Competition and Momentum Profits

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Abstract

? 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 returns from both price and earnings momentum. Both strategies are profitable when buy-side competition for exploiting profits from these strategies is low. Return and earnings momentum generate monthly alpha of more than 130 basis points and 40 basis points, respectively, when competition is low but neither strategy yields significant alpha when competition is high. We also present related evidence from the post-2008 momentum crash.

1 Introduction

A key question in finance is whether returns are predictable and if so, whether the predictability is an anomaly that challenges market efficiency (**?**, **?**, **?**). The finance literature documents considerable evidence of predictability. Among the most robust findings are those relating to the price momentum and earnings momentum anomalies. These anomalies are a subject of considerable interest decades after they were initially documented. In an article dissecting anomalies, **?** refer to price momentum, originally discovered by **?**, as the premier anomaly. Likewise, **?** terms the earnings momentum anomaly, which is also called the post-earnings announcement drift or "PEAD" and dates back to **?**, as the granddaddy of all underreaction events.[1]

We study the price and earnings momentum anomalies. We focus on a specific economic force, competition between buy-side investors, as a determinant of abnormal returns from these two anomalies. 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 aware of the potential anomaly and who are able to exploit it.

We develop measures of buy-side competition customized to each anomaly and examine whether competition explains price momentum and earnings momentum. We find affirmative results. Figure 1 shows our main results. Briefly, we find that the cumulative return to momentum is negligible among high competition stocks. However, it is economically large among low competition stocks where it generates significant excess returns. We find similar results for earnings momentum.

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[1]Price momentum has also been demonstrated by many earlier studies to exist in many markets. **?** provides initial evidence of international momentum effects, and subsequent research further confirms these findings (**?**, **?**). Many other papers examine cross-sectional variation in momentum patterns (**?**, **?**, **?**, **?**), momentum performance in different market conditions (**?**, **?**, **?**), the risk of momentum strategies (**?**, **?**, **?**), and historical evidence using longer histories (**?**, **?**). Others present theoretical models that can explain momentum: **?**, **?**, **?**, **?**. For a recent literature review of momentum, see **?**. Among others, papers that study both price and earnings momentum include Chan, Jegadeesh, Lakonishok (1996), **?**, **?**.

We now briefly explain our approach and the key results, and we relate these to the existing literature. To simplify exposition, we focus on the price momentum anomaly of **?**. We defer the analysis of earnings momentum to later sections of the discussion. Our workhorse tool is a spatial measure of competition specific to the momentum anomaly. We measure competition as the density of funds in a one dimensional space derived from the anomaly. Each fund is placed in the anomaly space based on its value weighted exposure to the anomaly. Section 2 gives more details but the main takeaway is that when several funds operate in close spatial vicinity to each other, it indicates that the local market has the focused attention of many buy-side investors with related portfolios. Competition is thus intense in this region of the anomaly space. The most interesting regions in the anomaly space are the regions that are significantly far from zero where the anomaly predicts positive returns. We test whether strong momentum effects are local only to areas where buy-side competition is low.

Our main result is that economically significant portions of the momentum and PEAD anomalies are explained by fund 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 (**?**) is 164 basis points per month. The Fama-French 5-factor alpha (**?**) 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 $t-2$). The excess returns and alphas are similarly large for the PEAD anomaly. In contrast, in the same subsample of large-cap stocks with high buy-side fund competition, we find no momentum or PEAD abnormal returns.

We further compare month t return distributions for long minus short momentum quintile 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 Ratios of the low competition momentum and PEAD portfolios in our sample are 0.69 and 0.59, respectively. These ratios decrease to 0.05 and 0.11, respectively, when buy-side competition is high. These results are particularly strong given that we focus only on large capitalization stocks, where trading costs are low and many anomalies are not robust.

Our results also shed light on the emerging literature on the crash risk of momentum strategies (**?**, **?**). We find that the high competition portfolios display markedly *negative* skewness. Figure 2 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 can help explain momentum crash risk, perhaps reflecting that liquidity problems such as those in 2008 can create highly sensitive market conditions in competitive markets in which funds rush to exit.

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. Analogously computed alphas last even longer for the PEAD anomaly. For instance, the 5-factor alpha for month seven is 45 basis points per month. Figure 3 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 anomaly profits is low, arbitrage capital moves slowly (**?**, **?**). As a consequence, anomalies survive longer.

We also analyze how anomaly returns vary cross-sectionally. To do so, we zoom in further on the largest and most liquid stocks. We observe similar results for price momentum in NYSE size quartile 3 as we do in quartile 4, and we find stronger PEAD results in the largest size quartile 4. These 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, and are also strong for the PEAD anomaly in these more recent years.

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. We examine this possibility. Our competition-based measures remain robust, consistent with the uniqueness of our empirical measures and also the economics that drives them. Our measures are more precisely tailored to each anomaly and do not overlap strongly with ownership breadth. Thus, our results are not explained by ownership breadth.

Our study also adds to the work on analyst following and momentum. As **?** point out, analyst coverage determines the informational environment of stocks. This is *sell-side* information production by analysts. We examine anomalies 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, **?** show that momentum profitability decreases sharply for larger firms. In contrast, our results do not rely on small firms and in fact, are somewhat stronger for larger firms, especially for the PEAD anomaly.

To summarize, our paper makes two contributions. First, we present a framework for measuring buy-side metrics of investor competition and incorporate them in a study of anomalies. We illustrate how micro-level holdings data can generate metrics of buy-side competition specific to individual anomalies. Second, we explain a significant slice of both price and earnings momentum. We do so in the sample of large capitalization stocks, where return anomalies are particularly hard to generate. We find that anomalous earnings and return 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 (**?**). 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 (Jegadeesh (1990), **?**) and profitability (**?**).

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 in many markets.[2] Second, mutual funds are known to focus heavily on large capitalization stocks, which comprise about 90% of the market. Hence, anomaly performance in these

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[2]Indeed, the returns of the value-weighted portfolio of mutual funds is close to the returns of the aggregate market (**?**).

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 and post-earnings announcement drift. Here we note an empirical motivation: these are the most important and robust anomalies. Additionally, these are dynamic anomalies, in the sense that the anomaly portfolios exhibit churn regarding the addition and subtraction of stocks depending on past returns or recent earnings. The half-life of these anomalies, 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). Regarding momentum strategies, our framework allows measurement of the time series variation in the relative location of the anomaly in our fund-space, the degree to which funds are exposed to it, and the intensity of buy-side competition for profits. We identify these forces through continuous recalculation of the anomaly space, and by dynamically considering our buy-side competition measures within this space.

The rest of the paper is organized as follows. Section 2 develops the hypotheses and discusses related work on spatial competition. Section 3 discusses the data. Section 4 discusses the main empirical results. Section 5 concludes. The Appendix collects the results of several robustness tests.

2 Competition and Momentum

2.1 Hypothesis and Framework

Our central prediction is that both price and earnings momentum will generate larger profits when buy-side competition is low. The intuition is straightforward: if these anomalies are 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 anomaly profits will be close to zero in markets with intense buy-side competition. In particular, competition increases arbitrage pressures as multiple funds trade in the same direction as they pursue scarce rents that are short-lived. In contrast, we expect that anomalies will persist longer and will be more profitable in concentrated markets.[3]

Understanding competition in the style space is central to our hypotheses. Our approach is thus quantitatively related to that in **?** (HKP), but we also note that the current study also offers novel innovations along multiple dimensions. For example, we extend measurement of competition from the fund level to the individual stock level, and we also customize measures of competition to each individual anomaly. 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 **?, ?, ?, ?**). Fund j is then deemed to be a competitor of fund i in quarter t if the spatial distance satisfies the condition $d_{i,j,t} \leq d^*$.

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[3]A parallel prediction obtains for negative anomaly stocks even if we assume that mutual funds are not allowed to short sell. In particular, buy side investors also have incentives to produce information for negative anomaly stocks, as an informative signal would indicate when the existing position in the stock should be sold. Hence, more funds will exit their investments when negative anomaly returns are expected, and hence negative anomaly returns should only exist when local buy-side markets become more concentrated.

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 **?**.

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 the price momentum or earnings momentum dimension. 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 two of the most robust asset pricing anomalies, price and earnings momentum, in a buy-side competition framework.

For example, when considering the price momentum anomaly, our one-dimensional space is simply the space of price 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 (**?**), 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 compe-

tition. 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. A second innovation is that we design customized measures of competition that are unique for each anomaly. These two innovations empower us to then examine anomaly profits, and to predict where they are likely to be largest or smallest. We calculate firm-level competition using three steps.

