Comomentum:

Inferring Arbitrage Capital from Return Correlations

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Abstract

We propose a novel measure of the amount of arbitrage capital allocated to the momentum strategy to test whether arbitrageurs can have a destabilizing effect in the stock market. Our measure, which we dub *comomentum*, aims to capture the extent to which momentum trades by arbitrageurs become crowded. Specifically, we define comomentum as the high-frequency abnormal return correlation among stocks that a typical momentum strategy would speculate on. 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 become unprofitable and tend to crash, reflecting prior overreaction due to the momentum crowd pushing prices away from fundamentals. Moreover, both firm-level and international versions of comomentum forecast returns in a manner consistent with our interpretation.

JEL classification: G12, N22

1 Introduction

Though researchers have identified many patterns in the cross section of average stock returns that are abnormal relative to the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), Fama and French (1996) show that many of these anomalous patterns can be explained by their eponymous three-factor model (Fama and French, 1993). Since Fama and French (1993), the finance literature has proposed several asset-pricing models that arguably do a good job providing an economic explanation for the size and book-to-market effects captured by Fama and French's model.[2] Thus, much progress has been made in understanding patterns in the cross section of average returns and the pricing of risks.

The momentum anomaly stands as a notable exception. 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, 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." As a consequence, these findings have led many to abandon neoclassical asset pricing and search for behavioral or friction-based explanations of short-run return continuation. Those explanations fall into several camps. The first camp argues that momentum is a pure underreaction phenomenon, perhaps due to trading costs and/or short-sell constraints such as in the model of Diamond and Verrecchia (1987). The second camp argues that momentum is initially an underreaction phenomenon that leads to eventual overreaction and reversal. This camp includes the diverse models of Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Stein (2009), and

[2] For example, recent work by Campbell, Giglio, Polk, and Turley (2012) explains these patterns and others with an economically-motivated three-beta intertemporal capital asset pricing model. Campbell, Giglio, Polk, and Turley argue that growth stocks underperform value stocks because they hedge two types of deterioration in investment opportunities: declining expected stock returns, and increasing volatility.

Vayanos and Woolley (2011). The final camp, including DeLong et al. (1990) and Daniel, Hirshleifer, and Subrahmanyam (1998) suggests that momentum is a pure overreaction phenomenon.

However, even this basic characteristic of abnormal momentum profits—whether momentum is a an underreaction or overreaction phenomenon—has been difficult to pin down (Jegadeesh and Titman, 2001). 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 and not consistent across subsets of stocks. More generally, such tests have low power and can be sensitive to the benchmark model. As a consequence, momentum remains a mystery.

We try to solve this mystery by linking both the profitability and any potential subsequent reversal of momentum strategy returns to a proxy for time-series variation in the amount of arbitrage capital invested in momentum. Our notion of arbitrage capital 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.[3] Indeed, we include in this definition any trader whose investment activity resembles a momentum strategy. We argue that times when standard momentum strategies are the most crowded by arbitrage capital should intuitively also be the times when those strategies are the least profitable and when long-horizon abnormal returns are the most negative.

We focus on crowded arbitrage trading due to the key role arbitrageurs play in financial

[3]See Hong and Stein (1999) for a model where arbitrageurs with bounded rationality generate overreaction in the presence of risk-averse but fully rational arbitrageurs. See Vayanos and Woolley (2011) for a friction-based but fully rational limits-to-arbitrage model of momentum.

markets. In most 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 capital that is available for arbitrage activities. It is, however, extremely difficult to measure arbitrage capital at any given point in time. For one thing, it is unclear ex-ante the exact composition of arbitrageurs in financial markets. 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. Finally, 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.[4]

Our innovation in this paper is that instead of identifying all potential arbitrageurs and then aggregating their capital across their investment decisions, we turn to a measure of crowded trades based on high-frequency movements in prices. Namely, we measure the extent of the momentum crowd by the past degree of *abnormal* return correlation among those stocks that a standard momentum arbitrageur would speculate on. The basic premise of our measure is that when arbitrageurs take long positions in winner stocks and short positions in loser stocks, such momentum trades can have *simultaneous* price impacts on momentum stocks and thus cause return comovement among these stocks. We dub this measure *comomentum*. Thus, by capturing the price impacts caused by arbitrage capital, our comomentum measure can then speak directly to whether the momentum crowd, and more generally arbitrage trading, is price stabilizing or destabilizing. As a consequence, our work provides important evidence on a long-standing debate in economics going back to at least Keynes (1936) and Hayek (1945).

[4] A notable exception is Hanson and Sunderam (2011) who exploit time variation in the cross section of short interest to infer the amount of arbitrage capital in quantitative trading strategies.

