Comomentum: Inferring Arbitrage Activity from Return Correlations

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Abstract

We propose a novel measure of arbitrage activity to examine whether arbitrageurs can have a destabilizing effect in the stock market. We apply our insight to stock price momentum, a classic example of an unanchored strategy that exhibits positive feedback since arbitrageurs buy stocks when prices rise and sell when prices fall. We define our measure, which we dub *comomentum*, as the high-frequency abnormal return correlation among stocks on which a typical momentum strategy would speculate. We show that during periods of low comomentum, momentum strategies are profitable and stabilizing, reflecting an underreaction phenomenon that arbitrageurs correct. In contrast, during periods of high comomentum, these strategies tend to crash and revert, reflecting prior overreaction resulting from crowded momentum trading pushing prices away from fundamentals. Theory suggests that we should not find destabilizing arbitrage activity in anchored strategies. Indeed, we find that a corresponding measure of arbitrage activity for the value strategy, *covalue*, positively forecasts future value strategy returns, and is positively correlated with the value spread, a natural anchor for the value-minus-growth trade. Additional tests at the firm, fund, and international level confirm that our approach to measuring arbitrage activity in the momentum strategy is sensible.

JEL classification: G02, G12, G23

1 Introduction

Arbitrageurs play a key role in financial markets yet their impact on prices is not well understood. Indeed, the debate on whether arbitrage activity 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.[1] An opposing view argues that arbitrage activity can at times become crowded; thus, too much arbitrage trading can destabilize prices.[2]

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 out risks; yet information regarding these activities is simply unobservable to researchers.[3] Finally, the effect of arbitrage activity on prices depends critically on the liquidity of the assets traded which may vary cross-sectionally and through time.[4] To summarize, 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*

[1] See, for example, Friedman (1953).

[2] Stein (1987) models how the introduction of imperfectly-informed rational speculators can make markets less stable. See DeLong, Shleifer, Summers, and Waldmann (1990) for a model where an increase in the amount of rational speculators can be destabilizing.

[3] Two notable exceptions are Hanson and Sunderam (2012) and Hwang and Liu (2012), who exploit time variation in the cross section of short interest to infer the amount of arbitrage capital in quantitative trading strategies.

[4] For example, a researcher using assets under management (AUM) as a measure of arbitrage activity must take a stance on the appropriate way to scale AUM so that it is comparable throughout the researcher's sample.

return correlations among those stocks that an arbitrageur would speculate on. 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.[5]

We use this insight to provide new evidence on the long-standing debate concerning the impact of arbitrageurs on prices.[6] We first link time-series variation in our new measure to variation in existing variables previously tied to arbitrage activity. We then forecast time variation in whether prices slowly correct or instead overshoot as a function of our arbitrage activity proxy. Thus, our approach enables us to identify periods when there is too little or too much arbitrage trading, depending on the subsequent return pattern.

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 (for example, 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 momentum profits (underreaction vs. overreaction) has been difficult to pin down (Jegadeesh and Titman, 2001).[7]

We focus on momentum not only because of the failure of rational models to explain

[5]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.

[6]See Singleton (2012) for recent work linking speculative activity to changes in prices.

[7]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. Unfortunately, these tests are inconclusive as results tend to be sample specific, not consistent across subsets of stocks, and sensitive to the benchmark model.

these stylized facts, but also because momentum is a classic example of a strategy without a fundamental anchor (Stein, 2009). 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. Consequently, from individual arbitrageurs' perspective, it is difficult, if not impossible, to gauge the amount of capital that has already been deployed in the strategy. An unanchored, positive-feedback trading strategy like momentum is thus the most likely place where arbitrage activity can be destabilizing when trading becomes too crowded (Stein, 2009).[8]

Since Stein's theory predicts that arbitrageurs will be stabilizing in strategies that are anchored, we also apply our novel measure of arbitrage activity to the value strategy. This profitable strategy (Fama and French, 1992) buys value stocks (e.g. stocks with relatively high book-to-market equity ratios) and sells growth stocks (e.g. stocks with relatively low book-to-market ratios). Note that this strategy has a clear anchor in terms of the value spread, i.e. the cross-sectional spread in book-to-market equity ratios. A narrow value spread is a clear signal to arbitrageurs to stop trading the value strategy. Indeed, Cohen, Polk, and Vuolteenaho (2003) document that the expected return on value-minus-growth strategies is atypically high when the value spread is wide.

We first identify the size of the momentum crowd by the relative degree of past abnormal return correlations among momentum stocks.[9] We dub this measure *comomentum*. We then link both the profitability and any subsequent reversal of momentum strategy returns to our comomentum variable. We argue that when comomentum is relatively low—i.e., 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

[8] DeLong, Shleifer, Summers, and Waldmann (1990) also argues that positive feedback trading strategies are prone to destabilizing behavior.

[9] Our notion of arbitrage activity is a broad one that potentially includes arbitrageurs that either exhibit bounded rationality by trading only on the momentum signal or face limits to arbitrage. Indeed, we include in this definition any trader whose investment activity resembles a momentum strategy.

phenomenon is being eliminated. However, when comomentum is relatively high, momentum strategies may become crowded. If so, arbitrage activity may actually be destabilizing, resulting in price overshooting relative to the fundamental value. Therefore, our key empirical prediction is that the underreaction or overreaction characteristic of momentum—i.e., whether momentum profits revert in the long run—is time-varying, crucially depending on the size of the momentum crowd.[10]

Our comomentum measure of the momentum crowd is a success based on several key empirical findings. First, comomentum is significantly correlated with existing variables plausibly linked to the size of arbitrage activity in this market. Second, when comomentum is relatively high, the *long-run* buy-and-hold returns to a momentum strategy are negative, consistent with relatively high amounts of arbitrage activity pushing prices further away from fundamentals. 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 10.4% lower returns over the first year, relative to its performance during the 20% of the sample period associated with low comomentum.[11] The momentum strategy continues to lose 14.4% (again, relative to the low comomentum subsample) in the second year after formation. This underperformance is true if one adjusts momentum profits for exposure to the Fama-French three-factor model (the return differential then becomes 9.5% and 9.4% in years one and two, respectively), or if one first orthogonalizes our comomentum measure to two other variables—past market returns and market volatility—that are known to forecast momentum profits (our corresponding results for this analysis are 9.8% and 15.1% respectively). We find

[10] Our crowded trading story does not have a clear prediction for momentum profits in the short run. In fact, momentum strategies can be more profitable with higher arbitrage trading as underreaction evolves into overreaction.

[11] 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.

that the degree of time-varying long-run reversal is particularly strong in the second half of the sample. This result is consistent with theory as one might expect more destabilizing arbitrage activity due to the phenomenal growth in mutual funds and hedge funds trading momentum over the last thirty years.

We find the exact opposite results when we analyze *covalue*, the relative degree of past abnormal return correlation among value stocks. Consistent with Stein's anchoring hypothesis, when the value spread is relatively narrow, covalue is also low, indicating that arbitrageurs allocate capital to the value strategy based on some measure of future profitability of the strategy. Moreover, times of relatively high covalue indeed forecast relatively high returns to a value strategy rather than relatively low returns (as in the case of price momentum). Furthermore, there is no evidence of any long-run reversal or negative skewness that can be linked to covalue.

These striking results are complemented by a long list of additional empirical findings. Consistent with our crowded-trade hypothesis, the results linking comomentum to long-run reversal of the momentum strategy are stronger for stocks with higher institutional ownership. We additionally show that a firm-level analogue, *stock comomentum*, defined as the extent to which a stock covaries with other momentum stocks during the formation period, strongly and positively forecasts cross-sectional variation in average returns. This return predictability is robust to controls for the momentum characteristic and a standard estimate of the momentum factor loading, as well as other characteristics linked to cross-sectional variation in average returns. Just as our momentum crowd hypothesis predicts, abnormal returns linked to stock comomentum eventually revert, and the magnitude of the reversal is particularly large when our aggregate comomentum measure is relatively high. In sum, we provide an alternative firm-level momentum strategy, motivated by theory, which performs as well as the standard price momentum strategy and yet is distinct from that strategy.

In what is effectively an out-of-sample test, we then show that results obtained from international data are consistent with the U.S. momentum-predictability findings. In every one of the 19 largest non-US stock markets that we examine, country-specific comomentum is negatively associated with subsequent profits from a standard momentum trading strategy. These estimates are economically and statistically significant; we can easily reject the hypothesis that the non-US comomentum effect is zero.

Finally, we use our novel measure of comomentum to understand time-series and cross-sectional variation in the performance of hedge funds, typically considered to be the classic example of an arbitrageur. We show that the typical long-short equity hedge fund decreases their exposure to the momentum factor when comomentum is relatively high. However, the ability of hedge funds to time momentum declines quickly in assets under management. These findings seem reasonable as we would expect large funds to be unable to time a momentum strategy as easily as small funds. Furthermore, such intuitive findings provide additional evidence that our measure is sensible and is indeed related to actual arbitrage activities.

Though we try various ways to control for common risk (and industry) factors when constructing our comomentum measure, we grant that our comomentum proxy could reflect the effect of one or more *unknown* risk factors. We find this alternative interpretation equally interesting. First of all, momentum's sensitivity to this risk factor is positively associated with existing proxies for arbitrage activity. More important, time variation in momentum's sensitivity to this risk factor strongly forecasts future momentum return characteristics. An understanding of this potential missing risk factor can thus help further our understanding of the determinants of both arbitrage activity and cross-sectional expected returns.

The organization of our paper is as follows. Section 2 lays out the intuition linking crowded trades to excess comovement as well as the destabilizing effect of crowded trades in strategies with no fundamental anchor. Section 3 describes the data and empirical methodology. Section 4 presents our main results. Section 5 concludes.

2 Motivation

We motivate our work with two theories that link price momentum to intermediated investment. Though these theories have different mechanisms and underlying assumptions, both theories argue that fund managers, trading a portfolio of stocks, can cause momentum and subsequent reversal.

Crowded trading

One potential theoretical underpinning of our empirical design comes from the work of Stein (2009), who argues that arbitrageurs with access to potentially unlimited capital would in some cases push prices further away from their fundamentals. Stein works within the framework of Hong and Stein (1999) where boundedly-rational "newswatchers" make forecasts based on signals that they privately observe about future firm fundamentals. Given only newswatchers, prices slowly adjust to new information, generating underreaction but never overreaction.

As in Hong and Stein (1999), Stein (2009) adds boundedly-rational arbitrageurs who are simple momentum traders. The key assumption in Stein's model is that each individual arbitrageur cannot know in real time how much capital is deployed by other arbitrageurs in a certain strategy. The inability of each trader to condition his trade on others' behavior then creates a coordination problem: sometimes there is too little arbitrage activity in a strategy, hence the mispricing is not fully corrected; while in other times, there is too much activity and the mispricing is overcorrected.

This intuitive result applies generally to arbitrage strategies that do not have a natural anchor. For strategies with an embedded anchor, such as the pairs-trading strategy, holding the amount of newswatchers' trading constant, rational investors can infer the amount of arbitrage capital already deployed from the deviation in price from the anchor. For example, in the case of the pairs-trading strategy, arbitrageurs would naturally stop investing in the strategy when the divergence in price between the pair of stocks has been eliminated. In contrast, when there does not exist a natural anchor or benchmark, gauging in real time exactly how many other traders are using the same arbitrage model or taking the same arbitrage positions becomes a much more challenging task.

We focus on the price momentum anomaly in this paper for two reasons. First, as discussed in the introduction, price momentum is one of the few asset pricing anomalies that are robust to virtually all asset classes and all geographic locations (Asness, Moskowitz, and Pedersen 2009). Second, and more important, the price momentum effect is a classic example of unanchored arbitrage. Consider a setting where newswatchers underreact to firm-specific information, because of limited attention or the disposition effect, for example. In such a setting, arbitrageurs can attempt to facilitate price correction by purchasing stocks that have recently gone up and selling stocks that have recently gone down. If arbitrageurs only condition their trading activity on a stock's past return, however, such a momentum strategy lacks a natural anchor.

Specifically, a high past return could mean that the firm has just received some good news; given that newswatchers underreact to information, arbitrageurs should then bid up the stock price. On the other hand, a high past return can also mean that other arbitrageurs have already exploited this opportunity to the extent that the price now correctly reflects the fundamental value. Simply by observing past stock returns, individual arbitrageurs cannot distinguish between these two scenarios, thus leading to a coordination problem among arbitrageurs.

