks peaks in the formation year and then slowly decays over the next 3 years, holding fixed the stocks in question. Figure 2 further shows that these event-time patterns are similar but stronger for years in which comomentum (i.e., the year 0 value of the abnormal comovement we plot in these graphs) is particularly high.

Table 1 provides similar statistics for the two existing variables that the literature has linked to time variation in expected momentum returns. Cooper, Gutierrez, and Hameed (2004) argue that momentum profits depend on the state of the market. Specifically, the momentum premium falls to zero when the past 3-year market return has been negative. In related work, Wang and Xu (2015) argue that relatively high market volatility forecasts relatively low momentum returns. Therefore, we include the past 2-year return on the market portfolio and the monthly market return volatility over the past 2 years as control variables in many of our tests. (Our results are robust to controlling for market returns and volatilities measured over different horizons.) Table 1 shows that comomentum is negatively correlated with the past return on the market (−0.368) and positively correlated with past market volatility (0.278).

2.1 Linking comomentum to arbitrage activity

Table 2 links comomentum to several variables that proxy for the size of arbitrage activity in the momentum strategy. Specifically, Table 2 forecasts year t comomentum with these proxies. The first variable we include is the performance of the momentum strategy (MOM_{t-1}) in year $t-1$ (prior to the construction of comomentum). One would expect that momentum capital would be positively related to recent performance. Our next variable is the aggregate institutional ownership of the winner decile, PIH_{t-1}^{W}, measured using the Thomson Financial Institutional Holdings 13F database. We include institutional ownership as these investors are typically considered smart money, at least relative to individuals. We also include the assets under management (AUM_{t-1}) of long-short equity hedge funds as of the end of year $t-1$.

Note that we find a positive but relatively weak trend in our comomentum variable.[18] The lack of a strong trend might be initially surprising, given

[18] A regression on monthly *CoMOM* on a trend produces a trend coefficient estimate of 0.00007551 with a t-statistic of 11.01. This estimate implies an increase of 0.0042 in *CoMOM* over the sample period. All results in the paper are robust to removing this trend from *CoMOM* prior to the analysis.

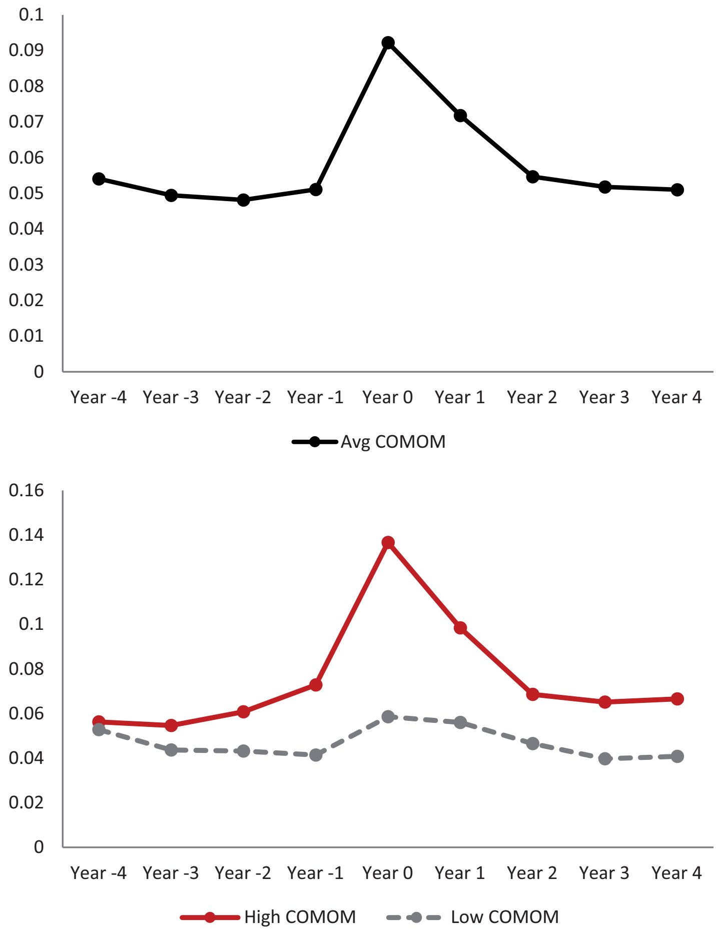


Figure 2
Event-time variation in the comomentum measure, with year 0 being the portfolio formation year
At the end of each month, we sort all stocks into decile portfolios based on their lagged 11-month cumulative returns (skipping the most recent month). We compute pairwise abnormal return correlations (after controlling for the Fama-French three factors) for all stocks in both the bottom and top deciles using weekly Fama-and-French 30-industry-adjusted stock returns in the previous 12 months. To mitigate the impact of microstructure issues, we exclude stocks with prices below \$5 a share and/or that are in the bottom NYSE size decile from the sample. *CoMOM* is the average of $CoMOM^L$ and $CoMOM^W$. The top panel shows the average *CoMOM* in event time for our entire sample; the bottom panel shows the average *CoMOM* in event time for high and low *CoMOM* periods separately.

the increase in the raw dollar amount of arbitrage capital over the last 40 years. However, comomentum is designed to capture the short-term price (co)fluctuations caused by arbitrage trading. Though it is true that more arbitrageurs are trading the momentum strategy over time, it seems reasonable that markets have generally become more liquid so that each dollar of arbitrage

Table 2
Determinants of comomentum

DepVar = Detrended $CoMOM_t$

	(1)	(2)	(3)	(4)	(5)	(6)
MOM_{t-1}	0.388***	0.457***		0.572***	0.379***	0.408***
	[0.132]	[0.140]		[0.148]	[0.143]	[0.129]
PIH^W_{t-1}		0.056*		0.093***	0.065***	0.063***
		[0.030]		[0.033]	[0.019]	[0.023]
AUM_{t-1}			0.011***	0.007**	0.007***	0.008***
			[0.004]	[0.003]	[0.003]	[0.003]
$MRET_{t-1}$					−0.024*	−0.034***
					[0.012]	[0.012]
$MVOL_{t-1}$					−0.047	−0.312
					[0.222]	[0.256]
PS_{t-1}					−0.150***	−0.173***
					[0.046]	[0.063]
NAT^L_t					−3.589***	
					[0.693]	
NAT^W_t					1.879**	
					[0.861]	
$NAT^W_t - NAT^L_t$						3.334***
						[0.837]
Adj. R^2	.09	.19	.11	.39	.56	.52
No. obs.	564	370	204	204	204	204