Our maintained assumption throughout the analysis is that absent momentum arbitrageurs, momentum profits are due to investors' underreaction. Thus, 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 contrast, when comomentum is relatively high, momentum strategies are crowded. Accordingly, abnormal returns on a standard momentum strategy should be low. Furthermore, we argue that crowded trades may actually be destabilizing, resulting in subsequent reversal of the initial momentum returns.[5] In short, we argue that whether momentum is an underreaction or overreaction phenomenon is time-varying, crucially depending on the size of the momentum crowd.

Thus, we propose a novel measure of arbitrage capital and test its effect on asset prices, with the particular goal of determining whether arbitrage capital can be destabilizing for the momentum anomaly. We focus on this anomaly not only because of the failure of both rational and behavioral models to explain stylized facts about momentum but also because momentum is a 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 strategy is the most likely place where arbitrage capital can be destabilizing (Stein, 2009). Indeed, in a placebo test, we document that a similarly-constructed measure of arbitrage capital in the value strategy can be linked to patterns that are consistent with price stabilization.

Our comomentum measure of the momentum crowd is a success based on a long list of empirical findings. First, comomentum is significantly correlated with existing variables plausibly linked to the size of arbitrage capital in this market. Second, comomentum forecasts

[5] For other evidence that speculators may be destabilizing see Brunnermeier and Nagle (2004).

relatively low holding-period (i.e., the year after portfolio formation) returns, relatively high holding-period return volatility, and relatively more negative holding-period return skewness for the momentum strategy. Third, 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 capital pushing prices further away from fundamentals. Finally, and again consistent with our crowded-trade hypothesis, these results are only present for stocks with high institutional ownership.

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. 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 (9.8% and 15.1% respectively).

We additionally show that a firm-level analogue, *stock comomentum*, strongly and positively forecasts stock returns in the cross-section in following months. 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 return 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 look at, 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.

In addition, we find that our country comomentum measures tend to move together over time, with an average pairwise correlation of 0.47, indicating times when global arbitrage capital is generally high or low. Despite this tendency to comove, we document a strong inter-country momentum timing strategy based on cross-country variation in comomentum. For example, only pursuing stock momentum strategies in countries with relatively low amounts of arbitrage capital (based on our country-specific comomentum proxies) generates statistically-significant abnormal returns of approximately 12% per year (18% if hedged to global market, size, and value factors and 6% if further hedged to a global momentum factor). A corresponding strategy of investing only in momentum strategies in countries with high amounts of arbitrage capital produces profits that are less than a quarter as large and are statistically insignificant from zero. A long-short strategy that goes long in country momentum where arbitrage capital is low and goes short in country momentum where arbitrage capital is high yields 8% a year after adjusting for the global market, size, value, and momentum factors.

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 decreases 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. Furthermore, such intuitive findings provide additional evidence that our measure is sensible and is indeed related to actual arbitrage activities.

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 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 capital in a strategy, hence the mispricing is not fully corrected; while in other times, there is too much capital 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, it becomes a much more challenging task to gauge in real time exactly how many other traders are using the same arbitrage model or taking the same arbitrage positions.

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, due, for example, to limited attention or the disposition effect, and arbitrageurs attempt to facilitate price correction by purchasing stocks that have recently gone up and selling stocks that have recently gone down. Such a momentum strategy lacks a natural anchor, if arbitrageurs only condition their trading activity on a stock's past return.

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 due to 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 due to 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 thus that 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 capital for a strategy that does not have a natural anchor. The main contribution of this paper is to directly take up this challenge by proposing one such measure.

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.[6] For the

[6]For example, Anton and Polk (2010), Greenwood and Thesmar (2011), and Lou (2012) find that mutual

momentum strategy, we can extract information about arbitrage capital in the strategy by looking at the return correlation among stocks in the winner portfolio as well as that among stocks in the loser portfolio (more details on variable constructions 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) 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. We control for the Fama-French three factors in computing these partial correlations to purge out any comovement in stock returns in the same momentum decile induced by known risk factors. $comom^L$ (loser comomentum) is the average pairwise partial correlation for the loser

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.

decile, and $comom^W$ (winner comomentum) 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,

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

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.[7] In analysis not reported, 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.[8]

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 the stocks that they are long losing value and the stocks they are short gaining value. Those stocks would then, all else equal, no longer be momentum stocks. Moreover, since our comomentum measure follows a bottom-up

[7] The results are very similar if we instead measure average excess correlation with a value-weight winner (loser) portfolio or measure the average correlation of stocks in the winner *and* loser deciles (with a minus sign in front of the return of losers) with a 10-1 momentum factor.

[8] 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. Again, all of our main results continue to hold.

approach (i.e., the average correlation across all stock pairs), it 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 abnormal correlation of 0.120 across the 46-year sample. However, this abnormal correlation can be as low as 0.053 and as high as 0.284. 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).

As we will ultimately argue that comomentum describes time-varying expected returns on the momentum strategy, 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 with past market volatility (0.125). Finally, Table

I documents that comomentum is persistent, with an autocorrelation of 0.351 and 0.217 for loser and winner comomentum respectively.

