# Competition and Momentum Profits

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**Abstract**

Fama and French (2008) point out that momentum is the premier anomaly confronting the finance profession. We develop a measure of buy-side competition for momentum investing and show that it explains abnormal momentum returns. Momentum is profitable when buy-side competition for exploiting momentum is low, including in the post-2000 sample. Momentum generates monthly alpha of more than 130 basis points, when competition is low, but does not yield significant alpha when competition is high.

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# 1 Introduction

"*...The whole momentum phenomenon gives me problems. It could be explained by risk, but if its risk, it changes much too quickly for me to capture it in any asset-pricing models...*" - Eugene Fama[1]

A key question in finance is whether returns are predictable and if so, whether the predictability is an anomaly that challenges market efficiency (Fama (1970), Fama (1991), Fama (1998)). The finance literature documents considerable evidence of predictability. Among the most robust findings are those relating to momentum. In an article dissecting anomalies, Fama and French (2008) refer to momentum, originally discovered by Jegadeesh and Titman (1993), as the premier anomaly.[2]

We study momentum through the lens of a specific economic force, competition between buy-side investors, as a determinant of abnormal momentum returns. Competition between investors is essentially competition for momentum profits, which itself is a function of competition for information. Our hypothesis follows from a traditional school of thought that when an anomaly yields trading profits, capable investors will exploit it through appropriate trading strategies and diminish the returns from the anomaly. Such pressures from the buy-side are more effective when there are a sufficient number of investors who are informed about the potential anomaly and who are able to exploit it.

We develop a measure of buy-side competition for momentum. One may think that the buy-side competition can be measured by the ownership breadth (number of funds that hold

[1] *Source: http://review.chicagobooth.edu/economics/2016/video/are-markets-efficient*

[2] Momentum has also been demonstrated by many earlier studies to exist in many markets. Rouwenhorst (1998) provides initial evidence of international momentum effects, and subsequent research further confirms these findings (Jegadeesh and Titman (2002), Asness, Moskowitz, and Pedersen (2013)). Many other papers examine cross-sectional variation in momentum patterns (Moskowitz and Grinblatt (1999), Lee and Swaminathan (2000), Avramov, Chordia, Jostova, and Philipov (2007), Liu and Zhang (2008)), momentum performance in different market conditions (Cooper, Gutierrez, and Hameed (2004), Griffin, Ji, and Martin (2003), Lou and Polk (2013)), the risk of momentum strategies (Grundy and Martin (2001), Barroso and Santa-clara (2015), Daniel and Moskowitz (2016)), and historical evidence using longer histories (Geczy (2013), Chabot, Ghysels, and Jagannathan (2014)). Others present theoretical models that can explain momentum: De Long, Shleifer, Summers, and Waldmann (1990), Hong and Stein (1999), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998). For a recent literature review of momentum, see Jegadeesh and Titman (2011).

the stock), but this is misleading. It ignores the information produced by many funds that *do not* hold the stock. Typically funds start with a universe of stocks in their local style space, gather information on such stocks, and then narrow down to a limited set of stocks which we observe in their portfolios. If we just focus on institutional funds that own a stock, it'll likely capture the information produced by these funds and sell-side analysts, as buy-side likely incorporates the sell-side information. However, just observing the funds that own a stock creates bias because we do not observe other funds that produce and compete for information, but eventually decide not to hold the stock. Such funds may have held the stock in the past or may hold the stock in future.

Our innovation is that we incorporate all funds that potentially gather and compete for information. The challenge is – how do we identify such funds? To solve this problem we employ a simple, intuitive and a novel idea. We start with the funds that hold the stock (call this set A), and then extend this set to the "competitors of funds that hold the stock" (call this set B). Both set A funds that hold the stock, and set B funds which are competitors of set A funds have very similar styles and compete for profitable opportunities in the same investment style space. The likely produce information on the same stocks, however some funds hold the stock, while others do not. Our buy-side competition considers both type of funds.

We first provide an illustration that builds intuition and then provide an example. Figure 1 shows the intuition behind our approach. The top figure shows the style locations of a stock and the funds that hold the stock. We first locate a stock in 3-dimensional normalized size, value and momentum space (red dot). We then locate the funds that hold the stock (blue dots). The location of a fund is just the value-weighted location of stocks in its portfolio. The bottom figure in Figure 1 plots both set A and B funds. One can clearly see the missing funds in top figure, by comparing it with the bottom figure. Prior studies have used more visible measures of information diffusion, such as sell-side analyst following (Hong, Lim, and Stein (2000)) and ownership breadth (Chen, Hong, and Stein (2002)). Our competition measure is more complete in the sense that is captures both "visible" and "invisible" buy-side information production.

We now provide an illustrative example for our buy-side competition measure (details in Section 2). Suppose there are $n$ stocks and $m$ funds in a given quarter. We first obtain momentum over the standard ($t-12$ to $t-2$) window for each of the n stocks, denoted by $r_1$, $r_2$,.., $r_n$. For simplicity, we omit the time subscript. We convert these momentum returns into $z$-scores, $z_{s1}$, $z_{s2}$,.., $z_{sn}$. From these $z$-scores, we obtain fund level $z$-scores, which are just the value-weighted $z$-score of stocks in its portfolio ($z_{f1}$, $z_{f2}$,.., $z_{fm}$). Now consider Figure 2, which shows the location of a stock $s$ (red color) and the location of the funds that hold this stock (blue color). In this case there are five funds that hold the stock.[3] We then obtain the competition around these funds as in Hoberg, Kumar, and Prabhala (Forthcoming). This competition is obtained by number of peer funds (green color) around the funds that hold the stock $s$.[4] For visual clarity, they are shown separately, but actually they are on the same line. These peer funds are very similar to the funds that hold the stock in their momentum orientation.[5] Finally, we obtain stock level competition measure as the average of competition around five funds. Intuitively, if this number is high, then the stocks $s$ is surrounded by a large number of funds that are very similar in their momentum orientation and are likely producing information on this stock. Our competition measure can be interpreted as a measure of *buy-side momentum attention*. If our buy-side competition measure is high, it likely indicates faster information diffusion.

We examine whether buy-side competition explains momentum. We find affirmative results. Figure 3 shows our main results. Briefly, we find that the cumulative return to momentum is negligible among stock that are characterized by high buy-side competition. Because of high buy-side competition, such stocks are more efficiently priced. However, momentum profits are economically large among low competition stocks where it generates significant excess returns. The low competition stocks are associated with slower information

[3]The ends of 1-dimensional momentum space are represented $\underline{z}$ and $\bar{z}$, where $\underline{z} = min(z_{s1}, z_{s2}, .., z_{sn})$ and $\bar{z} = max(z_{s1}, z_{s2}, .., z_{sn})$.

[4]Note that Hoberg, Kumar, and Prabhala (Forthcoming) obtain peer funds in 3-dimensional size, value and momentum space. However, here we are only trying to explain momentum, so we work with 1-dimensional momentum peers. Our results are similar, however, if we use 3-dimensional peers.

[5]In other words, they have similar fund level $z$-scores.

diffusion.

We now briefly explain our key results, and we relate these to the existing literature. Our main result is that economically significant portions of the momentum are explained by buy-side competition. We emphasize, in particular, that our tests are conducted on a universe of large-cap stocks. This approach directly address concerns about investibility and economic importance. Our sample comprises stocks with market capitalization in the top 50th percentile of the NYSE listed firms. This group accounts for over 90% of the total value of all U.S. public equities, and these stocks have fewer illiquidity concerns. We employ the standard momentum window of $t-12$ to $t-2$ months to identify winners and losers. In the segment of momentum stocks characterized as low buy-side investor competition, the one month ahead winner-loser value-weighted spread is an economically and statistically significant 139 basis points per month, or 16.7% on an annualized basis.

This winner-loser spread remains significant after adjusting for risk through various asset pricing models. For instance, the CAPM alpha is 143 basis points per month. The Fama-French 3-factor alpha (Fama and French (1993)) is 164 basis points per month. The Fama-French 5-factor alpha (Fama and French (2015)) is 137 basis points per month. These spreads are also statistically significant. We find similar results if we shrink the momentum look-back window to six months ($t-7$ to $t-2$) or even three months ($t-4$ to $t-2$). In contrast, in the same subsample of large-cap stocks with high buy-side fund competition, we find no momentum abnormal returns.

We further compare month $t$ return distributions for 5-1 long-short momentum portfolios in both high versus low buy-side competition markets. The low competition momentum portfolio displays similar volatility as the high competition portfolio, and because the low competition momentum stocks generate higher average returns, they also generate much higher Sharpe and Sortino ratios. The Sharpe ratio of the low competition momentum portfolio in our sample is 0.69, while it decreases to 0.05 when buy-side competition is high. These results are particularly strong given that we focus only on large capitalization stocks, where trading costs are relatively low.

Our results also shed light on the emerging literature on the crash risk of momentum strategies (Barroso and Santa-clara (2015), Daniel and Moskowitz (2016)). We find that the high competition portfolios display markedly *negative* skewness. Figure 4 illustrates this negative skewness. The portfolio has a skewness of -1.01, while the corresponding distribution for low competition portfolio returns has a skewness of 0.11. The contrast is more stark when we shrink the past return window to $t-7$ to $t-2$ months. The high competition momentum portfolio shows a skewness of -1.38, while the low competition portfolio shows positive skewness of 0.49. Stocks with focused buy-side interest and competition thus appear to contribute more to the crash risk of momentum. More broadly, these results suggest that the institutional buy-side attention can possibly help explain momentum crash risk, perhaps in competitive markets more funds rush to exit their strategies simultaneously.

We also examine longer-term excess returns. That is, we examine two months ahead alpha, three months ahead alpha and so on until 12-month ahead alpha. Our results persist, and we find that among low competition stocks, momentum returns are significant for up to 4 months after portfolio formation. For instance, the Fama-French 5-factor alpha in month $t+1$ is 118 basis points per month and remains significant up to month 4, when it is 74 basis points per month. Figure 5 shows the average raw returns through month 12. We observe that the spreads in the low competition stocks gradually decrease, while the spreads in the high competition stocks remain flat for most of the 12 months. When buy-side competition for momentum profits is low and hence information diffuses slowly, arbitrage capital also moves slowly (Mitchell, Pedersen, and Pulvino (2007), Duffie (2010)). As a consequence, momentum lasts longer.

We also analyze how momentum returns vary cross-sectionally with size and over time. To do so, we zoom in further on the largest and most liquid stocks. We observe similar results in NYSE size quartile 3 as we do in quartile 4. The quartile 4 stocks are largest and most liquid stocks, and cover most of the total market capitalization. Thus, our results are unlikely to be driven by illiquidity imperfections. A somewhat surprising finding is that our results are also *stronger* in more recent years. For instance, in the pre-1996 subsample, the low competition momentum stocks generate a statistically significant CAPM alpha of 97 basis points per month, while the post-1996 subsample exhibits a CAPM alpha of 180 basis points per month. The results are similarly strong if adjusted for risk using more advanced models.

Our results are related to and complement other studies based on ownership breadth (Chen, Hong, and Stein (2002)). One conjecture is whether the number of funds holding a given stock can also explain anomalies. As we illustrate earlier, it is an incomplete measure of information diffusion. We find that our competition-based measures remain robust, consistent with the uniqueness of our empirical measures and also the economics that drives them.

Our study also adds to the work on analyst following and momentum. As Hong, Lim, and Stein (2000) point out, analyst coverage determines the informational environment of stocks. This is *sell-side* information production by analysts. We examine momentum from the *buy*-side. Buy side analysts gather information regarding potential investments and then trade on it. Empirically, we note that our buy-side results are not explained by variation in the number of sell-side analysts. This conclusion is reinforced in sorts that condition on firm size. For example, Hong, Lim, and Stein (2000) show that momentum profitability decreases sharply for larger firms. In contrast, our results do not rely on small firms.

To summarize, our paper makes two contributions. First, we present a framework for measuring buy-side competition for momentum using micro-level holdings data. Second, we explain a significant slice of momentum. We do so in the sample of large capitalization stocks, where return anomalies are relatively hard to generate. We find that anomalous momentum returns exist only when fund competition is low. These results are economically significant, generate high excess returns, relatively long-lasting alphas, and avoid negative skewness when fund competition is low. Our results are robust in subsamples that are formed by size, by time, or by size and time. They are also robust to employing different sort methods (sequential or independent), or to using Fama-MacBeth cross sectional regressions (Fama and MacBeth (1973)). Our results also cannot be explained by analyst following, ownership breadth, and other controls such as size, book-to-market ratio, the short term reversal and post-earnings announcement drift (Jegadeesh (1990), Lehmann (1990)), Novy-Marx (2013), Chordia and Shivakumar (2006), Novy-marx (2015)).

While our framework is general and competition can be measured using any group of investors, we construct our measures using active mutual funds in the domestic U.S. equity market for three reasons. First, the mutual funds we consider are active, and as a group, own a large fraction of U.S. equities. The managers of these funds are likely interested in anomaly profits if they are driven by mispricing, and they are also likely to be marginal investors. Indeed, the returns of the value-weighted portfolio of mutual funds is close to the returns of the aggregate market (Fama and French (2010)). Second, mutual funds are known to focus heavily on large capitalization stocks, which comprise about 90% of the market. Hence, anomaly performance in these markets is very important. Third, mutual fund data is widely available for our sample period beginning in 1980. The long time horizon is necessary for testing anomalies given that anomalies are generally established using samples spanning over long time periods. Although one would be tempted to analyze the same using hedge fund holdings, we note that hedge funds are not required to report micro-level holdings at the fund level. They report more granular firm-level holdings data and it does not go back very long in time. Further, we know that our mutual fund data does not suffer from survivorship bias, which is an issue with hedge fund data.

A related question is why we focus specifically on momentum. Here we note an empirical motivation: momentum is the most important and robust anomaly. Additionally, momentum is dynamic, in the sense that the momentum portfolios exhibit churn regarding the addition and subtraction of stocks depending on past returns. The half-life of momentum, for example, is of the order of a few months, as returns normalize after this period. In our view, the presence or absence of buy-side competition is more likely to impact excess returns in such a dynamic setting than in a more static setting (for example, relatively the value premium is a more static anomaly).