An immediate prediction of the above setting is that when the amount of capital deployed in the price momentum strategy is low, price momentum is more likely to be an underreaction phenomenon; that is, we should observe price continuation in the short run, but no return reversal over the long run. In contrast, when the amount of arbitrage capital in the price momentum strategy is high, price momentum will tend to be an overreaction phenomenon; prices overshoot as a result of arbitrageurs' overcorrecting noise traders' underreaction to information. Consequently, we should see a reversal pattern in the long run. Moreover, when the strategy is crowded, if arbitrageurs are forced to withdraw capital from the momentum strategy, their collective unwinding of positions (either resulting from margin calls, or the flow-performance relation) can lead to abrupt momentum crashes.

Slow-moving capital

Another possible theoretical underpinning comes from the work of Vayanos and Woolley (2011) who propose a rational theory of momentum and subsequent reversal based on flows between investment funds that are driven by changes in investors' views about fund managers' efficiency. If flows exhibit inertia (e.g. either because of investor inertia or institutional constraints), Vayanos and Woolley (2011) show that rational prices excessively comove, underreact to expected future flows, and then ultimately revert. The idea that capital is slow-moving and, therefore, flows are persistent is a key component of a growing literature (Duffie, 2010).

One can intuitively link time variation in the Vayanos and Woolley effect to the amount of intermediated capital in the economy. Presumably, when arbitrage capital is low, these rational momentum and reversal effects are smaller. Moreover, as in Hong and Stein (1999) and Stein (2009), one can intuitively augment the Vayanos and Woolley model to have underreaction to news about fundamentals in the absence of intermediated capital.

Arbitrage capital and excess comovement

The challenge to econometricians in testing these 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 that does not have a natural anchor. The main contribution of this paper is to take up this challenge directly by proposing one such measure.[12]

Our measure is motivated by the observation (crucial to the Vayanos and Woolley model and implicit in the Stein story) 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. In contrast, newswatchers, almost by definition, trade stocks one at a time. To the extent that arbitrageurs' trading can move stock prices in the short run, we can then infer the amount of arbitrage capital deployed in a strategy by examining the high-frequency (i.e., daily or weekly) return correlation, over and beyond common risk factors, among the portfolio of stocks that are likely to be bought or sold simultaneously by arbitrageurs.[13] Thus, 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 portfolio. We provide more details on the construction of our variables in the next section.

3 Data and Methodology

The main dataset 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, stocks with prices below $5 a share and/or are in the bottom NYSE size decile are excluded from the sample. We then augment the stock return data with institutional ownership in individual stocks provided by Thompson Financial. We further obtain information on assets under management of long-short equity hedge funds from Lipper's Trading Advisor Selection System (TASS)

[12] Hu. Pan, and Wang (2012) measure "noise" in the Treasury Bond market which they define as price deviations in the Treasurey Bond market relative to a smooth yield curve. They argue that their measure captures the liquidity condition of the overall Treasury market.

[13] For example, Anton and Polk (2013), Greenwood and Thesmar (2011), 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.

and total assets of the shadow banking sector from the Federal Reserve Board. Since the assets managed by hedge funds and held by the shadow banking sector 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.

At the end of each month, we sort all stocks into deciles based on their previous 12-month return (skipping the most recent month). We then compute pairwise partial correlations using 52 weekly returns for all stocks in each decile *in the portfolio ranking period*.[14] We control for the Fama-French three factors when computing these partial correlations to purge out any comovement in stock returns in the same momentum decile induced by known risk factors. Loser comomentum ($comom^L$) is the average pairwise partial correlation for the loser decile, and winner comomentum ($comom^W$) is the average pairwise partial correlation for the winner decile. We operationalize this calculation by measuring the average correlation of the three-factor residual of every stock in a particular decile with the decile in question,

$$comom^L = \frac{1}{N^L}\sum_{i=1}^{N^L} partialCorr(retrf_i^L,\ retrf_{-i}^L \mid mktrf, smb, hml) \tag{1}$$

$$comom^W = \frac{1}{N^W}\sum_{i=1}^{N^W} partialCorr(retrf_i^W,\ retrf_{-i}^W \mid mktrf, smb, hml). \tag{2}$$

where $retrf_i^L$ ($retrf_i^W$) is the weekly return of stock i in the extreme loser (winner) decile, $retrf_{-i}^L$ ($retrf_{-i}^W$) is the weekly 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.

[14] One concern is that arbitrageurs will 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 relatively short as 3 months. Presumably many momentum traders are trading these momentum characteristics and thus would be generating excess comovement that our measure would pick up. 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.

All our results are robust to using either $comom^L$ or $comom^W$.[15] We have also measured *comom* using characteristics-adjusted stock returns (as in Daniel, Grinblatt, Titman, and Wermers 1997) that are orthogonalized not only to the Fama-French factors but also to each stock's industry return, and all our main results go through.[16] We present these and many other robustness tests in Table V.

As we only measure excess correlation across stocks that happen to be in the loser (winner) decile, our proxy mostly captures the relative amount of capital in the momentum strategy rather than capital flowing in and out. To illustrate, suppose that arbitrageurs were generating excess comovement among momentum stocks by exiting their stock positions. If so, the implied price pressure would result in arbitrageurs' long positions losing value and their short positions gaining value. Those stocks would then, all else being equal, no longer be momentum stocks. Moreover, our comomentum measure follows a bottom-up approach (i.e., we measure the average correlation across all stock pairs in either the winner or loser decile). Thus, our technique can capture a wide range of momentum strategies that involve trading a portfolio of momentum stocks, regardless of how diversified the strategies/portfolios are.

4 Results

We first document simple characteristics of our comomentum measure. Table I Panel A indicates that comomentum varies significantly through time. Since the Fama-French daily factor returns are available starting in July 1963, our final sample spans the period of 1964 to 2010. The average loser stock has an economically-large abnormal correlation of 0.118

[15]The results are very similar if we instead measure average excess correlation with a value-weight winner (loser) portfolio or measure the average pairwise correlation of stocks in the winner *and* loser deciles combined (with a minus sign in front of the return of losers).

[16]To ensure further that industry effects are not responsible for our findings, we have explored using industry-adjusted stock returns in both the formation and holding periods to isolate a pure intra-industry effect. We present these results in Table V. Again, all of our main results continue to hold.

during the formation period across the 46-year sample. However, this abnormal correlation can be as low as 0.028 and as high as 0.287. A similar range in variation can be seen for our winner stock comomentum measure. Indeed, Panel B of Table I indicates that loser and winner comomentum are highly correlated through time (correlation of 0.524).

Figure 1 plots comomentum for both the winner and loser deciles. For comparison, we also plot the average excess correlation for a momentum-neutral portfolio (decile 5 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. Focusing on loser comomentum, the serial correlation in the time series of comomentum is 0.35.[17] In analysis not tabulated, we confirm that comomentum is also persistent in event time. In particular, the average excess correlation for the loser decile is more than half of its Year 0 value. Moreover, the correlation between Year 0 and Year 1 comomentum is 0.5, and even Year 2 remains quite correlated with the Year 0 value (0.4).

We will ultimately document that comomentum describes time-varying expected returns on the momentum strategy in both the holding and post-holding periods. Therefore, Table I 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 three-year market return has been negative. In related work, Wang and Xu (2011) argue that relatively high market volatility forecasts relatively low momentum returns. Therefore, we will include the past three-year return on the market portfolio ($mktret36$) and the monthly market return volatility over the past three years ($mktvol36$) as control variables in some of our tests. Table I shows that loser comomentum is negatively correlated with the past return on the market (-0.187) and positively correlated

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

with past market volatility (0.125).

We find that comomentum is high during the tech boom when momentum strategies became quite popular. Figure 1 also shows an increase in comomentum leading up to the 2008 financial crisis. This increase might be initially surprising since capital was apparently leaving hedge funds. However, financial stocks were initially hit with bad news in 2007 and early 2008. As a consequence, investors sold even more financial stocks in late 2008. This reaction is a form of momentum trading, on the short side. We also find an interesting spike in comomentum in the early 1980s.[18] This increase coincides with a sharp increase in the popularity of active mutual funds.[19] A growing literature argues that the flow-performance relation can induce trading by active mutual funds that is very similar to a momentum strategy (Lou 2012).

4.1 Linking Comomentum to Arbitrage Capital

Table II links comomentum to several variables that proxy for the size of arbitrage activity in the momentum strategy. Specifically, Table II forecasts year t comomentum for both the loser and the winner portfolio with these proxies. The first variable we use is the aggregate institutional ownership of the winner decile, pih^{W}_{t-1}, 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, and we focus on their holdings in the winner decile as we do not observe their short positions in the loser decile.

[18] Since Jegadeesh and Titman wrote their paper in the early 1990s, one might initially think that any variation in comomentum before 1990 must be noise since momentum had not yet been "discovered". However, discussions of positive feedback trading (buying securities when prices rise and selling securities when prices fall) have a long history in the academic literature. For example, Delong, Shleifer, Summers, and Waldmann (1990) note that "many forms of behavior common in financial markets can be described as postive feedback trading." Indeed, Jegadeesh and Titman (1993) motivate their analysis based on anecdotal evidence that practitioners use relative strength rules based on price movements over the past 3 to 12 months. Jegadeesh and Titman (1993) also point out that Value Line, the investment research firm, historically had used a price momentum factor at least as early as 1984 when ranking stock's attractiveness. See footnote 3 in Jegadeesh and Titman (1993).

[19] We thank Sheridan Titman for pointing this fact out to us.

We additionally include a variable proposed by Adrian, Moench, and Shin (2010) as a proxy for the size of the shadow banking system (*shadow*). We further include the assets under management (AUM) of long-short equity hedge funds as of the end of year t-1. Finally, we also include the performance of the momentum strategy ($mom12$) in year $t-1$. All regressions include a trend to ensure that our results are not spurious.

The first three columns of Table II correspond to regressions forecasting loser comomentum while the last three report the complimentary winner comomentum forecasting regressions. In all six regressions, $mom12$ is a strong forecaster of future comomentum. 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.

We further find that a relatively high level of institutional ownership among winner stocks forecasts relatively high comomentum among both winner *and* loser stocks. This finding is consistent with our hypothesis as not only do we expect institutions to be the primary investors in momentum strategies but also we expect many institutional investors in momentum strategies to bet not only on winners but also against losers.

Finally, we find that more specific measures of arbitrage investors that focus on hedge fund activity forecast time-series variation in comomentum. In particular, in all six regressions, when *shadow* is relatively high, future comomentum is also high. Similarly, regressions (3) and (6) document that when AUM is relatively high, future comomentum is relatively high as well. As these variables are tied either indirectly or directly to hedge funds, these findings are consistent with an important component of arbitrage activity in the momentum strategy because of this industry.

Note that we find a positive but relatively weak trend in our comomentum variable.[20]

[20] A regression on monthly *comom* on a trend produces a trend coefficient estimate of 0.00008 with a t-statistic of 2.46. This estimate implies an increase of 0.045 in *comom* over the sample period. All results are robust to removing this trend from *comom* prior to the analysis.

The lack of a strong trend might initially be surprising, given the increase in the raw dollar amount of arbitrage capital over the last 40 years. However, comomentum is designed to capture short-term price (co-)fluctuations that are 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 trading causes a smaller price impact.

4.2 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 III tracks the profits on our momentum strategy over the three years subsequent to portfolio formation. Such an event time approach allows us to make statements about whether momentum profits revert.

Table III 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 12-month return. After 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 loser comomentum. (As shown in Table V, our results are robust to using winner comomentum.) Panel A reports the average returns in each of the subsequent three years (labeled Year 1 through Year 3) as well as the returns in the formation period (labeled Year 0) for each of these five groups as well as the difference between the extreme high and the extreme low comomentum groups. In addition to these sorts, Table III also reports the OLS coefficient from regressing the monthly series of realized Year 0, Year 1, Year 2, or Year 3 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 2.4% per month higher (t-statistic of 2.76) 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 0.87% per month *lower* (estimate = -0.87%, t-statistic of -2.11) when comomentum is in the highest quintile compared to the lowest quintile. Looking more closely, we see that momentum profits are still positive and statistically significant for the first three comomentum groups. However, the fourth comomentum group has momentum profits that are statistically indistinguishable from zero. Indeed, the realized momentum profits for the highest comomentum quintile are actually negative.