This table reports regressions of comomentum on variables related to arbitrage activity. At the end of year t, we sort all stocks into deciles based on their lagged 11-month cumulative returns (skipping the most recent month). We compute pairwise abnormal return correlations (after controlling for the Fama-French three factors) for all stocks in both the bottom and top deciles using weekly Fama-and-French 30-industry-adjusted stock returns in the previous 12 months. To mitigate the impact of micro-structure issues, we exclude stocks with prices below \$5 a share and/or that are in the bottom NYSE size decile from the sample. The dependent variable, detrended $CoMOM$ (average comomentum), is the detrended average of $CoMOM^L$ (loser comomentum) and $CoMOM^W$ (winner comomentum). $CoMOM^L$ is the pairwise abnormal return correlation in the loser decile in the ranking year t, while $CoMOM^W$ is the average pairwise abnormal return correlation in the winner decile in the ranking year t. MOM_{t-1} is the return to the momentum strategy in year t-1. PIH^W_{t-1} is the aggregate institutional ownership of the winner decile at the end of year t-1 (i.e., the winner decile is ranked based on cumulative returns in year t-1). $MRET_{t-1}$ and $MVOL_{t-1}$ are, respectively, the 2-year return and the monthly return volatility of the CRSP market portfolio. AUM_{t-1} is the detrended logarithm of the total assets under management of long-short equity hedge funds at the end of year t-1. PS_{t-1} is the Pastor and Stambaugh (2003) liquidity factor in year t-1. NAT^W_t and NAT^L_t are the net arbitrage trading of Chen, Da, and Huang (2019) for the winner and loser deciles, respectively. NAT measures the difference between quarterly abnormal hedge fund holdings and abnormal short interest. We correct standard errors, shown in brackets, for serial dependence with 12 lags. *p <.1; **p <.05; ***p <.01.

trading causes a smaller price impact. Nevertheless, we detrend all variables in Table 2 to ensure that our results are not spurious.

The first column of Table 2 documents that past performance on the strategy strongly forecasts $CoMOM$. This finding is consistent with our hypothesis as we expect arbitrageurs to move into the momentum strategy if past returns to the strategy have been strong. An increase in arbitrageurs will then cause the strategy to be more crowded and thus comomentum to be higher. Next, we show in column 2 that a relatively high level of institutional ownership among winner stocks forecasts relatively high comomentum. Column 3 documents that when AUM_{t-1} is relatively high, future comomentum is relatively high as well. This result is comforting as hedge funds are known to deploy momentum strategies. Column 4 confirms that when included in the same regression, MOM_{t-1}, PIH^{W}_{t-1}, and AUM_{t-1} continue to forecast time-series variation in *CoMOM*.

Chen, Da, and Huang (2019) propose a stock-level measure of net arbitrage trading, NAT, that combines hedge fund long positions and total short interest. In columns 5 and 6 of Table 2, we explain variation in comomentum with NAT. In column 5, we separately include measures of net arbitrage trading for the winner side, NAT^W, and the loser side, NAT^L. In column 6, we simply use the difference between those two measures. We find that both NAT^W and NAT^L provide incremental explanatory power that is economically and statistically significant. Indeed, the adjusted R^2 increases by 17 percentage points. The coefficients for these two variables have opposite signs, as one would expect, and are of similar magnitudes. Column 6 documents that when we combine these two measures into one composite variable, $NAT^W - NAT^L$, the combined measure explains a significant proportion of the variation in *CoMOM*.

2.2 Forecasting long-run momentum reversal

We now turn to the main empirical question of our paper: does variation in arbitrage activity forecast variation in the long-run reversal of momentum returns? Table 3 tracks the profits on our momentum strategy over the 4 years subsequent to portfolio formation. Such an event time approach allows us to make statements about whether momentum profits revert.

Table 3, panel A, reports the results of this analysis. In particular, at the end of each month $t-1$, we sort all stocks into deciles based on their past 11-month return (skipping a month). We then form a zero-cost portfolio that goes long a value-weight portfolio of the stocks in the top decile and short a value-weight portfolio of stocks in the bottom decile. All months are then classified into five groups based on their *CoMOM* after first orthogonalizing *CoMOM* to $mktret24$ and $mktvol24$.[19]

Panel A reports the average returns in each of the subsequent 4 years (tabulated as year 1, year 2, years 1 and 2, and years 3 and 4) as well as the returns in the formation period (labeled year 0) for each of these five groups. We also report the difference between the extreme high and low comomentum groups. In addition to these sorts, Table 3 also reports the ordinary least squares (OLS) coefficient from regressing the monthly series of realized year 0, year 1, year 2, years 1 and 2, or years 3 and 4 returns on the monthly series of comomentum ranks.

We find that year 0 returns are monotonically increasing in comomentum. On average, the momentum differential between winners and losers is

[19] Our results are robust to controlling for different measures of past market performance and volatility, including measuring the weekly volatility of market returns over the same window as our comomentum measure. Our results are also robust to not orthogonalizing comomentum at all.

Table 3
Forecasting momentum returns and skewness with comomentum

A. Raw momentum returns

Rank	No obs.	Year 0 Estimate	Year 1 Estimate	Year 2 Estimate	Years 1-2 Estimate	Years 3-4 Estimate
1	112	8.50%	0.88%	0.24%	0.56%	0.08%
2	113	9.00%	0.68%	−0.22%	0.23%	−0.30%
3	113	9.31%	0.71%	−0.43%	0.14%	−0.15%
4	113	9.90%	0.67%	−0.90%	−0.12%	−0.19%
5	113	11.09%	−0.18%	−0.84%	−0.51%	0.07%
5-1		**2.59%**	**−1.06%**	**−1.08%**	**−1.07%**	−0.01%
		(2.45)	(−2.72)	(−2.75)	(−3.35)	(−0.04)
OLS		**0.006**	**−0.002**	**−0.003**	**−0.002**	0.000
		(2.60)	(−2.42)	(−2.96)	(−3.53)	(0.13)

B. Three-factor-adjusted momentum returns

Rank	No obs.	Year 0 Estimate	Year 1 Estimate	Year 2 Estimate	Years 1-2 Estimate	Years 3-4 Estimate
1	112	8.44%	1.26%	0.41%	0.83%	0.27%
2	113	8.99%	1.21%	0.11%	0.66%	−0.17%
3	113	9.29%	1.10%	−0.12%	0.49%	0.02%
4	113	9.98%	0.90%	−0.35%	0.28%	0.04%
5	113	11.10%	0.23%	−0.43%	−0.10%	0.22%
5-1		**2.66%**	**−1.03%**	**−0.84%**	**−0.94%**	−0.05%
		(2.47)	(−2.65)	(−2.12)	(−2.74)	(−0.24)
OLS		**0.006**	**−0.002**	**−0.002**	**−0.002**	0.000
		(2.70)	(−2.87)	(−2.37)	(−3.17)	(0.22)

C. Five-factor-adjusted momentum returns

Rank	No obs.	Year 0 Estimate	Year 1 Estimate	Year 2 Estimate	Years 1-2 Estimate	Years 3-4 Estimate
1	112	8.27%	1.23%	0.41%	0.82%	0.27%
2	113	8.85%	1.15%	0.27%	0.71%	−0.13%
3	113	9.10%	1.04%	−0.07%	0.48%	0.07%
4	113	9.79%	0.86%	−0.34%	0.26%	0.10%
5	113	10.84%	0.10%	−0.35%	−0.13%	0.25%
5-1		**2.58%**	**−1.13%**	**−0.76%**	**−0.95%**	−0.02%
		(2.55)	(−2.78)	(−2.07)	(−2.87)	(−0.10)
OLS		**0.006**	**−0.003**	**−0.002**	**−0.002**	0.000
		(2.77)	(−2.96)	(−2.57)	(−3.41)	(0.44)