# 2 Competition and Momentum

## 2.1 Hypothesis and Framework

Our central prediction is that momentum will generate larger profits when buy-side competition is low. The intuition is straightforward: if momentum is driven by market frictions (such as informationally inefficient markets, underreaction, or other inefficiency-based or behavioral explanations), then buy-side investors have strong incentives to produce information to generate alpha. If in addition, information is difficult to produce in some local anomaly markets, and much less costly to produce in other markets, then the level of buy-side competition prevailing in local anomaly markets will vary widely. As we expect prices to be very efficient in competitive markets, we predict that momentum profits will be close to zero in markets with intense buy-side competition. In contrast, we expect that momentum will persist longer and will be more profitable in concentrated markets.

Understanding competition in the style space is central to our hypotheses. Our approach is thus quantitatively related to that in Hoberg, Kumar, and Prabhala (Forthcoming) (HKP), but we also note that the current study is different along multiple dimensions. For example, we extend measurement of competition from the fund level to the individual stock level, and our focus is on the most robust anomaly, momentum. We first summarize the HKP methodology and then develop our novel extended hypotheses.

One of the objectives of HKP is to derive active peer benchmarks for funds. They first place stocks in a $k$-dimensional space and funds inherit the value weighted style characteristics of their individual stocks (see for example Grinblatt and Titman (1989), Daniel, Grinblatt, Titman, and Wermers (1997), Chan, Chen, and Lakonishok (2002), Chan, Dimmock, and Lakonishok (2009)). Fund $j$ is then deemed to be a competitor of fund $i$ in quarter $t$ if the spatial distance satisfies the condition $d_{i,j,t} \leq d^*$. Here $d^*$ is a fixed radius specified by the researcher. Using a low value of $d^*$ generates narrow definitions of competition with few rivals, and a larger radius $d^*$ permits more distant funds to be defined as competitors.

HKP calibrate network granularity to match that of the Lipper classification system. Thus, each fund can have a different number of peers in their local style space. Some funds face high competition, whereas others are surrounded by few peer funds. The customized peers are updated dynamically in every quarter. For more details, we refer the reader to Hoberg, Kumar, and Prabhala (Forthcoming).

Although we partially draw upon HKP for methods indicating how to compute measures of competition using the characteristics of firms that funds invest in, we depart from HKP, as in this study we compute measures of competition only along momentum. In HKP, the objective is to examine competition in style based markets, which are useful for examining fund manager alphas relative to the well-defined benchmarks. In contrast, our goal in this study is to examine one of the most robust asset pricing anomalies, in a buy-side competition framework.

For example, when considering momentum, our one-dimensional space is simply the space of momentum loadings among funds. Each fund has a location on the one-dimensional line that represents momentum space. Two funds are deemed to be momentum competitors if the distance between them on the line satisfies $d_{i,j,t} \leq d^*$, where $d^*$ is a maximum distance used to separate rivals and non-rivals for a particular fund. This metric is specific to the momentum anomaly, and competition becomes particularly relevant in locations on the line that indicate high momentum exposures. When momentum appears in more contested markets, our prediction is that momentum profits will be low, and in contrast they will be high when competition in a given market is low.

Alternative measures including breadth, i.e. the number of funds holding a stock (Chen, Hong, and Stein (2002)), are incomplete for two reasons. First, if a stock is held by a certain number of funds, this stock is likely in the investment opportunity set of many other funds operating in the local market even if they currently have a zero position in the given stock. Hence, at best, the raw ownership count measure is incomplete and backward-looking as a measure of competition. Although their current position in the given stock might be zero, competing local neighborhood funds operate in the vicinity of the given stock and produce information on the stock's prospects. If a profitable opportunity arises in the stock, the funds in this vicinity are equipped to quickly enter and arbitrage away such an opportunity. We hypothesize that greater the competition surrounding a stock, the informational frictions and anomaly profits will be competed away quickly. Second, measures such as breadth are more "visible" measures and therefore may already be acted upon by funds in their investment decisions. Thus, we may find weaker results using such visible measures of competition.

## 2.2 Competition Measure

To empirically implement our test, we need to go beyond HKP, who only examine the competition surrounding individual funds. We go further and define a metric indicating the level of competition surrounding each individual stock. This innovation empowers us to then examine momentum profits, and to predict where they are likely to be largest or smallest. We calculate buy-side momentum competition around stocks using three steps.

1. Suppose there are $n$ stocks and $m$ funds in a given quarter. We first obtain momentum over the standard ($t-12$ to $t-2$) window for each of the $n$ stocks, denoted by $r_1$, $r_2$,.., $r_n$. We transform these momentum measures into $z$-scores, $z_{s1}$, $z_{s2}$,.., $z_{sn}$. This is done in each quarter separately. We omit the time subscript for simplicity. We then obtain fund level $z$-scores, which are just the value-weighted $z$-score of stocks in its portfolio ($z_{f1}$, $z_{f2}$,.., $z_{fm}$). For instance, if *Fund 1* holds $k$ stocks with weights $w_1$, $w_2$,..., $w_k$ then $z_{f1} = \sum_{j=1}^{k} w_j z_{sj}$.
2. We then identify which funds hold a given stock. Suppose, stock $s$ is held by $l$ funds ($j = 1, 2, ...l$) at the of quarter $T$. We locate this stock and the $l$ funds on 1-dimensional momentum space. We then identify customized rival funds for each of the $l$ mutual funds in 1-dimensional momentum space and then arrive at the fund level competition measure. HKP describe the method in detail. We only briefly discuss the steps. In the first step, all funds are located on the momentum line as described above in the hypothesis section. Two funds with similar momentum $z$-scores are defined as

momentum competitors if the distance between them is less than the critical distance, $d^*$. This critical distance is identified based on the Lipper classification. Based on this distance, each pair of funds in any quarter is classified as a pair or non-pair. This results in each of the $l$ funds getting its own set of customized peer funds. Let the competition around $l$ funds that hold the stock $s$ be denoted by $C_1$, $C_2$,...,$C_l$. This competition measure is based on the similarity between a fund and its customized rivals.

3. In the third step, we obtain the new firm-level competition measure. This is done as follows. We again note that the total similarity of a fund $j$ and its peer funds is a measure of the intensity of competition surrounding the given fund. The competition surrounding a given stock $s$, is thus best described as the average competition facing the funds that hold the given stock $i$, which we define (at the end of quarter $T$) as:

$$COMP_s = Average(C_1, C_2, ...., C_l) \tag{1}$$

If this measure is high, it indicates that the stock $s$ is surrounded by a large number of funds, *which are similar to the $l$ funds that hold stock $s$.* We then update the competition surrounding the stock $s$ at the end of quarter $T+1$. Thus, we have quarterly values of competition surrounding any stock $s$ at the end of any quarter $T$, $COMP_{s,T}$.

To implement our test in real time and avoid any look-ahead bias, we lag competition and take the average over the preceding two quarters. For instance, if month $t$ is July, then we do not use the $COMP_{s,T}$ obtained at the end of June.[6] Rather we take the average of $COMP_{s,T-1}$ and $COMP_{s,T-2}$, which are obtained at the end of March and at the end of December of previous year. Thus, we define competition for stock $i$ and month $t$ as

$$COMP_{s,t} = \frac{COMP_{s,T-1} + COMP_{s,T-2}}{2} \tag{2}$$

[6]We denote months by $t$ and quarters by $T$.

This will also be the competition around stock $s$ for the next two months, $t+1$ and $t+2$. We then update the competition metric for the next three months and so on. We take the average over the two quarters so that our metric is not driven by outliers in any quarter.[7]

# 3 Data

## 3.1 Firm Data

We obtain data on firms from CRSP and Compustat. We start with monthly data on all common stocks (share code = 10 or 11) listed on NYSE, AMEX and Nasdaq exchanges with non-missing price and outstanding shares to obtain firm size. We exclude financial firms, i.e. firms with SICCD between 6000 and 6999 and firms with price less than one at the end of month. We define this month as $t-1$. Next, we construct the following variables, including momentum with different look-back windows.

$MOM12_{t-1}$: Cumulative return from month $t-12$ to $t-2$.

$MOM6_{t-1}$: Cumulative return from month $t-7$ to $t-2$.

$MOM3_{t-1}$: Cumulative return from month $t-4$ to $t-2$.

$ME_{t-1}$: Market equity (price times shares outstanding) at the end of month $t-1$.

$BM_{t-1}$: Book-to-market ratio is book equity divided by market equity. We measure book equity as in Daniel and Titman (2006). Book equity is lagged by six months from month $t-1$. Market equity is current market equity at the end of month $t-1$.[8]

$RET1_{t-1}$: Return in month $t-1$.

$PROF_{t-1}$: Profitability is measured as in Novy-Marx (2013). It is defined as gross profits/total assets. Both gross profits and total assets are lagged by six months from month $t-1$.

[7] We get similar results if we define competition as $COMP_{s,t} = COMP_{s,T-1}$.

[8] We substitute firms with negative book-equity with a book-equity of zero. Our results are similar if we exclude firms with negative book equity.

$SUE_{t-1}$: We calculate standardized earnings surprise as in Chordia and Shivakumar (2006). We keep only those firms for which the earnings announcement date (RDQ) is within three months of fiscal quarter end date (DATADATE). We then obtain earnings changes using the seasonal random walk model. That is, we define the standardized earnings surprise at the end of month $t - 1 = (E_{iq} - E_{iq-4})/\sigma_{iq}$, where $E_{iq}$ is the most recently announced earnings and $\sigma_{iq}$ is the standard deviation of $(E_{iq} - E_{iq-4})$ over the past eight quarters with non-missing observations for a minimum of six quarters.

We winsorize all variables at 1/99 percentile to remove outliers. As our tests are designed for stocks where limits to arbitrage are less applicable, we work with large-cap stocks where illiquidity and transaction costs are not high compared to those of small-cap stocks. We follow Fama and French (2008) in identifying the large-cap stocks, which we define as stocks those above 50th percentile in the size distribution of all NYSE listed stocks. We also obtain analyst coverage from the IBES database as described in Section 4.2.7.

## 3.2 Fund Data

Our sample on mutual funds is same as in Hoberg, Kumar, and Prabhala (Forthcoming). We obtain data on actively managed, open-ended U.S. equity mutual funds from CRSP Survivor-Bias Free US Mutual Fund database. Our sample starts from January 1980. We only consider actively managed diversified equity funds, as we are interested in investors that produce information on stock that match their style, unlike index funds. To identify such funds, we follow a sequential algorithm similar to that in Kacperczyk, Sialm, and Zheng (2008). We first select funds whose Lipper Classification Code is one of the following: EIEI, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE. If the Lipper classification code is missing, we select funds whose "Strategic Insights" objective code is AGG, GMC, GRI, GRO, ING, or SCG. Where both codes are missing, we pick funds with Wiesenberger objective codes equal to G, G-I, GCI, LTG, MCG, or SCG or "Policy" code of CS. For the remaining funds, we require that the lifetime average invested in equity is at least 80%. We eliminate index funds by using the CRSP-defined index fund flags and by screening the names of funds for words such as “Index” or “S&P.” We further remove funds whose names have words such as “ETF.” We screen out funds for incubation bias as described later.

We obtain snapshots of the quarterly holdings of funds from the Thomson Reuters mutual fund holdings database. Since our focus is on U.S. equity mutual funds, we exclude all funds whose objective code is one of the following: International, Municipal Bonds, Bond & Preferred, Balanced, and Metals. For funds that do not report quarterly, which is less common in the later years of our sample, we extrapolate the previous quarter holdings to the current quarter. This is done for at most one quarter to avoid excessively stale data. Holdings disclosures before a quarter end are carried forward to the quarter end.

From the fund-quarter portfolios identified through the holdings data, we remove all funds whose total net assets (TNA) are less than $5 million. We do not necessarily eliminate fund-quarters with missing TNA because these observations are sometimes for funds that have large previously disclosed TNA. We eliminate survivorship bias due to newly incubated funds by excluding the first appearance of a fund-quarter in the Thomson Reuters dataset. These funds may appear in the data only if their prior performance has been satisfactory. Evans (2010) points out that this bias is not eliminated by simply screening on size.

We then combine the CRSP sample with the Thomson Reuters holdings sample using the MFLINKS dataset developed by Wermers (2000). After merging the datasets, we further remove fund-quarters that do not have a valid Lipper class in CRSP. We implement this screen only for fund-quarters after December 1999 because Lipper classifications are unavailable before that date. Our final sample consists of 3390 unique funds for which we have at least one disclosed portfolio from quarter 2 of 1980 to quarter 1 of 2012. We refer the reader to Hoberg, Kumar, and Prabhala (Forthcoming) for more details of the sample and summary statistics. Our final step is merging the CRSP and Compustat with fund holdings data as obtained above.

## 3.3 Summary Statistics

We start by discussing our sample coverage. Table A1 shows the number of stocks, average size, and total market capitalization at the end of different years and also shows the overall time-series average across all 381 months (1980:10 - 2012:06). We compare our sample with the CRSP large-cap stocks sample. We find that on an average our sample has about 863 stocks in a month with an average market capitalization of about \$7.55 billion. This is larger than the average market capitalization of CRSP large-cap stocks, which is about \$7.18 billion. Thus, our sample is skewed towards larger stocks even among the CRSP large-cap stocks. This further shows that our sample consists of highly liquid stocks. Table A1 also shows that our sample represents about 93.70% of market capitalization of large-cap stocks.

We now discuss summary statistics. Panel A of Table 1 reports time-series average of cross-sectional statistics. Specifically, at the end of each month, we obtain mean, median, standard deviation, 25th and 75th percentile of stock characteristics. We then take the time-series average of these statistics. We find that the variation in momentum increases as we increase the look-back window. Our sample has a median book-to-ratio of about 0.48, which shows that our sample doesn't have pronounced growth or value tilt.

Panels B of Table 1 report the competition statistics. We also report competition statistics for the earlier half and the later half of our sample. The later half of the sample starts from 1996:08. This covers both the dot-com crisis and as well as the financial crisis. We find that there is greater competition in the second half is consistent with the high growth of fund industry post-1995. There is also more variation in competition in the second half of the sample.

Panels C of Table 1 report the average monthly cross-sectional correlations (averaged across all months) between momentum and competition. We find that competition is negatively correlated with momentum. $COMP$ has a -0.24 Pearson correlation with $MOM12$. Further this correlation goes down as we decrease the look-back window. This is by construction since $COMP$ is measured with respect to the 12-month look-back window.

