Norwegian School of Economics
Bergen, Fall 2015

The Effect of Arbitrage Activity in Beta and Momentum Strategies on Abnormal Trading Profits

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Master Thesis within the main profile of International Business

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

The purpose of this thesis is to investigate the effect of arbitrage activity on abnormal trading profits based on the new measures of arbitrage proposed by Lou and Polk (2013) and Huang, Lou and Polk (2014), called Comom and Cobar, respectively. First, I replicate the process of Comom and Cobar construction and conduct an additional analysis of their specifications. I also create a combined measure Comom/Cobar that measures arbitrage in both strategies simultaneously. Second, I examine patterns of abnormal returns in momentum and beta strategy conditional on the computed arbitrage measures. The study is conducted over the period January 1970 – December 2011.

The results of this paper indicate that such parameters as asset-pricing model and inclusion of stocks below $5 into the sample do not affect the time series of the arbitrage measures, whereas the choice of decile may significantly change the outcome. Consequently, I suggest using the lowest decile for Comom and Cobar computation to avoid unrelated return comovements that may arise in the highest deciles. I also find that Cobar and Comom cannot substitute each other when used for abnormal return evaluation. After estimating abnormal returns through constructed measures, I find that the effect of arbitrage activity does not create common patterns in abnormal returns across beta and momentum strategies but rather produces specific price reactions in each strategy.

Acknowledgments

I would like to express my deepest gratitude to my advisor, Francisco Santos, for helping me to find an interesting topic and being available and supportive at all times during the writing process. I highly appreciate his professional and detailed guidance, caring, and patience. Without his support, it would not be possible to conduct this research study. I would also like to thank Stein Fossen for providing me an access to the data that I use in this study. In addition, I would like to thank NHH IT Support for helping me with the software, which played a crucial role in this work.

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Introduction

Arbitrage is an essential force in financial markets that allows establishing the value of many financial instruments. However, the role of arbitrageurs[1] has not been well understood. That provoked long-standing debates concerning the impact of arbitrageurs on asset prices. The question whether arbitrage activity stabilizes or destabilizes prices was first raised as early as 1930-s by Keynes (1936) and later by Hayek (1945). One view based on standard asset pricing models suggests that arbitrageurs might be the only force that ensures market efficiency, and, therefore, have stabilizing effect on prices (Friedman, 1953). According to an opposing view, institutions destabilize stock prices, pushing them far from fundamentals (Stein, 1987; De Long, Shleifer, Summers, and Waldmann, 1990). For example, Stein (1987) demonstrates that "introducing a new group of speculators into the spot market for a commodity can destabilize prices" (p. 1124). A more neutral approach suggests that institutional investors being heterogeneous pursue different portfolio strategies that ultimately offset each other, and, hence, neither stabilize nor destabilize prices (Lakonishok, Shleifer, & Vishny, 1992).

In order to investigate the impact of arbitrageurs on prices, it is necessary to measure arbitrage activity. However, it is very difficult to do. Traditional methods based on the estimation of *inputs* to the arbitrage process for a defined *subset of* arbitrageurs require information substantial part of which is unavailable or very hard to obtain (Lou & Polk, 2013).

Lou and Polk (2013) proposed a new method to measure arbitrage activity. Instead of using inputs to estimate arbitrage, they focused on the *outcome* of the arbitrage process. The idea is that arbitrageurs tend to buy or sell a portfolio of stocks at the same time. That induces high-frequency (i.e., daily or weekly) return correlation among the stocks that are traded (Lou & Polk, 2013). The new measure captures this return correlation and provides the information whether arbitrage activity is high or low.

Lou and Polk (2013) and Huang et al. (2014) use their novel measures of arbitrage activity to provide new evidence on the long-lasting debate regarding the effect of arbitrageurs on prices.

[1] Arbitrageur is a type of investor who attempts to profit from price inefficiencies in the market. “Arbitrageur”, “speculator”, and “investor” used interchangeably in this paper.

Lou and Polk (2013) first applied their insight to measure the effect of arbitrage activity on stock prices in momentum strategy (i.e., long the value-weight winner decile and short the value-weight loser decile). They called their measure *Comomentum* (in this paper referred as *Comom)*, which is defined as the high-frequency abnormal return correlation among stocks on which a momentum strategy speculate. In other words, high (low) value of Comom indicates high (low) activity in momentum strategy. To construct Comom, at the end of each month, the authors sort all stocks that are above $5 into deciles based on the previous 12-month return. Then they use 52 weekly stock returns to compute the average correlation of the residual from the three-factor model of every stock in the lowest momentum decile with the rest of the stocks in the same decile. As a result, they get Comom values for every month from 1964 to 2010. Lou and Polk (2013) found that during periods of low Comom, momentum strategies are profitable and stabilizing, reflecting an underreaction phenomenon that arbitrageurs correct; in contrast, during periods of high Comom, these strategies tend to crash and revert, reflecting prior overreaction resulting from crowded momentum trading.