Finally, we find that Year 2 returns are strongly monotonically decreasing in comomentum. On average, the post-formation monthly return on momentum stocks in Year 2 is 1.20% per month lower (estimate of -1.20%, t-statistic of -2.72) as comomentum moves from the highest to the lowest quintile. Panel B of Table IV documents that these conclusions are robust to controlling for the Fama and French (1993) three-factor model.[21]

Figure 2 shows the patterns in Table III Panel A graphically. The top panel in Figure 2 plots the cumulative returns to the momentum strategy in the three years after portfolio formation conditional on low comomentum or high comomentum. This plot shows that cumulative buy-and-hold return on the momentum strategy is clearly positive when comomentum is low and clearly negative when comomentum is high. The bottom panel in Figure 2 plots the cumulative buy-and-hold return to the momentum strategy *from the beginning of the formation year* to three years after portfolio formation, again conditional on low comomentum or high comomentum. This plot shows that when comomentum is low, cumulative

[21] Lee and Swaminathan (2000) argue that momentum stocks reverse in the very long run (years four and five) and that this reversal is especially strong for momentum strategies that bet on high-volume winners and against low-volume losers. However their conclusions are not robust to controlling for the three-factor model (see their Table VII Panel D).

buy-and-hold returns from the beginning of the portfolio formation year to three years subsequent clearly exhibit underreaction. However, when comomentum is high, the corresponding cumulative returns clearly exhibit overreaction as returns decline from a peak of 123.9% in month 4 of year 1 (including the formation period return spread) to 106.6% in month 3 of Year 3.

Interestingly, though there is no difference in Year 3 returns for the two extreme comomentum groups, the middle three comomentum groups experience negative returns that are economically and statistically different from zero. More specifically, the average returns in Year 3 for these three groups are increasing in the same way that the average returns for these three groups in Year 2 are decreasing. Thus, as comomentum increases, the overreaction appears to be not only stronger but also quicker to manifest and revert.

Table IV repeats the analysis of Table III Panel A replacing comomentum with past market returns and past market volatility. Consistent with the findings of Cooper, Gutierrez, and Hameed (2005), positive momentum profits in Year 1 are conditional on three-year market returns being above the 20th percentile. However, there is no other clear pattern in the post-formation returns and certainly nothing similar to the clear long-run reversal patterns documented for comomentum in Table III. Similarly, consistent with Wang and Xu (2011), Year 1 momentum profits appear to be generally decreasing in past market return volatility. Again, however, there is no other clear pattern in the post-formation returns. As further evidence that the patterns in Table IV are unique to our comomentum measure, the third block of Table IV repeats the analysis of Table III Panel A using comomentum orthogonalized to $mktret36$ and $mktvol36$. The results indicate that our comomentum findings are robust to controlling for extant predictors of momentum profits in this way.[22]

Figure 3 reports the fitted value and associated two-standard-error bound from a re-

[22] Additionally controlling for the formation period spread in momentum returns has no significant effect on our conclusions.

gression forecasting the two-year post-formation return on momentum with a third-order polynomial in *comom*. We mark those months where the fitted value is two standard errors above zero with a green circle. In these months, the buy-and-hold return on momentum stocks is significantly positive indicating too little arbitrage activity. Correspondingly, those months where the fitted value is two standard errors below zero are marked with a red diamond. In these months, the buy-and-hold return on momentum stocks is significantly negative indicating too much arbitrage activity. Based on this classification, we find that around 40% (20%) of the time there is too little (too much) arbitrage activity in the momentum strategy.

4.3 Robustness of Key Result

Table V examines variations to our methodology to ensure that our central finding linking comomentum to momentum overreaction is robust. For simplicity, we only report the difference in returns to the momentum strategy between the high and low $comom^L$ quintiles for Year 0 and for the combined return in Years 1 and 2. For comparison, the first row of Table V reports the baseline results from Table III Panel A. The average monthly return in Years 1 and 2 is 1.03% lower in the high comomentum quintile than in the low comomentum quintile. We can strongly reject the null hypothesis that this difference is zero as the associated t-statistic is -2.67; this hypothesis test is the key result of the paper.

In rows two and three, we conduct the same analysis for two subperiods (1963-1980 and 1981-2010). Our finding is stronger in the second subsample, consistent with the intuition that momentum trading by hedge funds has dramatically increased in popularity over the last thirty 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 -2.60. This point estimate is nearly twice as large as the corresponding estimate for the earlier period.

In the fourth row, we use comomentum from the winner decile, and the results are almost identical to those in the top row. In the fifth row, we stack winners and losers together (putting a minus sign in front of the losers) to compute a *comom* measure for this combined portfolio. We find that the point estimates are slightly less negative but still very economically and statistically significant. In row six, we rank months based on residual $comom^L$ after purging market returns, market volatilities and the average pairwise correlation in the market from $comom^L$. This adjustment allows us to control for the finding of Pollet and Wilson (2010). Our results are not only robust to this control but are actually slightly stronger compared to the benchmark case in row one. As Barroso and Santa-Clara (2012) show, the volatility of a momentum strategy is highly variable over time and quite predictable; therefore, row seven reports results when we also orthogonalize $comom^L$ to the contemporaneous standard deviation of Ken French's momentum portfolio, UMD. Our results remain economically and statistically significant.

In row eight, we compute $comom^L$ using characteristic-adjusted (as in Daniel, Grinblatt, Titman, and Wermers 1997) stock returns. Our results are robust to this methodological change. In row nine, we form an industry-neutral momentum strategy (i.e., we use industry-adjusted stock returns when ranking stocks in the formation period and when forming portfolios in the holding period). Thus, the winner and loser deciles are industry-balanced. In addition, we use industry-adjusted weekly returns to compute $comom^L$. We find very similar results to our baseline case.[23]

In rows ten and eleven, we compute $comom^L$ for momentum strategies based on weekly stock returns in months 2-7 and 8-13 before the portfolio construction. Thus, we can measure the interaction between our comomentum effect and the echo effect of Novy-Marx (2012). We find our comomentum effect continues to hold for momentum strategies formed on six-month returns (specifically months 2-7). We find a much smaller effect for the echo strategy

[23] Our results are also robust to controls for investor sentiment, such as the Baker and Wurgler (2006) investor sentiment index (see, also, Stambaugh, Yu, and Yuan 2012).

of Novy-Marx (2012). That result may not be surprising since the echo strategy deviates significantly from the standard positive-feedback response of classic momentum strategies.

Taken together, these results confirm that our comomentum measure of crowded momentum trading robustly forecasts times of strong reversal to the return of momentum stocks. Therefore, our novel approach is able to identify when and why momentum transitions from being an underreaction phenomenon to being an overreaction phenomenon.

4.4 Time-Varying Momentum Return Skewness

Daniel and Moskowitz (2011) and Daniel, Jagannathan, and Kim (2012) 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.[24] Table VI 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 month 1 and months 1-3) and weekly returns (months 1-6 and months 1-12).

As shown in Panel A, the skewness of daily momentum returns is noticeably lower when comomentum is high. Indeed, the skewness of daily returns in the first three months of the holding period is monotonically decreasing in comomentum. The difference is both economically and statistically significant. The 20 percent of the sample that corresponds to low values of comomentum has subsequent momentum returns that exhibit daily return skewness of -0.069 (t-statistic of -1.30) while the 20 percent of the sample that corresponds to high values of comomentum has subsequent momentum returns with a skewness of -0.391 (t-statistic of -5.96). These findings continue to hold when we examine weekly returns over a longer holding period.

[24] Daniel and Moskowitz (2011) show that market declines and high market volatility forecast momentum crashes. Daniel, Jagannathan, and Kim (2012) estimate a hidden Markov model that helps identify those times where momentum strategies experience severe losses.

In Panel B, we examine the fraction of "bad" momentum weeks in the six to twelve months post formation, following low vs. high comomentum periods. We define "bad" weeks as having a momentum return below -5%. The results are similar if we use other cut-offs (e.g., -10%, -15%, and -20%). This alternative measure of momentum crash risk ensures that the previous skewness results are not simply due to a small number of extremely negative returns to the momentum strategy. Consistent with the skewness result, the 20 percent of the sample associated with low comomentum is followed by significantly fewer bad momentum weeks compared to the top 20 percent of the sample associated with high comomentum. The differences between the two subperiods, 9% ($t = 4.06$) and 8.2% ($t = 3.66$) in the following 6 and 12 months respectively, are highly statistically significant.

4.5 A Placebo Test: The Value Strategy and Covalue

Implicit in our analysis is the idea that simple momentum trading is an unanchored strategy. The fact that momentum is unanchored makes it difficult for positive-feedback traders to know when to stop trading the strategy. Thus, we would expect that similar measures for anchored strategies reflect stabilizing rather than destabilizing arbitrage activity.

To show that arbitrage activity is generally stabilizing in anchored strategies, we turn to the other workhorse trading strategy studied by academics and implemented by practitioners: the value strategy. Value bets by their very nature have a clear anchor, the cross-sectional spread in book-to-market equity ratios, dubbed the value spread by Cohen, Polk, and Vuolteenaho (2003). A narrow value spread is a clear signal to arbitrageurs to stop trading the value strategy, whereas a large value spread should indicate significant trading opportunities. Consistent with this intuition, Cohen, Polk, and Vuolteenaho (2003) show that the value spread forecasts the return on value-minus-growth bets.

As a consequence, we study the comomentum analogue for the value strategy, which we dub *covalue*. In results not shown, we document that *covalue* is economically and statistically related to the value strategy's anchor, the value spread. Specifically, when we forecast *covalue* with the lagged value spread, we find an adjusted R^2 of 8.3% and a t-statistic of 3.39. The coefficient implies that every one standard deviation move in the value spread results in *covalue* moving approximately 30% of its time-series standard deviation.

Table VII shows the results of using *covalue* to predict buy-and-hold returns on the value strategy. Specifically, Table VII shows that times of relatively high comovement forecast relatively high returns to a value strategy rather than relatively low returns, with no evidence of any long-run reversal or relatively high negative skewness. These results are consistent with price stabilization.[25]

4.6 Cross-Sectional Tests

If crowded trading is responsible for overreaction in momentum profits, then one expects that our findings should be stronger among those stocks that are more likely to be traded by arbitrageurs. Table VIII tests this idea by splitting stocks (each year) into two groups based on the level of institutional ownership (as of the beginning of the year). Consistent with our story, we find that comomentum only forecasts time-variation in Year 1 and Year 2 momentum returns for high institutional ownership stocks. Given the results of Lee and Swaminathan (2000), we have also examined 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.

Since comomentum is a success at identifying times when arbitrage activity is high, we now examine whether our approach can help us identify arbitrage activity in the cross section. In particular, we develop trading strategies based on stocks' formation-year covariance with

[25] The evidence in Nagle (2005) is consistent with this conclusion. Nagle shows that the value effect is weaker among stocks with high institutional ownership.

momentum stocks. At the end of each month t, all stocks are sorted into deciles based on their past year cumulative return. We exclude micro-cap stocks to mitigate the impact of microstructure issues. For every stock, we calculate the partial correlation between its weekly returns and *minus* weekly returns to the bottom momentum decile in the formation year. We exclude, if necessary, that stock from the calculation of the decile returns. We dub this measure stock comomentum ($comom\_stock^L$). We expect stock comomentum to identify those stocks that arbitrageurs are trading as part of their more general quantitative strategy.[26] These stocks should perform well subsequently and, if aggregate comomentum is high, eventually reverse.

Table IX Panel A reports Fama-MacBeth estimates of cross-sectional regressions forecasting stock returns in month $t+1$ with time $t-1$ information (we skip the most recent month to avoid short-term return reversals). Regression (1) shows that stock comomentum strongly forecasts cross-sectional variation in monthly stock returns with a t-statistic over 4. We emphasize that stock comomentum is different from the typical measure of momentum risk sensitivity, i.e. the pre-formation loading on a momentum factor. To show this difference, we estimate the formation-period momentum beta ($beta\_UMD$) on Ken French's UMD factor using weekly returns over the same period in which we measure comomentum. Regression (2) shows that $beta\_UMD$ does not forecast cross-sectional variation in average returns. This failure is perhaps not surprising giving the literature emphasizing characteristics over covariances (Daniel and Titman, 1996). Nevertheless, the contrast between our measure's success in regression (1) and the failure of the corresponding typical measure in regression (2) is stark.