# 4 Results

We first discuss the unconditional momentum results in our sample and then discuss how competition impacts momentum. We then run a number of robustness tests and also examine how quickly alpha dissipates over time as we consider deeper informational lags.

## 4.1 Baseline Results

Table 2 presents average return, risk and performance ratios for momentum portfolios with different look-back windows. At the end of each month $t-1$, we sort stocks into quintile portfolios by $MOM12$, $MOM6$ and $MOM3$ in Panels A, B and C, respectively. We then calculate value-weighted portfolio returns (reported in percentage) for the next month $t$. We report time-series average monthly mean return ($\bar{r}$), average excess return ($\overline{r-r_f}$), volatility ($\sigma_r$), downside volatility ($\sigma_{r(r<0)}$), skewness, 1 percentile and minimum returns.[9] We also report annualized Sharpe and Sortino ratios. 5-1 represents zero-sum long-short portfolio that is long on quintile 5 and short on quintile 1.

We find that unconditional momentum is not profitable in our sample. The 5-1 $MOM12$ portfolio generates 0.41% per month with an insignificant $t$-statistic of 1.29. It shows a volatility of 6.22%, a downside volatility of 3.88% and is somewhat negatively skewed with a value of -0.17. It has a Sharpe ratio of 0.22 and a Sortino ratio of 0.36. The unconditional momentum portfolio also is not significant if we decrease the look-back window to six or three months. This weak result for unconditional momentum is likely explained by two factors as compared to past studies: (1) we focus exclusively on large capitalization stocks, which are harder to predict, and (2) our sample only includes observations from 1980 to 2012, and the financial crisis of 2008 is included in our sample. We note that although unconditional momentum strategies are not significantly profitable in this sample, we find strong results for momentum profits once we condition on buy-side competition as discussed in later sections.

[9] To obtain downside volatility, we replace positive portfolio returns with zero and then obtain the standard deviation of the time-series returns.

Table 3 reports risk-adjusted monthly alphas of the quintile portfolios. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (Fama and French (1993), FF3), and Fama-French 5 factors (Fama and French (2015), FF5). We report $t$-statistics in parentheses. Out of the nine specifications in Table 3, momentum is statistically significant in only one specification, FF3 alpha for $MOM12$. The CAPM and FF5 alphas are statistically insignificant for $MOM12$. The alphas generated by shorter look-back windows also are not significant. Overall, we conclude that the unconditional momentum is not profitable in our large-cap sample.

## 4.2 Competition

We now discuss the main results of the paper. We show that momentum generates greater profits in the low competition stocks. We first discuss the Fama-MacBeth (Fama and MacBeth (1973)) regression results and then discuss the performance statistics and alphas of the conditional portfolio strategies. We then run a series a robustness tests and find robust results.

### 4.2.1 Fama-MacBeth Regressions

Table 4 shows average cross-sectional regression coefficients from Fama-MacBeth regressions that predict monthly returns. We first run cross-sectional regressions each month by regressing month $t$ return on variables measured at the end of month $t-1$. We report the time-series average of the coefficients and the corresponding $t$-statistics in parentheses. In all regressions, the variable $X$ is either $MOM12$ or $MOM6$ or $MOM3$. The variable $X$ is defined at the top of the table. $LME$ is log of market equity, $LBM$ is log of (1 + book-to-market ratio), $RET1$ is month $t-1$ return, $PROF$ represents profitability measured by gross profits scaled by total assets (Novy-Marx (2013)), and $SUE_{t-1}$ is earnings momentum (Chordia and Shivakumar (2006), Novy-marx (2015)). At the end of $t-1$ month, we also sort stocks into terciles by momentum competition ($COMP_{t-1}$). Stocks in the lowest tercile are defined as the low competition stocks. *Low* is a dummy variable for low competition stocks. Similarly, we define $Med$ and $High$ dummy variables for the medium and high competition stocks, respectively. For ease of comparison, we standardize all RHS variables to zero mean and unit variance, except the dummy variables.

We find that when we do not interact ($MOM12$) in Models 1 and 2 with competition dummy variables, momentum appears to be profitable. A one standard deviation increase in $MOM12$ is associated with a 30 basis points increase in the next month's return. After controlling for other variables that are known to explain future returns, we find that the momentum predictability increases to about 40 basis points. However, in Models 3 and 4, when we interact $MOM12$ with dummy variables, we find that all predictability comes from low and medium competition stocks. The coefficient of interest is on the interaction term $X * Low$, which measures how the incremental expected returns in low competition stocks over high competition stocks vary with momentum ($\frac{E(r_t|Low)-E(r_t|High)}{MOM12_{t-1}}$). We find that for a one standard deviation increase in momentum, low competition stocks generate about 41 basis points per month higher return than do high competition stocks (Model 4). We also note that there are no momentum profits for high competition stocks as the corresponding coefficient is both statistically and economically insignificant.

We find even stronger results in Models 5-8 where the look-back window to measure momentum is six months ($MOM6$). For instance, Model 8 shows that on average, for a one standard deviation increase in momentum, low competition stocks generate about 56 basis points per month higher future return than do high competition stocks. These incremental returns are statistically significant with a $t$-statistic of 4.82. We also find similar results when we further reduce the look-back window to three months in Models 9-12.

We also note that our results do not rely on our use of dummy variables for competition in our above regressions. In particular, our regression results are fully robust if we instead use a continuous competition variable. Table A2 shows full sample results when competition is a continuous variable ($LCOMP$, log of competition). We find similar results (unreported) for the subsamples as well for the continuous competition variable. Overall, we find significant evidence for price and earnings momentum exhibiting greater profitability in low competition stocks.

### 4.2.2 Portfolio Analysis

Our Fama-MacBeth regression results thus far suggest that momentum generates higher profits for low competition stocks. Based on this insight, we now consider out-of-sample conditional time series portfolio strategies. We proceed as follows. At the end of each month $t-1$, we first sort stocks into terciles by momentum competition (Panels A, B and C) and then sort stocks within terciles into quintile portfolios by momentum with different look-back windows. We then calculate value-weighted portfolio returns (reported in percentage) for the next month $t$. We then report all return, risk, and performance statistics as in Table 2. Table 5 reports the performance statistics of these portfolios.

We focus on the 5-1 hedge portfolios. Panel A shows that $MOM12$ generates 1.39% per month return ($t$-statistic = 3.92) in the low competition stocks, while the returns in the high competition stocks are statistically and economically insignificant. The low competition stocks exhibit slightly higher volatility of 6.91% as compared to that by the high competition stocks (=5.42%). Both have similar downside volatilities of about 3.6% and 3.7%. However, the low competition 5-1 portfolio exhibits somewhat positive skewness of 0.11, while the high competition portfolio shows a markedly negative skewness of -1.01. Because of comparable volatilities and much higher average returns, it is not surprising that the low competition momentum portfolio shows a high Sharpe (0.69) and Sortino (1.26) ratios. This Sharpe ratio of 0.69 is three times the Sharpe ratio, 0.23, of the unconditional momentum portfolio that we noted earlier in Table 2.

The difference in performance of low and high competition momentum stocks becomes even more stark when we reduce the look-back window to six months. For instance, the low and high competition 5-1 portfolios generate an average return of 1.02% ($t$-statistic = 3.09) and -0.53% per month ($t$-statistic = -2.00), respectively. The low competition portfolio has an skewness of 0.49, while the high competition portfolio has a skewness of -1.38. The difference in Sharpe and Sortino ratios is also large. We find a similar pattern in Panel C where we measure momentum with a look-back window of three months. Figure 3 displays the cumulative returns to investing in 5-1 $MOM12$ portfolio. One can clearly see the differential return pattern in the low and high competition stocks.

We now discuss the risk-adjusted monthly alphas of the quintile portfolios. In Table 6, the alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). We report $t$-statistics in parentheses. For brevity, we only report alphas for quintile 1, quintile 5, and the 5-1 portfolio.

Panel A of Table 6 shows that $MOM12$ generates CAPM alpha of 1.43% per month ($t$-statistic = 4.00) for low competition stocks, while it generates an insignificant alpha of only 0.20% per month for high competition stocks. These spreads are also different from each other. We get similar results if we adjust risk using the FF3 and FF5 models. For instance, the 5-1 FF3 and FF5 spreads for the low competition stocks are 1.64% ($t$-statistic = 4.66) and 1.37% ($t$-statistic = 3.74) per month, respectively. The corresponding spreads in the high competition stocks are insignificant. We get similar results when we shrink the look-back windows to six and three months in Panels B and C, respectively.

We also note that our results are not affected by choice of sequential versus independent sorts. Table A3 shows 5-1 spreads when stocks are sorted independently into terciles by competition and into quintiles by momentum.[10] We find similar results both qualitatively and quantitatively.

#### 4.2.3 Longer Holding Periods

So far we sorted stocks into portfolios at the end of month $t-1$ and predicted next month $t$ alpha. We now predict two months ahead $t+1$ alpha, three months ahead $t+2$ alpha and so

[10] We show only 5-1 spreads for brevity. The complete results are available on request.

on until the month $t+11$. Table 7 displays the alphas of our 5-1 portfolios for $MOM12$.[11] We note that depending upon the risk-specification used, momentum remains profitable in the low competition stocks for up to 4 to 6 months after portfolio formation. The alphas progressively decrease. For instance, for the FF5 model, the alpha in month $t$ is 1.37% per month ($t$-statistic = 3.74). This alpha decreases to 1.18% per month ($t$-statistic = 3.58) in month $t+1$. We continue to observe significant alpha until month $t+4$ with a magnitude of 0.74% per month ($t$-statistic = 2.33). The difference in alphas between the low and high competition stocks persists for up to four months. Figure 5 shows the average returns of the 5-1 $MOM12$ for the next 12 months (marked 0 to 11 on the x-axis). We can clearly see that the spreads for the low and high competition stocks converge in the later six months. We conclude that there is a slower reaction by buy-side investors in the low competition stocks. These stocks slowly attract more attention and mispricing disappears gradually.

#### 4.2.4 Size

We recall that our sample consists of large-cap stocks where illiquidity concerns and transaction costs are lower. Our definition of large-cap stocks follows that of Fama and French (2008). They define large-cap stocks as those whose size is greater that the median sized NYSE listed stock. The median cutoff is applied cross-sectionally each month. We further conduct our analysis by splitting our sample into two categories: NYSE size quartile 4 and NYSE size quartile 3. We repeat our earlier analysis and predict month $t$ alphas.

Table 8 reports alphas of 5-1 portfolios. Panel A shows results for size quartile 4, while Panel B shows results for size quartile 3. Within both size quartiles, we find that irrespective of the model used for risk-adjustment, the alphas are large and statistically significant for the low competition stocks. In contrast, the high competition stocks do not exhibit significant alphas. This is in contrast to many other studies of anomalies, which find weaker results for larger firms. Our results are economically significant and important as the size quartile 4 covers most of the market capitalization.

[11] Our results are robust and similar for $MOM6$ and $MOM3$ as well.

#### 4.2.5 Subperiods

We report Fama-MacBeth regression and portfolio results for two subperiods. Table 9 shows results for the two subperiods. We find similar results as in Table 4, which shows the full sample results. The coefficient of interest is on the interaction term $X * Low$. We find similar magnitudes and statistical significance in both subperiods. For instance, when we measure momentum with a six month look-back widow, $MOM6$, the coefficient on the interaction in term Model 8 in first subperiod is 0.48 ($t$-statistic = 3.30), while in the second subperiod, it is 0.51 ($t$-statistic = 2.95). These results suggests that low for a one standard deviation increase in $MOM6$, low competition stocks generate about 50 basis points per month higher return than do high competition stocks.

We now confirm the same conclusion using the out-of-sample portfolio analysis. Panel A of Table 10 displays results for the first half of the sample, where the holding period month $t$ varies from 1980:11 to 1996:08, while in Panel B the holding period month $t$ varies from 1996:09 to 2012:07. Thus, the second half of the sample covers both the dot-com crisis and the 2008 financial crisis. We find similar results for both subperiods. However, we note an interesting observation. Although the low-high price momentum spreads are similar, the 5-1 portfolio alphas within the low-high spreads are higher in the second half. For instance, $MOM12$ CAPM alpha for low competition stocks in Panel A is 0.97% per month ($t$-statistic = 2.82), while it is 1.80% per month ($t$-statistic = 2.93) in Panel B.

Our earlier analysis noted that the high competition 5-1 portfolio displayed greater negative skewness, especially for $MOM6$. We know that momentum crashed in March and April 2009 (Barroso and Santa-clara (2015), Daniel and Moskowitz (2016)). This period could have contributed to the negative skewness of the high competition stocks, and therefore the difference in low-high spreads could be driven by these crashes. To check this possibility, we restrict our sample to the pre-crisis period until December 2007. Table 11 shows results from the pre-crisis subsample. Our results are not materially different from the full sample results in Table 6. We further split our sample by NYSE size quartile 4 and 3, and then by subperiods. Table A4 shows results for the four subsamples. We find consistent price momentum results in all subsamples.

#### 4.2.6 Ownership Breadth

We now conduct more robustness tests motivated by alternative explanations. We repeat our tests with ownership breadth as a measure of market competitiveness. We check whether sorting on breadth of ownership (Chen, Hong, and Stein (2002)) instead of our competition measures produces similar results. If sorting on breadth does produce similar results, then our competition measure does not contain any new information, which effectively means that the fund rivals which are also in the vicinity of a stock in the style space do not produce any significant information.

We first sort stocks by breadth and then by momentum. Table A5 shows that the momentum CAPM alphas of winner portfolios do not outperform losers in either the low breadth or the high breadth stocks. The low-high 5-1 spreads are also not different from each other. The FF5 adjustment generates higher spreads in the low breadth stocks, but the FF3 adjustment does not. Thus, we find inconsistent results.

#### 4.2.7 Analysts Coverage

Hong, Lim, and Stein (2000) shows that the profitability of momentum strategies is higher among stocks with lower analysts coverage. The idea is that firm specific information diffuses gradually and analyst coverage helps in increasing the rate of information flow. We examine whether our results are robust to analysts coverage. We proceed as follows.

We first obtain analyst coverage from the IBES Historical Summary File. As in Hong, Lim, and Stein (2000), we set the coverage in any given month equal to the number of IBES analysts who provide fiscal year 1 earnings estimates that month. If no IBES value is available, we set the coverage to zero. We then regress $LCOMP$) on $Log(1 + \#Analysts)$ at the end of each month $t - 1$, and compute the residual $LCOMP$). Thus, our residual measure of competition is net of public information production due to the analyst coverage.