4.1 Linking Comomentum to Arbitrage Capital

Table II links comomentum to several variables that arguably proxy for the size of arbitrage capital 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. We also forecast comomentum using the change in pih^W_{t-1} from the beginning to the end of year $t-1$, which we denote as Δpih^W_{t-1}. 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 $t-1$.

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 because we expect the typical investor in momentum strategies to bet both on winners and against losers.

Finally, we find that more specific measures of arbitrage investors that focus on hedge fund activity forecast time-series variation in comomentum. Regressions (1), (2), (4), and (5) show that 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 capital in the momentum strategy being due to this industry.

Note that we find a positive but relatively weak trend in our comomentum variable.[9] 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 Momentum Returns

We now turn to forecasting momentum profits with our comomentum measure. Table III Panel A reports the 46 annual observations of time $t-1$ comomentum (for both the loser

[9] 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 first removing this trend from *comom*.

and winner groups of stocks) and time t value-weight momentum returns. Figure 1 plots these data focusing on loser comomentum. The first thing to note is that comomentum is persistent; the serial correlation is approximately 0.3. Indeed, the excess correlation that comomentum measures is also persistent in event time for the stocks in question (correlation of 0.1). Looking carefully at the comomentum series, one might find it initially surprising that comomentum is high in 2008 during the financial crisis when capital was apparently leaving hedge funds. However, financial stocks were initially hit 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.

Finally, Table III Panel B reports the correlation between current comomentum and future momentum profits. Table III Panel B confirms what the eye can clearly see in Table III Panel A and in Figure 1; comomentum is negatively correlated (-0.183) with future momentum profits. Furthermore, the figure documents that this negative correlation is robust as the relation does not appear to be driven by outliers or subsamples. Interestingly, most of the negative correlation appears to be coming from the winner side of the momentum trade as the profits to the long side of a time-t momentum bet provide most of the negative correlation (-0.144). The short side of the momentum trade is relatively uncorrelated (0.018) with comomentum. Finally, all of these conclusions hold whether we measure comomentum using the loser group of stocks or the winner group of stocks.

With this general fact in hand, we now more carefully describe the extent and nature of the time-series variation in expected momentum returns linked to our comomentum measure. For one thing, we now focus on the information in the comomentum of the loser group of stocks. Also, whereas Table III examines 46 non-overlapping calendar observations of comomentum, we now exploit more of the information in comomentum by analyzing monthly overlapping observations of annual returns. Finally, and most importantly, we now track 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 IV 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. 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 IV 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, consistent with Table III and Figure 1, we find that post-formation returns in Year 1 are generally decreasing in the degree of comomentum. On average, the post-formation 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 indistinguishably 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 momentum return 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.

Figure 2 shows the patterns in Table IV 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 momentum profits are clearly positive (9.41%) when comomentum is low and clearly negative (-12.80%) when comomentum is high. The bottom panel in Figure 2 plots the cumulative returns 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 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 1.35 in year 0 to 1.22 in 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 not only be stronger but also quicker to manifest and revert.

Table V repeats the analysis of Table IV 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 patterns documented for comomentum in Table IV. 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 measure of comomentum, the third block of Table V repeats the analysis of Table IV 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.[10]

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 VI 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.

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.[11] Table VII reports the extent to which comomentum forecasts time-series variation in the skewness of momentum returns. As shown in Panel A, the skewness of weekly momentum returns for

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

[11] 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.

the six to twelve months post formation is decreasing in comomentum. The 20 percent of the sample that corresponds to low values of comomentum has subsequent momentum returns that exhibit weekly return skewness of -0.126 (t-statistic of -1.80) while the 20 percent of the sample that corresponds to high values of comomentum has subsequent momentum returns with a skewness of -0.536 (t-statistic of -5.31). The difference is both economically and statistically significant. 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%). 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.

Taken together, these results indicate that our comomentum measure of crowded momentum trading does forecast time-series variation in momentum profits. Consistent with crowded trading being destabilizing, comomentum also forecasts strong reversal. Therefore, we are able to identify when and why momentum profits transition from being due to underreaction to being due to overreaction.

Implicit in our analysis is the idea that simple momentum trading is an unanchored strategy and that we would not expect to have similar results for an anchored strategy, such as value. To confirm this intuition, in Table VIII we run a placebo test where we document that a similarly-constructed measure for the value strategy is consistent with price stabilization. Specifically, times of relatively high excess comovement for the value strategy are contemporaneously correlated with relatively low rather than relatively high formation returns. Furthermore, these 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.[12]

4.3 Cross-sectional tests

Since comomentum is a success at identifying times when arbitrage capital 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 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. 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 than the typical measure of momentum risk sensitivity, i.e. the pre-formation loading on a momentum factor. To show this, we

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

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.

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.

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.

4.4 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).[13] 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.