Huang et al. (2014) use the measure of arbitrage activity introduced by Lou and Polk (2013) to obtain a measure of the excess comovement of stocks in beta strategy (i.e., long the lowest value-weight decile and short the highest value-weight decile) that was called *Cobar*. High (low) value of Cobar indicates high (low) arbitrage activity in beta strategy. To construct Cobar, Huang et al. (2014) sort all stocks into deciles based on their pre-ranking market betas. To calculate these betas the authors use daily returns in the past twelve months. Then they measure the average correlation of the three-factor residual of every stock in the lowest beta decile with the rest of the stocks in the same decile. As a result, the authors get monthly Cobar values for the period 1965 – 2010. The main finding of Huang et al. (2014) related to Cobar has been that "when beta-arbitrage activity is low, the returns to beta-arbitrage strategies exhibit significant delayed correction. In contrast, when beta-arbitrage activity is high, the returns to beta-arbitrage activities reflect strong over-correction due to crowded arbitrage trading" (Huang et al., 2014).

In this paper, I want to investigate the effect of arbitrage activity in momentum and beta-arbitrage strategies on abnormal returns in these strategies by means of newly introduced Comom and Cobar measures. In order to do that, I also want to examine different specifications of the new measures. Thus, the research question of this paper is:

How does the arbitrage activity in momentum and beta-arbitrage strategies affect abnormal returns in these strategies?

Consequently, the focus of this paper is two-fold. First, I replicate the arbitrage measures, proposed by Lou and Polk (2013) and Huang et al. (2014) and explore additional specifications of these measures. Second, I investigate the effect of arbitrage in beta and momentum strategies on the stock prices using arbitrage measures mentioned above.

The first part of the paper is dedicated to the analysis of the arbitrage activity measures. Following the approach of Lou and Polk (2013) and Huang et al. (2014) I replicate Comom and Cobar measures. In an attempt to add value to the findings, I try to expand upon some of Lou and Polk (2013) and Huang et al. (2014) work by conducting an analysis of additional specifications of arbitrage measures, such as, asset-pricing model for residual computation (the Fama-French Three-factor model vs. the Six-factor model), decile (the lowest decile vs. the highest decile), and stocks below $5 (inclusion vs. exclusion from the dataset).

By changing the original specifications of Comom proposed by Lou and Polk (2013), I found that: First, the asset-pricing model, used for getting residuals should not affect the Comom time-series. I conducted correlation analysis between Comoms based on the three-factor and the six-factor models. Two measures showed the strong correlation of 0.841 with associated p-value <.0001. Hence, there is no need to adjust the model for additional risk factors. Second, Comom based on decile 1 has moderate correlation of 0.473 with Comom built on decile 10. The difference between two specifications means that later they will produce different results regarding the effect of arbitrage on abnormal returns. I suggest computing Comom using decile 1 because it captures the main effects on the stock prices in momentum strategy while decile 10 may display the comovements in the stock prices unrelated to the investigated strategy. Third, exclusion of penny stocks (stocks below $5) from the sample for Comom computation causes insignificant changes in time-series of Comom. Comom based on the sample that includes stocks below $5 has a strong correlation of 0.865 with associated p-value <.0001 with Comom based on the sample that excludes them. Therefore, it is not necessary to exclude penny stocks from the sample.

I got very similar results for Cobar measure. Cobar based on the three-factor model and Cobar based on the six-factor model are highly correlated with correlation coefficient equal to 0.928 with *p*-value <.0001. Thus, it is not necessary to adjust the model for additional risk factors. Cobar based on decile 1 turned to have no significant correlation with Cobar build on decile 10. Therefore, Cobar should be computed based on the lowest beta decile. Similar to Comom, Cobar based on the sample that includes penny stocks strongly correlates with Cobar based on the sample without these stocks. Hence, the step of penny stock exclusion can be eliminated from the process of Cobar computation.

In the second part of the paper, I explore the effect of arbitrage activity on abnormal returns in beta and momentum strategies using Cobar and Comom measures. I observe and compare abnormal returns obtained through the Fama-French three-factor model, the Carhart four-factor, the five- and the six-factor models, but the main results and conclusions are based on the four-factor model, following the approach of the original papers. The results indicate that when Comom is low, momentum strategies are profitable and stabilizing. This is in line with the findings of Lou and Polk (2013). However, my results do not provide the evidence that during periods of high Comom momentum strategies are destabilizing and tend to crash and revert, observed by Lou and Polk (2013). I found that during high Comom returns are realized in the long run appearing only in the third year after portfolio formation and equal 1.01% with associated *t*-statistic of 8.14.

Regarding the influence of arbitrage in beta strategy on abnormal returns in the same strategy, I found that during low Cobar abnormal returns are significantly positive through all holding periods after the six months increasing by the third year. In contrast, during high Cobar four-factor alphas are close to zero during two years after portfolio formation and get significantly negative in year 3.