D. Fraction of low-momentum-return times

Rank	No obs.	Months 1–3 Estimate	Months 1–6 Estimate	Months 1–12 Estimate
1	112	0.084	0.021	0.015
2	113	0.079	0.019	0.015
3	113	0.101	0.023	0.020
4	113	0.141	0.043	0.044
5	113	0.225	0.104	0.093
5-1		**0.141**	**0.083**	**0.078**
		(6.24)	(3.75)	(3.07)
OLS		**0.035**	**0.019**	**0.019**
		(6.86)	(3.89)	(3.28)

This table reports returns to the momentum strategy as a function of lagged comomentum. At the end of each month, we sort all stocks into deciles based on their lagged 11-month cumulative returns (skipping the most recent month). We exclude stocks with prices below $5 a share and/or that are in the bottom NYSE size decile from the sample. We then classify all months into five groups based on residual *CoMOM* which we compute by purging out the lagged 2-year market return and volatility. We report the returns to the momentum strategy (i.e., long the value-weight winner decile and short the value-weight loser decile) in each of the four years after portfolio formation during 1965 to 2015, following low to high *CoMOM*. Year zero is the portfolio ranking period. Panels A, B, and C report, respectively, the average monthly return, the average Fama-French three-factor alpha, and the average Fama-French five-factor alpha of the momentum strategy. Panel D reports the fraction of days during which the value-weighted long-short momentum strategy returns less than -1% in months 1 to 3 after portfolio formation, conditional on *CoMOM* ranks. Panel D also reports the fraction of weeks during which the value-weighted long-short momentum strategy returns less than -5% in months 1 to 6 and months 1 to 12 after portfolio formation, conditional on *CoMOM* ranks. "5-1" is the difference in the relevant statistic across high and low *CoMOM* ranks. "OLS" is the slope coefficient from the regression of the relevant statistic on ranks of *CoMOM*. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial-dependence up to 24 lags. We indicate statistical significance at the 5% level in bold.

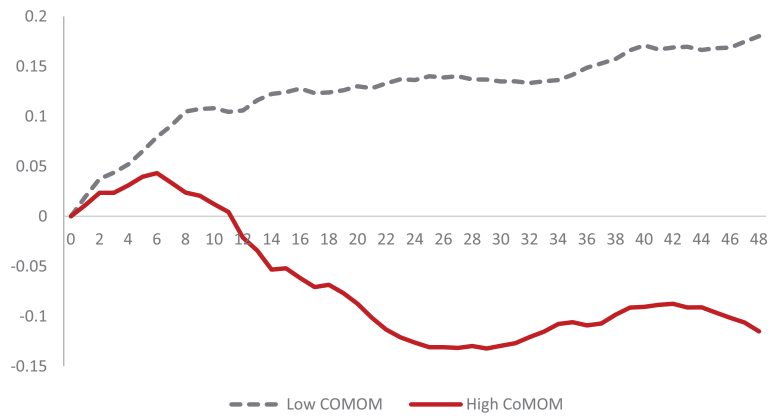
2.59% per month higher (t-statistic of 2.45) when comomentum is in the highest quintile compared to when it is in the lowest quintile. Though formation returns are higher when comomentum is high, we find that post-formation returns in year 1 are generally decreasing in the degree of comomentum. On average, the post-formation monthly momentum return is 1.06% per month *lower* (estimate $=-1.06\%$, t-statistic of -2.72) when comomentum is in the highest quintile compared to the lowest quintile.[20]

We also find that year 2 returns are strongly decreasing in comomentum. On average, the post-formation monthly return on momentum stocks in year 2 is 1.08% per month lower (estimate of -1.08%, t-statistic of -2.75) as comomentum moves from the highest to the lowest quintile. Given the strength of the year 1 and year 2 estimates, it is not surprising that the joint estimate is both economically and statistically very significant (estimate of -1.07%, t-statistic of -3.35). Indeed, panel A documents that returns for years 1 and 2 are strongly monotonically decreasing in comomentum. By the end of year 2, all reversal of the relative variation in year 0 returns has occurred, and we find no variation in cumulative returns related to comomentum. Panels B and C of Table 3 document that these conclusions are robust to controlling for the Fama and French (1993) three-factor model and the Fama and French (2015) five-factor model.[21]

Figure 3 graphically illustrates the patterns reported in Table 3, panel A. The top panel of Figure 3 plots the cumulative returns to the momentum strategy in the 4 years after portfolio formation conditional on low comomentum or high comomentum. This plot shows that the cumulative average buy-and-hold return on the momentum strategy is positive when comomentum is low and negative when comomentum is high. The bottom panel of Figure 3 plots the cumulative buy-and-hold return to the momentum strategy from the beginning of the formation year to 4 years after portfolio formation, again conditional on low comomentum or high comomentum. This plot shows that when comomentum is low, cumulative buy-and-hold returns from the beginning of the portfolio formation year to 4 years subsequent exhibit underreaction. However, when comomentum is high, the corresponding cumulative returns exhibit overreaction as returns decline from a peak of 267% in month 6 of year 1 (including the formation period return spread) to 192% in month 12 of year 4. Interestingly, this amount is roughly similar to the level of cumulative returns in low comomentum states, suggesting that the amount

[20] Following prior literature, we skip a month between momentum portfolio formation and holding periods. We observe a similar pattern in momentum returns in the skipped month; the momentum strategy yields almost 2% higher in low comomentum periods than in high comomentum periods in that month.

[21] A natural question to ask is whether our main finding is stronger when $CoMOM^L$ and $CoMOM^W$ are both in the highest rank. In unreported results, we find that a double sort on these two components of comomentum results in even stronger return predictability compared to our baseline result. Specifically, the difference in the years 1 and 2 premium is -2.06%, nearly twice the baseline result of -1.07%. We thank a referee for this suggestion.



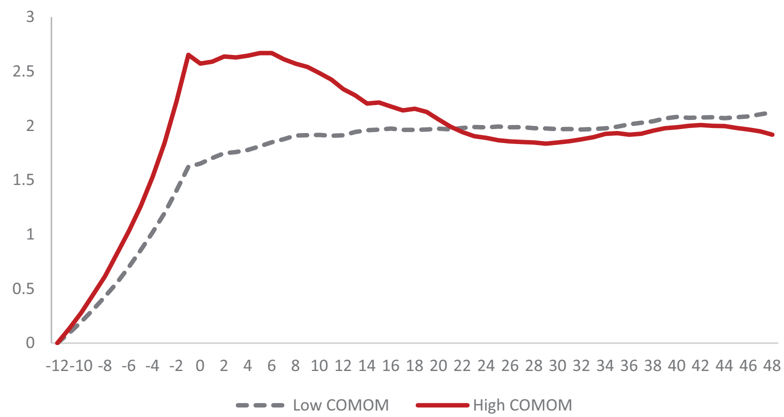


Figure 3
Returns to the momentum strategy as a function of the lagged comomentum measure
At the end of each month, we sort all stocks into deciles based on their lagged 11-month cumulative returns (skipping the most recent month). We compute pairwise abnormal return correlations (after controlling for the Fama-French three factors) for all stocks in both the bottom and top deciles using weekly Fama-and-French 30-industry-adjusted stock returns in the previous 12 months. To mitigate the impact of microstructure issues, we exclude stocks with prices below \$5 a share and/or that are in the bottom NYSE size decile from the sample. We then classify all months into five groups based on $CoMOM$, the average of $CoMOM^L$ and $CoMOM^W$. $CoMOM^L$ (loser comomentum) is the average pairwise abnormal return correlation in the loser decile in year t, while $CoMOM^W$ (winner comomentum) is the average pairwise abnormal return correlation in the winner decile. The top panel shows the compounded returns to a value-weight momentum strategy (i.e., winner minus loser deciles) in the four years after formation, following low and high $CoMOM$. The bottom panel shows the compounded returns to a value-weight momentum strategy (i.e., winner minus loser deciles) from the beginning of the formation year to 4 years post-formation following low and high $CoMOM$.

of fundamental news does not vary with the amount of arbitrage activity in the strategy.