In the first step, we identify which funds hold a given stock. Suppose, stock i is held by k funds ($j = 1, 2, ...k$) at the of quarter T. In the second step, we use HKP's method to identify customized rival funds for each of the k mutual funds in 1-dimensional momentum space and then arrive at the fund level competition measure.[4] This competition measure is based on the total similarity between fund j and its customized rivals. We term this total similarity as $TSIMM_j$.

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[4]HKP describe the method in detail. We only briefly discuss the steps. In the first step, funds are located on the momentum line as described above in the hypothesis section. Two funds with similar momentum loadings are defined as momentum competitors if the distance between then is less than the critical distance, d^*. This critical distance is identified based on the Lipper classification. Specifically, under the Lipper fund classification, 8.858% of fund pairs are in the same Lipper class. Thus, we require that our classification is equally granular such that 8.858% of fund pairs will be members of one another's customized peer groups. This is achieved by identifying d^* as the smallest number such that at least 8.858% of all d_{ij} permutations are less than d^*. 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 k funds getting its own set of customized peer funds.

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 is a measure of the intensity of competition surrounding the given fund. The competition surrounding a given firm i, 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:

$$AVGTSIMM_{i,T} = \frac{\sum_{j=1}^{k} TSIMM_{j,T}}{k} \tag{1}$$

This metric measures average level of similarity of funds that hold stock i based on the broader holdings of each such fund. If this measure is high, it indicates that the stock i is surrounded by a large number of funds, *which are similar to the k funds that hold stock i.* We then update the competition surrounding the stock i at the end of quarter $T+1$. Thus, we have quarterly values of competition surrounding any stock i at the end of any quarter T, $AVGTSIMM_{i,T}$.

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 $AVGTSIMM_{i,T}$ obtained at the end of June.[5] Rather we take the average of $AVGTSIMM_{i,T-1}$ and $AVGTSIMM_{i,T-2}$, 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

$$Comp_{i,t} = \frac{AVGTSIMM_{i,T-1} + AVGTSIMM_{i,T-2}}{2} \tag{2}$$

This will also be the competition around stock i 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.[6]

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[5]We denote months by t and quarters by T.

[6]We get similar results if we define competition as $Comp_{i,t} = AVGTSIMM_{i,T-1}$.

Depending upon the dimension on which the competition is measured (price momentum or earnings momentum), we define two variables: $COMPMOM_{i,t}$ that measures the buy-side price competition in stock i in month t, and similarly $COMPSUE_{i,t}$ measures the buy-side earnings momentum competition.

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 price momentum with different look-back windows and standardized earnings surprise (SUE) at the end of month $t-1$.

$MOM12_{t-1}$: 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 $t-2$.

SUE_{t-1}: We calculate standardized earnings surprise as in **?**. 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 σ_{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.

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 **?**. Book equity is lagged by six months from month $t-1$. Market equity is current market equity at the end of month $t-1$.[7]

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

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

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 **?** 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 **?**. 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 **?**. 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

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[7]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.

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. **?** 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 **?**. 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 **?** 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 and C 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 the mean and median are about the same and there is more variation in both momentum and SUE competition in the later half of the sample. This is especially true for SUE, where the second half standard deviation is 13.89 as compared to the first half standard deviation of 3.07. Overall, greater competition in the second half is consistent with the high growth of mutual fund industry post-1995.

Panels D and E 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 price and earnings momentum. $COMPMOM$ has a -0.24 Pear-

son correlation with $MOM12$, while $COMPSUE$ has a Pearson correlation of -0.12 with SUE. In case of price momentum, correlation goes down as we decrease the look-back window. This is by construction since $COMPMOM$ is measured with respect to the 12-month look-back window.

4   Results

We first discuss the unconditional price and earnings momentum results in our sample and then discuss how competition impacts momentum returns. 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, and also for standardized earnings surprise (SUE) portfolios. 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 and by SUE in Panel D. 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 (σ_r), downside volatility ($\sigma_{r(r<0)}$), skewness, 1 percentile and minimum returns.[8] 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 price 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

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

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 the present, 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.

In contrast to price momentum, SUE generates statistically significant average returns of about 0.38% even in the unconditional tests. It shows much lower volatility 2.92%, and lower 1 percentile and minimum returns. It also generates higher Sharpe (0.45) and Sortino Ratios (0.79).

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 (**?**, FF3), and Fama-French 5 factors (**?**, FF5). We report t-statistics in parentheses.

Consistent with our earlier tests, we continue to find that unconditional price momentum ($MOM12$) strategies do not generate statistically significant alpha with respect to the FF3 model. The CAPM and FF5 alphas are statistically insignificant. The alphas generated by shorter look-back windows also are not significant. We also find that unconditional SUE portfolios generate roughly similar CAPM alphas as $MOM12$ portfolios do, but with a t-statistic of 2.72. SUE alpha is also not subsumed when risk-adjustments are made by the FF3 and FF5 models. For example, the FF5 alpha is 0.28% per month (t-statistic = 2.06). Overall, we conclude that earnings momentum is more robust than price momentum. Our evidence is consistent with the findings of **?** and **?**.

4.2 Competition

We now discuss the main results of the paper. We show that both price and earnings momentum generate greater profits in the low competition stocks. We first discuss the Fama-MacBeth (**?**) 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. Panel A reports results for the full sample period, while Panels B and C report results from first and second half of the sample, respectively. In all regressions, the variable X is either $MOM12$ or $MOM6$ or $MOM3$ or standardized earnings surprise, SUE. The variable X is defined at the top of the panels. LME is log of market equity, LBM is log of $(1 + \text{book-to-market ratio})$, $RET1$ is month $t-1$ return, and $PROF$ represents profitability measured by gross profits scaled by total assets (**?**). At the end of $t-1$ month, we also sort stocks into terciles by momentum competition ($COMPMOM_{t-1}$) and SUE competition ($COMPSUE_{t-1}$). 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 find somewhat weaker results for SUE in Models 13-16. Models 13 and 14 show that SUE is profitable unconditionally. But when we interact the competition dummy variables with SUE in Model 16, we find that low competition stocks generate 11 basis points higher return per month (t-statistic = 2.23) than do high competition stocks. When we examine the sub-sample results in Panels B and C, we find that SUE is profitable only in the low competition stocks in the later half of the sample (post-1996). The lack of return predictability for high competition stocks matches our central prediction. The difference across the two time-series subsamples is not expected, but is consistent with the increased power in the later half the sample, where many more funds are present in the sample, and the variability in SUE competition is higher (see Table 1). Our subsample results also show that price momentum generates higher returns for low competition stocks, even in the later half of the sample.

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 (*LogComp*, 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 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) Ratio. 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 3 months. Panel D reports results for SUE, where we observe a similar pattern. The low competition SUE portfolio generates higher returns, similar volatilities, lower skewness, and higher Sharpe and Sortino Ratios than does the high competition portfolio. Figure 1 displays the cumulative returns to investing in 5-1 $MOM12$ and SUE portfolios. 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. Finally, we note that SUE also produces a similar pattern. Unlike the 5-1 high competition spreads, the low competition spreads are once again statistically and economically significant. They are also statistically different from each other except for the FF5 spreads. But as we discuss the longer holding period results in the next section, the evidence shows that for most of

the post-ranking holding period months, that the low-high 5-1 spreads are statistically and economically different from each other.

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.[9] We find similar results both qualitatively and quantitatively. As a more stringent robustness check, we also sorted stocks by residual momentum. That is, we first run a cross-sectional regression of momentum on competition and take the orthogonal component of momentum, which we call residual momentum. We then follow the same procedure of sorting stocks into 3 X 5 portfolios by competition and then by residual momentum. Table A4 reports next month 5-1 spreads. We again find similar results. This shows that our results are not driven by any correlation between competition and momentum. In unreported results, we further confirm that all our results hold if we employ residual momentum in sorts instead of raw momentum.

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 (denoted by 1 in Table 7), three months ahead $t+2$ alpha (denoted by 2 in Table 7) and so on until the month $t+11$. Table 7 displays the alphas of our 5-1 portfolios for $MOM12$ in Panel A and SUE in Panel B.[10] 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 0 is 1.37% per month (t-statistic $= 3.74$). This alpha decreases to 1.18% per month (t-statistic $= 3.58$) in month 1. We continue to observe significant alpha until month 5 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.