Figure 3 plots comomentum in these 19 countries and in the US from December 1986 to December 2011. It is clear from the plot that country-specific comomentum measures move together, with an average pairwise correlation of 0.47. This finding is reassuring as one might expect that there is a common global factor in country-specific measures of arbitrage capital. 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

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

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 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 capital 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 capital countries (t-statistic of 2.33).

4.5 Mutual and Hedge Fund Momentum Timing

Our final analysis takes our comomentum measure to the cross sections of 1) active mutual funds and 2) long-short equity hedge funds. In Table XI, we estimate 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, a fund's AUM, and the interaction between these two variables. To capture variation in a fund's AUM, we specifically 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. We find 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 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.

5 Conclusions

We propose a novel measure of momentum arbitrage capital based on high-frequency excess return comovement that we call *comomentum*. We examine the information in comomentum about future characteristics of the momentum strategy to determine whether arbitrage capital 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 strategy is the most likely place where arbitrage capital 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 capital 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 capital pushing prices further away from fundamentals. Further consistent with our motivation, these results are only present for stocks with high institutional ownership.

Additional tests confirm our approach to measuring arbitrage capital 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.

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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 $comom_t^L$ and $comom_{t+1}^L$ (and similarly for $comom_t^W$ and $comom_{t+1}^W$) 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

	$comom_t^L$	$comom_t^W$	$comom_{t+1}^L$	$comom_{t+1}^W$
$comom_t^L$	1.000			
$comom_t^W$	0.524	1.000		
$comom_{t+1}^L$	0.351	0.273	1.000	
$comom_{t+1}^W$	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^W_{t-1} is the aggregate institutional ownership of the winner decile at the end of year t-1 (i.e., the winner decile is ranked based on cumulative returns in year t-1), while Δpih^W_{t-1} is the change in aggregate institutional ownership of the winner decile from the beginning to the end of 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 logarithm of the size of the shadow banking sector, 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. 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		$comom^L_t$			$comom^W_t$	
	[1]	[2]	[3]	[4]	[5]	[6]
$Intercept$	0.105*	0.023	0.051	0.100***	0.031	0.042
	[0.054]	[0.018]	[0.032]	[0.031]	[0.028]	[0.027]
Δpih^W_{t-1}	0.211**			0.227**		
	[0.089]			[0.098]		
pih^W_{t-1}		0.177***	0.179***		0.158***	0.163***
		[0.068]	[0.057]		[0.046]	[0.044]
$mktret36_{t-1}$	-0.008	0.009	-0.009	-0.026**	-0.011	-0.018
	[0.019]	[0.015]	[0.018]	[0.012]	[0.011]	[0.015]
$mktvol36_{t-1}$	-0.225	0.545	0.212	-0.467	0.215	0.156
	[0.843]	[0.614]	[0.451]	[0.557]	[0.395]	[0.515]
$mom12_{t-1}$	0.500***	0.419***	0.775***	0.208**	0.163**	0.118*
	[0.182]	[0.155]	[0.275]	[0.101]	[0.077]	[0.065]
$shadow_{t-1}$	0.241**	0.228**	0.118	0.129**	0.099**	0.091*
	[0.100]	[0.091]	[0.093]	[0.057]	[0.047]	[0.056]
AUM_{t-1}			0.084***			0.057**
			[0.029]			[0.027]
Adj-R^2	0.08	0.17	0.33	0.15	0.30	0.39
No. Obs.	334	346	180	334	346	180

Table III: Comomentum and Momentum Returns

Panel A reports the time series of momentum returns and lagged comomentum measures 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). Stocks with prices below $5 a share and/or that are in the bottom NYSE size decile are excluded from the sample. These portfolios are then held for one year. $loser_t$ is the monthly value-weight return of the loser decile in year t, while $winner_t$ is the monthly value-weight return of the winner decile in year t. mom_t is the monthly return to the hedge portfolio that goes long the winner portfolio and short the loser portfolio in year t. $comom^L_{t-1}$ (loser comomentum) is the average pairwise partial return correlation in the loser decile measured in the ranking year t-1, while $comom^W_{t-1}$ (winner comomentum) is the average pairwise partial return correlation in the winner decile measured in the ranking year t-1. Panel B reports the correlations among $comom^L_{t-1}$, $comom^W_{t-1}$, $loser_t$, $winner_t$, and mom_t for the entire sample period.