Figure 3 also sheds light on the frequency at which positive feedback happens as all of the overreaction response occurs in the formation period.

In stark contrast, month t+1 holding period returns are not higher during high comomentum periods.[22]

Daniel and Moskowitz (2016) and Daniel, Jagannathan, and Kim (2019) study the non-normality of momentum returns with a particular focus on the negative skewness in momentum returns. Both papers argue that momentum crashes are forecastable.[23] To the extent that many quantitative momentum traders use leverage and/or have short-term capital, crowded trading may lead to forced unwinding of their positions and hence higher momentum crash risk. Panel D of Table 3 reports the extent to which comomentum forecasts time-series variation in the crash risk of momentum returns. We examine the fraction of "bad" momentum days in the 12 months post-formation, following low versus high comomentum periods. We define "bad" days as having a momentum return below -1%.[24] Panel D documents that this measure is strongly increasing in comomentum. For example, in the first 3 months post-portfolio formation, when comomentum is low, only 8.4% of the daily returns on momentum stocks are less than 1%. This percentage is more than doubled to 22.5%, when comomentum is high. On a related note, Internet Appendix Table A2 reports the extent to which comomentum forecasts time-series variation in the skewness of momentum returns. We examine both the skewness of daily returns (in months 1–3) and weekly returns (months 1–6 and months 1–12).[25]

2.3 Robustness tests

Table 4 provides a variety of robustness checks. For succinctness, we only report the difference in returns to the momentum strategy between the high and low *CoMOM* quintiles for year 0 and for the combined return in years 1 and 2. Panel A of Table 4 provides various subsample analysis. For comparison, the first row of Table 4 reports the baseline results from Table 3, panel A. The average monthly return in years 1 and 2 is 1.07% lower in the high comomentum quintile than in the low comomentum quintile. We can strongly reject the null

22 One interesting question is whether crowded trading can predictably increase the profitability of momentum strategies, at least in the short run. For example, can smart arbitrageurs profitably "ride the bubble" as in Abreu and Brunnermeier (2003) using a faster momentum strategy? As one way to address this question, we have redone our analysis on a 6-month momentum strategy. Using comomentum computed over this shorter window, we find that the three-factor-adjusted momentum strategy return in the top *CoMOM* quintile is an economically and statistically significant 2.21% (t=2.64) in the month following portfolio formation.

23 Daniel and Moskowitz (2016) show that market declines and high market volatility forecast momentum crashes. Daniel, Jagannathan, and Kim (2019) estimate a hidden Markov model that helps identify those times when momentum strategies experience severe losses.

24 The results are similar if we use other cutoffs to identify bad days (e.g., returns less than -2% or -3%).

25 In panel D of Internet Appendix Table A2, we also examine the way the betas of momentum portfolios (as well as their long and short components) change in the year after portfolio formation. Consistent with previous research (Chen, Singal, and Whitelaw 2016), we find that momentum portfolios tend to have betas that increase over the next year and that this increase is roughly attributable to both the long and short sides of the trade. However, we find no evidence that this effect varies with comomentum as the related point estimate (-0.046) is statistically insignificant (t-statistic of -0.42). These conclusions continue to hold even after zeroing in on the loser side of the portfolio.

Table 4
Robustness checks

	Year 0		Years 1–2	
	Estimate	*t*-stat	Estimate	*t*-stat
A. Subsample analyses				
Full sample: 1965–2015	**2.59%**	(2.45)	**−1.07%**	(−3.35)
Subsample: 1965–1980	−0.36%	(−1.46)	−0.51%	(−1.57)
Subsample: 1981–2015	**2.65%**	(2.55)	**−1.04%**	(−3.23)
Subsample: 1981–1994	0.74%	(1.90)	**−0.80%**	(−4.88)
Subsample: 1995–2015	2.00%	(1.91)	**−1.11%**	(−3.94)
Subsample: 1981–2015 (excld NASDAQ bubble)	**2.01%**	(2.82)	**−0.79%**	(−2.70)
Subsample: 1981–2015 (excld 2008–2009 crash)	**2.82%**	(2.31)	**−0.94%**	(−2.80)
Placebo sample: 1927-1964	−1.25%	(−0.88)	0.15%	(0.33)
Placebo Sample: Low IO stocks	2.65%	(1.91)	−0.54%	(−1.41)
High IO stocks	**2.87%**	(2.92)	**−1.42%**	(−4.36)
High-low IO stocks	0.22%	(0.51)	**−0.88%**	(−3.91)
B. Alternative ways to compute comomentum				
CoMOM measured over months 2–7	**2.28%**	(2.43)	**−0.97%**	(−2.90)
CoMOM without industry adjustment	**2.52%**	(2.72)	**−1.14%**	(−3.54)
$CoMOM^W$ without industry adjustment	**1.87%**	(2.17)	**−0.95%**	(−3.21)
$CoMOM^L$ without industry adjustment	**2.36%**	(2.76)	**−0.90%**	(−3.04)
CoMOM without industry or FF adjustment	**2.69%**	(2.22)	**−1.13%**	(−3.19)
Pooling winners and losers	**1.63%**	(2.84)	**−0.89%**	(−3.32)
PCA of *CoMOM* and *CoVAL*	**2.71%**	(2.25)	**−1.30%**	(−3.54)
C. Time-series controls				
Control for MKT CORR	**1.71%**	(3.21)	**−0.77%**	(−3.29)
Control for VOL(UMD)	1.23%	(1.91)	**−0.69%**	(−2.65)
Control for VOL(MKT)	**1.77%**	(2.61)	**−0.61%**	(−2.42)
Control for Panic	**2.25%**	(2.16)	**−0.82%**	(−2.29)
Control for *CoVAL*	**1.24%**	(2.22)	**−0.48%**	(−2.29)
Control for MOM spread	1.21%	(1.58)	**−0.77%**	(−2.83)
Control for MOM valuation spread	**2.35%**	(2.72)	**−0.65%**	(−2.10)
Control for deciles 5&6	**1.57%**	(2.83)	**−0.76%**	(−3.14)
Control for placebo *CoMOM*	1.22%	(1.22)	**−1.04%**	(−4.75)
Control for BW sentiment	**1.76%**	(2.08)	**−0.95%**	(−3.43)
Control for Michigan Consumer Index	**2.61%**	(2.42)	**−1.15%**	(−3.54)
D. Different performance adjustments				
DGTW-adjusted returns	**1.47%**	(2.41)	**−0.99%**	(−3.79)
Intraindustry returns	**1.98%**	(2.18)	**−0.76%**	(−3.24)
E. Other measures to forecast momentum returns				
MOM spread controlling for *CoMOM*	**4.13%**	(3.69)	−0.35%	(−0.65)
Deciles 5&6 controlling for *CoMOM*	1.26%	(0.82)	−0.29%	(−0.54)
Placebo *CoMOM* controlling for *CoMOM*	0.13%	(0.15)	0.18%	(0.53)
Mom stock vol controlling for *CoMOM*	**3.50%**	(2.66)	−0.48%	(−0.93)
F. Out-of-sample tests				
Rolling 10 years	**2.49%**	(2.42)	**−1.24%**	(−3.22)
Rolling 20 years	**3.23%**	(2.64)	**−1.21%**	(−2.58)

(*Continued*)

hypothesis that this difference is zero as the associated t-statistic is -3.35; this hypothesis test is the key result of the paper.