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

[10]To save space, we only show alphas of 5-1 $MOM12$ and SUE portfolios. Our results are robust and similar for $MOM6$ and $MOM3$ as well.

We largely find a similar pattern for SUE alphas in Panel B. For instance, when we adjust for risk using the CAPM model, the low competition stocks deliver alphas for up to seven months. The seven-month alpha is 0.41% per month (t-statistic = 1.98). We also observe that the difference in spreads between low and high competition stocks persists for up to six months. We find similar results when risk is adjusted using the FF3 and FF5 models. Figure 3 shows the average returns of the 5-1 $MOM12$ and SUE portfolios for the next 12 months. 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 identification is easier because illiquidity and transaction costs are lower. Our definition of large-cap stocks follows that of ?. 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. We further note that SUE produces stronger results in size quartile 4. For instance, the low-high spreads are statistically and economically different from each other in Panel A, but not in Panel B. 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.

4.2.5 Subperiods

Our Fama-MacBeth tests showed stronger results in the second half of the sample. We now confirm the same conclusion using portfolio analysis. Panel A of Table 9 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 two interesting observations. One, 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. The second difference is that the earnings momentum alpha is larger in the second half for the low competition stocks. The low-high SUE spreads in the first half are not statistically different from each other, while in the second half for all risk-adjusted alphas, they are different from each other. For instance, the FF5 SUE alpha is 0.76% per month (t-statistic = 2.31). This is perhaps not surprising given that $COMPSUE$ has greater variation in the second half (see Table 1).

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 (**?**, **?**). 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 1997. Table 10 shows results from the pre-crisis subsample. Our results are not materially different from the full sample results in Table 6. We conclude that momentum crashes do not drive the differential performance of low and high competition stocks.

We further split our sample by NYSE size quartile 4 and 3, and then by subperiods. Table A5 shows results for the four subsamples. We find consistent price momentum results in all subsamples. Also consistent with our earlier results, SUE results are stronger in in

the later half of the sample in NYSE size quartile 4.

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 (**?**) 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 A6 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. We also find similar inconsistent results for SUE and also for the shorter momentum look-back windows of six and three months.

4.2.7 Analysts Coverage

? 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 **?**, 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 $Log(COMPMOM)$ on $Log(1+\#Analysts)$ at the end of each month $t-1$, and compute the residual $Log(COMPMOM)$. Similarly for earnings momentum, we

regress $Log(COMPSUE)$ on $Log(1 + \#Analysts)$ and take the residual $Log(COMPSUE)$. Thus, our residual measure of competition is net of public information production due to the analyst coverage.

Table A7 displays the results for residual competition. We find even larger alphas for $MOM12$, and similar results for SUE as we reported earlier. 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 the price and earnings momentum anomalies in a buy-side competition framework. Our hypothesis is that both price and earnings momentum will generate larger profits when buy-side competition is low. The intuition is that if these anomalies are 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 measures of buy-side competition that are tailored to price and earnings momentum. We explain a significant slice of both price and earnings momentum. We focus on the sample of large capitalization stocks, where illiquidity related imperfections and transaction costs are lower. We find that both anomalies exist only when fund competition is low. In these low competition markets, these anomalies generate high excess returns, relatively long-lasting alphas, and they also are less exposed to negative skewness. 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

(**?**). 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), **?**), and profitability (**?**). Our results are consistent with the traditional school of thought that competition is a key source of market efficiency.

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

(a) Momentum

(b) Standardized Earnings Surprise

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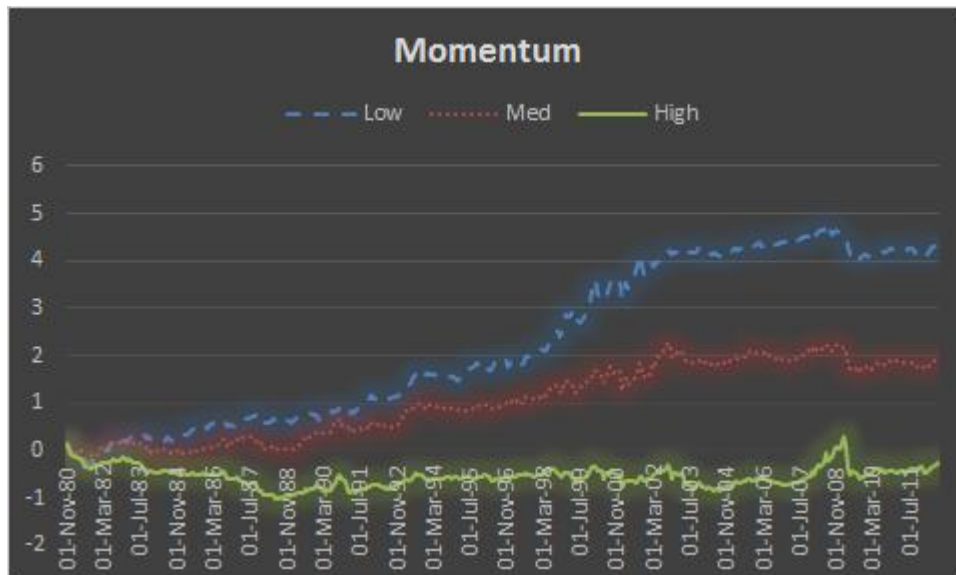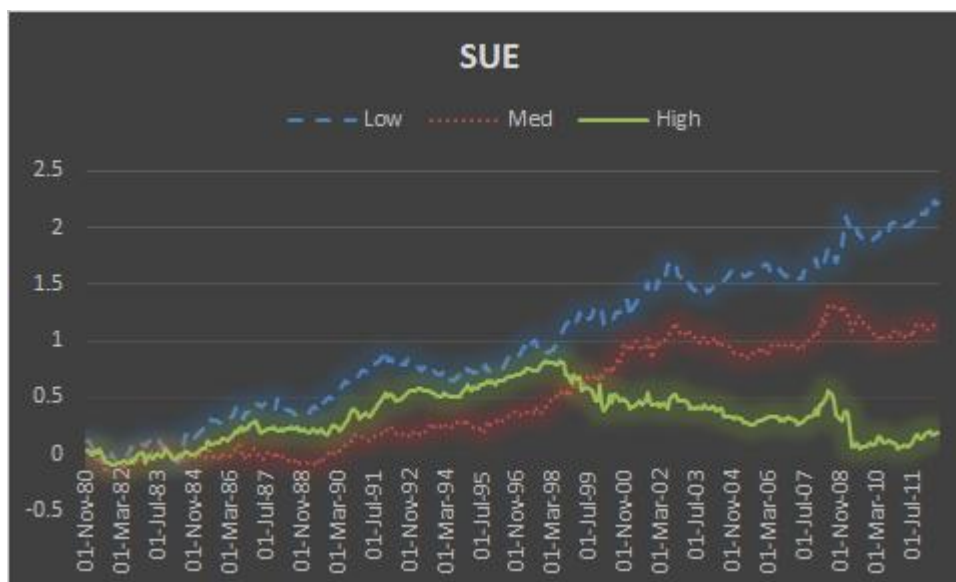
Figure 2: **Distribution of MOM and SUE Portfolio Returns**
This figure shows distribution of returns of 5-1 value-weighted price momentum and earnings momentum (measured as standardized earnings surprise, SUE) portfolios with monthly re-balancing in low and high competition stocks.