Table A6 displays the results for residual competition. We find even larger alphas for $MOM12$. This suggests that buy-side competition incorporates sell-side information in portfolio decisions. If buy-side investors further have in-house analysts as well, this can generate private information, which will diffuse slowly. In summary, it is unlikely that our results are driven by information production generated through analyst coverage.

# 5 Conclusion

We study momentum in a buy-side competition framework. Our hypothesis is that momentum will generate larger profits when buy-side competition is low, and hence information diffuses slowly. The intuition is that if momentum is driven by market frictions (such as informationally inefficient markets, underreaction, or other inefficiency-based or behavioral explanations), then buy-side investors have strong incentives to produce information to generate alpha. In such a case, profitable strategies will be arbitraged quickly, but only if investor competition for anomaly profits is high.

To test our hypotheses, we develop a measure of buy-side competition that is tailored to momentum. We explain a significant slice of momentum. We focus on the sample of large capitalization stocks, where illiquidity related imperfections and transaction costs are lower. We find that momentum exists only when buy-side competition is low. In these low competition markets, momentum generates high excess returns, relatively long-lasting alphas. We further find that our results are robust in subsamples that are formed by size, by time, or by size and time. They are also robust to whether we employ different sort methods (sequential or independent), or if we use Fama-MacBeth cross-sectional regressions (Fama and MacBeth (1973)). We test for alternative explanations, analyst following, ownership breadth and find that although useful, these alternatives are incomplete measures of buy-side competition. Our results are also robust to controls for firm-specific variables that are known to predict future returns such as size, book-to-market ratio, short term reversal (Jegadeesh (1990), Lehmann (1990)), profitability (Novy-Marx (2013)), and earnings momentum (Chordia and Shivakumar (2006) and Novy-marx (2015)). Our results are consistent with the traditional school of thought that competition is a key source of market efficiency.

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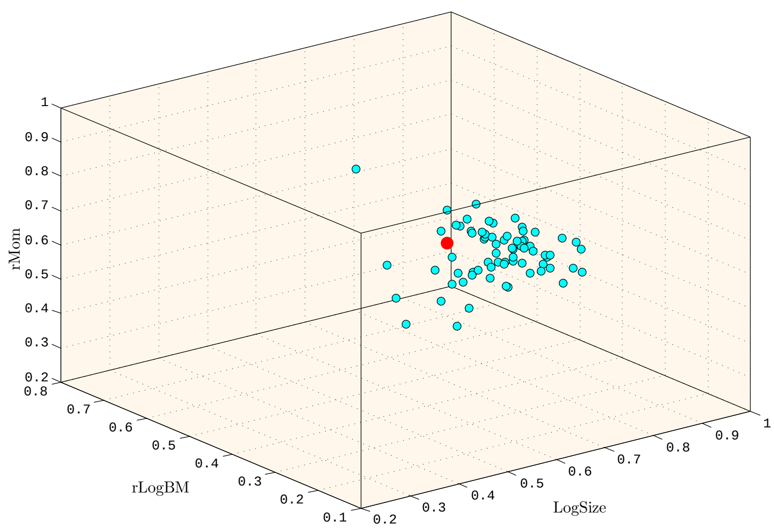
Figure 1: **Illustration: Buy-side Competition**

Top figure shows funds (in blue color) in the style space that hold the stock (in red color). Bottom figure shows all funds (in green color) that match the stock's style.

(a) Funds that hold the stock




(b) All funds that match the stock's style

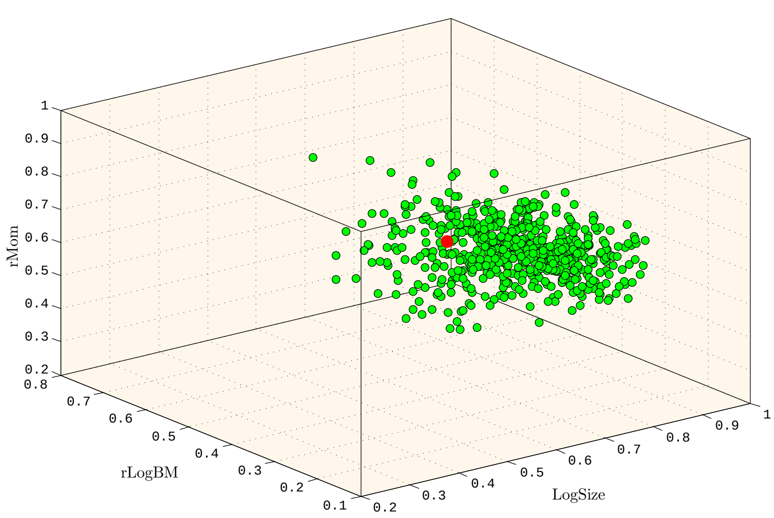


Figure 2: **Illustrative Example: Competition Calculation**
This figure illustrates competition calculation for a stock in 1-dimensional momentum space.

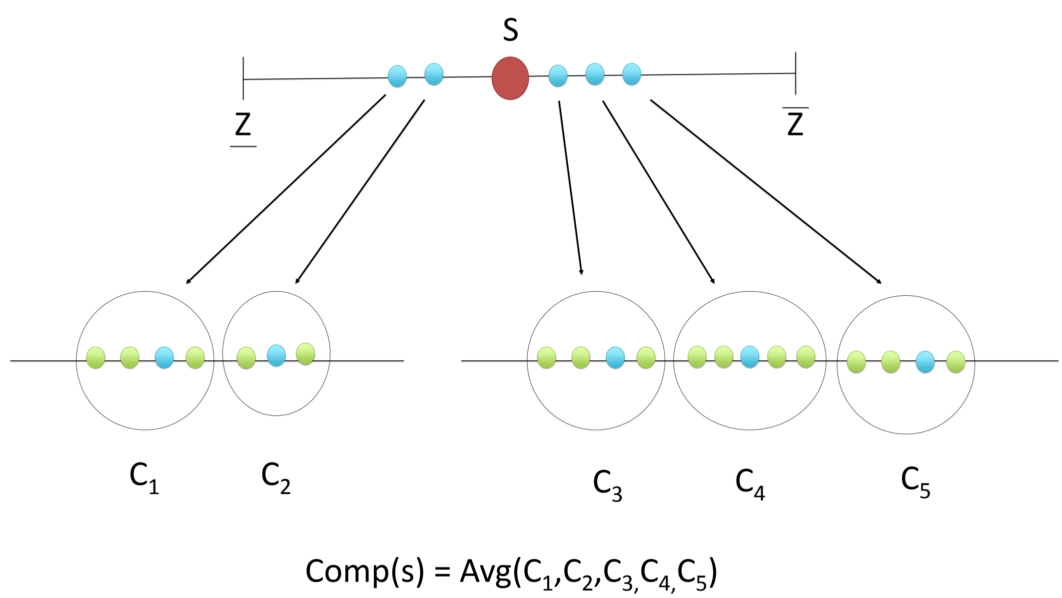


Figure 3: **Cumulative Returns**
This figure shows cumulative (sum of log) returns of 5-1 value-weighted momentum portfolios with monthly re-balancing in low, medium and high competition stocks.

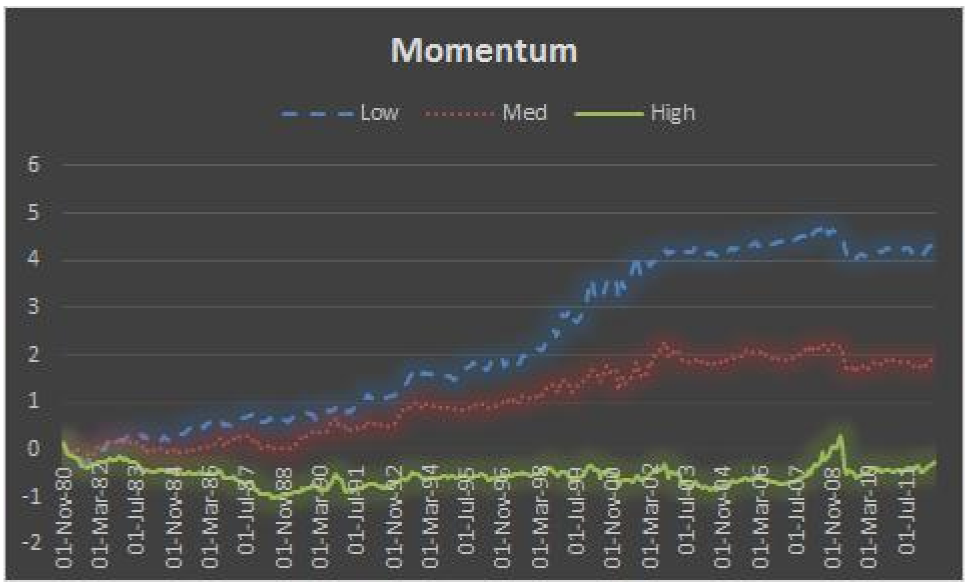


Figure 4: **Distribution of Momentum Portfolio Returns**
This figure shows distribution of returns of 5-1 value-weighted momentum portfolios with monthly re-balancing in low and high competition stocks.

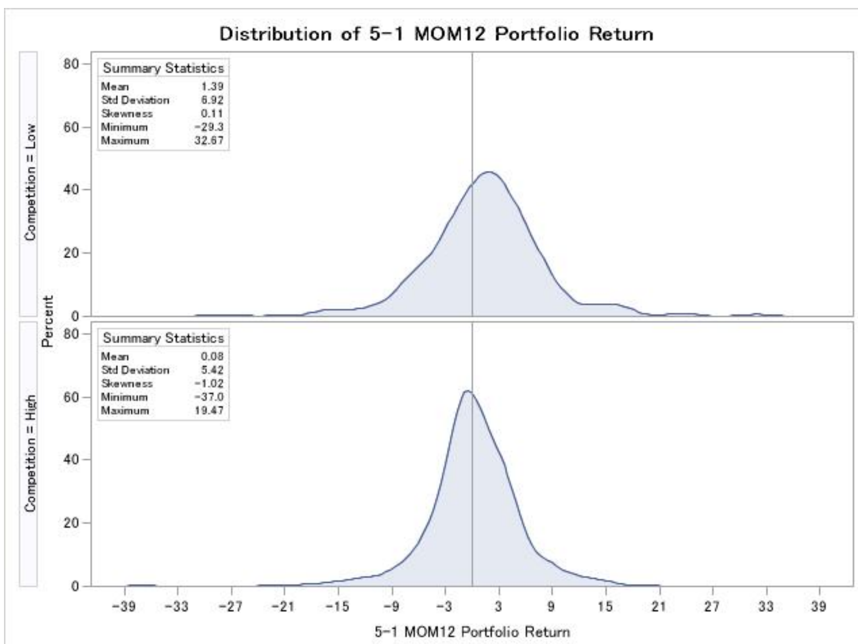
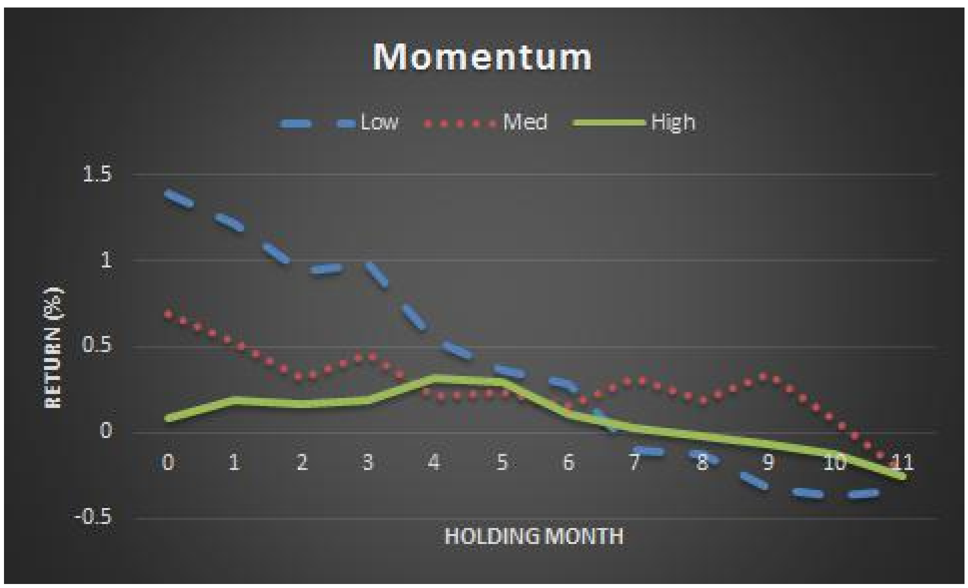


Figure 5: **Holding Period Average Return**

This figure shows average return of value-weighted 5-1 portfolios with monthly re-balancing in low, medium and high competition stocks. The holding period month varies from $t$ to $t + 11$.



**T**ABLE 1: **Summary Statistics**

This table reports summary statistics for various variables in Panel A, and momentum competition in Panel B. For each month, we first obtain the cross-sectional statistics and then take the time-series average. Panel C reports time-series average of cross-sectional correlation between momentum and competition (COMP). ME is measured in $millions.

| Panel A: Stock Characteristics | | | | | |
|---|---|---|---|---|---|
| Variable | Mean | Median | Std | P25 | P75 |
| MOM12 | 0.208 | 0.145 | 0.385 | -0.019 | 0.348 |
| MOM6 | 0.104 | 0.077 | 0.242 | -0.041 | 0.214 |
| MOM3 | 0.048 | 0.038 | 0.156 | -0.046 | 0.128 |
| ME | 7574.003 | 2619.373 | 17182.058 | 1503.470 | 6331.072 |
| BM | 0.565 | 0.481 | 0.431 | 0.276 | 0.751 |
| PROF | 0.317 | 0.267 | 0.245 | 0.123 | 0.461 |
| RET1 | 0.016 | 0.012 | 0.088 | -0.036 | 0.062 |
| SUE | 0.484 | 0.321 | 2.024 | -0.302 | 1.332 |

| Panel B: COMP | | | | | |
|---|---|---|---|---|---|
| Variable | Mean | Median | Std | P25 | P75 |
| First Half (N=190) | 25.793 | 26.991 | 5.691 | 22.485 | 29.860 |
| Second Half (N=191) | 110.203 | 113.446 | 18.774 | 98.119 | 124.595 |
| Full Sample (N=381) | 68.109 | 70.332 | 12.250 | 60.401 | 77.352 |

| Panel C: Correlation Between Momentum and Competition | | | | |
|---|---|---|---|---|
| Variable | MOM12 | MOM6 | MOM3 | COMP |
| MOM12 | 1 | | | |
| MOM6 | 0.718 | 1 | | |
| MOM3 | 0.500 | 0.681 | 1 | |
| COMP | -0.246 | -0.108 | -0.060 | 1 |

## **T**ABLE 2: **Performance Statistics**

This table reports average return, risk and performance statistics for the quintile portfolios. At the end of each month $t-1$, we sort stocks into quintile portfolios by momentum with different look-back windows (Panels A, B and C) and then calculate value-weighted portfolio returns (%) for the next month $t$. We report monthly mean return ($\bar{r}$), mean excess return ($\overline{r-r_f}$), the corresponding $t$-statistics, volatility ($\sigma_r$), downside volatility ($\sigma_{r(r<0)}$), skewness, 1 percentile and minimum returns. We also report annualized Sharpe and Sortino Ratios. 5-1 represents zero-sum long-short portfolio that is long on quintile 5 and short on quintile 1.