A potential source of differences between the findings of the authors and my results could be the difference in the dataset used for the study. I did not have an access to the information about institutional ownership in individual stocks, assets under management of long-short equity hedge funds and assets of the shadow-banking sector and, therefore, could not include them into my work. Furthermore, lack of detailed information regarding the sample construction process in the main articles gives some room for interpretation of the construction process and, therefore, can cause the differences in the findings.

The major input of this study is combining Comom and Cobar measures for further investigation of the effect of arbitrage on stock prices. I do it in two ways. First, I explore behavior of abnormal returns in *beta strategy* during high and low *Comom*. I found that when Comom is low the beta-arbitrage strategy shows no significant positive returns both in the short (within the first holding year) and in the long run (after year 1). However, when Comom is high, abnormal returns appear in the second and the third year after portfolio formation and are equal to 0.70% with t-statistic 4.95 and 0.61% with t-statistic 4.39, respectively. These patterns of returns are different from the patterns observed during high and low Cobar in the same strategy meaning that Comom and Cobar do not serve as substitutes for each other.

Second, I construct a combined measure based on Cobar and Comom that shows the simultaneous arbitrage activity in beta and momentum strategies. I found that the four-factor abnormal returns in beta strategy appear neither in the lowest nor in the highest Comom/Cobar group. Abnormal returns in momentum strategy are close to zero when Comom/Cobar is low in all periods, but when Comom/Cobar is high, significant positive returns occur in the third year after portfolio formation and equal 0.96% per month with *t*-statistic 5.45.

Overall, the results of this paper indicate that arbitrage activity generates different price reactions in beta and momentum strategies and, therefore, does not create a common pattern in abnormal returns across these strategies.

This paper is organized as follows. Chapter 1 provides a review of literature related to the discussed topic. Chapter 2 introduces the details on Cobar and Comom measures. Chapter 3 describes portfolio construction process. Chapter 4 is dedicated to portfolio return analysis. Chapter 5 presents limitations and suggestions for further research. Chapter 6 concludes the results of this study.

1. Literature Review

1.1 Arbitrage

In the traditional finance paradigm, arbitrage opportunities cannot exist in a competitive market because they would be instantly exploited and consequently eliminated by arbitrageurs. This is valid for riskless arbitrage opportunities, however does not hold for risky arbitrage that requires capital. Such constraints as, for example, solvency requirements, limited capital or leverage targets impose limits on arbitrageurs' ability to benefit from risky arbitrage opportunities. Therefore, the trading activity of arbitrageurs will not be sufficient to close the arbitrage opportunities but will affect the equilibrium (Hugonnier & Prieto, 2015).

Measurement of arbitrage activity is an extremely difficult task. First, it is not possible to know the exact composition of arbitrageurs in financial markets. Second, for a significant fraction of institutional investors accurate high-frequency data on capital under management is unavailable. Third, information about such activities as leverage, short selling, and derivatives contracts that are widely used by arbitrageurs is also unavailable. Finally, the effect of arbitrage activity on prices depends critically on the liquidity of the assets traded, which may be exposed to cross-sectional and time variations. Therefore, the main problem is that there is no proper measurement of the inputs to the arbitrage process for a subset of arbitrageurs (Lou & Polk, 2013).

Lou and Polk (2013) proposed a proxy that measures the outcome of the arbitrage process, that is, the past degree of abnormal return correlations among those stocks that an arbitrageur would trade. Two measures of momentum and beta-arbitrage activity, Comom and Cobar, have been introduced as a result of the new approach. I will explain more in detail and describe the exact methodology of original Cobar and Comom in chapter 2.

1.2 Factor-based Investing

Momentum and beta strategy represent factor-based investing, that has currently become a widely discussed topic in investment world; nevertheless, the related concepts have a long history in financial economics. For example, the benefits of value investing (another type of factor-based investing) have been known since the 1930-s, first introduced by Graham and Dodd (1934).

Factors are the underlying exposures relating a group of securities that explain an investment's risk and return. Factor investing strategy is an investing that integrates factor exposure decisions into the portfolio construction process (Pappas & Dickson, 2015). While originally this type of strategies was based on a weighting by a single factor such as value, momentum, high dividends or low volatility, as the theory evolved portfolio managers have increasingly developed strategies based on combination of factors (Pielichata, 2015). That gives me an additional motivation to explore abnormal trading profits when investors are active in both momentum and beta strategies.

1.3 Momentum Strategy

Momentum strategy first documented by Jegadeesh and Titman (1993) is an investment strategy that aims to capitalize on the continuance of existing trends in the market, that is, on the fact that past losers tend to be future losers and past winners tend to be future winners.

Momentum appears due to the biased way investors interpret or act on information. Daniel et al. (2001) argue that investors are overconfident about private information and, as a result, overreact to private signals and push prices too far from fundamentals, generating momentum. Hong and Stein (1999) assume that the slow diffusion of information into prices triggers underreaction and thereby have similar price impact.

Other theories suggest the imperfect information available to all investors and imperfect market structure act as a ground for the momentum strategy. Imperfect information induced by the agency problem refers to strong incentives for management to promote good news and hide bad news. While being able to arbitrage good news, the vast majority are unable to exploit bad news due to short-selling constraints what is, in practice, an imperfect market structure (Mainie, 2015).