Panel A: Time Series							
year t	mom_t	$comom^L_{t-1}$	$comom^W_{t-1}$	year t	mom_t	$comom^L_{t-1}$	$comom^W_{t-1}$
1965	1.00%	0.097	0.042	1988	-1.54%	0.110	0.100
1966	1.96%	0.136	0.167	1989	1.89%	0.076	0.054
1967	0.50%	0.139	0.101	1990	0.41%	0.072	0.046
1968	0.61%	0.153	0.100	1991	-0.99%	0.104	0.081
1969	1.15%	0.115	0.113	1992	0.21%	0.069	0.071
1970	0.55%	0.135	0.095	1993	2.61%	0.055	0.090
1971	-0.31%	0.151	0.112	1994	-0.53%	0.071	0.090
1972	1.56%	0.144	0.152	1995	1.61%	0.083	0.094
1973	3.15%	0.098	0.061	1996	0.01%	0.053	0.077
1974	2.03%	0.117	0.149	1997	0.86%	0.091	0.080
1975	-0.73%	0.061	0.085	1998	3.17%	0.115	0.072
1976	0.50%	0.099	0.119	1999	0.51%	0.102	0.077
1977	2.84%	0.101	0.098	2000	-2.25%	0.114	0.109
1978	1.78%	0.082	0.031	2001	-0.95%	0.147	0.125
1979	0.17%	0.088	0.081	2002	2.16%	0.216	0.178
1980	3.47%	0.124	0.101	2003	0.36%	0.199	0.094
1981	-2.03%	0.193	0.142	2004	0.54%	0.145	0.134
1982	1.62%	0.100	0.103	2005	1.21%	0.147	0.113
1983	0.25%	0.284	0.125	2006	-0.28%	0.108	0.105
1984	0.20%	0.072	0.064	2007	1.46%	0.119	0.097
1985	1.04%	0.082	0.085	2008	2.80%	0.152	0.119
1986	1.90%	0.076	0.055	2009	-5.42%	0.230	0.264
1987	1.17%	0.102	0.091	2010	1.47%	0.211	0.183

Panel B: Correlations with Momentum Returns					
	$comom^L_{t-1}$	$comom^W_{t-1}$	$loser_t$	$winner_t$	mom_t
$comom^L_{t-1}$	1				
$comom^W_{t-1}$	0.524	1			
$loser_t$	0.018	0.020	1		
$winner_t$	-0.144	-0.158	0.624	1	
mom_t	-0.183	-0.180	-0.478	0.387	1

Table IV: 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 V: 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 VI: 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 VII: 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 weekly returns to the value-weight winner minus loser portfolio in months 1 to 6 and months 1 to 12 after portfolio formation during 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

		Months 1-6		Months 1-12	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat
1	110	-0.126	(-1.80)	-0.123	(-1.79)
2	111	**-0.339**	(-3.91)	**-0.359**	(-5.28)
3	111	**-0.249**	(-3.44)	**-0.282**	(-4.50)
4	111	**-0.363**	(-6.05)	**-0.355**	(-4.00)
5	111	**-0.536**	(-5.31)	**-0.510**	(-3.54)
5-1		**-0.409**	(-3.40)	**-0.388**	(-2.44)
OLS		**-0.084**	(-3.13)	**-0.077**	(-2.28)

Panel B: Fraction of "Bad" 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 VIII: 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: Two-Factor 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 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 as of the end of month *t-1*. 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. $size_{t-1}$ 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]
$comom_{t-1}^L$	0.000	0.000	0.000	0.001	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
$umd_t * comom_{t-1}^L$	-0.009	-0.004	-0.005	-0.000	-0.022**	-0.032**
	[0.010]	[0.011]	[0.015]	[0.018]	[0.011]	[0.014]
$size_{t-1}$		-0.000		-0.000		-0.000
		[0.000]		[0.000]		[0.001]
$umd_t * size_{t-1}$		0.021		0.021		-0.006
		[0.014]		[0.019]		[0.029]
$comom_{t-1}^L * size_{t-1}$		0.000		0.000		0.000
		[0.000]		[0.000]		[0.000]
$umd_t * comom_{t-1}^L$		-0.005		-0.004		0.010**
$* size_{t-1}$		[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