In rows 2 and 3, we conduct the same analysis for two subperiods (1965–1980 and 1981–2015). Our finding is stronger in the second subsample, consistent with the intuition that momentum trading by mutual funds and hedge funds has dramatically increased in popularity over the last 30 years. The second subsample has an average monthly return differential in years 1 and 2 across the high and low comomentum quintiles of -1.04%, with an associated t -statistic of -3.23. This point estimate is nearly twice as large as the corresponding estimate for the earlier period.

Table 4
(Continued)

	G. Other strategies			
CoVAL forecasting value	**−2.41%**	(−4.20)	**1.17%**	(2.39)
CoVAL (control for *CoMOM*) forecasting value	**−2.18%**	(−4.21)	**0.98%**	(2.17)
PCA of *CoMOM* and *CoVAL* forecasting value	**−2.13%**	(−3.30)	**1.10%**	(2.25)
CoEMOM forecasting earnings momentum	**0.87%**	(2.79)	−0.04%	(−0.27)
CoLTR forecasting long-term reversal	−0.43%	(−0.89)	**1.22%**	(3.10)

This table reports returns to the momentum strategy as a function of lagged comomentum. At the end of each month, we sort all stocks into deciles based on their lagged 11-month cumulative returns (skipping the most recent month). We exclude stocks with prices below $5 a share and/or that are in the bottom NYSE size decile from the sample. We then classify all months into five groups based on *CoMOM*. We report the difference in returns to the momentum strategy between high *CoMOM* years and low *CoMOM* years. Year zero is the portfolio ranking period. Panel A provides subsample analysis. Row 1 shows the baseline results that are also reported in Table 3, panel A. In rows 2 through 11 of the panel, we conduct the same analysis for various subperiods or subsamples based on institutional ownership splits. Panel B documents that the results are robust to using different methods of measuring comomentum. In row 1, we measure comomentum only in months t-7 to t-2 during the formation period. In rows 2 through 4 of the panel, we do not industry-adjust returns before measuring comomentum. In row 5, we do not control for industry or the Fama-French size and value factors in measuring comomentum. In row 6 of the panel, we stack winners and losers together (putting a minus sign in front of the losers) and compute a *CoMOM* measure for this combined portfolio. In row 7, we calculate the principal component of *CoMOM* and *CoVAL*. Panel C documents that our findings are robust to controlling for a variety of time-series variables by first orthogonalizing comomentum to the variable in question. Row 1 of panel C controls for the average weekly pairwise correlation of all stocks in the formation year. Row 2 of panel C controls for the weekly return volatility of the momentum factor in the formation year. Row 3 of panel C controls for the weekly return volatility of the market index in the formation year. Row 4 of panel C controls for the Daniel and Moskowitz (2016) Panic variable. Row 5 of panel C controls for our *CoVAL* measure. Row 6 of panel C controls for the formation-period spread between the winner and loser deciles. Row 7 of panel C controls for the spread in the book-to-market ratio between the winner and loser deciles. Row 8 of panel C controls for the average pairwise abnormal return correlation of stocks in deciles 5 and 6 ranked by lagged 12-month cumulative returns. Row 9 of panel C controls for placebo comomentum which is based on the same set of winner/loser stocks but measured in the year prior to the formation period. Rows 10 and 11 of panel C control for measures of sentiment from Baker and Wurgler (2006) and the Michigan Consumer Index, respectively. Panel D shows our results are robust to various performance adjustments including using Daniel et al. (1997) (DGTW)-adjusted returns or industry-adjusted returns to measure abnormal momentum returns. Panel E documents that other variables do not forecast the same long-run reversal that comomentum does. Panel F conducts out-of-sample tests by estimating and ranking *CoMOM* in 10- and 20-year rolling windows. Panel G documents the extent to which similar comovement measures for the value, earnings momentum (EMOM), and long-term reversal (LTR) strategies forecast long-horizon returns on those strategies. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial-dependence up to 24 lags and indicate statistical significance at the 5% level in bold.

In rows 4 and 5 of panel A, we further split the post-1980 sample into two halves since momentum strategies are known to have dramatically crashed in 2009. Our effect is roughly similar in both halves of the post-1980 sample. Indeed, the t-statistic is more than 20% larger in absolute magnitude in the 1981–1994 portion of the sample that does not include the momentum crash of 2009. More broadly, the evidence in rows 6 and 7 of the panel documents that large declines in momentum holding period returns do not drive comomentum's strong predictability in the 1981–2011 subperiod. In particular, our finding is robust to excluding years in which realized momentum holding period returns were relatively low.

Row 8 of Table 4, panel A, examines the pre-1965 subperiod. This sample provides a potentially useful placebo test of our hypothesis that institutional ownership is responsible for the overnight momentum pattern, as institutional ownership was very low for all but the largest stocks (see Blume and Keim 2014). Consistent with our hypothesis, we find no predictable variation in years

1 and 2 returns linked to comomentum in the pre-1965 period. In fact, the estimate is not only insignificant but also the wrong sign.

We exploit a similar idea using a cross-sectional approach in the post-1980 period. The last three rows of panel A present those results. Specifically, the years 1 and 2 predictability associated with moving from low to high $CoMOM$ subperiods among only low-institutional-ownership stocks is a statistically insignificant −0.54% per month (t-statistic of −1.41). In stark contrast, moving from low to high *CoMOM* states among only high-institutional-ownership stocks is associated with a predictable difference in years 1 and 2 returns of −1.42% per month (t-statistic of −4.36). A test that the difference in these years 1 and 2 differences across these two nonoverlapping groups of stocks is different from zero has a t -statistic of −3.91, which rejects at the 0.1% level of significance. [26]

Panel B of Table 4 confirms that our main finding is robust to different ways of measuring comomentum. Our results continue to hold if we simply measure comomentum over months $t-7$:$t-2$ in the formation period, if we use raw excess returns instead of industry-adjusted returns, or if we focus on just one side of the momentum bet to measure comomentum. Our results also continue to hold if we neither industry-adjust nor control for the Fama-French three-factor model or if we first pool all of the stocks in the winner and loser deciles before calculating comomentum (when doing so, we stack winners and losers together and put a minus sign in front of the losers).