Despite the popularity of momentum strategies in the investment community the effect still persist. Momentum trading strategies that exploit this phenomenon have been consistently profitable not only in the United States but also in many major markets throughout the world (Jegadeesh & Titman, Momentum. Working paper, 2001).

Momentum is an example of a strategy without a fundamental anchor meaning that arbitrageurs do not base their demand on an independent estimate of fundamental value but use lagged asset returns to base their decisions on (Stein, 2009). This unanchored positive-feedback trading (buying past winners and selling past losers) is associated with the fact of destabilizing effect of arbitrage activity on stock prices (Stein, 2009). According to Stein (2009), inability of arbitrageurs to infer the amount of arbitrage capital already deployed creates a coordination problem: simply by observing past stock returns, individual arbitrageurs cannot distinguish whether the price correctly reflects the fundamental value or there is underreaction among arbitrageurs that allows exploiting the opportunity. Thus, the main empirical prediction of Lou and Polk (2013) in their study is that the underreaction or overreaction characteristic of momentum, that is, whether momentum profits revert in the long run, varies through time, crucially depending on the size of the momentum crowd. The same idea of destabilizing effect during excessive arbitrage activity is investigated by Huang et al. (2014).

1.4 Beta Strategy

The basic premise of beta arbitrage strategy is that the market overestimates high beta stocks and underestimates low beta stocks offering a long-short arbitrage opportunity along the theoretical risk-return axis of the CAPM's security market line (SML). This opportunity can be exploited by taking a long position in low beta stocks and shorting high-beta stocks.

The Capital Asset Pricing Model (CAPM) of William Sharpe (1964) and John Lintner (1965) suggests that the expected return on any stock is linearly proportional to its market beta. However since early 1970-s, by Black (1972), Black, Jensen, and Scholes (1972), and Haugen and Heins (1975) it was documented that the relation between beta and return is much flatter than CAPM model predicts. Initially tests of the CAPM were conducted for the U.S. equity market. Fama and French (1992) provided evidence that the relation between beta and U.S. stock returns is flat over the period 1963–1990, especially after correcting for size factor. More support for a flat, or even negative, relation between risk and return can be found in the works of Black (1993), Haugen and Baker (1991, 1996), Falkenstein (1994), and Baker, Bradley and Wurgler (2011) who observed similar or longer sample periods.

Later empirical tests in many international equity markets revealed the same phenomenon. The research of Blitz and van Vliet (2007) shows that the relation between risk and return is negative not only in the U.S., but also in the European and Japanese equity markets over the period 1986-

2006. Frazzini and Pedersen (2014) confirmed the same idea with their study of 20 international markets over 1984 to 2012. They also showed that a strategy of betting against beta has delivered positive returns both as an industry-neutral bet within each industry and as a pure bet across industries. Therefore, empirical evidence of the outperformance of low volatility portfolios driven by its market beta is robust across time-periods and geographies.

A study of Baker et al. (2011) attributed beta anomaly to the fact that many institutional investors face fixed-benchmark mandate that discourage investments in low-volatility stocks. Typical institutional investors overweight high-beta stocks and underweight low-beta stocks due to an implicit or explicit mandate to maximize the “information ratio” relative to a specific benchmark, as a result, bidding up high beta stocks and pushing down low-beta stocks.

Black (1972) and Frazzini and Pedersen (2014) suggested another explanation for the efficacy of low-beta investing based on leverage constraints: low-risk investing may have been not “arbitraged” away over many decades because investors face constraints and because betting against this phenomenon involves risk.

1.5 Return Comovements

The novel measures of arbitrage activity introduced by Lou and Polk (2013) and Huang et al. (2014) are grounded on the idea of return comovements. Barberis, Shleifer and Wurgler (2005) argue that return comovements can be explained not only by correlations in news about the fundamental value of securities as traditional model suggests, but also by correlated investor demand shifts for securities. In particular, Barberis et al. (2005) propose two alternative models of return comovements in addition to the traditional model. One is “Category-based” comovement, which occurs when investors classify different securities into the same asset class and trade them in correlated ways. Another one is “Habitat-based" comovement that arises when a group of investors trade a restricted set of securities in tandem (Barberis, Shleifer, & Wurgler, 2005). Thus, Barberis et al. (2005) show that an asset price may depend not only on its fundamentals, but also on such factors as asset categories a security belongs to and categories that investors trade. In other words, price comovements can be also induced by arbitrage activity. That, in turn, provides evidence that arbitrage indeed can be measured through price comovements.

2. Comom and Cobar

This chapter is dedicated to replication of Cobar and Comom measures and analysis of their different specifications. First, I will describe the original Comom and Cobar and the main findings obtained by Lou and Polk (2013) and Huang et al. (2014) through these measures. Then I will present the original data and methodology of Cobar and Comom construction. After these sections, I will move to description of the process conducted in this paper. I will briefly discuss the regression models and the statistical software that I use. Then I will describe in detail the process of Comom and Cobar construction undertaken in this paper and the changes that I implement to obtain different Comom and Cobar specifications. The subsequent section will provide the empirical analysis of Cobar and Comom specifications and their influence on the result. The last section summarizes the results of this chapter.