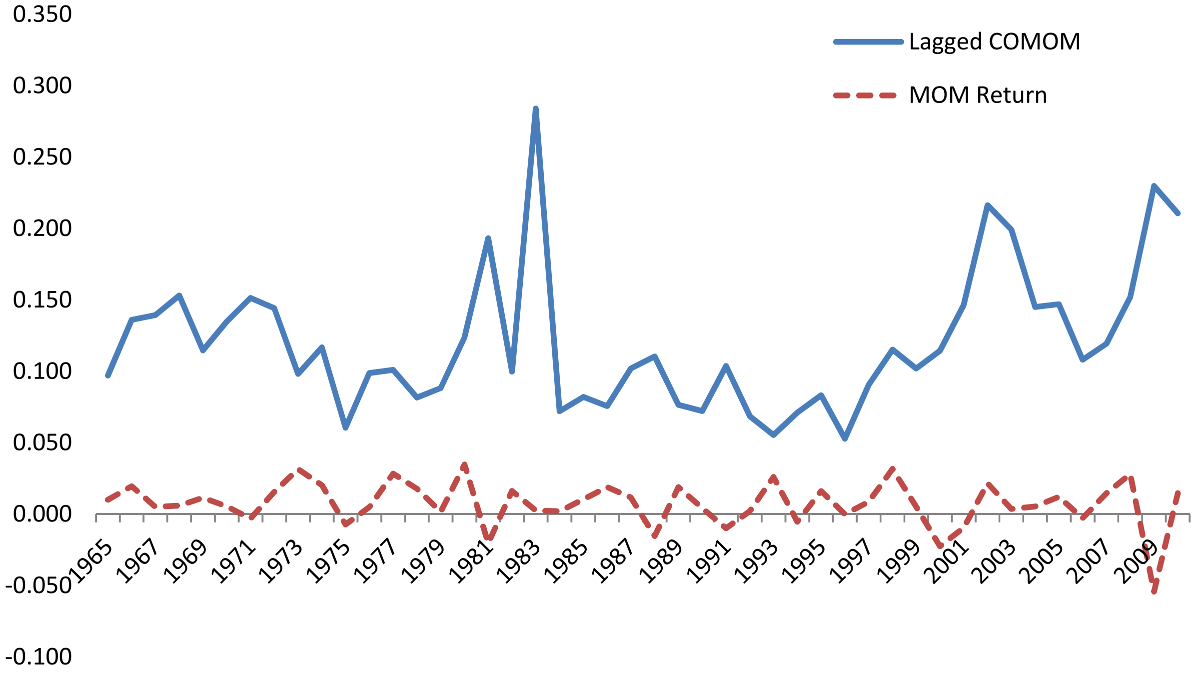
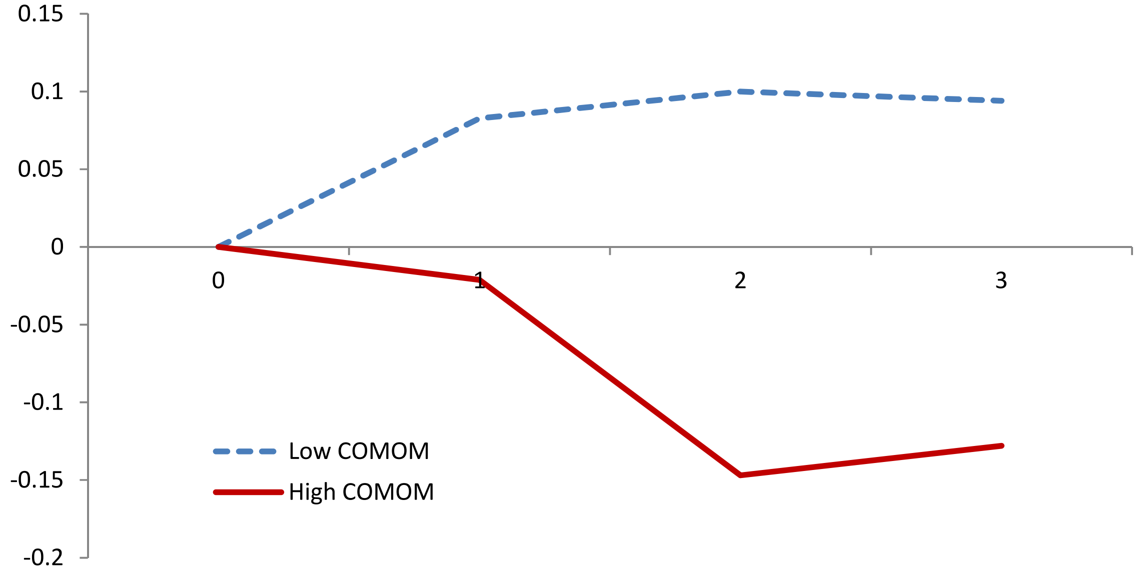


Figure 1: This figure shows the time series of momentum returns and the lagged comomentum measures at the end of each year. At the end of year t-1, all stocks are sorted into decile portfolios based on their lagged 12-month cumulative returns (skipping the most recent month). mom_t is the monthly return on the zero-cost portfolio that is long the value-weight winner decile and short the value-weight loser decile in year t. $comom_{t-1}$ (comomentum) is the average pairwise partial return correlation in the loser decile measured in the ranking year t-1.