Panel A: MOM12

| Quintile | $\bar{r}$ | $t$-stat | $\overline{r-r_f}$ | $t$-stat | $\sigma_r$ | $\sigma_{r(r<0)}$ | Skewness | 1 percentile | Min | Sharpe | Sortino |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.781 | (2.424) | 0.380 | (1.181) | 6.288 | 3.594 | -0.005 | -17.735 | -23.668 | 0.210 | 0.367 |
| 2 | 0.943 | (3.966) | 0.542 | (2.280) | 4.639 | 2.597 | -0.263 | -12.324 | -18.646 | 0.405 | 0.723 |
| 3 | 0.844 | (3.853) | 0.444 | (2.022) | 4.276 | 2.484 | -0.593 | -9.701 | -22.900 | 0.359 | 0.618 |
| 4 | 1.039 | (4.512) | 0.639 | (2.769) | 4.496 | 2.528 | -0.400 | -10.993 | -21.379 | 0.492 | 0.875 |
| 5 | 1.193 | (3.963) | 0.792 | (2.629) | 5.874 | 3.368 | -0.305 | -15.535 | -26.759 | 0.467 | 0.815 |
| 5-1 | 0.412 | (1.292) | 0.412 | (1.292) | 6.220 | 3.886 | -0.170 | -17.833 | -28.562 | 0.229 | 0.367 |

Panel B: MOM6

| Quintile | $\bar{r}$ | $t$-stat | $\overline{r-r_f}$ | $t$-stat | $\sigma_r$ | $\sigma_{r(r<0)}$ | Skewness | 1 percentile | Min | Sharpe | Sortino |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.911 | (2.885) | 0.510 | (1.616) | 6.163 | 3.502 | -0.039 | -16.847 | -24.242 | 0.287 | 0.505 |
| 2 | 1.118 | (4.567) | 0.717 | (2.927) | 4.777 | 2.588 | -0.119 | -12.332 | -18.569 | 0.520 | 0.960 |
| 3 | 1.042 | (4.615) | 0.642 | (2.842) | 4.407 | 2.465 | -0.414 | -11.329 | -20.666 | 0.504 | 0.902 |
| 4 | 0.823 | (3.610) | 0.422 | (1.851) | 4.448 | 2.633 | -0.652 | -10.806 | -23.313 | 0.329 | 0.555 |
| 5 | 1.016 | (3.581) | 0.615 | (2.168) | 5.537 | 3.115 | -0.155 | -13.728 | -23.641 | 0.385 | 0.684 |
| 5-1 | 0.105 | (0.366) | 0.105 | (0.366) | 5.585 | 3.638 | -0.329 | -17.994 | -30.309 | 0.065 | 0.100 |

Panel C: MOM3

| Quintile | $\bar{r}$ | $t$-stat | $\overline{r-r_f}$ | $t$-stat | $\sigma_r$ | $\sigma_{r(r<0)}$ | Skewness | 1 percentile | Min | Sharpe | Sortino |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.019 | (3.243) | 0.619 | (1.967) | 6.136 | 3.602 | -0.359 | -18.343 | -27.079 | 0.349 | 0.595 |
| 2 | 1.145 | (4.803) | 0.745 | (3.121) | 4.654 | 2.538 | -0.329 | -10.546 | -18.717 | 0.554 | 1.016 |
| 3 | 1.008 | (4.397) | 0.607 | (2.653) | 4.473 | 2.553 | -0.514 | -11.797 | -21.364 | 0.470 | 0.824 |
| 4 | 0.874 | (3.880) | 0.474 | (2.100) | 4.399 | 2.535 | -0.530 | -10.671 | -22.430 | 0.373 | 0.647 |
| 5 | 0.918 | (3.351) | 0.517 | (1.887) | 5.344 | 3.108 | -0.328 | -12.681 | -23.637 | 0.335 | 0.576 |
| 5-1 | -0.102 | (-0.396) | -0.102 | (-0.396) | 5.030 | 3.168 | 0.227 | -14.130 | -23.665 | -0.070 | -0.112 |

**T**ABLE 3: **Alpha**

This table reports alphas with respect to the various factor models. At the end of each month $t-1$, we sort stocks into quintile portfolios by momentum with different look-back windows, and then calculate value-weighted portfolio returns for the next month $t$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). The alphas are percentage monthly. 5-1 represents zero-sum long-short portfolio that is long on quintile 5 and short on quintile 1. $t$-statistics are reported in parentheses.

| | MOM12 | | | MOM6 | | | MOM3 | | |
|---|---|---|---|---|---|---|---|---|---|
| Quntile | CAPM | FF3 | FF5 | CAPM | FF3 | FF5 | CAPM | FF3 | FF5 |
| 1 | -0.246 | -0.354 | -0.122 | -0.122 | -0.132 | 0.049 | -0.031 | -0.037 | 0.087 |
| | (-1.363) | (-1.967) | (-0.663) | (-0.738) | (-0.786) | (0.282) | (-0.205) | (-0.241) | (0.553) |
| 2 | 0.036 | -0.069 | -0.121 | 0.191 | 0.118 | 0.095 | 0.228 | 0.169 | 0.085 |
| | (0.361) | (-0.779) | (-1.307) | (1.952) | (1.310) | (1.000) | (2.516) | (2.039) | (0.991) |
| 3 | -0.034 | -0.084 | -0.224 | 0.148 | 0.104 | -0.030 | 0.103 | 0.069 | -0.049 |
| | (-0.419) | (-1.189) | (-3.137) | (1.834) | (1.552) | (-0.454) | (1.331) | (1.026) | (-0.719) |
| 4 | 0.138 | 0.120 | -0.075 | -0.076 | -0.095 | -0.257 | -0.022 | -0.031 | -0.152 |
| | (1.593) | (1.493) | (-0.962) | (-0.924) | (-1.217) | (-3.341) | (-0.286) | (-0.412) | (-2.026) |
| 5 | 0.196 | 0.358 | 0.364 | 0.043 | 0.119 | 0.098 | -0.045 | 0.016 | 0.048 |
| | (1.210) | (2.378) | (2.306) | (0.298) | (0.848) | (0.667) | (-0.343) | (0.120) | (0.354) |
| 5-1 | 0.442 | 0.712 | 0.486 | 0.165 | 0.251 | 0.050 | -0.015 | 0.052 | -0.039 |
| | (1.376) | (2.297) | (1.510) | (0.574) | (0.874) | (0.166) | (-0.058) | (0.202) | (-0.143) |

## TABLE 4: **Fama-MacBeth Regressions**

This table reports average Fama-MacBeth regression coefficients from cross-sectional regressions that predict monthly returns. We first run cross-sectional regressions each month by regressing month $t$ return on various variables measured at the end of month $t-1$. We report the time-series average of the coefficients and the corresponding $t$-statistics in parentheses. In all regressions, the variable X is momentum with different look-back windows. LME is log of market equity, LBM is log of (1 + book-to-market ratio), RET1 is month $t-1$ return, PROF represents profitability measured by Gross Profits/Total Assets, and SUE represents standardized earnings surprise. Each month, we also sort stocks into terciles by momentum competition. Stocks in the lowest tercile are defined as the low competition stocks. Low is a dummy variable for low competition stocks. Similarly, we define Med dummy variable for medium competition stocks. We standardize all RHS variables to zero mean and unit variance, except the dummy variables.

| | X = MOM12 | | | | X = MOM6 | | | | X = MOM3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Intercept | 1.031 | 1.283 | 1.090 | 1.452 | 1.058 | 1.258 | 1.101 | 1.389 | 1.068 | 1.285 | 1.109 | 1.414 |
| | (4.049) | (3.967) | (4.637) | (4.772) | (4.139) | (3.916) | (4.671) | (4.572) | (4.183) | (3.986) | (4.714) | (4.655) |
| X | 0.261 | 0.301 | -0.020 | -0.013 | 0.108 | 0.122 | -0.241 | -0.246 | 0.049 | 0.059 | -0.186 | -0.189 |
| | (1.912) | (2.492) | (-0.118) | (-0.086) | (0.788) | (1.019) | (-1.625) | (-1.809) | (0.370) | (0.527) | (-1.373) | (-1.579) |
| Low | | | -0.225 | -0.255 | | | -0.157 | -0.198 | | | -0.098 | -0.160 |
| | | | (-1.407) | (-1.759) | | | (-0.946) | (-1.351) | | | (-0.563) | (-1.084) |
| Med | | | 0.011 | -0.025 | | | -0.002 | -0.032 | | | -0.008 | -0.047 |
| | | | (0.143) | (-0.353) | | | (-0.024) | (-0.450) | | | (-0.113) | (-0.672) |
| X * Low | | | 0.410 | 0.421 | | | 0.541 | 0.539 | | | 0.405 | 0.409 |
| | | | (3.007) | (3.291) | | | (4.440) | (4.626) | | | (3.581) | (3.760) |
| X * Med | | | 0.345 | 0.338 | | | 0.313 | 0.295 | | | 0.163 | 0.166 |
| | | | (3.203) | (3.238) | | | (3.148) | (3.031) | | | (1.640) | (1.719) |
| LME | | -0.118 | | -0.203 | | -0.091 | | -0.161 | | -0.104 | | -0.167 |
| | | (-1.393) | | (-2.365) | | (-1.085) | | (-1.898) | | (-1.210) | | (-1.972) |
| LBM | | 0.407 | | 0.330 | | 0.352 | | 0.268 | | 0.339 | | 0.275 |
| | | (4.871) | | (4.965) | | (3.868) | | (3.842) | | (3.438) | | (3.580) |
| RET1 | | -0.278 | | -0.291 | | -0.246 | | -0.264 | | -0.221 | | -0.236 |
| | | (-2.856) | | (-3.118) | | (-2.521) | | (-2.788) | | (-2.213) | | (-2.457) |
| PROF | | 0.246 | | 0.227 | | 0.222 | | 0.200 | | 0.209 | | 0.191 |
| | | (4.781) | | (4.518) | | (4.395) | | (4.032) | | (4.048) | | (3.755) |
| SUE | | 0.152 | | 0.159 | | 0.179 | | 0.182 | | 0.181 | | 0.185 |
| | | (5.586) | | (5.999) | | (6.361) | | (6.642) | | (6.317) | | (6.610) |

## TABLE 5: **Performance Statistics: Competition**

This table reports average return, risk and performance statistics for the quintile portfolios within low, medium and high competition stocks. At the end of each month $t-1$, we first sort stocks into terciles by momentum competition (Panels A, B and C) and then sort stocks within terciles into quintile portfolios by momentum. We measure momentum with different look-back windows. We then calculate value-weighted portfolio returns (%) for the next month $t$. We report monthly mean return ($\bar{r}$), mean excess return ($\overline{r-r_f}$), the corresponding $t$-statistics, volatility ($\sigma_r$), downside volatility ($\sigma_{r(r<0)}$), skewness, 1 percentile and minimum returns. We also report annualized Sharpe and Sortino Ratios. 5-1 represents zero-sum long-short portfolio that is long on quintile 5 and short on quintile 1.

Panel A: MOM12

| Comp | Quintile | $\bar{r}$ | $t$-stat | $\overline{r-r_f}$ | $t$-stat | $\sigma_r$ | $\sigma_{r(r<0)}$ | Skewness | 1 percentile | Min | Sharpe | Sortino |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Low | 1 | 0.218 | (0.547) | -0.183 | (-0.460) | 7.759 | 4.971 | -0.622 | -25.380 | -36.328 | -0.082 | -0.127 |
| Low | 5 | 1.607 | (4.060) | 1.206 | (3.045) | 7.724 | 4.279 | -0.168 | -20.053 | -37.188 | 0.541 | 0.976 |
| Low | 5-1 | 1.389 | (3.921) | 1.389 | (3.921) | 6.915 | 3.798 | 0.110 | -16.764 | -29.282 | 0.696 | 1.267 |
| Med | 1 | 0.602 | (1.738) | 0.202 | (0.582) | 6.766 | 3.993 | -0.088 | -19.268 | -22.327 | 0.103 | 0.175 |
| Med | 5 | 1.296 | (4.600) | 0.896 | (3.175) | 5.501 | 3.082 | -0.331 | -13.435 | -26.379 | 0.564 | 1.007 |
| Med | 5-1 | 0.694 | (2.232) | 0.694 | (2.232) | 6.069 | 3.760 | -0.709 | -15.665 | -34.710 | 0.396 | 0.640 |
| High | 1 | 0.898 | (2.769) | 0.497 | (1.536) | 6.328 | 3.690 | -0.107 | -21.505 | -29.378 | 0.272 | 0.467 |
| High | 5 | 0.981 | (4.208) | 0.581 | (2.487) | 4.553 | 2.666 | -0.628 | -11.751 | -23.989 | 0.442 | 0.755 |
| High | 5-1 | 0.084 | (0.302) | 0.084 | (0.302) | 5.425 | 3.622 | -1.017 | -16.781 | -37.041 | 0.054 | 0.080 |