(a) Momentum

(b) Standardized Earnings Surprise

28
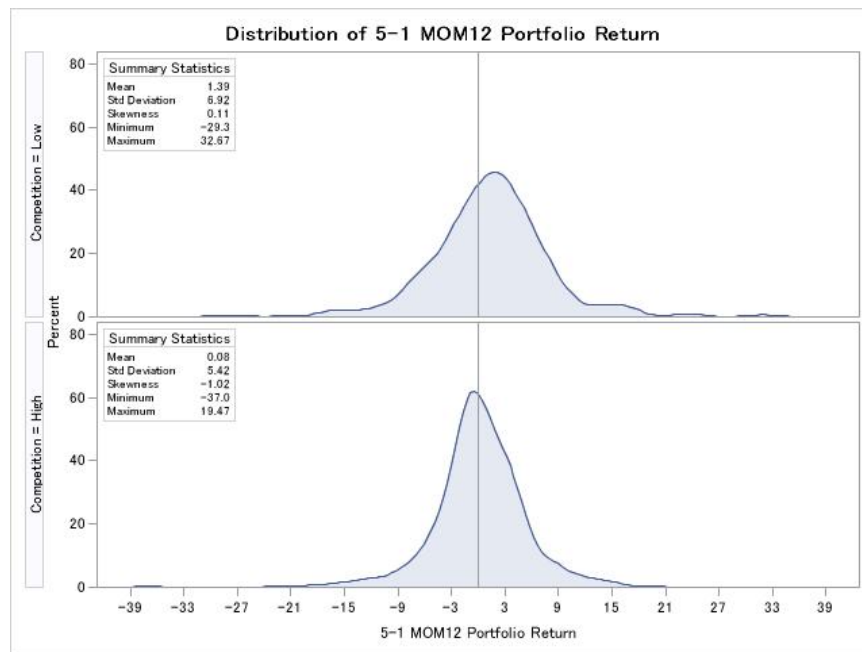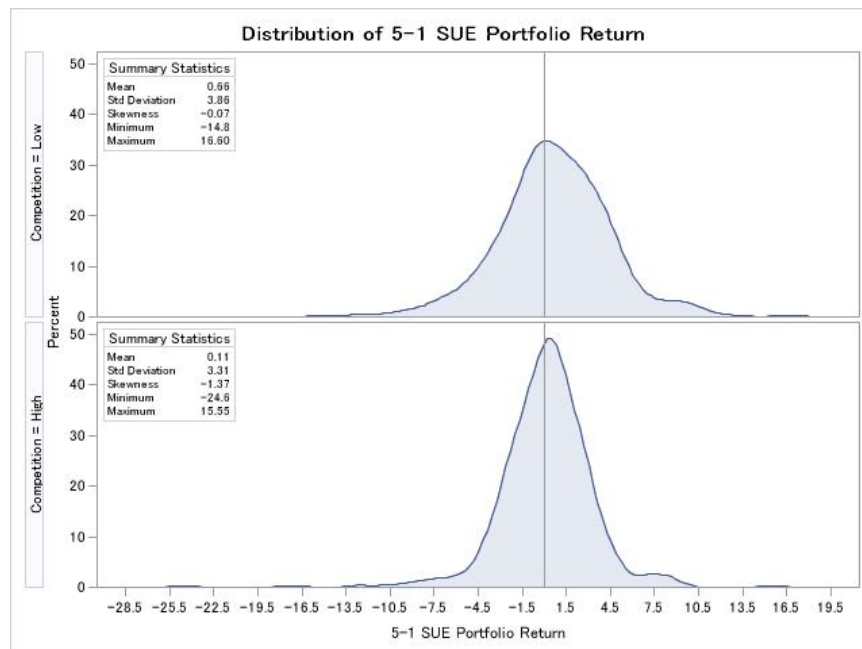
Figure 3: **Holding Period Average Return**
This figure shows average return of value-weighted 5-1 portfolios with monthly re-balancing in low, medium and high competition stocks. The holding period month varies from t to $t + 11$.
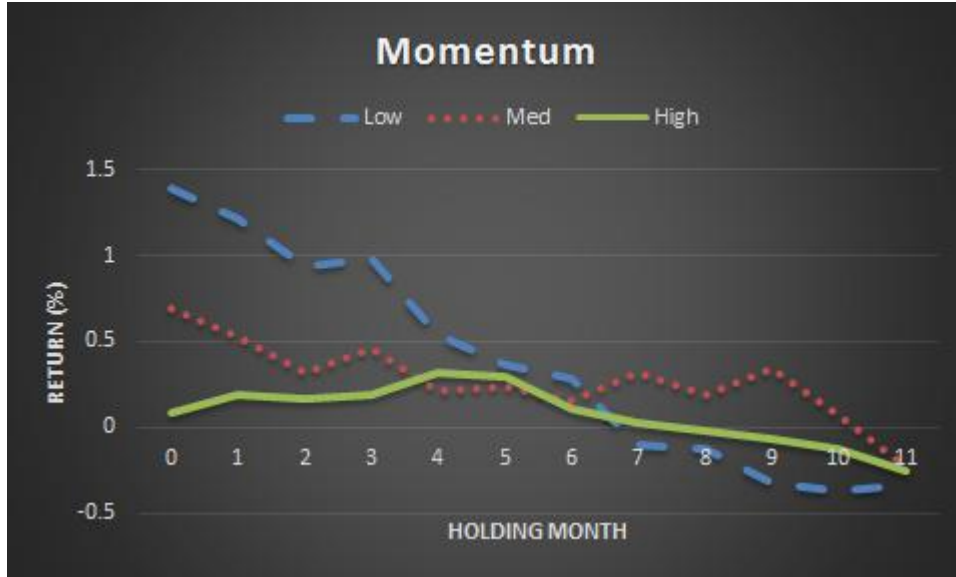
(a) Momentum
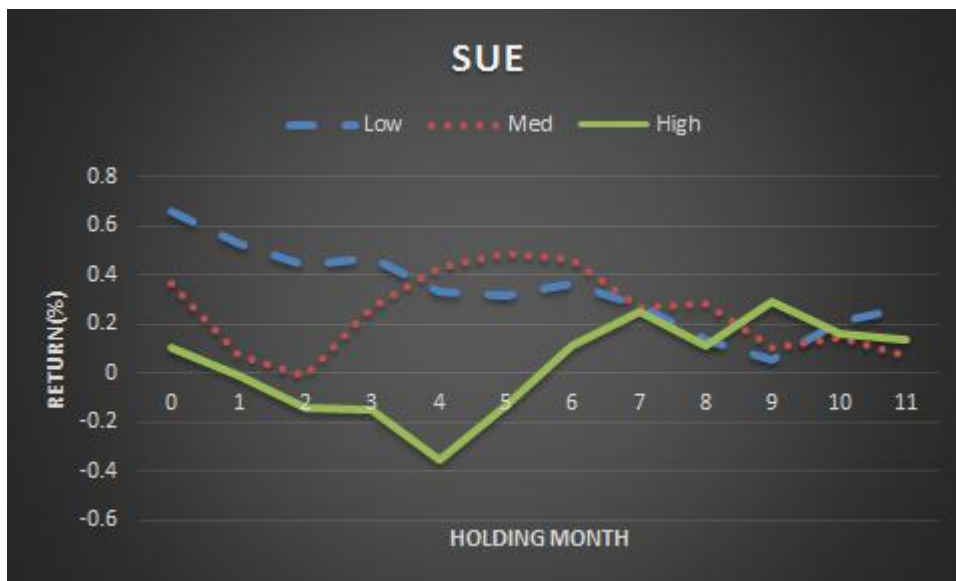
(b) Standardized Earnings Surprise

TABLE 1: **Summary Statistics**

This table reports summary statistics for various variables in Panel A, momentum competition in Panel B and standardized earnings surprise, SUE, competition in Panel C. For each month, we first obtain the cross-sectional statistics and then take the time-series average. Panel D reports time-series average of cross-sectional correlation between momentum and momentum competition (COMPMOM), and Panel E reports time-series average of cross-sectional correlation between SUE and SUE competition (COMPSUE). 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
SUE	0.484	0.321	2.024	-0.302	1.332
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

Panel B: COMPMOM					
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: COMPSUE					
Variable	Mean	Median	Std	P25	P75
First Half (N=190)	23.021	23.535	3.078	21.547	24.957
Second Half (N=191)	113.889	114.678	13.896	108.902	119.326
Full Sample (N=381)	68.574	69.226	8.501	65.339	72.265

Panel D: Correlation Between Momentum and Competition				
Variable	MOM12	MOM6	MOM3	COMPMOM
MOM12	1			
MOM6	0.718	1		
MOM3	0.500	0.681	1	
COMPMOM	-0.246	-0.108	-0.060	1

Panel E: Correlation Between SUE and Competition		
Variable	SUE	COMPSUE
SUE	1	
COMPSUE	-0.120	1

TABLE 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 standardized earnings surprise, SUE (Panel D) 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 (σ_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.