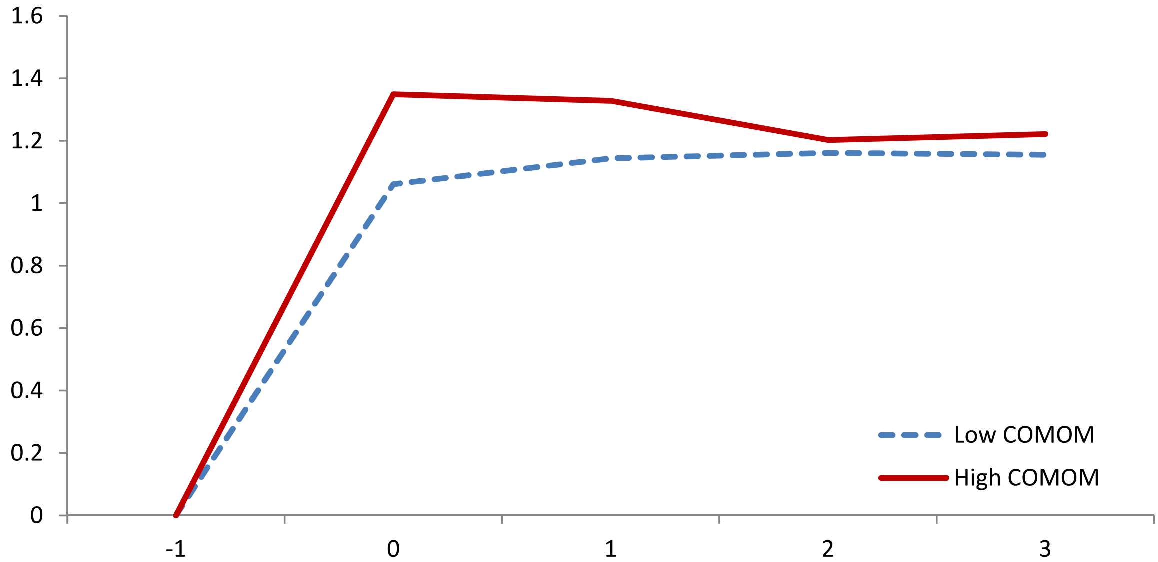


Figure 2: These figures show returns to the momentum strategy as a function of the lagged comomentum measure. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Stocks with prices below \$5 a share and/or are 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 $comom^L$.