[26] Wahal and Yavuz (2013) show that the past return on a stock's style predicts cross-sectional variation in average returns and that momentum is stronger among stocks that covary more with their style. Wahal and Yavuz measure style as the corresponding portfolio from the Fama and French (1993) 25 size and book-to-market portfolios. However, those portfolios may not be industry neutral (Cohen, Polk, and Vuolteenaho 2003) and may covary due to fundamentals (Cohen, Polk, and Vuolteenaho 2009). In contrast, our analysis not only focuses on comovement among momentum stocks (rather than stocks sorted on book-to-market and/or size) but also is careful to measure *excess* comovement, i.e. comovement controlling for the Fama and French (1993) market, size, and value factors.

Regression (3) documents that the momentum characteristic ($ret12$) works very well over this time period. However, regression (4) shows that our stock comomentum measure remains significant in the presence of the momentum characteristic. Finally, regression (5) adds several other control variables including log size ($mktcap$), log book-to-market ratio (BM), idiosyncratic volatility ($IdioVol$), and turnover ($turnover$). Stock comomentum continues to be statistically significant.[27]

In Panel B of Table IX, we examine returns on a standard hedge portfolio based on stock-comomentum-sorted value-weight decile portfolios. Our goal with this simple approach is to confirm that the abnormal performance linked to stock comomentum is robust as well as to examine the buy-and-hold performance of the strategy. In particular, we report average (abnormal) monthly returns over months 1-6, months 7-12, and months 13-24. We find that the abnormal performance linked to stock comomentum lasts for six months. Then returns are essentially flat. Finally, all of the abnormal performance reverts in Year 2. These results are consistent with arbitrageurs causing overreaction that subsequently reverts.

Finally, Panel C documents the ability of aggregate comomentum to forecast the returns on our stock comomentum strategy. As before, we classify all months into five groups based on $comom$. In the row labeled "5-1", we report the difference in portfolio buy-and-hold returns over various horizons to the stock comomentum strategy based on investing in high comomentum periods (5) versus low periods (1). In the row labeled "OLS", we report the corresponding slope coefficient from the regression of the overlapping annual stock comomentum strategy returns (either in Year 0, 1, or 2) on comomentum ranks. Standard errors in brackets are Newey-West adjusted with 12 lags. Similar to what we find for the standard momentum strategy, the performance of the stock comomentum strategy is decreasing in aggregate comomentum, both in Year 1 and in Year 2.

[27] In unreported results, following Lee and Swaminathan (2000), we have also interacted $ret12$ with both $turnover$ and BM. These interactions have little effect on the ability of $comom\_stock^L$ to describe cross-sectional variation in average returns.

4.7 International Tests

As an out-of-sample test of our findings, we examine the predictive ability of comomentum in an international dataset consisting of the returns to momentum strategies in the 19 largest markets (after the US).[28] These countries are Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), Great Britain (GBR), Hong Kong (HKG), Italy (ITA), Japan (JPN), Netherland (NLD), Norway (NOR), New Zealand (NZL), Singapore (SGP), and Sweden (SWE). In each market, we calculate the country-specific comomentum measure in a manner similar to our US measure.

We find that our country-specific comomentum measures move together, with an average pairwise correlation of 0.47 over the subsample where we have data for all 19 countries (from December 1986 to December 2011). This finding is reassuring as one might expect that there is a common global factor in country-specific measures of arbitrage activity. Figure 4 plots equal-weight averages of the country-specific comomentums for each of three regions: Asia-Pacific, Europe, and North America. In the figure, North American comomentum declines very quickly after the 1987 crash and remains low until the late 1990s. The other two regions' comomentums decline slowly over this period. Then, all three regions' comomentums begin to move more closely together, generally increasing over the next 15 years.

Table X Panel A reports the estimate from a regression forecasting that country's time-t momentum monthly return with time-$t-1$ country-specific comomentum. Panel A also reports the regression coefficient after controlling for country-specific market, size, and value factors. We find that in every country these point estimates are negative. In particular, for the regression where we control for country-specific factors, seven estimates have t-statistics greater than two, and 13 estimates have t-statistics greater than one. As a statistical test of the comomentum's forecasting ability in the international sample, we form a value-weight

[28] We thank Andrea Frazzini for providing these data.

world momentum strategy (WLD) across these 19 non-US markets and forecast the resulting return with a corresponding value-weight comomentum measure (both without and with the corresponding global market, size, and value factors). The results confirm that international comomentum is strongly statistically significant as the t-statistics are -2.60 and -2.68 respectively.

If comomentum forecasts time-series variation in country-specific momentum and if our country comomentum measures are not perfectly correlated, a natural question to ask is whether there is cross-sectional (i.e. inter-country) information in our international comomentum measures. Thus, in Panel B of Table X, each month we sort countries into quintiles based on their comomentum measure, investing in the momentum strategies of the countries in the bottom quintile and shorting the momentum strategies of the countries in the top quintile. We then adjust these monthly returns using world (including the US) market, size, value, and momentum factors.

We find that comomentum strongly forecasts the cross section of country-specific momentum strategies. Momentum strategies in low comomentum countries outperform momentum strategies in high comomentum countries by a factor of 4. (1.01% per month versus 0.24% per month) and the difference (0.77%) is statistically significant with a t-statistic of 3.19. These results continue to hold after controlling for market, size, and value factors. A strategy that only invests in momentum in those countries with low arbitrage activity and hedges out exposure to global market, size, and value factors earns 18% per year with a t-statistic of 6. Controlling for global momentum reduces this outperformance to a still quite impressive 6% per year which is statistically significant from zero (t-statistic of 3.87) and from the corresponding strategy in high arbitrage activity countries (t-statistic of 2.33).

4.8 Mutual and Hedge Fund Momentum Timing

Our final analysis takes our comomentum measure to the cross section of average returns on active mutual funds and long-short/market-neutral equity US hedge funds. Specifically, Table XI reports estimates of panel regressions of monthly fund returns on the Fama-French-Carhart four-factor model. In particular, we augment the four-factor model by allowing the coefficient on the momentum factor to vary as a function of comomentum (as measured by the monthly series of comomentum ranks), a fund's AUM, and the interaction between these two variables. To capture variation in a fund's AUM, we create a dummy variable, $size_{i,t}$ that takes the value of zero if the fund is in the smallest AUM tercile (within the active mutual fund or long-short equity hedge fund industry, depending on the returns being analyzed) in the previous month, one if it is in the middle tercile, and two otherwise. The first four columns analyze active mutual fund returns while the last two columns analyze hedge fund returns.

We are unable to reject the null hypothesis that mutual funds cannot successfully time momentum. However, we do find that the typical long-short equity hedge fund decreases their exposure to the momentum factor when comomentum is relatively high. For the 20% of the sample period that is associated with the lowest values of comomentum, the typical hedge fund's UMD loading is 0.145. This loading decreases by 0.022 for each increase in comomentum rank. Thus, when comomentum is in the top quintile, the typical hedge fund's UMD loading is 0.057, more than 60% smaller.

Adding the interaction with AUM reveals that the ability of hedge funds to time momentum is decreasing in the size of the fund's assets under management. These findings seem reasonable as we would expect large funds to be unable to time a momentum strategy as easily as small funds. For the 20% of the sample period that is associated with the lowest values of comomentum, the typical small hedge fund's UMD loading is 0.152. This loading decreases by 0.032 for each increase in comomentum rank. Thus, when comomentum is in the top quintile, the typical small hedge fund's momentum is 0.024, more than 84% smaller. Large hedge fund's UMD loading moves from 0.14 to only 0.10 across the five comomentum quintiles, a decline of only 27% (statistically insignificant).

5 Conclusions

We propose a novel approach to measuring arbitrage activity 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 in this context. We focus on 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 the classic example of a strategy with no fundamental anchor (Stein, 2009). 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 the most likely place where arbitrage activity can be destabilizing (Stein, 2009).

Our comomentum measure of the momentum crowd is a success based on three 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. Further consistent with our motivation, these results are only present for stocks with high institutional ownership.

Interestingly, we find that a similar measure for the value strategy, *covalue*, is consistent with value arbitrageurs stabilizing prices. As Stein's (2009) AFA presidential address points out, this finding is to be expected as the value strategy has a natural anchor in the value spread (Cohen, Polk, and Vuolteenaho, 2003).

Additional tests confirm our approach to measuring arbitrage activity is sensible. Both firm-specific and international versions of comomentum forecast returns in a manner consistent with our interpretation. Comomentum also describes time-series and cross-sectional variation in hedge funds' sensitivity to a momentum strategy.

References

Adrian, Tobias, Emanuel Moench, and Hyun Song Shin, 2010, New York Federal Reserve Bank working paper 422

Anton, Miguel and Christopher Polk, 2013, Connected Stocks, *Journal of Finance*, Forthcoming.

Asness, Cliff, Tobias Moskowitz, and Lasse Pedersen, 2008, Value and Momentum everywhere, University of Chicago working paper.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor Sentiment and the Cross-section of Stock Returns, *Journal of Finance* 61, 1645¨C1680.

Barberis, Nicholas and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68 161-199.

Barberis, Nick, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005, Comovement, *Journal of Financial Economics* 75 283-317.

Barroso, Pedro and Pedro Santa-Clara, 2012, Managing the Risk of Momentum, Nova School of Business and Economics working paper.

Brunnermeier, Markus K and Stefan Nagle, 2004, Hedge Funds and the Technology Bubble, *Journal of Finance* 59(5), 2013-2040.

Campbell, John Y., Stefano Giglio, Christopher Polk, and Robert Turley, 2012, An Intertemporal CAPM with Stochastic Volatility, London School of Economics working paper.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003, The Value Spread, *Journal of Finance* 58(2), 609-641.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2009, The Price is (Almost) Right, *Journal of Finance* 64(6), 2739-2782.

Cooper, Michael J., Roberto C. Gutierrez, and Allaudeen Hameed, 2005, Market States and Momentum, *Journal of Finance* 59, 1345–1365.

Daniel, Kent and Tobias Moskowitz, 2011, Momentum Crashes, Columbia University working paper.

Daniel, Kent, Ravi Jagannathan, and Soohun Kim, 2012, Tail Risk in Momentum Strategy Returns, Columbia University working paper.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 2001, Investor Psychology and Security Market Under- and Over-reactions, *Journal of Finance* 53, 1839–1886.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic Based Benchmarks, *Journal of Finance 52*, 1035-1058.

DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert Waldmann, 1990, Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379–395.

Diamond, Doug and Robert Verrecchia, 1987, Constraints on Short-Selling and Asset Price Adjustment to Private Information, *Journal of Financial Economics* 18, 277—311.

Duffie, Darrell, 2010, Presidential Address: Asset Price Dynamics with Slow-Moving Capital, *Journal of Finance* 65, 1237-1267.

Fama, Eugene F. and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F. and Kenneth R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance* 51, 55–84.

Freidman, Milton, 1953, The Case for Flexible Exchange Rates, in Milton Friedman, ed.: *Essays in Positive Economics* (University of Chicago Press, Chicago, IL).

Greenwood, Robin and David Thesmar, 2011, Stock Price Fragility, *Journal of Financial Economics*, Forthcoming.

Hayek, Friedrich, 1945, The Use of Knowledge in Society, *American Economic Review* 35, 519-530.

Hanson, Samuel and Adi Sunderam, 2012, The Growth and Limits of Arbitrage: Evidence from Short Interest, Harvard Business School working paper.

Hong, Harrison and Jeremy Stein, 1999, A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets, *Journal of Finance* 54, 2143–2184.

Hu, Xing, Jun Pan, and Jiang Wang, 2012, Noise as Information for Illiquidity, Massachusetts Institute of Technology working paper.

Hwang, Byoung-Hyoun and Baixaio Liu, 2012, Which Anomalies are More Popular? And Why?, Purdue University working paper.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91.

Jegadeesh, Narasimhan and Sheridan Titman, 2001, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *Journal of Finance* 56, 699–720.

Keynes, John Maynard, 1936, *The General Theory of Employment, Interest, and Money.* London: Macmillan.

Lee, Charles M. C. and Bhaskaran Swaminathan, 2000, Price Momentum and Trading Volume, *Journal of Finance* 55, 2017–2069.

Lintner, John, 1965, The Valuation of Risky Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, *Review of Economics and Statistics* 47, 13–37.

Lou, Dong, 2012, A Flow-Based Explanation for Return Predictability, *Review of Financial Studies*, 25, 3457-3489.

Nagle, Stefan, 2005, Short Sales, Institutional Investors, and the Cross-Section of Stock Returns, *Journal of Financial Economics* 78(2), 277-309.