Quintile	$\bar{r}$	t-stat	$\overline{r-r_f}$	t-stat	σ_r	$\sigma_{r(r<0)}$	Skewness	1 percentile	Min	Sharpe	Sortino
				Panel A: MOM12							
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							
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							
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
				Panel D: SUE							
1	0.772	(3.059)	0.372	(1.473)	4.929	3.056	-0.714	-16.336	-20.148	0.261	0.422
2	0.816	(3.465)	0.415	(1.762)	4.595	2.842	-0.832	-12.585	-20.246	0.313	0.506
3	1.007	(4.320)	0.607	(2.598)	4.551	2.603	-0.492	-10.207	-21.480	0.462	0.808
4	0.983	(4.095)	0.583	(2.426)	4.688	2.720	-0.584	-11.959	-23.294	0.431	0.742
5	1.156	(4.834)	0.755	(3.159)	4.666	2.466	-0.246	-10.856	-20.939	0.561	1.061
5-1	0.383	(2.553)	0.383	(2.553)	2.929	1.668	-0.120	-7.601	-11.657	0.453	0.796

TABLE 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 standardized earnings surprise, SUE, 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.

Quntile	MOM12			MOM6			MOM3			SUE		
	CAPM	FF3	FF5	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	-0.179	-0.258	-0.092
	(-1.363)	(-1.967)	(-0.663)	(-0.738)	(-0.786)	(0.282)	(-0.205)	(-0.241)	(0.553)	(-1.968)	(-2.906)	(-1.041)
2	0.036	-0.069	-0.121	0.191	0.118	0.095	0.228	0.169	0.085	-0.110	-0.219	-0.235
	(0.361)	(-0.779)	(-1.307)	(1.952)	(1.310)	(1.000)	(2.516)	(2.039)	(0.991)	(-1.542)	(-3.396)	(-3.524)
3	-0.034	-0.084	-0.224	0.148	0.104	-0.030	0.103	0.069	-0.049	0.082	0.068	-0.007
	(-0.419)	(-1.189)	(-3.137)	(1.834)	(1.552)	(-0.454)	(1.331)	(1.026)	(-0.719)	(1.246)	(1.071)	(-0.102)
4	0.138	0.120	-0.075	-0.076	-0.095	-0.257	-0.022	-0.031	-0.152	0.044	0.088	-0.014
	(1.593)	(1.493)	(-0.962)	(-0.924)	(-1.217)	(-3.341)	(-0.286)	(-0.412)	(-2.026)	(0.641)	(1.341)	(-0.218)
5	0.196	0.358	0.364	0.043	0.119	0.098	-0.045	0.016	0.048	0.232	0.327	0.195
	(1.210)	(2.378)	(2.306)	(0.298)	(0.848)	(0.667)	(-0.343)	(0.120)	(0.354)	(2.727)	(4.417)	(2.696)
5-1	0.442	0.712	0.486	0.165	0.251	0.050	-0.015	0.052	-0.039	0.411	0.586	0.287
	(1.376)	(2.297)	(1.510)	(0.574)	(0.874)	(0.166)	(-0.058)	(0.202)	(-0.143)	(2.727)	(4.103)	(2.066)

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. Panel A reports results for the full sample period, while Panels B and C report results from first and second half of the sample, respectively. In all regressions, the variable X is either momentum with different look-back windows or standardized earnings surprise, SUE. LME is log of market equity, LBM is log of (1 + book-to-market ratio), RET1 is month $t-1$ return, and PROF represents profitability measured by Gross Profits/Total Assets. Each month, we also sort stocks into terciles by momentum competition (COMPMOM) and SUE competition (COMPSUE). 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: Full Period

	X = MOM12				X = MOM6				X = MOM3				X = SUE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Intercept	0.993	1.234	1.086	1.404	1.021	1.216	1.093	1.313	1.041	1.240	1.094	1.323	1.064	1.296	1.090	1.417
	(3.845)	(3.771)	(4.630)	(4.609)	(3.930)	(3.736)	(4.647)	(4.314)	(4.014)	(3.797)	(4.650)	(4.328)	(4.261)	(4.012)	(4.449)	(4.442)
X	0.305	0.396	0.011	0.094	0.166	0.223	-0.211	-0.157	0.100	0.134	-0.146	-0.112	0.140	0.190	0.099	0.133
	(2.241)	(3.330)	(0.066)	(0.623)	(1.222)	(1.883)	(-1.416)	(-1.165)	(0.757)	(1.191)	(-1.069)	(-0.925)	(3.600)	(6.200)	(2.095)	(3.251)
Low			-0.312	-0.274			-0.216	-0.175			-0.140	-0.118			-0.094	-0.130
			(-1.808)	(-1.810)			(-1.212)	(-1.163)			(-0.765)	(-0.778)			(-1.038)	(-1.693)
Med			0.015	-0.006			0.004	-0.005			0.012	-0.006			0.013	-0.017
			(0.213)	(-0.086)			(0.059)	(-0.068)			(0.162)	(-0.090)			(0.223)	(-0.312)
X * Low			0.440	0.414			0.579	0.566			0.392	0.384			0.085	0.113
			(3.248)	(3.248)			(4.677)	(4.820)			(3.476)	(3.557)			(1.560)	(2.235)
X * Med			0.334	0.301			0.282	0.249			0.158	0.143			0.050	0.057
			(3.202)	(2.925)			(2.935)	(2.637)			(1.644)	(1.506)			(1.084)	(1.358)
LME		-0.089		-0.173		-0.068		-0.123		-0.074		-0.124		-0.114		-0.169
		(-1.028)		(-2.022)		(-0.787)		(-1.446)		(-0.845)		(-1.452)		(-1.327)		(-1.892)
LBM		0.381		0.293		0.294		0.211		0.268		0.209		0.334		0.308
		(4.202)		(4.270)		(2.989)		(2.913)		(2.558)		(2.631)		(2.977)		(2.815)
RET1		-0.238		-0.256		-0.204		-0.224		-0.180		-0.197		-0.249		-0.255
		(-2.437)		(-2.733)		(-2.063)		(-2.349)		(-1.773)		(-2.033)		(-2.309)		(-2.400)
PROF		0.262		0.238		0.230		0.205		0.215		0.198		0.219		0.217
		(5.100)		(4.767)		(4.505)		(4.138)		(4.131)		(3.894)		(4.068)		(4.068)

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

	X = MOM12				X = MOM6				X = MOM3				X = SUE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Intercept	1.235	1.427	1.348	1.450	1.303	1.443	1.386	1.434	1.329	1.457	1.405	1.438	1.279	1.470	1.341	1.560
	(3.727)	(3.446)	(4.350)	(3.716)	(3.912)	(3.501)	(4.524)	(3.702)	(3.973)	(3.528)	(4.616)	(3.722)	(3.968)	(3.568)	(4.376)	(3.890)
X	0.323	0.458	0.031	0.174	0.031	0.128	-0.281	-0.168	-0.020	0.033	-0.145	-0.092	0.188	0.276	0.225	0.282
	(2.276)	(3.676)	(0.170)	(1.022)	(0.236)	(1.099)	(-1.828)	(-1.177)	(-0.155)	(0.282)	(-0.976)	(-0.661)	(4.049)	(7.731)	(4.184)	(5.738)
Low			-0.279	-0.118			-0.178	-0.043			-0.131	0.006			-0.203	-0.159
			(-1.905)	(-0.994)			(-1.139)	(-0.350)			(-0.803)	(0.047)			(-1.825)	(-1.774)
Med			-0.062	0.003			-0.052	-0.002			-0.079	-0.030			0.007	0.014
			(-0.867)	(0.049)			(-0.716)	(-0.032)			(-1.102)	(-0.449)			(0.104)	(0.210)
X * Low			0.472	0.428			0.558	0.516			0.302	0.289			-0.019	0.021
			(2.837)	(2.668)			(3.787)	(3.579)			(2.266)	(2.275)			(-0.261)	(0.316)
X * Med			0.248	0.203			0.234	0.182			0.004	-0.019			-0.051	-0.030
			(2.041)	(1.713)			(2.097)	(1.636)			(0.032)	(-0.169)			(-0.899)	(-0.549)
LME		-0.057		-0.051		-0.044		-0.026		-0.040		-0.018		-0.086		-0.117
		(-0.499)		(-0.463)		(-0.392)		(-0.233)		(-0.355)		(-0.161)		(-0.756)		(-1.009)
LBM		0.418		0.393		0.303		0.294		0.291		0.293		0.427		0.408
		(4.407)		(4.518)		(2.984)		(3.235)		(2.783)		(3.173)		(4.172)		(4.150)
RET1		-0.296		-0.321		-0.297		-0.321		-0.283		-0.300		-0.300		-0.310
		(-2.770)		(-3.051)		(-2.717)		(-2.981)		(-2.607)		(-2.812)		(-2.699)		(-2.842)
PROF		0.307		0.298		0.270		0.260		0.256		0.251		0.280		0.278
		(4.668)		(4.584)		(4.198)		(4.075)		(3.967)		(3.906)		(4.177)		(4.177)