Panel B: MOM6

| Comp | Quintile | $\bar{r}$ | $t$-stat | $\overline{r-r_f}$ | $t$-stat | $\sigma_r$ | $\sigma_{r(r<0)}$ | Skewness | 1 percentile | Min | Sharpe | Sortino |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Low | 1 | 0.399 | (1.024) | -0.001 | (-0.003) | 7.612 | 4.906 | -0.746 | -25.859 | -40.334 | -0.001 | -0.001 |
| Low | 5 | 1.419 | (3.735) | 1.019 | (2.680) | 7.416 | 3.911 | 0.220 | -16.847 | -27.213 | 0.476 | 0.902 |
| Low | 5-1 | 1.020 | (3.098) | 1.020 | (3.098) | 6.424 | 3.405 | 0.497 | -17.035 | -27.664 | 0.550 | 1.037 |
| Med | 1 | 0.861 | (2.514) | 0.460 | (1.343) | 6.682 | 3.787 | -0.022 | -17.739 | -23.286 | 0.239 | 0.421 |
| Med | 5 | 1.012 | (3.600) | 0.611 | (2.173) | 5.485 | 3.105 | -0.307 | -12.410 | -23.321 | 0.386 | 0.682 |
| Med | 5-1 | 0.151 | (0.525) | 0.151 | (0.525) | 5.621 | 3.686 | -0.710 | -17.920 | -29.891 | 0.093 | 0.142 |
| High | 1 | 1.184 | (3.816) | 0.784 | (2.527) | 6.056 | 3.317 | 0.177 | -18.996 | -22.174 | 0.448 | 0.818 |
| High | 5 | 0.653 | (2.798) | 0.252 | (1.080) | 4.554 | 2.793 | -0.596 | -12.404 | -22.683 | 0.192 | 0.313 |
| High | 5-1 | -0.531 | (-2.008) | -0.531 | (-2.008) | 5.164 | 3.771 | -1.380 | -16.368 | -35.021 | -0.356 | -0.488 |

Panel C: MOM3

| Comp | Quintile | $\bar{r}$ | $t$-stat | $\overline{r-r_f}$ | $t$-stat | $\sigma_r$ | $\sigma_{r(r<0)}$ | Skewness | 1 percentile | Min | Sharpe | Sortino |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Low | 1 | 0.674 | (1.687) | 0.274 | (0.684) | 7.803 | 4.960 | -0.775 | -27.126 | -39.970 | 0.122 | 0.191 |
| Low | 5 | 1.257 | (3.456) | 0.857 | (2.353) | 7.099 | 3.906 | -0.058 | -15.930 | -34.258 | 0.418 | 0.760 |
| Low | 5-1 | 0.583 | (1.867) | 0.583 | (1.867) | 6.093 | 3.550 | 0.231 | -17.373 | -23.954 | 0.331 | 0.569 |
| Med | 1 | 0.973 | (2.977) | 0.573 | (1.750) | 6.383 | 3.801 | -0.441 | -20.790 | -24.736 | 0.311 | 0.522 |
| Med | 5 | 0.876 | (3.192) | 0.475 | (1.730) | 5.357 | 3.158 | -0.466 | -14.258 | -21.288 | 0.307 | 0.522 |
| Med | 5-1 | -0.098 | (-0.388) | -0.098 | (-0.388) | 4.905 | 3.072 | -0.078 | -14.609 | -20.944 | -0.069 | -0.110 |
| High | 1 | 1.159 | (3.767) | 0.759 | (2.465) | 6.007 | 3.359 | 0.007 | -18.708 | -24.223 | 0.438 | 0.782 |
| High | 5 | 0.702 | (2.955) | 0.302 | (1.268) | 4.637 | 2.816 | -0.661 | -11.460 | -26.907 | 0.225 | 0.371 |
| High | 5-1 | -0.457 | (-1.822) | -0.457 | (-1.822) | 4.898 | 3.402 | -0.716 | -15.894 | -26.178 | -0.323 | -0.466 |

## TABLE 6: **Competition and Alpha**

This table reports alphas with respect to the various factor models for competition conditional portfolios. At the end of each month $t-1$, we first sort stocks into terciles by momentum competition and then sort stocks within terciles into quintile portfolios by momentum. We measure momentum with different look-back windows in Panels A, B and C. We then calculate value-weighted portfolio returns for the next month $t$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). The alphas are percentage monthly. 5-1 represents zero-sum long-short portfolio that is long on quintile 5 and short on quintile 1. $t$-statistics are reported in parentheses.

Panel A: MOM12

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quintile | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| 1 | -0.943 | -0.450 | -0.080 | -0.863 | -0.820 | -0.480 | -0.376 | -0.444 | -0.334 | -0.127 | -0.227 | -0.106 |
| | (-4.073) | (-2.160) | (-0.377) | (-3.157) | (-3.604) | (-2.267) | (-1.971) | (-1.926) | (-1.489) | (-0.595) | (-1.144) | (-0.450) |
| 5 | 0.487 | 0.336 | 0.123 | 0.365 | 0.827 | 0.401 | 0.025 | 0.802 | 1.036 | 0.297 | -0.251 | 1.287 |
| | (1.935) | (2.230) | (0.956) | (1.290) | (3.920) | (2.637) | (0.204) | (3.703) | (4.723) | (1.876) | (-2.079) | (5.997) |
| 5-1 | 1.430 | 0.786 | 0.202 | 1.228 | 1.648 | 0.881 | 0.401 | 1.246 | 1.370 | 0.424 | -0.024 | 1.393 |
| | (4.008) | (2.527) | (0.733) | (4.040) | (4.667) | (2.795) | (1.465) | (4.070) | (3.745) | (1.320) | (-0.085) | (4.375) |

Panel B: MOM6

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quintile | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| 1 | -0.755 | -0.203 | 0.227 | -0.982 | -0.574 | -0.165 | -0.001 | -0.573 | -0.167 | 0.084 | -0.013 | -0.154 |
| | (-3.403) | (-1.045) | (1.132) | (-3.673) | (-2.694) | (-0.837) | (-0.008) | (-2.551) | (-0.783) | (0.415) | (-0.067) | (-0.677) |
| 5 | 0.329 | 0.055 | -0.204 | 0.533 | 0.622 | 0.082 | -0.338 | 0.960 | 0.832 | 0.020 | -0.563 | 1.394 |
| | (1.359) | (0.363) | (-1.581) | (1.900) | (3.044) | (0.534) | (-2.778) | (4.437) | (3.912) | (0.124) | (-4.606) | (6.415) |
| 5-1 | 1.084 | 0.258 | -0.431 | 1.515 | 1.197 | 0.247 | -0.336 | 1.533 | 0.999 | -0.064 | -0.549 | 1.548 |
| | (3.276) | (0.899) | (-1.638) | (5.381) | (3.619) | (0.846) | (-1.263) | (5.410) | (2.908) | (-0.212) | (-1.983) | (5.252) |

Panel C: MOM3

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quintile | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| 1 | -0.513 | -0.093 | 0.197 | -0.710 | -0.322 | -0.076 | -0.029 | -0.293 | 0.051 | 0.127 | -0.089 | 0.141 |
| | (-2.339) | (-0.569) | (1.015) | (-2.499) | (-1.538) | (-0.455) | (-0.160) | (-1.183) | (0.242) | (0.746) | (-0.465) | (0.562) |
| 5 | 0.191 | -0.080 | -0.166 | 0.357 | 0.462 | -0.088 | -0.294 | 0.756 | 0.728 | -0.109 | -0.462 | 1.189 |
| | (0.834) | (-0.575) | (-1.278) | (1.335) | (2.323) | (-0.623) | (-2.450) | (3.656) | (3.555) | (-0.733) | (-3.744) | (5.753) |
| 5-1 | 0.704 | 0.013 | -0.363 | 1.067 | 0.785 | -0.013 | -0.265 | 1.049 | 0.676 | -0.236 | -0.372 | 1.049 |
| | (2.267) | (0.051) | (-1.454) | (3.715) | (2.510) | (-0.051) | (-1.048) | (3.639) | (2.075) | (-0.900) | (-1.409) | (3.499) |

## TABLE 7: **Competition and Alpha: Longer Holding Period**

This table reports alphas with respect to the various factor models for competition conditional portfolios for different future monthly holding periods. At the end of each month $t-1$, we first sort stocks into terciles by momentum competition and then sort stocks within terciles into quintile portfolios by momentum. We then calculate value-weighted portfolio returns for the future holding month. The future holding month varies from $t$ to $t+11$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). We report quintile 5-1 portfolio spreads in percentage. $t$-statistics are reported in parentheses.

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Month | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| t | 1.430 | 0.786 | 0.202 | 1.228 | 1.648 | 0.881 | 0.401 | 1.246 | 1.370 | 0.424 | -0.024 | 1.393 |
| | (4.008) | (2.527) | (0.733) | (4.040) | (4.667) | (2.795) | (1.465) | (4.070) | (3.745) | (1.320) | (-0.085) | (4.375) |
| t+1 | 1.216 | 0.587 | 0.293 | 0.923 | 1.416 | 0.696 | 0.455 | 0.961 | 1.188 | 0.334 | 0.136 | 1.051 |
| | (3.752) | (1.974) | (1.175) | (3.235) | (4.419) | (2.311) | (1.824) | (3.340) | (3.589) | (1.082) | (0.535) | (3.518) |
| t+2 | 0.891 | 0.401 | 0.282 | 0.609 | 1.175 | 0.554 | 0.447 | 0.729 | 0.983 | 0.234 | 0.155 | 0.828 |
| | (2.792) | (1.357) | (1.174) | (2.214) | (3.795) | (1.860) | (1.863) | (2.650) | (3.048) | (0.760) | (0.632) | (2.884) |
| t+3 | 0.923 | 0.513 | 0.295 | 0.628 | 1.286 | 0.738 | 0.514 | 0.772 | 1.170 | 0.588 | 0.250 | 0.921 |
| | (2.908) | (1.718) | (1.206) | (2.270) | (4.257) | (2.482) | (2.137) | (2.790) | (3.716) | (1.896) | (1.007) | (3.195) |
| t+4 | 0.462 | 0.278 | 0.430 | 0.032 | 0.807 | 0.544 | 0.666 | 0.141 | 0.745 | 0.375 | 0.418 | 0.327 |
| | (1.455) | (0.955) | (1.809) | (0.112) | (2.648) | (1.901) | (2.881) | (0.489) | (2.339) | (1.259) | (1.754) | (1.085) |
| t+5 | 0.299 | 0.283 | 0.400 | -0.101 | 0.651 | 0.592 | 0.648 | 0.002 | 0.534 | 0.541 | 0.457 | 0.077 |
| | (0.941) | (0.987) | (1.731) | (-0.344) | (2.132) | (2.128) | (2.894) | (0.008) | (1.674) | (1.858) | (1.966) | (0.248) |
| t+6 | 0.196 | 0.209 | 0.201 | -0.005 | 0.570 | 0.543 | 0.500 | 0.070 | 0.530 | 0.520 | 0.330 | 0.199 |
| | (0.651) | (0.734) | (0.864) | (-0.018) | (1.994) | (1.985) | (2.272) | (0.252) | (1.769) | (1.819) | (1.444) | (0.688) |
| t+7 | -0.187 | 0.385 | 0.091 | -0.278 | 0.155 | 0.704 | 0.381 | -0.226 | 0.048 | 0.697 | 0.203 | -0.155 |
| | (-0.654) | (1.429) | (0.414) | (-1.086) | (0.566) | (2.732) | (1.839) | (-0.867) | (0.167) | (2.589) | (0.946) | (-0.569) |
| t+8 | -0.233 | 0.199 | 0.027 | -0.261 | 0.118 | 0.516 | 0.299 | -0.182 | 0.142 | 0.554 | 0.091 | 0.051 |
| | (-0.804) | (0.802) | (0.129) | (-0.970) | (0.427) | (2.200) | (1.492) | (-0.666) | (0.492) | (2.262) | (0.438) | (0.179) |
| t+9 | -0.456 | 0.314 | -0.038 | -0.419 | -0.144 | 0.612 | 0.243 | -0.387 | -0.083 | 0.586 | 0.054 | -0.137 |
| | (-1.573) | (1.284) | (-0.184) | (-1.526) | (-0.514) | (2.626) | (1.273) | (-1.389) | (-0.287) | (2.395) | (0.270) | (-0.481) |
| t+10 | -0.536 | 0.051 | -0.108 | -0.429 | -0.174 | 0.320 | 0.153 | -0.326 | 0.072 | 0.307 | 0.095 | -0.023 |
| | (-1.805) | (0.216) | (-0.566) | (-1.574) | (-0.614) | (1.412) | (0.859) | (-1.185) | (0.248) | (1.294) | (0.507) | (-0.082) |
| t+11 | -0.481 | -0.268 | -0.211 | -0.270 | -0.092 | 0.007 | 0.058 | -0.150 | 0.226 | 0.072 | -0.037 | 0.263 |
| | (-1.608) | (-1.090) | (-1.106) | (-0.964) | (-0.328) | (0.028) | (0.331) | (-0.532) | (0.792) | (0.290) | (-0.198) | (0.918) |

**TABLE 8: Competition and Alpha: Size**

This table reports alphas by firm size with respect to the various factor models for competition conditional portfolios. At the end of each month $t-1$, we first classify stocks into NYSE 3rd and 4th size quartile. Panels A and B report results for the 4th quartile and 3rd quartile sub-samples, respectively. Within each size group, we sort stocks into terciles by momentum competition and then finally sort stocks within terciles into quintile portfolios by momentum. We measure momentum with different look-back windows. We then calculate value-weighted portfolio returns for the next month $t$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). We report quintile 5-1 portfolio spreads in percentage. $t$-statistics are reported in parentheses.