Novy-Marx, Robert, 2012, Is Momentum Really Momentum?, *Journal of Financial Economics* 103, 429-453.

Pollet, Joshua and Mungo Wilson, 2010, Average Correlation and Stock Market Returns, *Journal of Financial Economics* 96, 364-380.

Sharpe, William, 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance* 19, 425–442.

Singleton, Kenneth J., 2012, Investor's Flows and the 2008 Boom/Bust in Oil Prices, Stanford University working paper.

Stambaugh, Robert, Jianfeng, Yu and Yuan Yu, 2012, The Short of It: Investor Sentiment and Anomalies, *Journal of Financial Economics* 104, 288-302.

Stein, Jeremy, 1987, Informational Externalities and Welfare-Reducing Speculation, *Journal of Political Economy* 95, 1123-1145.

Stein, Jeremy, 2009, Sophisticated Investors and Market Efficiency, *Journal of Finance* 64, 1517–1548.

Vayanos, Dimitri and Paul Woolley, 2012, An Institutional Theory of Momentum and Reversal, *Review of Financial Studies*, Forthcoming.

Wahal, Sunil and M. Denis Yavuz, 2013, Style Investing, Comovement, and Return Predictability, *Journal of Financial Economics* 107, 136-154.

Wang, Kevin and Will Xu, 2011, Market Volatility and Momentum, University of Toronto working paper.

Table I: Summary Statistics

This table provides key characteristics of "comomentum," the formation-period excess comovement of the momentum strategy over the period 1964 to 2010. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Pairwise partial return correlations (after controlling for the Fama-French three factors) for all stocks in both the bottom and top deciles are computed based on weekly stock returns in the previous 12 months. To mitigate the impact of microstructure issues, stocks with prices below \$5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. $comom^L$ (loser comomentum) is the average pairwise partial return correlation in the loser decile in year t, while $comom^W$ (winner comomentum) is the average pairwise partial return correlation in the winner decile. $mktret36$ is the three-year return on the CRSP market portfolio from year t-2 to t, and $mktvol36$ is the monthly return volatility of the CRSP market portfolio in years t-2 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 $comom^L$ and $comom^W$, where $comom^L_t$ and $comom^L_{t+1}$ (and similarly for $comom^W_t$ and $comom^W_{t+1}$) are computed in non-overlapping 12-month windows.

Panel A: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
$comom^L$	559	0.118	0.046	0.028	0.287
$comom^W$	559	0.096	0.036	0.021	0.264
$mktret36$	559	0.360	0.331	-0.419	1.231
$mktvol36$	559	0.043	0.011	0.020	0.067

Panel B: Correlation

	$comom^L$	$comom^W$	$mktret36$	$mktvol36$
$comom^L$	1.000			
$comom^W$	0.524	1.000		
$mktret36$	-0.187	-0.350	1.000	
$mktvol36$	0.125	0.092	-0.393	1.000

Panel C: Autocorrelation

	$comom^L_t$	$comom^W_t$	$comom^L_{t+1}$	$comom^W_{t+1}$
$comom^L_t$	1.000			
$comom^W_t$	0.524	1.000		
$comom^L_{t+1}$	0.351	0.273	1.000	
$comom^W_{t+1}$	0.300	0.217	0.527	1.000

Table II: Determinants of Comomentum

This table reports regressions of comomentum, described in Table I, on variables related to arbitrage capital. At the end of year t, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). To mitigate the impact of micro-structure issues, stocks with prices below $5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. The dependent variable in the first three columns, $comom^L$ (loser comomentum), is the average pairwise partial return correlation in the loser decile in the ranking year t, while the dependent variable in columns four through six, $comom^W$ (winner comomentum), is the average pairwise partial return correlation in the winner decile in the ranking year t. pih_{t-1}^W 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). $mktret36_{t-1}$ and $mktvol36_{t-1}$ are, respectively, the three-year return and the monthly return volatility of the CRSP market portfolio. $mom12_{t-1}$ is the return to the momentum strategy in year t-1. $shadow_{t-1}$ is the flow to the shadow banking system, and AUM_{t-1} is the logarithm of the total assets under management of long-short equity hedge funds at the end of year t-1. A trend dummy is included in all regression specifications. Standard errors, shown in brackets, are corrected for serial-dependence with 12 lags. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

Dependent Variable	$comom_t^W$			$comom_t^L$		
	[1]	[2]	[3]	[4]	[5]	[6]
pih_{t-1}^W	0.103***	0.117***	0.190***	0.112**	0.110**	0.095**
	[0.035]	[0.035]	[0.063]	[0.050]	[0.047]	[0.045]
$shadow_{t-1}$	0.151***	0.130***	0.093*	0.256***	0.285***	0.200**
	[0.044]	[0.044]	[0.055]	[0.083]	[0.082]	[0.094]
$mom12_{t-1}$	0.203**	0.228**	0.226**	0.438***	0.383***	0.409***
	[0.091]	[0.091]	[0.113]	[0.144]	[0.140]	[0.137]
AUM_{t-1}			0.058***			0.079***
			[0.018]			[0.017]
$mktret36_{t-1}$		-0.009*	-0.009		0.011	0.001
		[0.005]	[0.007]		[0.007]	[0.010]
$mktvol36_{t-1}$		0.120	0.215		0.218	-0.290
		[0.166]	[0.358]		[0.221]	[0.341]
TREND	YES	YES	YES	YES	YES	YES
Adj-R^2	0.34	0.34	0.38	0.18	0.19	0.47
No. Obs.	357	357	180	357	357	180

Table III: Forecasting Momentum Returns with Comomentum

This table reports returns to the momentum strategy as a function of lagged comomentum. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Stocks with prices below $5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. All months are then classified into five groups based on $comom^L$, the average pairwise partial return correlation in the loser decile ranked in the previous 12 months. Reported below are 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 three years after portfolio formation during 1965 to 2010, following low to high $comom^L$. Year zero is the portfolio ranking period. Panels A and B report, respectively, the average monthly return and the average Fama-French three-factor alpha of the momentum strategy, respectively. "5-1" is the difference in monthly returns to the momentum strategy following high vs. low $comom^L$. "OLS" is the slope coefficient from the regression of monthly momentum returns on ranks of $comom^L$. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Raw Momentum Returns

		Year 0		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	110	**8.84%**	(29.59)	**0.69%**	(4.56)	0.14%	(0.56)	-0.05%	(-0.21)
2	111	**8.94%**	(24.66)	**1.05%**	(6.67)	-0.27%	(-1.09)	**-0.54%**	(-2.64)
3	111	**9.19%**	(15.66)	**0.73%**	(3.15)	-0.51%	(-1.66)	**-0.52%**	(-2.89)
4	111	**9.51%**	(16.57)	0.44%	(1.54)	**-0.58%**	(-2.39)	-0.46%	(-1.81)
5	111	**11.24%**	(13.58)	-0.18%	(-0.35)	**-1.05%**	(-2.81)	0.16%	(0.45)
5-1		**2.40%**	(2.76)	**-0.87%**	(-2.11)	**-1.20%**	(-2.72)	0.21%	(0.61)
OLS		**0.006**	(2.83)	**-0.002**	(-2.02)	**-0.003**	(-2.81)	0.000	(0.45)

Panel B: Three-Factor Adjusted Momentum Returns

		Year 0		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	110	**8.45%**	(24.33)	**0.70%**	(3.63)	-0.03%	(-0.10)	-0.15%	(-1.07)
2	111	**8.53%**	(19.67)	**1.06%**	(5.00)	**-0.44%**	(-2.33)	**-0.87%**	(-3.46)
3	111	**8.74%**	(13.91)	**0.61%**	(3.22)	**-0.67%**	(-3.17)	**-0.70%**	(-2.74)
4	111	**9.13%**	(14.31)	0.35%	(1.53)	**-0.61%**	(-2.35)	**-0.69%**	(-2.28)
5	111	**10.81%**	(13.14)	-0.08%	(-0.18)	**-0.80%**	(-2.31)	0.14%	(0.90)
5-1		**2.37%**	(2.64)	**-0.79%**	(-2.22)	**-0.78%**	(-2.33)	0.28%	(0.95)
OLS		**0.006**	(2.65)	**-0.002**	(-2.09)	**-0.002**	(-2.38)	0.000	(0.64)

Table IV: Controlling for Past Market Returns and Market Volatilities

This table reports returns to the momentum strategy as a function of lagged comomentum. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Stocks with prices below $5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. All months are then classified into five groups based on $mktret36$, the cumulative CRSP index return in the previous three years (Panel A), $mktvol36$, the monthly CRSP index volatility in the previous three years (Panel B), and residual $comom^L$, the residual component of $comom^L$ that is orthogonalized with regard to $mktret36$ and $mktvol36$ (Panel C). $comom^L$ is the average pairwise partial return correlation in the loser decile. Reported below are the average monthly returns to the momentum strategy (i.e., long the value-weight winner decile and short the value-weight loser decile) in each of the three years after portfolio formation during 1965 to 2010, following low to high $comom_t^L$. Year zero is the portfolio ranking period. (5-1) is the difference in monthly returns to the momentum strategy following high vs. low $comom^L$. OLS is the slope coefficient from the regression of monthly momentum returns on ranks of $comom^L$. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Momentum Returns Ranked by $mktret36$									
		Year 0		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	110	**9.96%**	(24.06)	-0.17%	(-0.44)	-0.12%	(-0.48)	-0.19%	(-0.64)
2	111	**8.81%**	(21.91)	**1.30%**	(4.10)	**-0.55%**	(-2.08)	-0.16%	(-0.87)
3	111	**8.97%**	(27.53)	**1.02%**	(3.28)	**-0.46%**	(-2.36)	**-0.39%**	(-3.17)
4	111	**9.41%**	(28.64)	0.29%	(1.65)	0.06%	(0.31)	-0.10%	(-0.54)
5	111	**10.59%**	(16.56)	0.27%	(0.65)	**-1.15%**	(-2.03)	**-0.45%**	(-2.43)
5-1		0.63%	(0.63)	0.44%	(0.67)	-1.03%	(-1.63)	-0.26%	(-0.53)
OLS		0.002	(0.80)	0.000	(-0.11)	-0.001	(-1.06)	-0.001	(-0.50)

Momentum Returns Ranked by $mktvol36$									
		Year 0		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	110	**9.17%**	(31.82)	**0.96%**	(3.91)	0.09%	(0.37)	-0.17%	(-0.90)
2	111	**8.85%**	(29.90)	**0.88%**	(3.54)	**-0.61%**	(-3.32)	**-0.57%**	(-2.89)
3	111	**9.06%**	(31.92)	**0.67%**	(3.03)	**-0.55%**	(-2.55)	-0.26%	(-1.19)
4	111	**11.02%**	(16.31)	-0.44%	(-1.11)	**-1.31%**	(-2.48)	-0.22%	(-0.68)
5	111	**9.63%**	(25.74)	**0.67%**	(2.45)	0.20%	(0.97)	-0.04%	(-0.26)
5-1		0.46%	(0.59)	-0.29%	(-0.81)	0.11%	(0.25)	0.13%	(0.32)
OLS		0.003	(1.45)	-0.002	(-1.89)	-0.001	(-0.52)	0.001	(0.51)

Momentum Returns Ranked by *residual* $comom^L$									
		Year 0		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	110	**8.78%**	(31.77)	**0.69%**	(4.90)	0.02%	(0.08)	-0.14%	(-0.73)
2	111	**8.87%**	(25.35)	**0.89%**	(5.92)	0.03%	(0.16)	**-0.31%**	(-2.04)
3	111	**9.06%**	(27.11)	**0.87%**	(4.44)	-0.52%	(-1.69)	**-0.64%**	(-4.44)
4	111	**9.79%**	(16.27)	0.41%	(1.51)	**-0.56%**	(-2.00)	-0.25%	(-1.66)
5	111	**11.23%**	(18.86)	-0.13%	(-0.25)	**-1.23%**	(-4.87)	0.09%	(0.37)
5-1		**2.46%**	(2.93)	**-0.82%**	(-2.04)	**-1.26%**	(-2.76)	0.23%	(0.68)
OLS		**0.006**	(3.05)	**-0.002**	(-1.98)	**-0.003**	(-3.02)	0.000	(0.44)

Table V: Robustness Checks

This table reports returns to the momentum strategy as a function of lagged comomentum. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Stocks with prices below $5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. All months are then classified into five groups based on $comom^L$, the average pairwise partial return correlation in the loser decile ranked in the previous 12 months. Reported below is the difference in returns to the momentum strategy between high $comom^L$ years and low $comom^L$ years. Year zero is the portfolio ranking period. Row 1 shows the baseline results which are also reported in Table IV Panel A. In rows 2 and 3, we conduct the same analysis for two subperiods. In row 4, we use COMOM computed from the winner decile. In row 5, 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 6, we rank months based on residual $comom^L$ after purging out market returns, market volatilities and the average pairwise correlation in the market. In row 7, we further purge out the volatility in UMD in the past 36 months from $comom^L$. In row 8, we subtract from weekly stock returns the value-weighted return of a size/BM matched portfolio following the DGTW procedure before computing $comom^L$. In row 9, we form an industry-neutral momentum strategy (i.e., use industry-adjusted stock returns to rank portfolios and also in the holding period); in addition, we use industry-adjusted weekly returns to compute $comom^L$. Finally, in rows 10 and 11, we compute $comom^L$ using weekly stock returns in months 2-7 and 8-13 before the portfolio construction, respectively. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 or 24 lags, as appropriate. 5% statistical significance is indicated in bold.