	Panel C: Sub-period (1996:09 - 2012:07)															
	X = MOM12				X = MOM6				X = MOM3				X = SUE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Intercept	0.751	1.042	0.826	1.358	0.740	0.989	0.801	1.193	0.755	1.025	0.783	1.208	0.850	1.122	0.842	1.275
	(1.899)	(2.055)	(2.348)	(2.899)	(1.858)	(1.964)	(2.249)	(2.538)	(1.906)	(2.024)	(2.190)	(2.549)	(2.229)	(2.255)	(2.202)	(2.567)
X	0.286	0.334	-0.009	0.016	0.300	0.318	-0.141	-0.147	0.219	0.235	-0.146	-0.131	0.091	0.105	-0.027	-0.016
	(1.235)	(1.651)	(-0.033)	(0.062)	(1.262)	(1.541)	(-0.553)	(-0.640)	(0.957)	(1.221)	(-0.639)	(-0.665)	(1.474)	(2.132)	(-0.353)	(-0.248)
Low			-0.345	-0.429			-0.254	-0.306			-0.149	-0.241			0.014	-0.101
			(-1.105)	(-1.545)			(-0.792)	(-1.118)			(-0.455)	(-0.878)			(0.100)	(-0.810)
Med			0.093	-0.015			0.061	-0.007			0.103	0.018			0.019	-0.047
			(0.738)	(-0.126)			(0.467)	(-0.060)			(0.806)	(0.154)			(0.199)	(-0.556)
X * Low			0.409	0.400			0.600	0.615			0.481	0.479			0.188	0.205
			(1.908)	(2.017)			(3.013)	(3.318)			(2.647)	(2.743)			(2.303)	(2.676)
X * Med			0.421	0.398			0.329	0.315			0.312	0.304			0.151	0.144
			(2.477)	(2.371)			(2.107)	(2.068)			(2.009)	(1.973)			(2.072)	(2.230)
LME		-0.122		-0.293		-0.091		-0.220		-0.108		-0.229		-0.142		-0.221
		(-0.927)		(-2.269)		(-0.701)		(-1.705)		(-0.804)		(-1.759)		(-1.100)		(-1.623)
LBM		0.344		0.194		0.284		0.128		0.245		0.125		0.241		0.209
		(2.228)		(1.832)		(1.690)		(1.141)		(1.350)		(0.972)		(1.210)		(1.070)
RET1		-0.181		-0.190		-0.112		-0.128		-0.076		-0.095		-0.198		-0.199
		(-1.106)		(-1.232)		(-0.681)		(-0.814)		(-0.447)		(-0.585)		(-1.073)		(-1.095)
PROF		0.217		0.178		0.190		0.151		0.174		0.146		0.158		0.156
		(2.752)		(2.355)		(2.399)		(1.991)		(2.130)		(1.847)		(1.881)		(1.878)

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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 (σ_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 D reports results for standardized earnings surprise, SUE.

						Panel A: MOM12						
Comp	Quintile	$\bar{r}$	t-stat	$\overline{r-r_f}$	t-stat	σ_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	σ_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	σ_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
						Panel D: SUE						
Comp	Quintile	$\bar{r}$	t-stat	$\overline{r-r_f}$	t-stat	σ_r	$\sigma_{r(r<0)}$	Skewness	1 percentile	Min	Sharpe	Sortino
Low	1	0.547	(1.904)	0.146	(0.509)	5.604	3.554	-0.689	-16.796	-25.313	0.090	0.142
Low	5	1.205	(4.462)	0.805	(2.976)	5.272	2.756	-0.162	-11.822	-23.629	0.529	1.012
Low	5-1	0.659	(3.329)	0.659	(3.329)	3.862	2.143	-0.074	-9.711	-14.844	0.591	1.065
Med	1	0.775	(2.933)	0.374	(1.417)	5.156	3.111	-0.599	-16.704	-21.055	0.251	0.417
Med	5	1.135	(4.666)	0.735	(3.022)	4.749	2.598	-0.374	-10.817	-19.810	0.536	0.979
Med	5-1	0.361	(2.205)	0.361	(2.205)	3.191	1.738	0.138	-7.180	-11.129	0.391	0.719
High	1	0.931	(3.473)	0.531	(1.978)	5.235	3.090	-0.302	-16.497	-21.107	0.351	0.595
High	5	1.039	(3.971)	0.638	(2.441)	5.107	2.987	-0.253	-19.565	-23.028	0.433	0.740
High	5-1	0.107	(0.633)	0.107	(0.633)	3.310	2.260	-1.366	-10.615	-24.558	0.112	0.165

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 (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. 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 D reports results for standardized earnings surprise, SUE.

Panel A: MOM12

Quintile	CAPM Low	Med	High	Low-High	FF3 Low	Med	High	Low-High	FF5 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

Quintile	CAPM Low	Med	High	Low-High	FF3 Low	Med	High	Low-High	FF5 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

Quintile	CAPM Low	Med	High	Low-High	FF3 Low	Med	High	Low-High	FF5 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)

Panel D: SUE

Quintile	CAPM Low	Med	High	Low-High	FF3 Low	Med	High	Low-High	FF5 Low	Med	High	Low-High
1	-0.451	-0.177	-0.020	-0.432	-0.514	-0.248	-0.119	-0.395	-0.275	-0.151	0.029	-0.304
	(-3.410)	(-1.471)	(-0.153)	(-2.382)	(-3.859)	(-2.068)	(-0.932)	(-2.150)	(-2.057)	(-1.229)	(0.221)	(-1.601)
5	0.259	0.219	0.108	0.152	0.413	0.248	0.142	0.271	0.145	0.174	0.163	-0.019
	(1.879)	(2.119)	(0.821)	(0.800)	(3.171)	(2.422)	(1.066)	(1.441)	(1.207)	(1.624)	(1.173)	(-0.103)
5-1	0.711	0.396	0.127	0.583	0.927	0.496	0.261	0.667	0.420	0.325	0.135	0.285
	(3.584)	(2.415)	(0.746)	(2.824)	(4.923)	(3.019)	(1.551)	(3.198)	(2.395)	(1.917)	(0.772)	(1.375)

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 (Panel A) 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 $t=1$ to $t=12$. 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 B reports results for standardized earnings surprise, SUE.

	Panel A: MOM12											
	CAPM				FF3				FF5			
Month	Low	Med	High	Low-High	Low	Med	High	Low-High	Low	Med	High	Low-High
0	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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)
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)