2.1 Comom Description

Lou and Polk (2013) introduced a new method to measure arbitrage activity based on the observation that arbitrageurs tend to buy or sell a diversified portfolio of stocks at the same time. That induces high-frequency (i.e., daily or weekly) price comovements among the stocks that are traded. In the case of momentum strategy, arbitrageurs usually buy a portfolio of winner stocks and sell a portfolio of loser stocks simultaneously. To the extent that arbitrageurs' trading can move stock prices in the short run, it is possible to infer the amount of arbitrage capital deployed in a strategy by examining the high-frequency return correlation among the portfolio of stocks that are likely to be bought or sold simultaneously by arbitrageurs. The price correlation among momentum stocks is high during the periods of high arbitrage activity in the momentum strategy and low when there is little activity in corresponding strategy. Therefore, Comom measure shows the degree of arbitrage activity in momentum stocks (Lou & Polk, 2013). Comom allows identifying the periods of active or little speculation on stocks in momentum strategy and examining the effect of arbitrageurs' activity on abnormal returns in these periods.

2.2 Data and Methodology of original Comom construction

Lou and Polk (2013) provide the following details on the construction of Comom. The dataset used in their study is the stock return data from the Center for Research in Security Prices

(CRSP). They augment this data with institutional ownership in individual stocks provided by Thompson Financial, assets under management of long-short equity hedge funds from Lipper.s Trading Advisor Selection System (TASS), and total assets of the shadow-banking sector from the Federal Reserve Board. They also use monthly returns of actively managed equity mutual funds and long-short equity hedge funds from the CRSP survivorship-bias free mutual fund database and the Lipper TASS database, respectively.

At the end of each month, the authors sort all stocks into deciles based on their previous 12-month return skipping the most recent month. They take the stocks from the loser and winner deciles and compute for them pair wise partial correlations using 52 weekly returns in each decile in the portfolio-ranking period[2]. To be more specific, the authors measure the average correlation of the three-factor residual of every stock in the winner (loser) decile with the rest of the winner (loser) decile. Their formula looks as follows:

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

$$Comom^{W} = \frac{1}{N^{W}} \sum_{i=1}^{N^{W}} partialCorr(retrf_i^{W}, retrf_{-i}^{W} \, | mktrf, smb, hml),$$

where $retrf_i^L$ ($retrf_i^W$) is the weekly return of stock i in the extreme loser (winner) decile, $retrf_{-i}^L$ ($retrf_{-i}^W$) is the weekly return of the equal-weight extreme loser (winner) decile excluding stock i, and N^L (N^W) is the number of stocks in the loser (winner) decile.

To put it in other words, they compute 52 weekly returns for the equal-weight portfolio of all the stocks in the winner (loser) decile excluding stock i and for every individual stock i. Then the authors calculate three-factor residuals based on the obtained returns. In the end, they measure correlations of the residual of every stock in the winner (loser) decile with the rest of the stocks in the decile.

[2] Portfolio-ranking period here means the period when portfolios of stocks are constructed and ranked into the groups according to Comom or Cobar. The process of portfolio construction and ranking is described in Chapter 3.

As a result, Lou and Polk (2013) obtain 559 monthly values of Comom based on decile 1 and the same number of Comom based on decile 10, for the period January 1964 – July 2010.

2.3 Cobar Description

Cobar shows the degree of beta arbitrage activity. When arbitrageurs take long positions in low beta stocks and short positions in high beta stocks, such beta trades can have simultaneous, temporary price impacts on all beta stocks and thus cause return comovement among these stocks. Cobar allows identifying the periods of active or little speculation on stocks in beta strategy and examining the effect of arbitrageurs' activity on abnormal returns in beta strategy in these periods.

2.4 Data and Methodology of original Cobar construction

Huang et al. (2014) use the same dataset for Cobar construction as Lou and Polk (2013) for construction of Comom, that is, the stock returns from CRSP, stock return data about institutional ownership in individual stocks, assets under management of long-short equity hedge funds, and total assets of the shadow banking sector.

At the end of each month, the authors arrange all stocks into deciles based on pre-ranking market betas of these stocks. To find beta of each stock they use OLS regression. To account for illiquidity and non-synchronous trading Huang et al. (2014) include five lags of market excess returns on the right hand side of the OLS regression equation. The pre-ranking beta is the sum of the six coefficients from the OLS regression.

In their study of beta arbitrage, the authors work only with the lowest beta decile to measure the excess comovement of stocks involved in beta arbitrage. They compute the average correlation of the residual (using the Fama-French three-factor model) of every stock in the lowest beta decile with the rest of the stocks in the same decile. To compute residuals, they use 52 weekly returns for all stocks in the lowest decile in the portfolio-ranking period. The formula is:

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

where $retrf_i^L$ is the weekly return of stock i in the (L)owest beta decile, $retrf_{-i}^L$ is the weekly return of the equal-weight lowest beta decile excluding stock i, and N is the number of stocks in the lowest beta decile.