	Year 0		Years 1 and 2	
Full sample: 1963-2010	**2.40%**	(2.76)	**-1.03%**	(-2.67)
Subsample: 1963-1980	0.32%	(1.03)	-0.57%	(-1.55)
Subsample: 1981-2010	**2.76%**	(2.91)	**-1.04%**	(-2.60)
Winner COMOM	**2.39%**	(2.22)	**-1.14%**	(-3.19)
Pooling Winners and Losers	**2.06%**	(3.32)	**-0.84%**	(-2.96)
Controlling for MKT CORR	**2.70%**	(3.15)	**-1.06%**	(-2.78)
Controlling for VOL(UMD)	**1.58%**	(2.09)	**-0.71%**	(-2.29)
DGTW-Adjusted Returns	**2.61%**	(2.79)	**-1.00%**	(-2.94)
Intra-Industry Returns	**2.14%**	(2.70)	**-0.82%**	(-2.39)
Sort on Months 2-7	**2.07%**	(2.45)	**-1.10%**	(-2.35)
Sort on Months 8-13	1.35%	(1.65)	-0.43%	(-1.68)

Table VI: Forecasting Momentum Return Skewness

This table reports the skewness of momentum returns as a function of lagged comomentum. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Stocks with prices below $5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. All months are then classified into five groups based on $comom^L$, the average pairwise partial return correlation in the loser decile ranked in the previous 12 months. Panel A reports the skewness in daily (weekly) returns to the value-weight winner minus loser portfolio in months 1 to 3 (1 to 6 and 1 to 12) after portfolio formation in the period of 1965 to 2010, following low to high $comom^L$. Panel B reports the fraction of weeks of 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, following low to high $comom^L$. Year zero is the portfolio ranking period. "5-1" is the difference in skewness of momentum returns following high vs. low $comom^L$. "OLS" is the slope coefficient from the regression of the skewness in momentum returns on ranks of $comom^L$. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Momentum Skewness

		Month 1		Months 1-3		Months 1-6		Months 1-12	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	110	-0.039	(-1.18)	-0.069	(-1.30)	-0.126	(-1.80)	-0.123	(-1.79)
2	111	**-0.180**	(-2.73)	**-0.183**	(-3.72)	**-0.339**	(-3.91)	**-0.359**	(-5.28)
3	111	**-0.164**	(-2.88)	**-0.209**	(-4.81)	**-0.249**	(-3.44)	**-0.282**	(-4.50)
4	111	**-0.212**	(-3.61)	**-0.319**	(-5.23)	**-0.363**	(-6.05)	**-0.355**	(-4.00)
5	111	**-0.300**	(-3.42)	**-0.391**	(-5.96)	**-0.536**	(-5.31)	**-0.510**	(-3.54)
5-1		**-0.261**	(-2.40)	**-0.322**	(-3.81)	**-0.409**	(-3.40)	**-0.388**	(-2.44)
OLS		**-0.049**	(-2.41)	**-0.078**	(-4.19)	**-0.084**	(-3.13)	**-0.077**	(-2.28)

Panel B: Fraction of Low-Momentum-Return Weeks

		Months 1-6		Months 1-12	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat
1	110	**0.015**	(3.02)	**0.011**	(3.68)
2	111	**0.015**	(4.95)	**0.015**	(6.01)
3	111	**0.036**	(3.91)	**0.032**	(2.90)
4	111	**0.049**	(3.66)	**0.041**	(3.25)
5	111	**0.105**	(4.89)	**0.093**	(4.18)
5-1		**0.090**	(4.06)	**0.082**	(3.66)
OLS		**0.686**	(4.13)	**0.586**	(3.78)

Table VII: Covalue and Value Strategy Returns

This table reports returns to the value strategy as a function of lagged covalue. At the end of each month, all stocks are sorted into deciles based on their book-to-market ratios. Stocks with prices below $5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. All months are then classified into five groups based on *covalue*, the average pairwise partial return correlation in the value decile in the previous 12 months. Reported below are the returns to the value strategy (i.e., long the value-weight value decile and short the value-weight growth decile) in each of the three years after portfolio formation during 1965 to 2010, following low to high *covalue*. Year zero is the portfolio ranking period. Panels A and B report the average monthly return and the alpha (with respect to Fama and French market and size factors), respectively. "5-1" is the difference in monthly return to the value strategy following high vs. low *covalue*. "OLS" is the slope coefficient from the regression of monthly value returns on ranks of *covalue*. Panel C reports the skewness in weekly returns on the value minus growth portfolio in months 1 to 6 and months 1 to 12 after portfolio formation, following high vs. low *covalue*. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Raw Value Strategy Returns

		Year 0		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	110	**-3.52%**	(-8.13)	0.09%	(0.39)	0.05%	(0.23)	0.46%	(1.89)
2	111	**-4.33%**	(-14.60)	0.35%	(1.66)	0.30%	(1.03)	0.11%	(0.28)
3	111	**-4.00%**	(-9.96)	0.30%	(1.06)	**0.97%**	(5.40)	**0.83%**	(5.29)
4	111	**-4.41%**	(-7.98)	**0.84%**	(2.77)	**1.29%**	(5.29)	**0.79%**	(4.21)
5	111	**-5.67%**	(-5.56)	**1.61%**	(3.82)	**1.61%**	(5.36)	**0.69%**	(1.98)
5-1		-2.16%	(-1.94)	**1.52%**	(3.18)	**1.57%**	(4.22)	0.24%	(0.56)
OLS		-0.004	(-1.86)	**0.004**	(3.35)	**0.004**	(4.92)	0.001	(1.21)

Panel B: Market- and Size- Adjusted Value Strategy Returns

		Year 0		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	110	**-3.12%**	(-6.27)	0.26%	(0.92)	0.24%	(0.93)	**0.56%**	(2.10)
2	111	**-4.05%**	(-12.77)	**0.64%**	(3.02)	0.43%	(1.40)	0.26%	(0.73)
3	111	**-3.75%**	(-9.98)	0.57%	(1.95)	**1.12%**	(6.20)	**1.03%**	(6.23)
4	111	**-4.29%**	(-8.13)	**0.96%**	(3.86)	**1.25%**	(4.00)	**0.87%**	(3.79)
5	111	**-5.43%**	(-5.60)	**1.65%**	(3.90)	**1.72%**	(5.07)	0.55%	(1.20)
5-1		**-2.31%**	(-2.11)	**1.39%**	(2.73)	**1.48%**	(3.46)	-0.01%	(-0.02)
OLS		**-0.005**	(-2.10)	**0.003**	(2.86)	**0.004**	(3.97)	0.001	(0.52)

Panel C: Skewness in value returns

		Months 1-6		Months 1-12	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat
1	110	**0.199**	(3.14)	**0.264**	(4.49)
2	111	0.106	(1.28)	0.046	(0.93)
3	111	-0.012	(-0.19)	0.071	(1.18)
4	111	0.141	(1.09)	0.088	(0.77)
5	111	**0.293**	(2.13)	0.112	(0.73)
5-1		0.094	(0.62)	-0.152	(-0.92)
OLS		0.024	(0.67)	-0.025	(-0.67)

Table VIII: Institutional Ownership and the Comomentum Effect

This table reports returns to the momentum strategy as a function of lagged comomentum. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Stocks with prices below $5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. All months are then classified into five groups based on $comom^L$, the average pairwise partial return correlation in the loser decile ranked in the previous 12 months. Reported below are 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 three years after portfolio formation during 1982 to 2010, following low to high $comom^L$. Year zero is the portfolio ranking period. Panels A and B report the average monthly returns to the momentum strategy constructed solely based on stocks with low and high institutional ownership (as of the beginning of the holding period), respectively. "5-1" is the difference in monthly returns to the momentum strategy following high vs. low $comom^L$. "OLS" is the slope coefficient from the regression of monthly momentum returns on ranks of $comom^L$. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Stocks with Low Institutional Ownership

		Year 0		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	65	**10.26%**	(22.27)	**0.54%**	(2.18)	-0.20%	(-0.84)	**-0.49%**	(-2.09)
2	66	**10.36%**	(25.41)	**0.94%**	(4.00)	**-0.58%**	(-2.47)	-0.68%	(-1.56)
3	66	**10.94%**	(9.74)	0.35%	(1.09)	**-0.74%**	(-2.51)	-0.06%	(-0.10)
4	66	**11.66%**	(9.53)	-0.17%	(-0.39)	-0.26%	(-0.72)	-0.15%	(-0.28)
5	66	**12.22%**	(11.46)	-0.14%	(-0.24)	-0.59%	(-1.61)	0.01%	(0.02)
5-1		**1.95%**	(2.02)	-0.68%	(-1.09)	-0.39%	(-0.62)	0.50%	(0.90)
OLS		**0.006**	(2.10)	-0.002	(-1.57)	-0.001	(-0.35)	0.002	(1.02)

Panel B: Stocks with High Institutional Ownership

		Year 0		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	65	**8.91%**	(21.87)	**0.65%**	(2.92)	0.23%	(0.66)	0.20%	(0.75)
2	66	**9.34%**	(25.22)	**0.90%**	(4.61)	-0.08%	(-0.26)	-0.36%	(-1.71)
3	66	**9.71%**	(10.80)	0.32%	(0.93)	-0.59%	(-1.66)	**-0.69%**	(-2.31)
4	66	**10.14%**	(11.78)	-0.13%	(-0.29)	-0.43%	(-1.52)	-0.04%	(-0.13)
5	66	**11.82%**	(14.09)	-0.29%	(-0.43)	**-1.30%**	(-2.89)	0.20%	(0.54)
5-1		**2.91%**	(2.95)	**-0.95%**	(-2.32)	**-1.53%**	(-2.77)	0.00%	(0.01)
OLS		**0.007**	(2.99)	-0.003	(-1.88)	**-0.004**	(-2.73)	0.000	(0.05)

Table IX: An Alternative Momentum Strategy

This table reports the return to trading strategies based on stocks' formation-year covariance with momentum stocks. Panel A reports Fama-MacBeth estimates of cross-sectional regressions forecasting stock returns in month t+1. At the end of each month t, all stocks are sorted into deciles based on their past year cumulative return (skipping the most recent month to avoid short-term return reversals and excluding micro-cap and low-price stocks to mitigate the impact of microstructure issues). The main independent variable is $comom\_stock^{L}_{t-1}$, the partial correlation between weekly returns of a stock and *minus* weekly returns to the bottom momentum decile in the formation year (excluding, if necessary, that stock from the calculation of the decile returns). Other control variables include the formation-period momentum beta with regard to the weekly UMD factor ($beta\_UMD$), lagged one year stock return ($ret12$), log size ($mktcap$), log book-to-market ratio (BM), idiosyncratic volatility ($IdioVol$), and turnover ($turnover$). Panel B reports the average monthly buy-and-hold return over various horizons to a long-short $comom\_stock^{L}$ strategy formed from monthly-rebalanced value-weight decile portfolios. Panel C documents the ability of $comom^{L}$ to forecast the $comom\_stock^{L}$ strategy. All months are classified into five groups based on $comom^{L}$. "5-1" is the difference in portfolio buy-and-hold returns over various horizons to the $comom\_stock^{L}$ strategy based on investing in high (5) vs. low (1) $comom^{L}$ groups. "OLS" is the corresponding slope coefficient from the regression of $comom\_stock^{L}$ returns on ranks of $comom^{L}$. Standard errors in brackets are Newey-West adjusted with 12 lags. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