This last robustness test also relates to a simple test of our story. If arbitrageurs are simultaneously buying winners and shorting losers, then not only will the correlation among winners be higher and the correlation among losers be higher, but also the correlation between winners and losers will be more negative. Consistent with our story, we find that the correlation between *CoMOM* and the negative of the correlation between the winner and loser portfolios is 21.4%. That estimate is significant at the 1% level of significance.

Finally, row 7 of Table 4, panel B, documents that the principal component of comomentum and covalue forecasts time-series variation in the returns on momentum stocks in years 1 and 2 with a t-statistic of −3.54. This principal component also forecasts time-series variation in the returns on value stocks in years 1 and 2 with a t-statistic of 2.25 (see row 3 of Table 4, panel G). We discuss these results in more detail in Section 4.2 after we summarize our model in Section 4.1.

Table 4, panel C, shows that our results are robust to orthogonalizing comomentum to a variety of other time-series variables before running our tests. We first confirm that our results are robust to controlling for volatility estimates

26 Internet Appendix Table A3 shows the results from these tests in more detail. Given the results of Lee and Swaminathan (2000), we also examine splitting the sample in a similar fashion based on turnover and the book-to-market ratio. In either case, we find no difference in comomentum's ability to forecast time variation in momentum's long-run reversal.

measured contemporaneous with our comomentum variable that are calculated using weekly returns over the exact same period of time during the formation period. Pollet and Wilson (2010) document that the average correlation among stocks forecasts the equity premium. Row 1 of panel C confirms that our findings are robust to controlling for their variable. As Barroso and Santa-Clara (2015) show, the volatility of a momentum strategy is highly variable over time and quite predictable; therefore, row 2 of panel C reports results when we orthogonalize *CoMOM* to the contemporaneous weekly standard deviation of a standard momentum portfolio. Row 3 reports the robustness of our results to controlling for the volatility of weekly returns on the market.

Row 4 of panel C controls for Daniel and Moskowitz's (2016) panic variable, while row 5 controls for *CoVAL*, a measure of excess comovement in the value strategy that we discuss in detail in section 4.2. Rows 6 and 7 control for standard measures of the ex ante attractiveness of a strategy, namely, the spread in the characteristic across the winner and loser deciles (MOM spread) and the spread in valuation ratios across the winner and loser deciles (MOM valuation spread).[27] Row 8 controls for the corresponding comovement measure for momentum deciles 5 and 6. In all cases, our results remain economically and statistically significant. Row 9 of Table 4 exploits a clever way of controlling for omitted factors that might be driving comomentum by controlling for a lagged (in event time) version of our measure. By controlling for this "Placebo *CoMOM*," we increase the absolute magnitude of the t-statistic on our key finding by more than 40%.

As we show in the context of our model, stronger underreaction on the part of noise traders clearly leads to intensified arbitrage activity, if all else is equal. While we agree that our comomentum measure could, in theory, be partly driven by this demand-side consideration, we find in the data that comomentum is only weakly correlated with popular measures of investor sentiment, namely, the Baker and Wurgler (2006) index, as well as the University of Michigan Consumer Sentiment Index. More importantly, the return predictability of comomentum is virtually unaffected when we control for these proxies for investor sentiment (results reported in Table 4, panel C). For example, after controlling for the Baker and Wurgler (2006) index, comomentum continues to forecast time-series variation in momentum returns in years 1 and 2; the point estimate is -0.95%/month and has an associated t-statistic of -3.43. After controlling for the Michigan Consumer index, comomentum continues to forecast time-series variation in the post-formation returns on momentum stocks in years 1 and 2 with a point estimate of -1.15%/month with a t-statistic and associated t-statistic of -3.54.

27 In Internet Appendix Table A4, we document the inability of these traditional variables to forecast momentum holding-period returns. Both formation-period spreads in the momentum characteristic (panel A) and formation-period spreads in valuation ratios across winner and loser stocks (panel B) do not predict abnormal holding period returns on momentum strategies.

Panel D of Table 4 documents that our key result is robust to alternative ways of adjusting momentum performance including using DGTW-adjusted returns or industry-adjusted returns. Panel E documents that other variables do not forecast time-series variation in *long-horizon* returns on momentum strategies. These variables include the aforementioned MOM spread, the comovement of deciles 5 and 6, Placebo *CoMOM*, and the average momentum stock formation period volatility.

The MOM spread variable warrants additional discussion. One might suggest that using the cross-sectional spread in past 12-month returns should indicate the degree of underreaction/return-continuation in the market and thus forecast both the profitability of a momentum strategy and arbitrageur demand. However, using the preformation return spread across momentum deciles is potentially flawed by exactly the endogenous mechanism that we model and estimate in the paper. Conceptually, a large spread in preformation returns might mean that a lot of news has not been fully incorporated into prices. Alternatively, it could mean that just the right amount of reaction by market participants has taken place. A third interpretation is that a significant amount of overreaction to initial news has occurred that will continue. Finally, a large preformation return spread might indicate that a significant amount of overreaction to initial news has already occurred and is now due to reverse. Empirically, we find that the past return spread does not predict higher momentum holding-period returns in the data (Internet Appendix Table A4, panel A). Moreover, as row 1 of Table 4, panel E, documents, the return spread does not forecast post-holding period returns on momentum stocks in the presence of our comomentum measure.

On a related note, one might worry that our results are a repackaging of the long-run reversal pattern in returns. This concern is unwarranted for a variety of reasons: (1) Comomentum is an average correlation of residuals from a factor regression and thus is unaffected by the realized average return of momentum stocks during the formation period. (2) Comomentum subsumes the return spread when forecasting time variation in the expected holding and post-holding period returns of momentum stocks. (3) Our result is robust to controlling for the value factor of Fama and French, which prices the long-run reversal effect (Fama and French 1996).

Table 4, panel E, row 4, documents that the difference in momentum returns between high and low momentum-stock-volatility periods is -0.48% per month (t-statistic$=-0.93$) in the 2 years after portfolio formation. This result shows that our focus on correlations when measuring comomentum is sensible. That component of portfolio volatility more likely reveals the activity of a quant arbitrageur, who trades a portfolio of stocks, than the activity of a noise trader, who more likely trades a solitary winner or loser. Table 4, panel F, confirms that our results are robust to measuring the predictability finding of the paper on an out-of-sample basis. These tests ensure that the trading strategy implicit in the analysis is fully implementable.

Taken together, these results confirm that our comomentum measure of crowded momentum trading robustly forecasts times of strong reversal to the returns of momentum stocks and does not simply represent a repackaging of some existing variable. Therefore, our novel approach to measuring momentum arbitrage activity is a robust and unique way of identifying when and why momentum transitions from being an underreaction phenomenon to being an overreaction phenomenon.

Finally, we revisit our key result of Figure 3 using an instrumental variables approach. Table 2 documents that more arbitrage trading flows to the momentum strategy when the strategy has recently performed well. An alternative interpretation of our findings might be that variation in *CoMOM* reflects arbitrageurs optimally allocating more capital to the momentum trade when it is viewed as more profitable, for example, because of stronger underreaction on the part of noise traders. We note the absence of strong evidence that momentum holding period returns are persistent. Moreover, as we detailed above, standard measures of the attractiveness of momentum holding period returns deteriorate markedly when comomentum increases. Nevertheless, some end investors and/or portfolio managers may hold this erroneous belief. This tension leads to a natural test.