Panel A: NYSE Size Quartile 4

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 1.222 | 0.367 | 0.044 | 1.178 | 1.450 | 0.491 | 0.244 | 1.206 | 1.239 | 0.117 | -0.067 | 1.306 |
| | (3.160) | (1.170) | (0.164) | (3.528) | (3.815) | (1.553) | (0.909) | (3.598) | (3.131) | (0.360) | (-0.244) | (3.738) |
| MOM6 | 0.766 | -0.191 | -0.411 | 1.177 | 0.881 | -0.174 | -0.325 | 1.206 | 0.749 | -0.396 | -0.528 | 1.277 |
| | (2.147) | (-0.672) | (-1.595) | (3.816) | (2.486) | (-0.605) | (-1.250) | (3.900) | (2.026) | (-1.322) | (-1.951) | (3.967) |
| MOM3 | 0.586 | -0.303 | -0.336 | 0.922 | 0.630 | -0.266 | -0.269 | 0.899 | 0.642 | -0.444 | -0.437 | 1.079 |
| | (1.798) | (-1.176) | (-1.362) | (3.003) | (1.934) | (-1.017) | (-1.074) | (2.938) | (1.883) | (-1.629) | (-1.673) | (3.391) |

Panel B: NYSE Size Quartile 3

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 1.242 | 0.738 | 0.255 | 0.987 | 1.398 | 0.819 | 0.453 | 0.945 | 0.976 | 0.396 | 0.061 | 0.915 |
| | (3.352) | (2.460) | (0.840) | (2.946) | (3.780) | (2.692) | (1.495) | (2.813) | (2.568) | (1.278) | (0.196) | (2.612) |
| MOM6 | 1.056 | 0.287 | -0.009 | 1.065 | 1.098 | 0.333 | 0.130 | 0.968 | 0.768 | -0.004 | -0.055 | 0.823 |
| | (3.124) | (1.033) | (-0.031) | (3.356) | (3.214) | (1.179) | (0.433) | (3.013) | (2.174) | (-0.015) | (-0.177) | (2.455) |
| MOM3 | 0.818 | 0.112 | 0.028 | 0.790 | 0.847 | 0.140 | 0.164 | 0.683 | 0.694 | -0.054 | 0.039 | 0.655 |
| | (2.537) | (0.446) | (0.109) | (2.520) | (2.592) | (0.546) | (0.633) | (2.154) | (2.033) | (-0.203) | (0.145) | (1.975) |

## TABLE 9: **Fama-MacBeth Regressions: Subperiods**

This table reports average Fama-MacBeth regression coefficients from cross-sectional regressions that predict monthly returns. We first run cross-sectional regressions each month by regressing month $t$ return on various variables measured at the end of month $t-1$. We report the time-series average of the coefficients and the corresponding $t$-statistics in parentheses. In all regressions, the variable X is momentum with different look-back windows. LME is log of market equity, LBM is log of (1 + book-to-market ratio), RET1 is month $t-1$ return, PROF represents profitability measured by Gross Profits/Total Assets, and SUE represents standardized earnings surprise. Each month, we also sort stocks into terciles by momentum competition. Stocks in the lowest tercile are defined as the low competition stocks. Low is a dummy variable for low competition stocks. Similarly, we define Med dummy variable for medium competition stocks. We standardize all RHS variables to zero mean and unit variance, except the dummy variables. Panel A and B report results for the first and second half of the sample, respectively.

Panel A: Sub-period (1980:11 - 1996:08)

| | X = MOM12 | | | | X = MOM6 | | | | X = MOM3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Intercept | 1.240 | 1.434 | 1.332 | 1.468 | 1.306 | 1.442 | 1.375 | 1.475 | 1.331 | 1.461 | 1.397 | 1.478 |
| | (3.780) | (3.483) | (4.291) | (3.751) | (3.964) | (3.528) | (4.494) | (3.808) | (4.025) | (3.571) | (4.592) | (3.830) |
| X | 0.282 | 0.340 | 0.028 | 0.071 | -0.007 | 0.021 | -0.293 | -0.259 | -0.044 | -0.033 | -0.169 | -0.168 |
| | (1.950) | (2.617) | (0.151) | (0.408) | (-0.051) | (0.176) | (-1.898) | (-1.801) | (-0.326) | (-0.270) | (-1.115) | (-1.184) |
| Low | | | -0.214 | -0.119 | | | -0.141 | -0.090 | | | -0.096 | -0.040 |
| | | | (-1.506) | (-0.999) | | | (-0.936) | (-0.722) | | | (-0.616) | (-0.314) |
| Med | | | -0.061 | -0.004 | | | -0.055 | -0.015 | | | -0.088 | -0.046 |
| | | | (-0.862) | (-0.056) | | | (-0.746) | (-0.220) | | | (-1.216) | (-0.671) |
| X * Low | | | 0.412 | 0.406 | | | 0.516 | 0.486 | | | 0.311 | 0.305 |
| | | | (2.429) | (2.479) | | | (3.404) | (3.304) | | | (2.263) | (2.326) |
| X * Med | | | 0.256 | 0.221 | | | 0.265 | 0.225 | | | 0.035 | 0.029 |
| | | | (2.119) | (1.850) | | | (2.340) | (1.978) | | | (0.305) | (0.256) |
| LME | | -0.082 | | -0.082 | | -0.068 | | -0.065 | | -0.070 | | -0.059 |
| | | (-0.729) | | (-0.739) | | (-0.607) | | (-0.583) | | (-0.635) | | (-0.537) |
| LBM | | 0.483 | | 0.462 | | 0.403 | | 0.385 | | 0.406 | | 0.398 |
| | | (5.398) | | (5.572) | | (4.264) | | (4.462) | | (4.211) | | (4.546) |
| RET1 | | -0.310 | | -0.333 | | -0.315 | | -0.337 | | -0.305 | | -0.317 |
| | | (-2.874) | | (-3.122) | | (-2.847) | | (-3.091) | | (-2.776) | | (-2.928) |
| PROF | | 0.297 | | 0.292 | | 0.259 | | 0.253 | | 0.251 | | 0.246 |
| | | (4.507) | | (4.514) | | (4.069) | | (4.002) | | (3.923) | | (3.876) |
| SUE | | 0.232 | | 0.236 | | 0.272 | | 0.270 | | 0.275 | | 0.272 |
| | | (7.008) | | (7.290) | | (8.091) | | (8.270) | | (7.979) | | (8.125) |

Panel B: Sub-period (1996:09 - 2012:07)

| | X = MOM12 | | | | X = MOM6 | | | | X = MOM3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Intercept | 0.823 | 1.132 | 0.849 | 1.436 | 0.807 | 1.110 | 0.822 | 1.350 | 0.812 | 1.075 | 0.828 | 1.303 |
| | (2.113) | (2.268) | (2.407) | (3.077) | (2.074) | (2.226) | (2.295) | (2.874) | (2.078) | (2.167) | (2.313) | (2.781) |
| X | 0.240 | 0.261 | -0.067 | -0.097 | 0.141 | 0.151 | -0.202 | -0.210 | 0.222 | 0.222 | -0.190 | -0.233 |
| | (1.036) | (1.284) | (-0.243) | (-0.385) | (0.616) | (0.797) | (-0.901) | (-1.088) | (0.930) | (1.078) | (-0.749) | (-1.011) |
| Low | | | -0.235 | -0.390 | | | -0.100 | -0.280 | | | -0.173 | -0.305 |
| | | | (-0.822) | (-1.479) | | | (-0.322) | (-1.050) | | | (-0.585) | (-1.153) |
| Med | | | 0.082 | -0.046 | | | 0.070 | -0.048 | | | 0.051 | -0.049 |
| | | | (0.632) | (-0.370) | | | (0.540) | (-0.395) | | | (0.384) | (-0.392) |
| X * Low | | | 0.409 | 0.436 | | | 0.498 | 0.513 | | | 0.566 | 0.592 |
| | | | (1.910) | (2.215) | | | (2.776) | (2.955) | | | (2.963) | (3.271) |
| X * Med | | | 0.434 | 0.454 | | | 0.290 | 0.303 | | | 0.360 | 0.364 |
| | | | (2.433) | (2.659) | | | (1.803) | (1.945) | | | (2.205) | (2.309) |
| LME | | -0.155 | | -0.322 | | -0.137 | | -0.275 | | -0.115 | | -0.258 |
| | | (-1.213) | | (-2.484) | | (-1.046) | | (-2.125) | | (-0.909) | | (-2.001) |
| LBM | | 0.330 | | 0.199 | | 0.272 | | 0.153 | | 0.301 | | 0.152 |
| | | (2.347) | | (1.927) | | (1.584) | | (1.218) | | (1.937) | | (1.390) |
| RET1 | | -0.247 | | -0.251 | | -0.137 | | -0.155 | | -0.178 | | -0.191 |
| | | (-1.519) | | (-1.631) | | (-0.825) | | (-0.979) | | (-1.104) | | (-1.234) |
| PROF | | 0.195 | | 0.162 | | 0.168 | | 0.137 | | 0.184 | | 0.148 |
| | | (2.473) | | (2.115) | | (2.067) | | (1.718) | | (2.356) | | (1.932) |
| SUE | | 0.073 | | 0.083 | | 0.088 | | 0.098 | | 0.086 | | 0.095 |
| | | (1.708) | | (2.003) | | (1.965) | | (2.233) | | (1.958) | | (2.196) |

# TABLE 10: **Competition and Alpha: Subperiod Analysis**

This table reports alphas for sub-periods with respect to the various factor models for competition conditional portfolios. Panels A and B report results for first and second half of the sample, respectively. At the end of each month $t-1$, we first sort stocks into terciles by momentum competition and then sort stocks within terciles into quintile portfolios by momentum. We measure momentum with different look-back windows. We then calculate value-weighted portfolio returns for the next month $t$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). We report quintile 5-1 portfolio spreads in percentage. $t$-statistics are reported in parentheses.

Panel A: Sub-Period (1980:11 - 1996:08)

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 0.978 | 0.497 | -0.308 | 1.286 | 1.274 | 0.628 | -0.158 | 1.432 | 1.023 | 0.240 | -0.673 | 1.696 |
| | (2.822) | (1.490) | (-1.062) | (4.181) | (3.574) | (1.814) | (-0.528) | (4.515) | (2.562) | (0.630) | (-2.123) | (4.852) |
| MOM6 | 0.581 | -0.031 | -0.758 | 1.338 | 0.711 | 0.003 | -0.691 | 1.402 | 0.408 | -0.247 | -0.787 | 1.195 |
| | (1.752) | (-0.108) | (-2.966) | (4.473) | (2.051) | (0.009) | (-2.635) | (4.545) | (1.058) | (-0.747) | (-2.691) | (3.457) |
| MOM3 | 0.444 | -0.154 | -0.487 | 0.931 | 0.656 | -0.106 | -0.391 | 1.047 | 0.368 | -0.345 | -0.653 | 1.022 |
| | (1.373) | (-0.570) | (-1.806) | (3.327) | (1.954) | (-0.372) | (-1.402) | (3.643) | (0.983) | (-1.089) | (-2.102) | (3.158) |

Panel B: Sub-Period (1996:09 - 2012:07)

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 1.803 | 0.979 | 0.612 | 1.190 | 1.879 | 0.984 | 0.722 | 1.157 | 1.645 | 0.536 | 0.311 | 1.334 |
| | (2.931) | (1.917) | (1.359) | (2.272) | (3.110) | (1.910) | (1.624) | (2.199) | (2.593) | (0.997) | (0.674) | (2.447) |
| MOM6 | 1.526 | 0.470 | -0.179 | 1.705 | 1.530 | 0.378 | -0.166 | 1.696 | 1.423 | 0.109 | -0.378 | 1.801 |
| | (2.694) | (0.968) | (-0.398) | (3.580) | (2.739) | (0.775) | (-0.369) | (3.545) | (2.418) | (0.212) | (-0.795) | (3.620) |
| MOM3 | 0.899 | 0.116 | -0.310 | 1.208 | 0.868 | 0.025 | -0.264 | 1.132 | 1.038 | -0.110 | -0.180 | 1.218 |
| | (1.717) | (0.283) | (-0.753) | (2.410) | (1.660) | (0.061) | (-0.637) | (2.258) | (1.895) | (-0.253) | (-0.409) | (2.334) |

**T**ABLE 11: **Competition and Alpha: Pre-Crisis Period**

This table reports alphas for the pre-2008 crisis period with respect to the various factor models for competition conditional portfolios. At the end of each month $t-1$, we first sort stocks into terciles by momentum competition and then sort stocks within terciles into quintile portfolios by momentum. We measure momentum with different look-back windows. We then calculate value-weighted portfolio returns for the next month $t$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). We report quintile 5-1 portfolio spreads in percentage. $t$-statistics are reported in parentheses.

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 1.674 | 0.928 | 0.008 | 1.666 | 1.968 | 0.995 | 0.098 | 1.870 | 1.742 | 0.652 | -0.147 | 1.889 |
| | (4.268) | (2.751) | (0.032) | (5.119) | (4.967) | (2.845) | (0.368) | (5.670) | (4.309) | (1.850) | (-0.544) | (5.603) |
| MOM6 | 1.285 | 0.460 | -0.444 | 1.728 | 1.426 | 0.379 | -0.439 | 1.864 | 1.273 | 0.143 | -0.564 | 1.837 |
| | (3.520) | (1.491) | (-1.787) | (5.711) | (3.843) | (1.187) | (-1.705) | (6.060) | (3.355) | (0.442) | (-2.141) | (5.860) |
| MOM3 | 0.806 | 0.158 | -0.475 | 1.281 | 0.946 | 0.110 | -0.417 | 1.363 | 0.869 | -0.068 | -0.515 | 1.383 |
| | (2.323) | (0.584) | (-1.991) | (4.395) | (2.669) | (0.394) | (-1.688) | (4.608) | (2.386) | (-0.239) | (-2.029) | (4.584) |

# Appendix A

This Appendix reports results of robustness tests that are briefly described in the text. Additional details are available from the authors upon request.