Panel A: Fama-MacBeth Regressions					
Dependent Variable	Stock Returns in Month t+1				
	[1]	[2]	[3]	[4]	[5]
$comom\_stock^{L}_{t-1}$	0.023***			0.011***	0.009***
	[0.005]			[0.004]	[0.003]
$beta\_UMD_{t-1}$		0.001		0.000	0.000
		[0.001]		[0.001]	[0.001]
$ret12_{t-1}$			0.007***	0.006***	0.007***
			[0.002]	[0.001]	[0.002]
$mktcap_{t-1}$					-0.002**
					[0.001]
BM_{t-1}					0.002**
					[0.001]
$IdioVol_{t-1}$					-0.005***
					[0.001]
$turnover_{t-1}$					-0.001
					[0.001]
Adj-R^2	0.02	0.02	0.04	0.06	0.10
No. Obs.	211,042	211,042	211,042	211,042	211,042

Panel B: Portfolio Returns Ranked by $comom\_stock^{L}$									
Decile	Excess Return	CAPM Alpha	FF Alpha	Excess Return	CAPM Alpha	FF Alpha	Excess Return	CAPM Alpha	FF Alpha
	Months 1-6			Months 7-12			Year 2		
10 - 1	**0.78%**	**0.88%**	**1.13%**	0.01%	0.06%	0.36%	**-0.48%**	**-0.45%**	**-0.42%**
	(2.64)	(3.00)	(3.73)	(0.03)	(0.21)	(1.43)	(-2.16)	(-2.17)	(-2.08)

Panel C: Portfolio Returns Ranked by $comom\_stock^{L}$ in Different Periods								
	Year 0		Year 1		Year 2		Year 3	
Rank	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
5-1	**3.49%**	(5.68)	**-1.25%**	(-2.27)	**-0.76%**	(-2.20)	0.11%	(0.46)
OLS	**0.008**	(5.00)	**-0.003**	(-2.31)	**-0.002**	(-2.26)	0.000	(0.50)

Table X: International Evidence

This table reports returns to international momentum strategies as a function of lagged country-specific comomentum. In Panel A, at the end of each month, stocks in each market are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). We then compute a $comom^L$ measure as the average pairwise return correlation in the loser decile ranked in the previous 12 months. CoefEst1 is the regression coefficient of the month t momentum return on $comom^L$ computed at the end of month t-1, while CoefEst2 is the corresponding regression coefficient, controlling for country-specific market, size, and value factors. We examine the world's largest 19 stock markets (after the US). We also compute a value-weight world (excluding the US) momentum strategy (WLD) and forecast that strategy with the corresponding value-weight world $comom^L$ measure. In Panel B, we report the monthly returns to an inter-country (including the US) momentum timing strategy, which goes long country-specific momentum strategies whose corresponding $comom^L$ is in the bottom quintile in the previous month, and short those country-specific momentum strategies whose corresponding $comom^L$ is in the top quintile. We then adjust these monthly returns using world (including the US) market, size, value, and momentum factors. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Regression Coefficients in Other Countries

Country	No months	CoefEst1	CoefEst2	Country	No months	CeofEst1	CeofEst2
AUS	302	-0.0494	-0.0351	GBR	300	-0.0501	**-0.0402**
		(-0.94)	(-0.48)			(-1.87)	(-2.11)
AUT	302	-0.0581	-0.0866	HKG	300	**-0.0646**	**-0.0796**
		(-1.76)	(-1.17)			(-3.77)	(-2.21)
BEL	300	**-0.1025**	-0.0946	ITA	300	-0.0108	-0.0239
		(-2.40)	(-1.95)			(-0.43)	(-0.73)
CAN	336	**-0.1652**	**-0.1341**	JPN	300	-0.0564	**-0.0535**
		(-2.70)	(-2.31)			(-1.63)	(-2.54)
CHE	300	-0.0347	**-0.0753**	NLD	300	**-0.0801**	**-0.0805**
		(-1.53)	(-2.35)			(-2.47)	(-2.02)
DEU	300	-0.0546	-0.0957	NOR	297	-0.0096	-0.1090
		(-1.72)	(-1.82)			(-0.16)	(-1.58)
DNK	300	-0.0248	-0.0200	NZL	271	**-0.0879**	-0.0462
		(-1.06)	(-0.63)			(-2.15)	(-1.67)
ESP	300	-0.0097	-0.0075	SGP	300	**-0.0791**	**-0.1189**
		(-0.28)	(-0.20)			(-2.36)	(-3.86)
FIN	300	-0.0110	-0.0046	SWE	300	-0.0107	-0.0091
		(-0.29)	(-0.12)			(-0.29)	(-0.11)
FRA	300	**-0.0725**	-0.0486	WLD	300	**-0.0851**	**-0.0569**
		(-2.06)	(-1.13)			(-2.60)	(-2.68)

Panel B: Long-Short Portfolios of Country Momentum

Quintile	No Months	Excess Return	CAPM Alpha	FF Alpha	Carhart Alpha
S	300	0.24%	0.36%	**0.68%**	-0.20%
		(0.94)	(1.49)	(2.98)	(-0.96)
L	300	**1.01%**	**1.07%**	**1.49%**	**0.46%**
		(3.74)	(4.34)	(6.00)	(3.87)
L-S	300	**0.77%**	**0.71%**	**0.81%**	**0.66%**
		(3.19)	(3.04)	(3.30)	(2.33)

Table XI: Momentum Timing Ability

This table reports regressions of monthly mutual fund and hedge fund returns on lagged comomentum. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Stocks with prices below $5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. $comom^L$ is the average pairwise partial return correlation in the loser decile ranked in the previous 12 months, measured at the end of month *t-1*. $Dcomom^L$ is a dummy variable which corresponds to the five quintiles of $comom^L$. The dependent variable in the first four columns is the monthly excess return of actively-managed equity mutual funds, and that in columns 5 and 6 is the monthly excess return of long-short equity hedge funds in month t. $mktrf$, smb, hml, and umd are the Fama-French three factors and momentum factor, respectively. $Dsize_{t-1}$ is a dummy variable that takes the value of zero if the fund is in the smallest AUM tercile (within the respective group) in the previous month, one if it is in the middle tercile, and two otherwise. Standard errors, shown in bracket, are clustered at the month level. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

	Equity Mutual Funds				Equity Hedge Funds	
	1982-1995		1996-2010		1996-2010	
	[1]	[2]	[3]	[4]	[5]	[6]
$mktrf_t$	0.966***	0.966***	0.999***	0.998***	0.340***	0.340***
	[0.011]	[0.011]	[0.014]	[0.014]	[0.021]	[0.021]
smb_t	0.223***	0.223***	0.177***	0.177***	0.148***	0.148***
	[0.013]	[0.013]	[0.017]	[0.017]	[0.027]	[0.027]
hml_t	-0.127***	-0.127***	0.048**	0.048**	-0.050*	-0.050*
	[0.018]	[0.018]	[0.020]	[0.020]	[0.027]	[0.027]
umd_t	0.057**	0.035*	0.026	0.017	0.145**	0.152**
	[0.021]	[0.021]	[0.048]	[0.039]	[0.068]	[0.064]
$Dcomom^L_{t-1}$	0.000	0.000	0.000	0.001	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
$umd_t * Dcomom^L_{t-1}$	-0.009	-0.004	-0.005	-0.000	-0.022**	-0.032**
	[0.010]	[0.011]	[0.015]	[0.018]	[0.011]	[0.014]
$Dsize_{t-1}$		-0.000		-0.000		-0.000
		[0.000]		[0.000]		[0.001]
$umd_t * Dsize_{t-1}$		0.021		0.021		-0.006
		[0.014]		[0.019]		[0.029]
$Dcomom^L_{t-1} * Dsize_{t-1}$		0.000		0.000		0.000
		[0.000]		[0.000]		[0.000]
$umd_t * Dcomom^L_{t-1}$		-0.005		-0.004		0.010**
$* Dsize_{t-1}$		[0.005]		[0.005]		[0.004]
Adj-R^2	0.76	0.76	0.69	0.69	0.14	0.14
No. Obs.	68,289	68,289	256,465	256,465	148,799	148,799

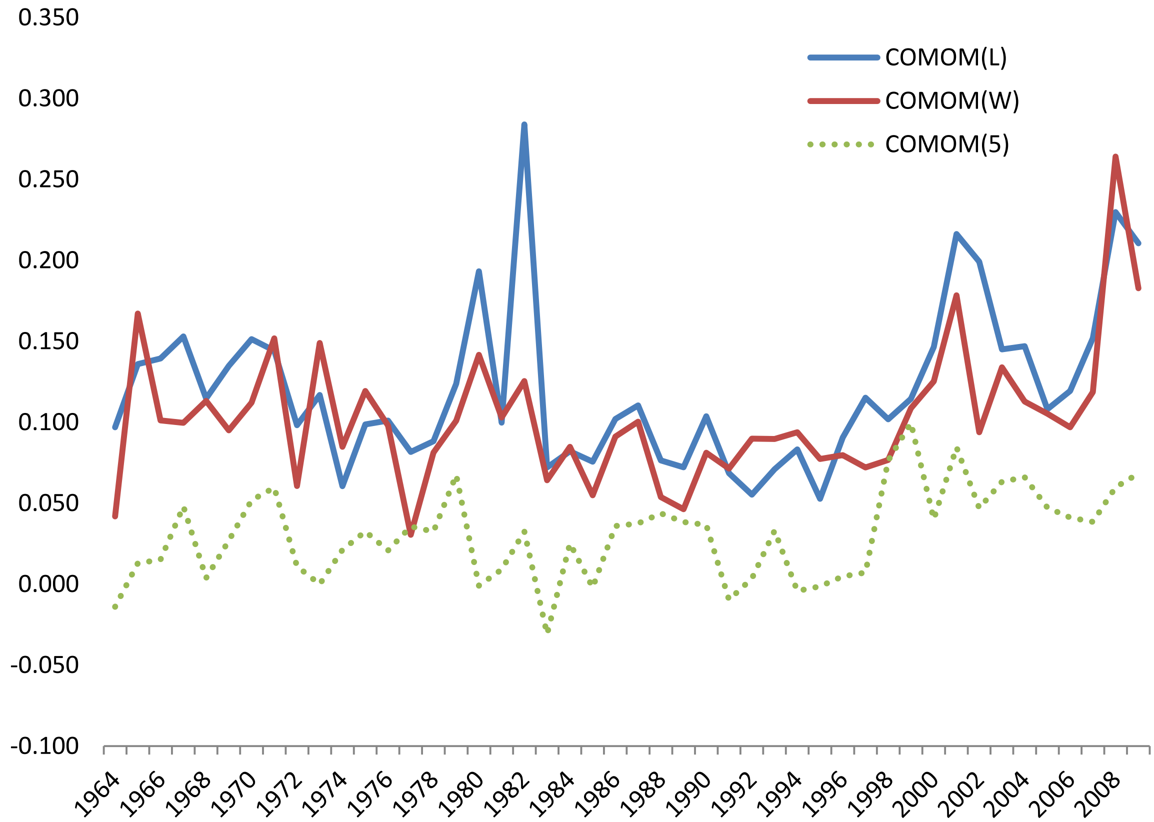

Figure 1: This figure shows the time series of the comomentum measure at the end of each year. At the end of year t-1, all stocks are sorted into decile portfolios based on their lagged 12-month cumulative returns (skipping the most recent month). $comom_L$ is the average pairwise partial return correlation in the loser decile measured in the ranking year t-1, $comom_W$ is the average pairwise partial return correlation in the winner decile measured in the ranking year t-1, and $comom_5$ is the average pairwise partial return correlation in the median decile measured in the ranking year t-1.