	Panel B: SUE											
	CAPM				FF3				FF5			
Month	Low	Med	High	Low-High	Low	Med	High	Low-High	Low	Med	High	Low-High
1	0.711	0.396	0.127	0.583	0.927	0.496	0.261	0.667	0.420	0.325	0.135	0.285
	(3.584)	(2.415)	(0.746)	(2.824)	(4.923)	(3.019)	(1.551)	(3.198)	(2.395)	(1.917)	(0.772)	(1.375)
2	0.575	0.102	0.010	0.565	0.811	0.207	0.088	0.723	0.368	0.095	-0.092	0.460
	(2.831)	(0.612)	(0.066)	(2.578)	(4.186)	(1.243)	(0.555)	(3.330)	(1.969)	(0.547)	(-0.574)	(2.052)
3	0.493	0.006	-0.135	0.628	0.724	0.099	-0.013	0.737	0.315	-0.015	-0.151	0.466
	(2.415)	(0.034)	(-0.917)	(2.846)	(3.713)	(0.600)	(-0.086)	(3.349)	(1.643)	(-0.086)	(-1.005)	(2.056)
4	0.535	0.283	-0.151	0.686	0.808	0.367	-0.040	0.848	0.455	0.350	-0.183	0.638
	(2.668)	(1.764)	(-1.019)	(3.095)	(4.306)	(2.276)	(-0.267)	(3.846)	(2.440)	(2.103)	(-1.203)	(2.786)
5	0.391	0.443	-0.346	0.737	0.675	0.567	-0.247	0.921	0.353	0.521	-0.394	0.747
	(1.894)	(2.785)	(-2.277)	(3.216)	(3.510)	(3.585)	(-1.627)	(4.062)	(1.832)	(3.182)	(-2.524)	(3.166)
6	0.363	0.516	-0.132	0.495	0.649	0.636	-0.031	0.681	0.330	0.529	-0.188	0.517
	(1.794)	(3.144)	(-0.803)	(2.030)	(3.482)	(3.893)	(-0.190)	(2.814)	(1.785)	(3.127)	(-1.111)	(2.053)
7	0.414	0.496	0.109	0.305	0.718	0.601	0.257	0.461	0.455	0.403	0.148	0.307
	(1.984)	(2.851)	(0.751)	(1.340)	(3.748)	(3.444)	(1.812)	(2.037)	(2.379)	(2.283)	(1.006)	(1.312)
8	0.320	0.279	0.269	0.051	0.601	0.399	0.441	0.160	0.273	0.299	0.242	0.031
	(1.550)	(1.597)	(1.750)	(0.219)	(3.128)	(2.293)	(2.980)	(0.684)	(1.448)	(1.660)	(1.598)	(0.128)
9	0.162	0.321	0.105	0.056	0.435	0.484	0.244	0.191	0.147	0.368	0.078	0.069
	(0.759)	(1.733)	(0.654)	(0.220)	(2.172)	(2.658)	(1.538)	(0.744)	(0.730)	(1.972)	(0.476)	(0.257)
10	0.074	0.137	0.318	-0.244	0.295	0.311	0.442	-0.147	-0.058	0.300	0.306	-0.364
	(0.347)	(0.779)	(1.974)	(-0.938)	(1.437)	(1.823)	(2.768)	(-0.563)	(-0.286)	(1.704)	(1.836)	(-1.350)
11	0.194	0.147	0.165	0.029	0.383	0.329	0.330	0.053	0.120	0.394	0.248	-0.128
	(1.018)	(0.852)	(0.994)	(0.125)	(2.066)	(1.964)	(2.040)	(0.225)	(0.639)	(2.282)	(1.463)	(-0.523)
12	0.251	0.106	0.130	0.121	0.430	0.281	0.259	0.171	0.099	0.374	0.124	-0.025
	(1.355)	(0.591)	(0.862)	(0.583)	(2.383)	(1.617)	(1.745)	(0.813)	(0.549)	(2.101)	(0.805)	(-0.113)

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. We also report the corresponding results for standardized earnings surprise, SUE.

	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	1.317	0.285	0.087	1.230	1.553	0.412	0.303	1.251	1.338	0.054	-0.023	1.360
	(3.371)	(0.911)	(0.320)	(3.669)	(4.053)	(1.305)	(1.127)	(3.716)	(3.354)	(0.165)	(-0.083)	(3.878)
MOM6	0.851	-0.204	-0.431	1.282	0.964	-0.186	-0.343	1.307	0.813	-0.409	-0.560	1.373
	(2.362)	(-0.718)	(-1.636)	(4.120)	(2.701)	(-0.644)	(-1.286)	(4.199)	(2.185)	(-1.361)	(-2.020)	(4.232)
MOM3	0.653	-0.277	-0.313	0.966	0.702	-0.242	-0.242	0.944	0.691	-0.410	-0.404	1.095
	(1.972)	(-1.078)	(-1.255)	(3.108)	(2.117)	(-0.925)	(-0.957)	(3.036)	(1.992)	(-1.505)	(-1.533)	(3.385)
SUE	0.768	0.382	0.104	0.664	0.970	0.514	0.201	0.769	0.492	0.368	0.072	0.420
	(3.637)	(2.131)	(0.597)	(2.819)	(4.771)	(2.889)	(1.149)	(3.257)	(2.537)	(1.994)	(0.395)	(1.773)

	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	1.337	0.876	0.204	1.133	1.497	0.967	0.397	1.101	1.083	0.533	0.055	1.028
	(3.624)	(2.889)	(0.668)	(3.339)	(4.069)	(3.147)	(1.297)	(3.234)	(2.862)	(1.705)	(0.173)	(2.898)
MOM6	1.042	0.345	-0.015	1.057	1.073	0.397	0.112	0.961	0.716	0.028	-0.039	0.755
	(3.046)	(1.245)	(-0.050)	(3.269)	(3.096)	(1.410)	(0.369)	(2.933)	(2.001)	(0.098)	(-0.122)	(2.211)
MOM3	0.837	0.069	0.012	0.825	0.868	0.109	0.140	0.728	0.686	-0.122	0.063	0.623
	(2.572)	(0.271)	(0.048)	(2.588)	(2.633)	(0.418)	(0.543)	(2.259)	(1.995)	(-0.453)	(0.233)	(1.852)
SUE	0.560	0.354	0.551	0.009	0.758	0.463	0.622	0.136	0.540	0.238	0.524	0.015
	(2.717)	(2.010)	(3.121)	(0.039)	(3.770)	(2.679)	(3.558)	(0.584)	(2.652)	(1.356)	(2.886)	(0.064)

TABLE 9: 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. We also report the corresponding results for standardized earnings surprise, SUE.

	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)
SUE	0.389	0.179	0.375	0.014	0.996	0.403	0.562	0.434	0.612	0.205	0.466	0.146
	(1.633)	(0.886)	(2.108)	(0.057)	(5.047)	(1.983)	(3.150)	(1.855)	(2.964)	(0.904)	(2.336)	(0.585)

	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)
SUE	0.943	0.571	-0.136	1.078	1.043	0.607	-0.024	1.067	0.567	0.498	-0.197	0.764
	(3.188)	(2.256)	(-0.469)	(3.391)	(3.627)	(2.378)	(-0.086)	(3.347)	(1.977)	(1.845)	(-0.662)	(2.311)

TABLE 10: **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. We also report the corresponding results for standardized earnings surprise, SUE.

	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)
SUE	0.605	0.365	0.169	0.436	0.806	0.478	0.293	0.513	0.377	0.326	0.171	0.206
	(2.961)	(2.157)	(1.004)	(2.029)	(3.972)	(2.752)	(1.712)	(2.317)	(2.102)	(1.862)	(0.986)	(0.957)

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.

TABLE 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.

Year	Sample			CRSP (Large Cap)			Percentage		
	#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

TABLE 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 either momentum with different look-back windows or standardized earnings surprise, SUE. LogComp is the natural log of competition. For momentum, LogComp is Log(COMPMOM) and for SUE, LogComp is Log(COMPSUE). LME is log of market equity, LBM is log of $(1 +$ book-to-market ratio), RET1 is month $t-1$ return, and PROF represents profitability measured by Gross Profits/Total Assets. We standardize all RHS variables to zero mean and unit variance.

	X = MOM12				X = MOM6				X = MOM3				X = SUE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Intercept	0.993	1.234	0.983	1.317	1.021	1.216	1.021	1.258	1.041	1.240	1.050	1.290	1.064	1.296	1.060	1.341
	(3.845)	(3.771)	(3.803)	(4.218)	(3.930)	(3.736)	(3.948)	(4.037)	(4.014)	(3.797)	(4.065)	(4.120)	(4.261)	(4.012)	(4.243)	(4.130)
X	0.305	0.396	0.282	0.337	0.166	0.223	0.064	0.103	0.100	0.134	0.028	0.056	0.140	0.190	0.136	0.184
	(2.241)	(3.330)	(2.138)	(2.806)	(1.222)	(1.883)	(0.511)	(0.893)	(0.757)	(1.191)	(0.239)	(0.530)	(3.600)	(6.200)	(3.626)	(6.040)
LogComp			0.165	0.154			0.104	0.095			0.062	0.057			0.021	0.037
			(1.955)	(1.940)			(1.215)	(1.222)			(0.709)	(0.733)			(0.526)	(1.119)
X * LogComp			-0.129	-0.119			-0.205	-0.194			-0.140	-0.139			-0.031	-0.046
			(-3.099)	(-3.001)			(-4.658)	(-4.621)			(-3.338)	(-3.553)			(-1.465)	(-2.215)
LME		-0.089		-0.188		-0.068		-0.130		-0.074		-0.132		-0.114		-0.150
		(-1.028)		(-2.147)		(-0.787)		(-1.499)		(-0.845)		(-1.540)		(-1.327)		(-1.705)
LBM		0.381		0.265		0.294		0.193		0.268		0.201		0.334		0.315
		(4.202)		(4.100)		(2.989)		(2.858)		(2.558)		(2.725)		(2.977)		(2.875)
RET1		-0.238		-0.267		-0.204		-0.241		-0.180		-0.213		-0.249		-0.254
		(-2.437)		(-2.878)		(-2.063)		(-2.551)		(-1.773)		(-2.214)		(-2.309)		(-2.384)
PROF		0.262		0.233		0.230		0.202		0.215		0.197		0.219		0.216
		(5.100)		(4.709)		(4.505)		(4.102)		(4.131)		(3.909)		(4.068)		(4.054)

TABLE 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. We also report the corresponding results for standardized earnings surprise, SUE.