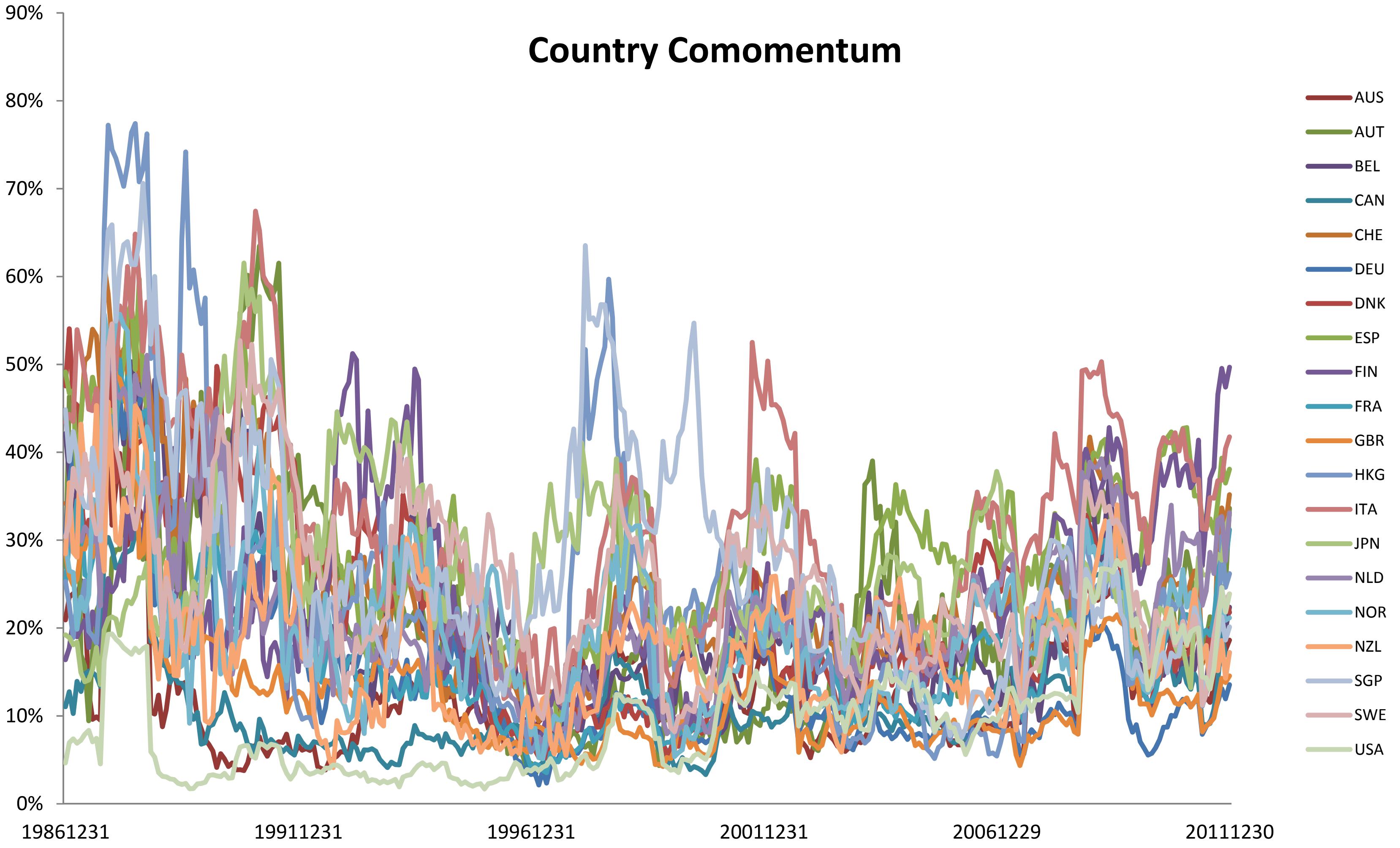


Figure 3: This figure shows the time series of country-specific comomentum measures. At the end of each month, all stocks in a country are sorted into decile portfolios based on their lagged 12-month cumulative returns (skipping the most recent month). Comomentum is the average pairwise return correlation in the loser decile measured in the ranking month. 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), Sweden (SWE), and the United States (USA).

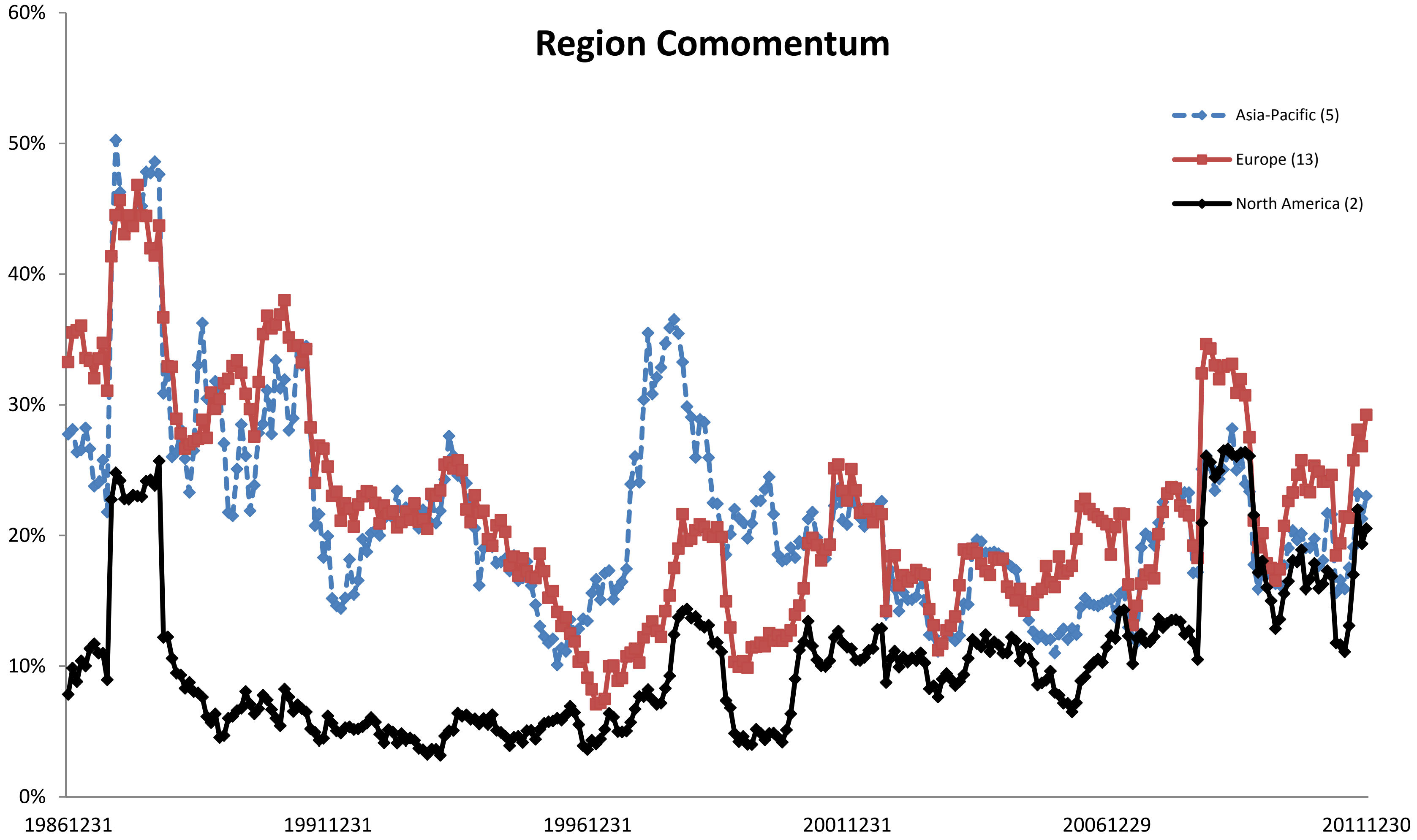


Figure 4: This figure shows the time series of region-specific comomentum measures. At the end of each month, all stocks in a country are sorted into decile portfolios based on their lagged 12-month cumulative returns (skipping the most recent month). Country comomentum is the average pairwise return 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.