**T**ABLE A1: **Sample**

This table reports sample coverage statistics for different years at five year interval and for the full sample. For each month, we first obtain cross-sectional statistics, such as the number of firms, average size and total market capitalization in the sample and in the CRSP large-cap category. We then calculate the time-series average for the full sample and report this average in the last row of the table. We compare our sample with the CRSP sample.

| | Sample | | | CRSP (Large Cap) | | | Percentage | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | #Stocks | Avg Mcap ($M) | Tot Mcap ($M) | #Stocks | Avg Mcap ($M) | Tot Mcap ($M) | #Stocks | Avg Mcap ($M) | Tot Mcap ($M) |
| 1985 | 784 | 2167 | 1698949 | 915 | 1969 | 1801559 | 85.68 | 110.06 | 94.30 |
| 1990 | 735 | 3210 | 2359042 | 850 | 2945 | 2503611 | 86.47 | 108.97 | 94.23 |
| 1995 | 1026 | 5050 | 5180907 | 1162 | 4818 | 5598809 | 88.30 | 104.80 | 92.54 |
| 2000 | 1107 | 11506 | 12736948 | 1262 | 10751 | 13567283 | 87.72 | 107.02 | 93.88 |
| 2005 | 885 | 14068 | 12450370 | 956 | 13924 | 13311325 | 92.57 | 101.04 | 93.53 |
| 2010 | 901 | 13991 | 12605665 | 998 | 13372 | 13344817 | 90.28 | 104.63 | 94.46 |
| Average | 863 | 7574 | 6803164 | 978 | 7187 | 7243989 | 88.67 | 105.82 | 93.70 |

**T**ABLE A2: **Fama-MacBeth Regression: Continuous Competition Variable**

This table reports average Fama-MacBeth regression coefficients from cross-sectional regressions that predict monthly returns. We first run cross-sectional regressions each month by regressing month $t$ return on various variables measured at the end of month $t-1$. We report the time-series average of the coefficients and the corresponding $t$-statistics in parentheses. In all regressions, the variable X is momentum with different look-back windows. LogComp is the natural log of competition. LCOMP is Log of COMP, LME is log of market equity, LBM is log of (1 + book-to-market ratio), RET1 is month $t-1$ return, PROF represents profitability measured by Gross Profits/Total Assets, and SUE represents standardized earnings surprise. We standardize all RHS variables to zero mean and unit variance.

| | X = MOM12 | | | | X = MOM6 | | | | X = MOM3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Intercept | 1.031 | 1.283 | 1.014 | 1.348 | 1.058 | 1.258 | 1.046 | 1.296 | 1.068 | 1.285 | 1.074 | 1.334 |
| | (4.049) | (3.967) | (3.943) | (4.342) | (4.139) | (3.916) | (4.070) | (4.189) | (4.183) | (3.986) | (4.191) | (4.297) |
| X | 0.261 | 0.301 | 0.242 | 0.243 | 0.108 | 0.122 | 0.030 | 0.017 | 0.049 | 0.059 | -0.009 | -0.011 |
| | (1.912) | (2.492) | (1.802) | (1.986) | (0.788) | (1.019) | (0.239) | (0.143) | (0.370) | (0.527) | (-0.073) | (-0.101) |
| LCOMP | | | 0.113 | 0.127 | | | 0.076 | 0.096 | | | 0.037 | 0.065 |
| | | | (1.393) | (1.632) | | | (0.911) | (1.227) | | | (0.437) | (0.828) |
| X * LCOMP | | | -0.118 | -0.120 | | | -0.201 | -0.198 | | | -0.164 | -0.168 |
| | | | (-2.762) | (-2.966) | | | (-4.402) | (-4.555) | | | (-3.788) | (-4.157) |
| LME | | -0.118 | | -0.202 | | -0.091 | | -0.153 | | -0.104 | | -0.161 |
| | | (-1.393) | | (-2.339) | | (-1.085) | | (-1.793) | | (-1.210) | | (-1.895) |
| LBM | | 0.407 | | 0.314 | | 0.352 | | 0.258 | | 0.339 | | 0.273 |
| | | (4.871) | | (4.948) | | (3.868) | | (3.889) | | (3.438) | | (3.786) |
| RET1 | | -0.278 | | -0.303 | | -0.246 | | -0.280 | | -0.221 | | -0.252 |
| | | (-2.856) | | (-3.268) | | (-2.521) | | (-2.984) | | (-2.213) | | (-2.652) |
| PROF | | 0.246 | | 0.222 | | 0.222 | | 0.195 | | 0.209 | | 0.189 |
| | | (4.781) | | (4.456) | | (4.395) | | (3.954) | | (4.048) | | (3.726) |
| SUE | | 0.152 | | 0.161 | | 0.179 | | 0.183 | | 0.181 | | 0.184 |
| | | (5.586) | | (6.014) | | (6.361) | | (6.649) | | (6.317) | | (6.503) |

## **T**ABLE A3: **Independent Sort**

This table reports alphas with respect to the various factor models for competition conditional portfolios. At the end of each month $t-1$, we independently sort stocks into terciles by momentum competition and into quintiles by momentum. We measure momentum with different look-back windows. We then calculate value-weighted portfolio returns for the next month $t$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). We report quintile 5-1 portfolio spreads in percentage. $t$-statistics are reported in parentheses.

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 1.290 | 0.731 | 0.142 | 1.148 | 1.438 | 0.865 | 0.346 | 1.092 | 1.024 | 0.455 | -0.030 | 1.054 |
| | (4.078) | (2.215) | (0.484) | (4.125) | (4.517) | (2.609) | (1.185) | (3.863) | (3.143) | (1.341) | (-0.099) | (3.555) |
| MOM6 | 0.967 | 0.298 | -0.335 | 1.302 | 1.045 | 0.297 | -0.240 | 1.285 | 0.822 | -0.002 | -0.438 | 1.260 |
| | (3.300) | (1.005) | (-1.158) | (4.870) | (3.526) | (0.991) | (-0.824) | (4.726) | (2.669) | (-0.005) | (-1.439) | (4.419) |
| MOM3 | 0.676 | 0.118 | -0.491 | 1.168 | 0.716 | 0.103 | -0.461 | 1.176 | 0.543 | -0.112 | -0.684 | 1.227 |
| | (2.385) | (0.454) | (-1.845) | (4.256) | (2.489) | (0.389) | (-1.706) | (4.264) | (1.811) | (-0.409) | (-2.433) | (4.251) |

## TABLE A4: **Competition and Alpha: Size × Time**

This table reports alphas by firm size and sub-periods with respect to the various factor models for competition conditional portfolios. At the end of each month $t-1$, we first classify stocks into NYSE 3rd and 4th size quartile. Panels A and B report results for the 4th quartile for first and second half sub-samples, respectively. Similarly, Panels C and D report results for the 3rd quartile. Within each size group, we sort stocks into terciles by momentum competition and then finally sort stocks within terciles into quintile portfolios by momentum. We measure momentum with different look-back windows. We then calculate value-weighted portfolio returns for the next month $t$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). We report quintile 5-1 portfolio spreads in percentage. $t$-statistics are reported in parentheses.

Panel A: NYSE Size Quartile 4, Sub-Period 1

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 0.752 | 0.142 | -0.523 | 1.275 | 0.915 | 0.231 | -0.383 | 1.298 | 0.744 | -0.171 | -0.880 | 1.624 |
| | (2.150) | (0.418) | (-1.778) | (3.661) | (2.526) | (0.657) | (-1.253) | (3.622) | (1.830) | (-0.441) | (-2.685) | (4.087) |
| MOM6 | 0.411 | -0.484 | -0.809 | 1.221 | 0.477 | -0.436 | -0.771 | 1.248 | 0.313 | -0.692 | -0.869 | 1.182 |
| | (1.244) | (-1.528) | (-3.121) | (4.047) | (1.377) | (-1.350) | (-2.850) | (3.990) | (0.805) | (-1.916) | (-2.893) | (3.368) |
| MOM3 | 0.316 | -0.244 | -0.679 | 0.995 | 0.350 | -0.153 | -0.590 | 0.939 | 0.160 | -0.419 | -0.892 | 1.052 |
| | (0.985) | (-0.795) | (-2.486) | (3.414) | (1.043) | (-0.480) | (-2.076) | (3.145) | (0.426) | (-1.183) | (-2.831) | (3.145) |

Panel B: NYSE Size Quartile 4, Sub-Period 2

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 1.622 | 0.503 | 0.501 | 1.121 | 1.738 | 0.527 | 0.604 | 1.134 | 1.467 | 0.165 | 0.431 | 1.036 |
| | (2.374) | (0.979) | (1.162) | (1.974) | (2.620) | (1.030) | (1.433) | (1.996) | (2.099) | (0.307) | (0.970) | (1.742) |
| MOM6 | 1.051 | 0.044 | -0.102 | 1.154 | 1.052 | -0.048 | -0.097 | 1.150 | 0.979 | -0.237 | -0.243 | 1.222 |
| | (1.680) | (0.094) | (-0.239) | (2.148) | (1.724) | (-0.104) | (-0.227) | (2.147) | (1.517) | (-0.488) | (-0.538) | (2.186) |
| MOM3 | 0.790 | -0.422 | -0.072 | 0.861 | 0.740 | -0.470 | -0.068 | 0.807 | 1.008 | -0.518 | -0.034 | 1.042 |
| | (1.408) | (-1.036) | (-0.180) | (1.594) | (1.338) | (-1.155) | (-0.167) | (1.506) | (1.740) | (-1.198) | (-0.079) | (1.862) |

Panel C: NYSE Size Quartile 3, Sub-Period 1

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 1.237 | 0.471 | 0.320 | 0.917 | 1.724 | 0.513 | 0.483 | 1.241 | 1.297 | 0.021 | -0.092 | 1.389 |
| | (3.280) | (1.554) | (1.084) | (2.604) | (4.593) | (1.613) | (1.572) | (3.462) | (3.109) | (0.061) | (-0.278) | (3.462) |
| MOM6 | 0.878 | -0.156 | -0.068 | 0.946 | 1.186 | -0.106 | 0.067 | 1.119 | 0.921 | -0.256 | -0.069 | 0.991 |
| | (2.510) | (-0.561) | (-0.253) | (2.596) | (3.303) | (-0.364) | (0.239) | (2.950) | (2.291) | (-0.796) | (-0.222) | (2.332) |
| MOM3 | 0.744 | -0.162 | -0.007 | 0.751 | 1.007 | -0.008 | 0.189 | 0.818 | 0.748 | -0.151 | 0.042 | 0.707 |
| | (2.031) | (-0.599) | (-0.027) | (2.322) | (2.657) | (-0.030) | (0.726) | (2.412) | (1.765) | (-0.484) | (0.143) | (1.852) |

Panel D: NYSE Size Quartile 3, Sub-Period 2

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 1.154 | 0.922 | 0.091 | 1.063 | 1.119 | 0.952 | 0.230 | 0.889 | 0.844 | 0.564 | -0.102 | 0.946 |
| | (1.844) | (1.820) | (0.177) | (1.862) | (1.797) | (1.862) | (0.451) | (1.578) | (1.292) | (1.058) | (-0.190) | (1.618) |
| MOM6 | 1.153 | 0.644 | -0.014 | 1.167 | 1.055 | 0.607 | 0.048 | 1.007 | 0.863 | 0.289 | -0.142 | 1.005 |
| | (2.027) | (1.377) | (-0.026) | (2.244) | (1.853) | (1.294) | (0.092) | (1.946) | (1.438) | (0.585) | (-0.257) | (1.864) |
| MOM3 | 0.830 | 0.325 | 0.008 | 0.822 | 0.732 | 0.286 | 0.067 | 0.665 | 0.863 | 0.259 | 0.027 | 0.837 |
| | (1.581) | (0.776) | (0.019) | (1.530) | (1.394) | (0.675) | (0.151) | (1.241) | (1.556) | (0.575) | (0.056) | (1.489) |

**T**ABLE A5: **Breadth**

This table reports alphas with respect to the various factor models for breadth (#funds that hold a stock) conditional portfolios. At the end of each month $t-1$, we first sort stocks into terciles by breadth and then sort stocks within terciles into quintile portfolios by momentum. We measure momentum with different look-back windows. We then calculate value-weighted portfolio returns for the next month $t$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). We report quintile 5-1 portfolio spreads in percentage. $t$-statistics are reported in parentheses.

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 0.424 | 0.503 | 0.456 | -0.032 | 0.829 | 0.800 | 0.683 | 0.146 | 0.825 | 0.572 | 0.367 | 0.457 |
| | (1.204) | (1.405) | (1.376) | (-0.127) | (2.578) | (2.317) | (2.080) | (0.604) | (2.497) | (1.593) | (1.082) | (1.884) |
| MOM6 | 0.286 | 0.280 | 0.000 | 0.285 | 0.518 | 0.455 | 0.057 | 0.461 | 0.437 | 0.181 | -0.165 | 0.602 |
| | (0.896) | (0.812) | (0.001) | (1.122) | (1.695) | (1.337) | (0.188) | (1.878) | (1.389) | (0.513) | (-0.522) | (2.420) |
| MOM3 | 0.266 | 0.200 | -0.142 | 0.409 | 0.405 | 0.304 | -0.099 | 0.504 | 0.471 | 0.166 | -0.263 | 0.734 |
| | (0.889) | (0.695) | (-0.519) | (1.748) | (1.369) | (1.063) | (-0.359) | (2.152) | (1.536) | (0.556) | (-0.910) | (3.075) |

**TABLE A6: Competition Orthogonal to #Analysts**

This table reports alphas with respect to the various factor models for residual competition (competition orthogonal to the number of analysts) conditional portfolios. At the end of each month $t-1$, we first obtain residual competition by regressing log of competition on log of (1+#analysts) that follow a stock. We sort stocks into terciles by residual competition and then sort stocks within terciles into quintile portfolios by momentum. We measure momentum with different look-back windows. We then calculate value-weighted portfolio returns for the next month $t$. The alphas are obtained by running a time-series regression of excess portfolio returns (returns in excess of risk-free rate) on market factor (CAPM), Fama-French 3 factors (FF3), and Fama-French 5 factors (FF5). We report quintile 5-1 portfolio spreads in percentage. $t$-statistics are reported in parentheses.

| | CAPM | | | | FF3 | | | | FF5 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | Low-High | Low | Med | High | Low-High | Low | Med | High | Low-High |
| MOM12 | 1.589 | 0.370 | 0.226 | 1.363 | 1.785 | 0.497 | 0.456 | 1.329 | 1.427 | 0.070 | 0.101 | 1.326 |
| | (4.367) | (1.200) | (0.850) | (4.484) | (4.918) | (1.598) | (1.743) | (4.319) | (3.808) | (0.219) | (0.377) | (4.122) |
| MOM6 | 1.154 | 0.003 | -0.425 | 1.578 | 1.253 | 0.019 | -0.342 | 1.595 | 1.018 | -0.357 | -0.502 | 1.520 |
| | (3.454) | (0.012) | (-1.720) | (5.464) | (3.724) | (0.066) | (-1.369) | (5.446) | (2.918) | (-1.224) | (-1.925) | (4.991) |
| MOM3 | 0.719 | -0.225 | -0.313 | 1.032 | 0.790 | -0.228 | -0.195 | 0.986 | 0.655 | -0.463 | -0.265 | 0.920 |
| | (2.181) | (-0.897) | (-1.302) | (3.361) | (2.372) | (-0.896) | (-0.808) | (3.176) | (1.884) | (-1.755) | (-1.045) | (2.842) |