	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)
SUE	0.660	0.360	0.153	0.506	0.852	0.457	0.286	0.566	0.358	0.307	0.186	0.172
	(3.330)	(2.155)	(0.858)	(2.306)	(4.466)	(2.729)	(1.622)	(2.544)	(1.990)	(1.772)	(1.014)	(0.770)

TABLE A4: **Residual Momentum and SUE**

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 residual momentum. The residual momentum is obtained at the end of month $t-1$ by regressing momentum (obtained from different look-back windows) on competition. 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. We also report the corresponding results for standardized earnings surprise, SUE.

	CAPM				FF3				FF5			
	Low	Med	High	Low-High	Low	Med	High	Low-High	Low	Med	High	Low-High
MOM12	1.451	0.863	0.199	1.252	1.590	0.892	0.387	1.202	1.186	0.326	-0.015	1.201
	(4.446)	(2.812)	(0.740)	(4.481)	(4.834)	(2.861)	(1.445)	(4.244)	(3.522)	(1.044)	(-0.056)	(4.078)
MOM6	1.132	0.412	-0.442	1.574	1.204	0.366	-0.355	1.559	0.924	-0.018	-0.561	1.486
	(3.634)	(1.444)	(-1.705)	(5.803)	(3.819)	(1.264)	(-1.350)	(5.668)	(2.836)	(-0.061)	(-2.055)	(5.205)
MOM3	0.713	-0.011	-0.417	1.130	0.780	-0.042	-0.325	1.105	0.613	-0.253	-0.421	1.034
	(2.326)	(-0.045)	(-1.681)	(3.984)	(2.511)	(-0.168)	(-1.295)	(3.844)	(1.891)	(-0.985)	(-1.604)	(3.451)
SUE	0.655	0.424	0.106	0.550	0.843	0.529	0.235	0.608	0.353	0.371	0.111	0.242
	(3.299)	(2.609)	(0.621)	(2.578)	(4.421)	(3.259)	(1.398)	(2.821)	(1.972)	(2.207)	(0.636)	(1.120)

TABLE A5: Competition and Alpha: Size X 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. We also report the corresponding results for standardized earnings surprise, SUE.

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	0.785	0.057	-0.393	1.178	0.961	0.191	-0.232	1.192	0.800	-0.186	-0.753	1.552
	(2.254)	(0.165)	(-1.337)	(3.370)	(2.667)	(0.539)	(-0.760)	(3.319)	(1.977)	(-0.478)	(-2.311)	(3.902)
MOM6	0.439	-0.499	-0.775	1.214	0.479	-0.408	-0.731	1.210	0.269	-0.666	-0.805	1.074
	(1.330)	(-1.562)	(-2.960)	(4.047)	(1.385)	(-1.249)	(-2.687)	(3.916)	(0.695)	(-1.827)	(-2.669)	(3.105)
MOM3	0.389	-0.163	-0.639	1.028	0.422	-0.090	-0.548	0.971	0.213	-0.373	-0.825	1.038
	(1.218)	(-0.535)	(-2.311)	(3.473)	(1.266)	(-0.281)	(-1.914)	(3.226)	(0.569)	(-1.053)	(-2.590)	(3.072)
SUE	0.404	0.115	0.296	0.108	0.927	0.309	0.461	0.466	0.614	0.232	0.334	0.280
	(1.625)	(0.500)	(1.567)	(0.406)	(4.136)	(1.314)	(2.400)	(1.756)	(2.535)	(0.878)	(1.555)	(0.961)

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	1.782	0.422	0.455	1.326	1.902	0.441	0.567	1.335	1.604	0.146	0.375	1.229
	(2.570)	(0.828)	(1.047)	(2.329)	(2.831)	(0.867)	(1.340)	(2.342)	(2.269)	(0.272)	(0.841)	(2.058)
MOM6	1.191	0.033	-0.176	1.367	1.194	-0.059	-0.169	1.363	1.091	-0.214	-0.355	1.446
	(1.882)	(0.071)	(-0.396)	(2.510)	(1.938)	(-0.128)	(-0.383)	(2.514)	(1.677)	(-0.438)	(-0.760)	(2.551)
MOM3	0.848	-0.452	-0.065	0.913	0.806	-0.494	-0.067	0.873	1.052	-0.519	-0.042	1.094
	(1.479)	(-1.111)	(-0.162)	(1.672)	(1.422)	(-1.214)	(-0.164)	(1.600)	(1.768)	(-1.200)	(-0.098)	(1.919)
SUE	1.052	0.604	-0.106	1.158	1.158	0.672	-0.046	1.204	0.632	0.527	-0.174	0.807
	(3.228)	(2.238)	(-0.364)	(3.057)	(3.631)	(2.510)	(-0.159)	(3.189)	(1.992)	(1.868)	(-0.564)	(2.066)

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	1.282	0.570	0.282	1.000	1.729	0.608	0.451	1.278	1.239	0.197	-0.129	1.368
	(3.462)	(1.899)	(0.947)	(2.966)	(4.655)	(1.932)	(1.455)	(3.698)	(3.016)	(0.572)	(-0.387)	(3.534)
MOM6	0.775	-0.198	-0.049	0.824	1.083	-0.155	0.065	1.017	0.818	-0.296	-0.107	0.925
	(2.201)	(-0.715)	(-0.183)	(2.242)	(2.995)	(-0.537)	(0.232)	(2.664)	(2.023)	(-0.923)	(-0.339)	(2.164)
MOM3	0.713	-0.177	-0.059	0.772	0.977	-0.019	0.118	0.859	0.626	-0.175	-0.019	0.645
	(1.961)	(-0.650)	(-0.230)	(2.370)	(2.598)	(-0.069)	(0.444)	(2.517)	(1.493)	(-0.558)	(-0.064)	(1.686)
SUE	0.816	0.451	1.042	-0.227	1.399	0.662	1.184	0.215	0.982	0.436	1.084	-0.102
	(2.899)	(2.194)	(5.207)	(-0.747)	(5.455)	(3.221)	(5.742)	(0.722)	(3.565)	(1.909)	(4.716)	(-0.318)

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	1.300	1.088	0.042	1.258	1.277	1.128	0.181	1.096	1.006	0.720	-0.088	1.094
	(2.076)	(2.123)	(0.080)	(2.136)	(2.052)	(2.181)	(0.349)	(1.883)	(1.539)	(1.337)	(-0.161)	(1.806)
MOM6	1.228	0.790	-0.040	1.268	1.122	0.766	0.016	1.106	0.880	0.414	-0.111	0.991
	(2.126)	(1.707)	(-0.075)	(2.383)	(1.938)	(1.643)	(0.029)	(2.089)	(1.443)	(0.848)	(-0.197)	(1.796)
MOM3	0.899	0.244	0.031	0.868	0.800	0.216	0.088	0.712	0.891	0.158	0.127	0.764
	(1.681)	(0.575)	(0.071)	(1.583)	(1.497)	(0.503)	(0.200)	(1.303)	(1.578)	(0.349)	(0.274)	(1.330)
SUE	0.267	0.203	0.054	0.213	0.357	0.277	0.135	0.223	0.279	0.101	0.044	0.235
	(0.903)	(0.736)	(0.190)	(0.604)	(1.215)	(1.020)	(0.482)	(0.627)	(0.895)	(0.359)	(0.151)	(0.624)

TABLE A6: **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. We also report the corresponding results for standardized earnings surprise, SUE.

	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)
SUE	0.546	0.350	0.411	0.135	0.642	0.555	0.604	0.039	0.484	0.388	0.267	0.217
	(3.698)	(2.009)	(2.375)	(0.789)	(4.457)	(3.340)	(3.661)	(0.226)	(3.284)	(2.296)	(1.659)	(1.228)

TABLE A7: **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. We also report the corresponding results for standardized earnings surprise, SUE.

	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)
SUE	0.664	0.367	0.177	0.487	0.877	0.497	0.270	0.607	0.393	0.363	0.127	0.266
	(3.308)	(2.211)	(1.052)	(2.295)	(4.579)	(3.023)	(1.614)	(2.854)	(2.176)	(2.125)	(0.731)	(1.241)