In particular, we instrument comomentum with the cash flow news component of lagged momentum strategy returns. We solely focus on this component of returns since doing so allows us to remove any feedback effect that momentum trading generates. Indeed, in a world in which arbitrage activity in momentum stocks is just enough to eliminate underreaction, but not so much as to result in overreaction, holding period returns to momentum strategies should consist of *only* cash flow news. The results from this test are consistent with our proposed supply-side mechanism and inconsistent with the alternative demand-side explanation. As we show in Internet Appendix Table A5, periods of high instrumented comomentum are followed by a stronger reversal to the momentum strategy. In particular, both holding period and post-holding period returns to the momentum strategy are markedly lower. Figure A8 shows these patterns in pre- and post-formation returns to the momentum strategy using instrumented comomentum. As the figure shows, we continue to find that arbitrage activity in the momentum strategy can be destabilizing.

3. A Simple Model and Additional Predictions

To help motivate and interpret our empirical work, the Internet Appendix presents a simple model of crowded trading, building on the work of Hong and Stein (1999). In their model, Hong and Stein study the interaction of newswatchers and quantitative traders following well-known strategies, and assume that the number of quantitative traders is fixed. We extend their setting to incorporate a *time-varying* number of quantitative traders (or, equivalently, time-varying aggregate risk tolerance), to reflect the fact that arbitrage capital can change stochastically.

We summarize the key results as follows. First, momentum returns peak in the short run and then gradually and partially reverse in subsequent periods. Second, all else equal, a larger amount of momentum capital is associated with a larger return effect at the time of the arbitrageurs' trades and then a smaller drift subsequently. In other words, as more capital arrives, momentum traders incorporate more information into prices as they trade, consequently making the momentum strategy less profitable. Third, a larger amount of momentum capital is also associated with a larger reversal in the long run, consistent with the idea that momentum trading can be destabilizing.

3.1 Arbitrage activity and strategy returns

To speak more directly to our empirical tests, we compare periods in our model with high momentum (value) activity versus periods with low momentum (value) activity. Momentum spreads in the formation period are larger in high momentum activity periods than in low activity periods. There is also a larger reversal to the momentum strategy after periods with high momentum activity than periods with low activity. Momentum returns in the holding period, however, depend on arbitrageur's risk tolerance. When momentum traders are relatively risk-averse, momentum returns in period 1 are larger in high momentum activity periods than in low activity periods; when momentum traders are relatively risk-tolerant, the reverse is true.

For the value strategy, in both the holding and post-holding periods, returns are strictly larger after high realizations of value activity than low realizations of value activity. The reason that our model has different predictions for momentum and value is that value is a negative-feedback strategy. Though value traders' demand is a linear function of the value signal as well, the resultant demand also shrinks the signal. This fact has two implications: (1) The equilibrium value signal is a positive predictor of future value strategy returns (in contrast, the momentum signal can be a negative predictor of future returns). (2) High value activity is accompanied by a relatively large value signal, which in turn indicates high expected returns to the value strategy. See Section 2.2 of the Internet Appendix for a detailed discussion.

3.2 Value (and other) strategy returns

As our model predicts that arbitrage activity is generally stabilizing in negative-feedback strategies, we turn to the other workhorse trading strategy studied by academics, implemented by practitioners, and modeled in our theory: the value strategy. We study the comomentum analogue for the value strategy, which we dub *CoVAL*. Table 4, panel G, shows the results of using *CoVAL* to predict buy-and-hold returns on the value strategy. Consistent with our model, times of relatively high comovement among value stocks forecast relatively high returns to a value strategy rather than relatively low returns. Furthermore, we find that there is no evidence of any long-run reversal (Table 4, panel G, rows 1–3, and Internet Appendix Table A6, panel A) or relatively high negative skewness (Internet Appendix Table A6, panel B) associated with *CoVAL*. These results are consistent with price stabilization.

In our model, value arbitrageurs are rationally pursing value bets when they are more attractive. We test this in the data by analyzing the relation between *CoVAL* and the cross-sectional spread in book-to-market equity ratios, dubbed the value spread by Cohen, Polk, and Vuolteenaho (2003). [28] Cohen, Polk, and Vuolteenaho (2003) derive the way the value spread should be related to the relative attractiveness of the value strategy and show that the value spread forecasts the return on the value-minus-growth bet. The *CoVAL* measure is indeed economically and statistically related to the value spread. The contemporaneous correlation between covalue and the value spread is a highly statistically significant 0.17. Moreover, when we forecast *CoVAL* with the lagged value spread, we find an adjusted R^2 of 6.02% and a t -statistic of 6.09. Interestingly, covalue remains a significant (albeit weaker) predictor of future value returns after controlling for the value spread, suggesting that arbitrageurs use more information than what is included in our measure of the value spread.

We argue that the negative-feedback nature of a value strategy is what generates a positive relation between arbitrage activity and subsequent long-horizon returns on value stocks. To confirm this aspect of our model, we examine another negative-feedback strategy: LTR, that buys long-term losers and sells long-term winners (based on the last 3 years of returns). Row 5 of Table 4, panel G, shows that *CoLTR* forecasts time-series variation in the post-formation returns to the long-term reversal strategy in years 1 and 2 with a point estimate of 1.22%/month and an associated t-statistic of 3.10.

A particularly interesting test in Table 4, panel B, uses the principal component of comomentum and covalue. We find that comomentum and covalue have a correlation of 0.51. If we use the common component of these two measures, our forecasting results remain strong. In particular, the principal component of comomentum and covalue forecasts time-series variation in the returns on momentum stocks in years 1 and 2 with a t-statistic of -3.54 and also forecasts time-series variation in the returns on value stocks in years 1 and 2 with a t-statistic of 2.25. This finding is consistent with the extended version of our model where variation in arbitrage activity is at the industry level, not the strategy level, and arbitrageurs optimally choose the extent to which they combine value and momentum signals. We verify that this common component is tied to an observable measure of arbitrage capital: the correlation between the common component of *CoMOM* and *CoVAL* and the logarithm of aggregate

[28] Asness et al. (2000) also link variation in the value spread to the subsequent profitability of value strategies.

long-short equity hedge fund AUM is 58.3%. This striking result provides nice confirmation of our paper's core idea.

Table 4 also shows that both comomentum and covalue have incremental information about subsequent returns on their respective strategies controlling for the other. In particular, comomentum, controlling for covalue, forecasts time-series variation in the returns on momentum stocks in years 1 and 2 with a t-statistic of -2.29. Covalue, controlling for comomentum, forecasts time-series variation in the returns on value stocks in years 1 and 2 with a t-statistic of 2.17. This finding is also sensible as it is reasonable to expect that not all arbitrageurs use both types of strategies.