Consequently, Huang et al. (2014) get 546 monthly values of Cobar based on decile 1 for the period January 1965 – June 2010.

2.5 Dataset

The stock return data used in this study was extracted from CRSP. Following the procedure of analysis completed by Lou and Polk (2013) and Huang et al. (2014) I include all companies listed on NYSE, Amex and NASDAQ from January 1970 to December 2011 (share code 11). However, I do not include institutional ownership in individual stocks, assets under equity of long-short equity hedge funds, and assets of the shadow banking sector due to lack of access to the sources of this information. The Fama-French three factors as well as profitability and investment factors I obtain from Kenneth R. French Data Library. The investigated period in this study constitutes 504 months and includes a total of 3604237 observations.

2.6 Regression Models

For arbitrage measure computation, I need the Fama–French three-factor model. In addition, I use the six-factor model to investigate the effect of a choice of an asset-pricing model on the Cobar and Comom values. For my further analysis of portfolios' abnormal returns, which will be presented in the next chapter, I use the Fama–French three-factor model, the Carhart four-factor model, the five-factor and the six-factor models. For this reason, in this section I will briefly discuss all regression models used in this study.

1) Fama-French Three-factor model

The Fama-French three-factor model is an empirical asset-pricing model. While standard asset pricing models work forward, by making assumptions about the relation between risk and expected return, empirical asset pricing models work backward taking as given the patterns in average returns and proposing models to capture them. The Fama-French Three-factor model is based on CAPM and designed to capture the anomalies relating to the CAPM, such as the outperformance of value and small cap stocks (Fama & French, A Five-Factor Asset Pricing Model. Working paper, 2013). The regression model is:

$$R_i - r_f = \alpha_i + \beta_i\left[R_m - r_f\right] + s_i SMB + h_i HML + e_i \ ,$$

where R_i is the expected return on security or portfolio i, r_f is the risk-free rate, R_m is the return on the value-weight market portfolio, α_i is the deviation from SML, and e_i is a zero-mean residual.

2) Carhart Four-factor model

The Carhart four-factor model is an extension of the Fama–French three-factor model that includes a momentum factor, which is referred as MOM. The idea of momentum is that the price of the assets is more likely to keep moving in the same direction than to change directions. The Carhart four-factor model is:

$$R_i - r_f = \alpha_i + \beta_i\left[R_m - r_f\right] + s_i SMB + h_i HML + p_i UMD + e_i \ ,$$

where p_i is the coefficient of momentum factor.

3) Five-factor model

Motivated by the evidence that three factors miss much of the variation in average returns related to profitability and investment, Fama and French (2015) add profitability and investment factors to the three-factor model:

$$R_i - r_f = \alpha_i + \beta_i\left[R_m - r_f\right] + s_i SMB + h_i HML + p_i UMD + r_i RMW + c_i CMA + e_i \ ,$$

where RMW is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, CMA is the difference between the returns on diversified portfolios of the stocks of low and high investment firms, called conservative and aggressive, r_i is the coefficient of profitability factor, and c_i is the coefficient of investment factor.

4) Six-factor model

The six-factor model includes momentum factor in addition to the five factors proposed by Fama and French (2015). The regression model is:

$$R_i - r_f = \alpha_i + \beta_i\left[R_m - r_f\right] + s_i SMB + h_i HML + p_i UMD + \ r_i RMW + c_i CMA + p_i UMD + e_i$$

2.7 Statistical Software

All the computations of arbitrage measures and portfolio returns are conducted in SAS 9.4. That required coding of every step of data construction and calculations. Since SAS allows processing data in many different ways, I will describe the methodology referring to the steps that I performed in SAS.

Saving information from CRSP for the whole period of 42 years takes a lot of time. As mentioned before, the whole dataset consists of 3604237 observations in total. Therefore, first, the most operations are conducted at WRDS server in order not save large sets of data on the PC. Second, the data for arbitrage measure construction is divided into seven periods to make the procedure easier for execution. In the end, all data is merged together.

2.8 Comom computation

In this section, I replicate the original Comom using the methodology of Lou and Polk (2013) and compute additional specifications of Comom for further analysis.

Before the beginning of actual computations, I have to prepare the necessary data in a way that it can be easily accessed during calculations in SAS. I create three files with Fama-French six factors: daily, weekly and monthly data. In addition, I make a file, which contains lagged time series. More specifically, there are six columns of dates in this file. The first column contains dates starting from 1970 until 2011. Five columns next to it have dates that are lagged for 13 months, 12 months, and 1 month. This file will be useful for extraction of the stocks' past returns.