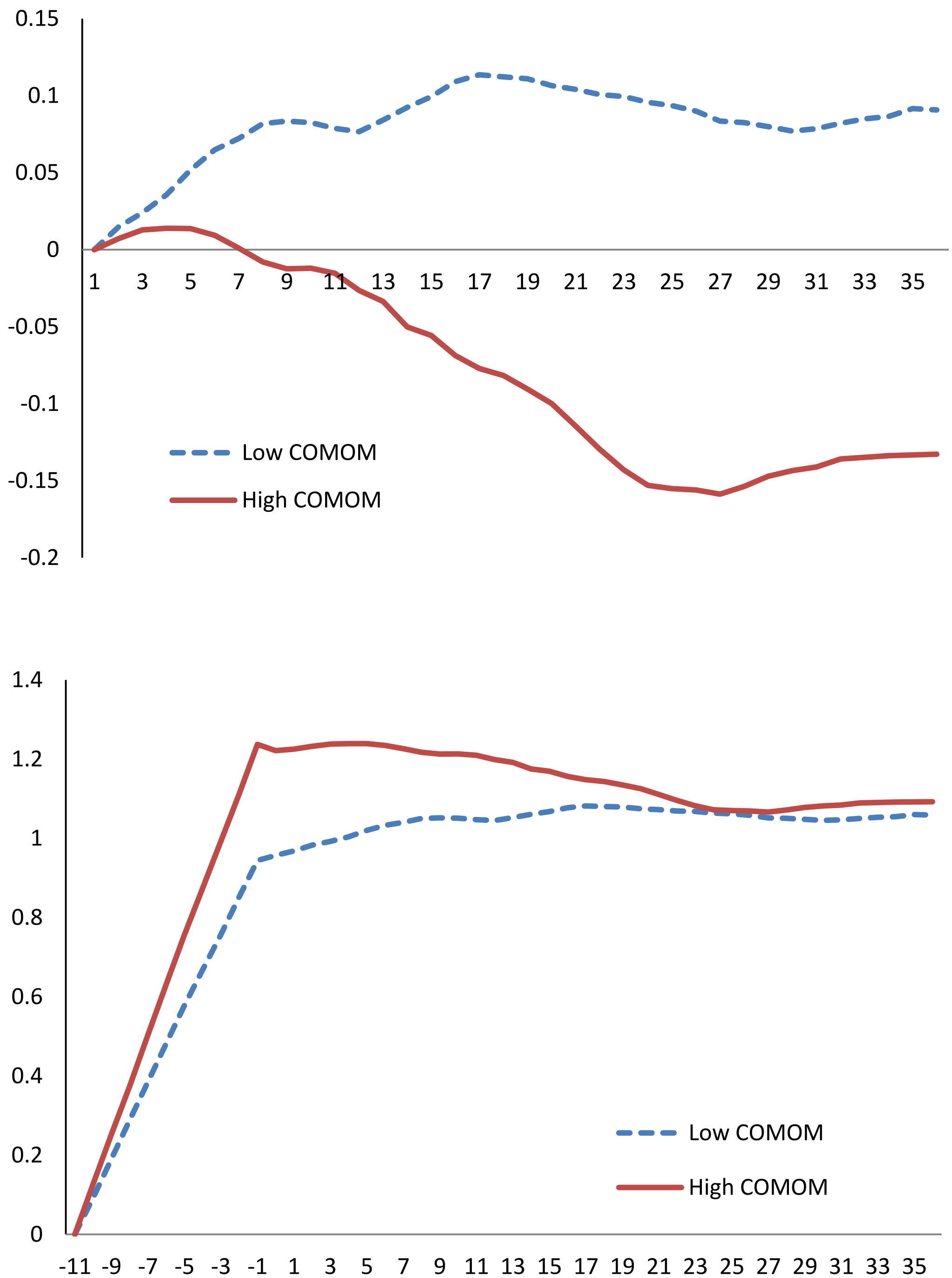

Figure 2: These figures show returns to the momentum strategy as a function of the lagged comomentum measure. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Stocks with prices below \$5 a share and/or are in the bottom NYSE size decile are excluded from the sample. All months are then classified into five groups based on $comom^L$, the average pairwise partial return correlation in the loser decile ranked in the previous 12 months. The top panel shows the cumulative returns to a value-weight momentum strategy (i.e., winner minus loser deciles) in the three years after formation during 1965 to 2010, following low and high $comom^L$. The bottom panel shows the cumulative returns to a value-weight momentum strategy (i.e., winner minus loser deciles) from the beginning of the formation year to three years post-formation following low and high $comom^L$.

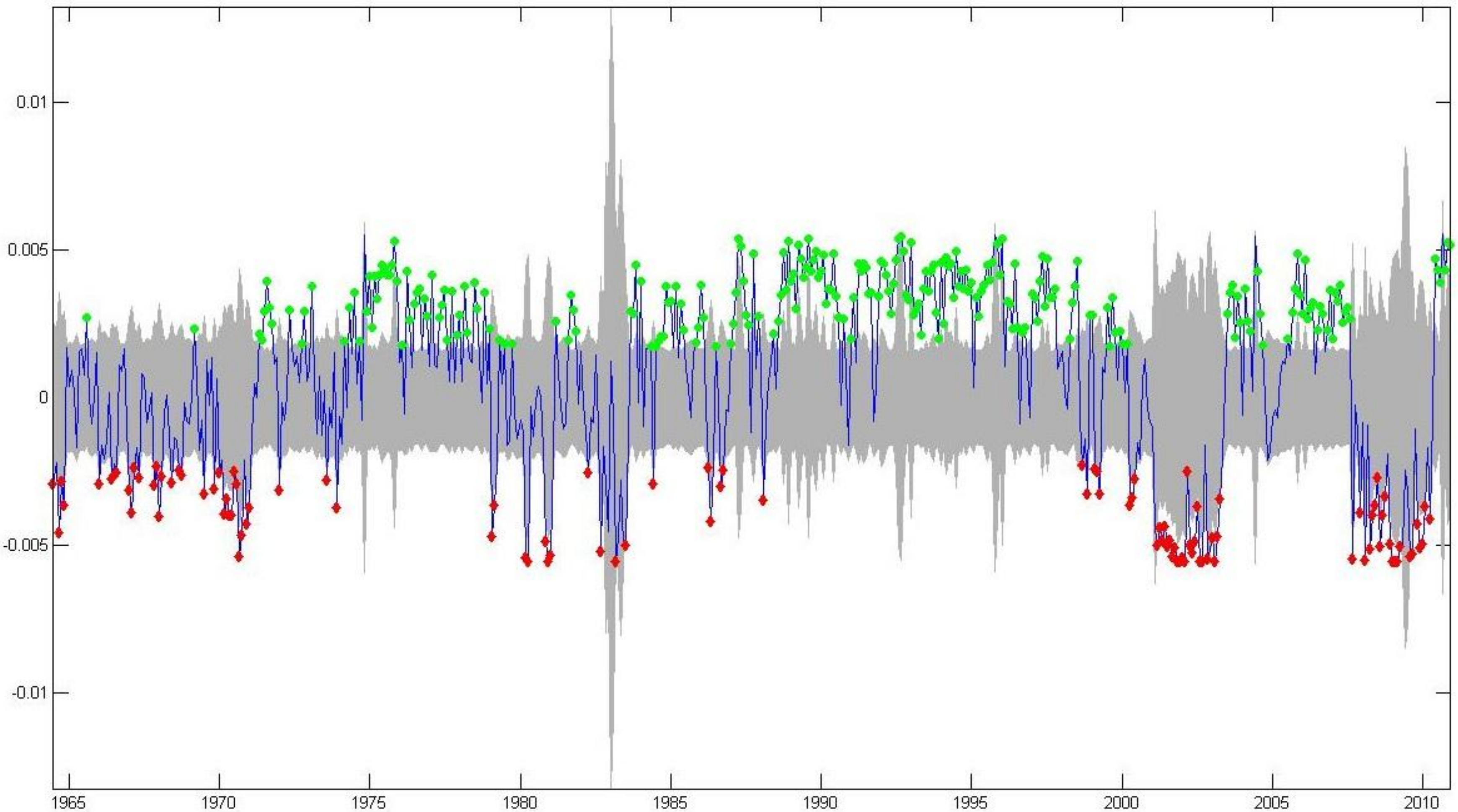

Figure 3: This figure forecasts the cumulative return in years 1 and 2 to the long-short momentum portfolio formed at the end of each month using a third-order polynomial of the COMOM variable, measured over the previous 12 months. The blue curve shows the time series of the fitted value from the regression. The grey area shows the range of -1.96 to +1.96 standard deviations of each fitted value. If the fitted value in a month is larger than +1.96 standard deviations (i.e., significantly positive), it is depicted with a green circle; if the fitted value in a month is smaller than -1.96 standard deviations (i.e., significantly negative), it is depicted with a red diamond.

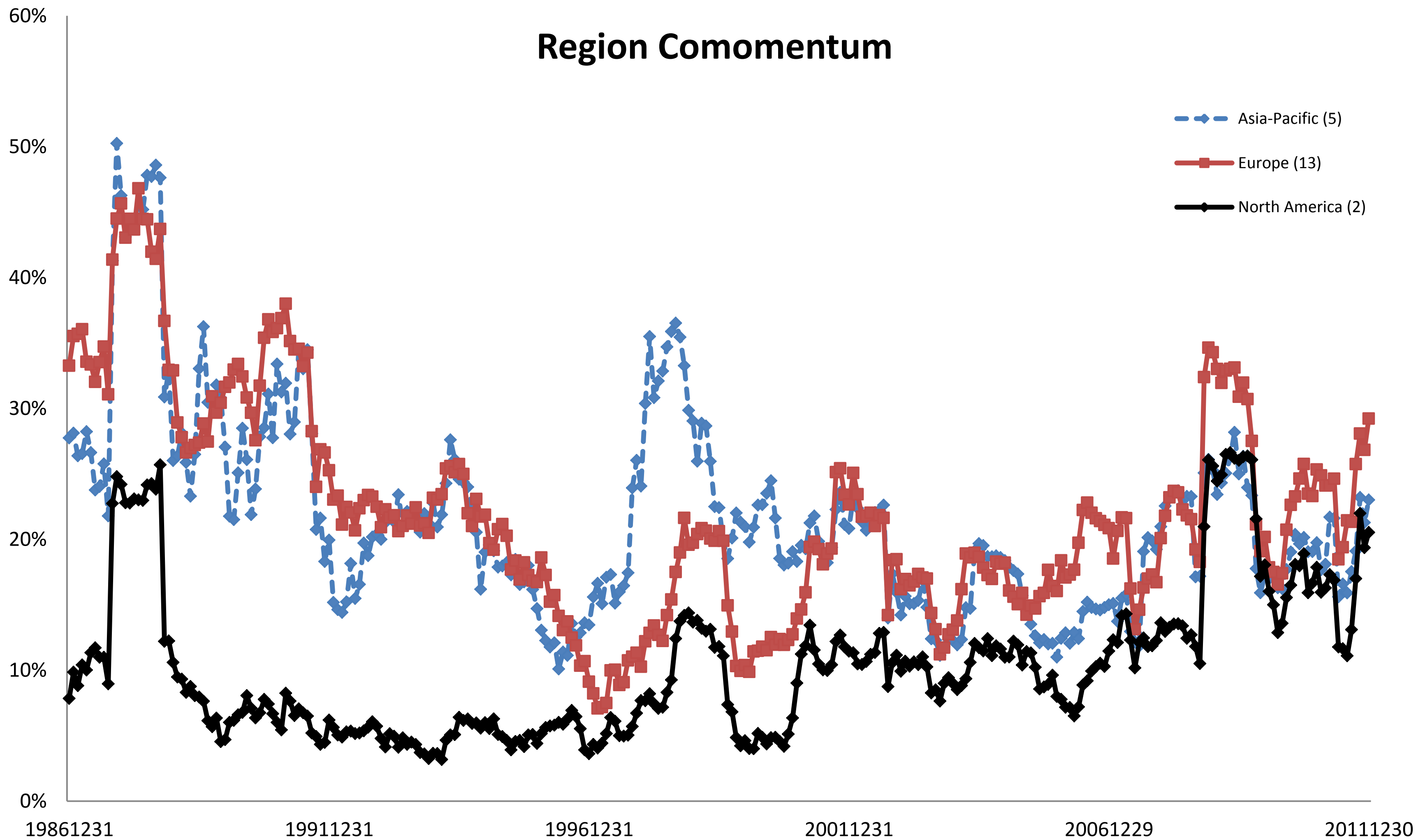

Figure 4: This figure shows the time series of region-specific comomentum measures. At the end of each month, all stocks in a country are sorted into decile portfolios based on their lagged 12-month cumulative returns (skipping the most recent month). Country comomentum is the average pairwise return correlation in the loser decile measured in the ranking month. We calculate region comomentum as the equal-weight country momentum in the region. These regions are Asia-Pacific, Europe, and North America.