Finally, earnings momentum strategies should exhibit much less destabilizing trading behavior than price momentum strategies as arbitrageurs observe the actual earnings surprise and not just the price response to earnings information. In particular, the signal is not affected by arbitrageurs' trading, so there is no positive-feedback loop. Consistent with the above intuition, Table 4, panel G, shows that destabilizing predictability identified using *CoEMOM* for the standard earnings momentum strategy of Bernard and Thomas (1989) is statistically insignificant with a point estimate of -0.04% (t-statistic$=-0.27$).

4. Conclusions

Over the last several decades, professional money managers have grown to dominate asset markets. The typical presumption is that these sophisticated investors will make markets more efficient and stabilize prices. We propose a novel approach to measuring the extent and consequence of these sorts of investors based on high-frequency excess return comovement. We exploit this idea in the context of the price momentum strategy of Jegadeesh and Titman (1993), measuring the comovement of momentum stocks in the formation period. We link this *comomentum* measure to future characteristics of the momentum strategy to determine whether arbitrage activity can be destabilizing. We focus on price momentum not only because of the failure of both rational and behavioral models to explain stylized facts about that strategy but also because momentum is a classic example of a positive-feedback strategy where coordination problems are particularly severe. For this class of trading strategies, arbitrageurs do not base their demand on an independent estimate of fundamental value; instead, their demand for an asset is an increasing function of price. Thus, this type of positive-feedback trading strategy is a likely place in which arbitrage activity can be destabilizing, which we confirm in a model of time-varying arbitrage activity.

Our comomentum measure of the momentum crowd is a success based on three main empirical findings. First, comomentum is significantly correlated with existing variables plausibly linked to the size of arbitrage activity in this market. Second, comomentum forecasts relatively low holding-period returns, relatively high holding-period return volatility, and relatively more negative holding-period return skewness for the momentum strategy. Finally, when comomentum is relatively high, the long-run buy-and-hold returns to a momentum strategy are negative, consistent with times of relatively high amounts of arbitrage activity pushing prices further away from fundamentals. These results are only present for stocks with high institutional ownership and during the modern period. In sharp contrast but as predicted by our model, a similar measure for the value strategy, *covalue*, positively forecasts future value strategy returns. This finding is consistent with arbitrageurs stabilizing prices when following negative-feedback strategies. Taken together, our results provide novel evidence that arbitrage activity can be destabilizing in strategies characterized by positive-feedback trading.

References

Abreu, D., and M. K. Brunnermeier. 2003. Bubbles and crashes. *Econometrica* 71:173–204.

Anton, M., and C. Polk. 2014. Connected stocks. *Journal of Finance* 69:1099–127.

Asness, C. S., J. A. Friedman, R. J. Krail, and J. M. Liew. 2000. Style timing: Value versus growth. *Journal of Portfolio Management* 26:50–60.

Baker, M., and J. Wurgler. 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance* 61:1645–80.

Barberis, N., and A. Shleifer. 2003. Style investing. *Journal of Financial Economics* 68:161–99.

Barberis, N., A. Shleifer, and J. Wurgler. 2005. Comovement. *Journal of Financial Economics* 75:283–317.

Barroso, P., and P. Santa-Clara. 2015. Momentum has its moments. *Journal of Financial Economics* 116:111–20.

Bernard, V. L., and J. K. Thomas. 1989. Post-earnings-announcement drift: Price response or risk premium? *Journal of Accounting Research* 27:1–36.

Blume, M. E., and D. Keim. 2014. The changing nature of institutional stock investing. *Critical Finance Review* 6:1–41.

Boehmer, E., C. M. Jones, and X. Zhang. 2008. Which shorts are informed? *Journal of Finance* 63:491–527.

Brunnermeier, M. K., and S. Nagel. 2004. Hedge funds and the technology bubble. *Journal of Finance* 59:2013–40.

Cao, C., Y. Chen, W. N. Goetzmann, and B. Liang. 2018. Hedge funds and stock price formation. *Financial Analysts Journal* 74:54–69.

Chen, Y., Z. Da, and D. Huang. 2019. Arbitrage trading: The long and the short of it. *Review of Financial Studies* 32:1608–46.

Chen, H., V. Singal, and R. F. Whitelaw. 2016. Comovement revisited. *Journal of Financial Economics* 121:624–44.

Cho, T. 2020. Turning alphas into betas: Arbitrage and endogenous risk. *Journal of Financial Economics* 137:550–70.

Cohen, R. B., C. Polk, and T. Vuolteenaho. 2003. The value spread. *Journal of Finance* 58:609–41.

Cooper, M. J., R. C. Gutierrez, and A. Hameed. 2004. Market states and momentum. *Journal of Finance* 59:1345–65.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance* 52:1035–58.

Daniel, K., and T. Moskowitz. 2016. Momentum crashes. *Journal of Financial Economics* 122:221–47.

Daniel, K., R. Jagannathan, and S. Kim. 2019. Tail risk in momentum strategy returns. Working Paper, Columbia University.

DeLong, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann. 1990. Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance* 45: 379–95.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

———. 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51:55–84.

———. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116:1–22.

Friedman, M. 1953. The case for flexible exchange rates. In *Essays in positive economics*, 157–203. Chicago: University of Chicago Press.

Frazzini, A., R. Israel, and T. J. Moskowitz. 2020. Trading costs of asset pricing anomalies. Working Paper, New York University.

Griffin, J. M., and J. Xu. 2009. How smart are the smart guys? A unique view from hedge fund stock holdings. *Review of Financial Studies* 22:2531–70.

Hayek, F. A. 1945. The use of knowledge in society. *American Economic Review* 35:519–530.

Hanson, S. G., and A. Sunderam. 2014. The growth and limits of arbitrage: Evidence from short interest. *Review of Financial Studies* 27:1238–86.

Hwang, B. H., B. Liu, and W. Xu. 2019. Arbitrage involvement and security prices. *Management Science* 65:2858–75.

Hong, H., and J. C. Stein. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54:2143–84.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48:65–91.

Jegadeesh, N., and S. Titman. 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *Journal of Finance* 56:699–720.

Keynes, J. M. 1936. *The general theory of employment, interest, and money*. London, UK: Macmillan.

Lee, C. M. C., and B. Swaminathan. 2000. Price momentum and trading volume. *Journal of Finance* 55:2017–69.

Lewellen, J., and S. Nagel. 2006. The conditional CAPM does not explain asset-pricing anomalies. *Journal of Financial Economics* 82:289–314.

Loomis, C. 1966, The Jones nobody keeps up with. *Fortune* April:237–47.

Lou, D. 2012. A flow-based explanation for return predictability. *Review of Financial Studies* 25:3457–89.

Pástor, Ľ., and R. F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111:642–85.

Pollet, J. M., and M. Wilson. 2010. Average correlation and stock market returns. *Journal of Financial Economics* 96:364–80.

Stein, J. C. 1987. Informational externalities and welfare-reducing speculation. *Journal of Political Economy* 95:1123–45.

———. 2009. Presidential address: Sophisticated investors and market efficiency. *Journal of Finance* 64:1517–48.

Wang, K. Q., and J. Xu. 2015. Market volatility and momentum. *Journal of Empirical Finance* 30:79–91.

Welch, I., and A. Goyal. 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 21:1455–508.

Yan, P. 2014. Crowded trades, short covering, and momentum crashes. Working Paper, Goldman Sachs Asset Management.