Next step is to merge the file that contains lagged time series with data from CRSP that contains permanent numbers (PERMNOs) of all stocks in the database with HEXD equal to 1, 2 or 3 and share code 11. Thus, for all stocks I get contemporaneous dates (the dates of portfolio ranking) and lagged dates. Next, from all the obtained stocks, I keep only those, which are traded during at least ten months prior to portfolio-ranking period. Then I have to rank the stocks according to their returns. For every stock I need to get previous 12-months return skipping the last month. In

SAS, I do it by using lagged dates. First, I merge the monthly returns from CRSP with the existing file by PERMNOs and dates that lie between 13 months and 1 month before portfolio ranking period. Then I need to calculate 12-month return for each stock. In SAS in order to apply a multi-period return formula, I use an exponential function:

$$ret(12) = exp(\sum_{t=1}^{12} log(1 + ret_t)) - 1 \text{ ,}$$

where $ret(12)$ is 12-month return of stock *i* and ret_t is monthly return of stock *i* in month *t*.

Then I sort all the stocks into deciles according to their 12-month returns. I keep deciles 1 and 10 in order to build Comom based on these deciles. In addition, I keep decile 5 in order to compute additional specification of CoBAR. Further in this section, I will refer only to the lowest decile in order not to make description of the process more confusing. However, all the operations carried out for the lowest decile are also conducted for deciles 5 and 10.

The next step is to compute the average correlation of the three-factor residual of every stock in the lowest momentum decile with the rest of the stocks in the same decile excluding stock *i*. According to Lou and Polk (2013), these correlations are based on 52 weekly returns of all the stocks in each decile in the portfolio-ranking period. Thus, I extract from CRSP daily returns for all the stocks for the period that starts 13 months prior to the portfolio-ranking period and finishes 1 month before the portfolio-ranking period. Then I need to convert daily returns into weekly. Again, I have to use an exponential function:

$$ret_w = exp(\sum_{t=1}^{N} log(1 + ret_t)) - 1 \text{ ,} \qquad (1)$$

where ret_w is weekly return of a stock i, ret_t is daily return of stock i, and N is number of trading days in a week.

At this point, I have a file that contains portfolio-ranking dates, lagged dates, and weekly returns on every stock for the previous 12 months (skipping the last month prior to portfolio-ranking date). In order to compute residuals using the Fama-French three-factor model, I need to merge this file with weekly Fama-French factors, which I prepared beforehand.

When all the necessary data is gathered in one file, first, I calculate excess return for every stock by subtracting weekly risk free rate from weekly stock return. Second, next to the weekly returns of stock *i,* I calculate the return of portfolio of all stocks of the lowest decile excluding stock *i*. The procedure is as follows. By every week, I sum the excess return of all the stocks in the lowest decile. Then I subtract the excess return of stock *i* from the sum of the excess returns. The obtained value I divide by the number of observations in the portfolio, that is, N-1, meaning that N is the number of stocks in the lowest decile. The formula used is:

$$ExRet_{-i} = \frac{\sum_{i=1}^{n} ExRet_i - ExRet_i}{N-1},$$

where $ExRet_{-i}$ is the excess return of portfolio of all stocks in the lowest momentum decile excluding stock i, $ExRet_i$ is the excess return of stock *i,* N is the number of stocks in the lowest momentum decile.

Then I can compute residuals for stock *i* and for portfolio that excludes stock *i*. For this purpose, I use Fama-French three-factor model.

In addition to three-factor residuals proposed by Lou and Polk (2013), I compute six-factor residuals. I need this specification in order to explore the difference between measures that are constructed by means of different asset-pricing models. Therefore, I also use the six-factor regression model.

After three- and six-factor residuals are obtained, I measure the correlation of the three-factor residual of every stock in the decile 1 with the portfolio of all stocks in the lowest decile excluding stock *i.* I do the same for six-factor residuals. I compute Pearson correlation coefficient:

$$\mathrm{r_{xy}} = \frac{1}{\mathrm{n}-1}\sum\left(\frac{\mathrm{X}-\overline{\mathrm{X}}}{\mathrm{S_x}}\right)\left(\frac{\mathrm{Y}-\overline{\mathrm{Y}}}{\mathrm{S_y}}\right)$$

Finally, when all correlations are obtained, I compute Comom by getting the average of the correlations by months. As a result, I have 504 monthly values of Comom based on the lowest decile. In addition, I have 504 Comoms based on decile 5 and the same number of Comoms based on decile 10. I also have Comoms based on three- and six-factor model. In total, I get six types of Comom measure:

- Comom based on decile 1, three-factor model;

- Comom based on decile 5, three-factor model;
- Comom based on decile 10, three-factor model;
- Comom based on decile 1, six-factor model;
- Comom based on decile 5, six-factor model;
- Comom based on decile 10, six-factor model.

2.9 Cobar computation

Cobar construction process is very similar to Comom construction. The SAS code used for Cobar is almost the same as for Comom but with some necessary changes. Thus, the process of Cobar construction in this section will largely repeat the previous section.

I use the same files prepared before the process of Comom computation: the file with the Fama-French six factors and the file with lagged time-series.

I use the file with lagged time series, which I merge with data from CRSP that contains PERMNOs of all stocks with HEXD equal to 1, 2 or 3 and share code 11. Thus, for all stock I get contemporaneous dates (the dates of portfolio ranking) and lagged dates. As a result, I have a file with returns for all the stock that I am going to work with. In order to have a sufficient number of observations to obtain regression coefficients, which are required for beta calculation, I include only stocks with not less than 200 trading days in a year prior to portfolio-ranking period. Next, I get excess return for every stock by subtracting risk-free rate from the stock returns. When the data is ready, I move to the steps of Comom construction described in the main article.

According to by Huang et al. (2014), the first step in Cobar construction is to calculate pre-ranking betas using daily returns in the past twelve months. To compute betas I use OLS regression. Following the procedure in the main article, on the right hand side of the regression equation I include five lags of market excess returns. Therefore, the model looks as follows:

$$Excess\ return = \alpha + \beta mrkrf + \beta_1 mrkrf1 + \beta_2 mrkrf2 + \beta_3 mrkrf3 + \beta_4 mrkrf4 + \beta_5 mrkrf5\ ,$$

where $mrkrf$ is the contemporaneous market excess return, $mrkrf1$ is the one-day lagged market excess return, $mrkrf2$ is the two-day lagged market excess return, $mrkrf3$ is the three-day lagged market excess return, $mrkrf4$ is the four-day lagged market excess return, β is beta of the securities on contemporaneous market, and β_1, β_2, β_3, β_4 and β_5 are betas of the securities on lagged market.

The pre-ranking beta is a sum of six coefficients (betas) from OLS regression. After I get betas for each stock, I rank the stocks conditional on their betas. I keep decile 1 with stocks that have the lowest beta. Besides, I also keep decile 5 and 10 in order to compute additional specifications of Cobar. As in the previous section, I will describe all the process of Cobar computation based on decile 1. However, the same steps are also conducted for decile 5 and 10.

Now I will compute the average correlation of the three-factor residual of every stock in the lowest beta decile with the rest of the stocks in the same decile excluding stock *i*. According to Huang et al. (2014), I have to use 52 weekly returns of all the stocks in each decile in the portfolio-ranking period. CRSP does not provide weekly data; therefore, I extract daily returns for all the stocks for the period of 12 months before the portfolio-ranking period. I do not need to skip the last month as I had to in Comom section. Then I convert daily returns into weekly using exponential function (1).

Now I have a file that contains portfolio-ranking dates, lagged dates, and weekly returns of every stock for the previous 12 months. In order to compute residuals using the Fama-French three-factor model, I merge this file with weekly Fama-French six factors. Then I calculate excess return for every stock by subtracting weekly risk free rate from weekly stock return. Afterwards, I compute the return of portfolio that consists of all stocks in the lowest decile excluding stock i. The procedure is following: First, by every week, I sum the excess return of all the stocks in the lowest decile. Second, I subtract the excess return of stock i from the sum of the excess returns. The obtained value I divide by the number of observations in the portfolio, that is, N-1, meaning that N is the number of stocks in the lowest decile. The formula used is:

$$ExRet_{-i} = \frac{\sum_{i=1}^{n} ExRet_i - ExRet_i}{N-1},$$

where $ExRet_{-i}$ is the excess return of portfolio of all stocks in the lowest beta decile excluding stock i, $ExRet_i$ is the excess return of stock i, N is the number of stocks in the lowest beta decile.

Then I can compute three-factor residuals for stock *i* and for portfolio that excludes stock *i* following the procedure of Huang et al. (2014). Besides, I compute additional specification of Cobar based on six-factor model.

After residuals are obtained, I measure the correlation of the three-factor residual of stock *i* in the decile 1 with the portfolio of all stocks in the lowest decile excluding stock *i.* I do the same for six-factor residuals. I use Pearson correlation coefficient.

As a final point, I compute Comom by calculating the average of the obtained correlations by months. As a result, I get 504 Cobars in each of six specifications for every month of the period 1970-2011. The specifications are[3]:

- Cobar based on decile 1, three-factor model;
- Cobar based on decile 5, three-factor model;
- Cobar based on decile 10, three-factor model;
- Cobar based on decile 1, six-factor model;
- Cobar based on decile 5, six-factor model;
- Cobar based on decile 10, six-factor model.

2.10 Empirical Analysis of Comom and Cobar

In this section, I analyze how different specifications of arbitrage measures affect the time series of these measures. In three subsections, I will discuss the results for each specification. I will also present the simple statistic for the two measures.

2.10.1 Decile testing

I get three different specifications of Cobar and Comom based on decile 1, 5 and 10. I measure correlation between these specifications in order to conclude which of them produce similar results and are redundant for the further research. Decile 5 serves as a check: it reflects the moderate activity in arbitrage and, hence, is supposed to show low or no correlation with extreme deciles.

[3] Additional specification – formation period – of Comom and Cobar have been also computed but not included in this study.

Table 1 Panel A reports correlations between the Comom measures based on different deciles. Analysis of correlation between the specifications of Comom shows that there is moderate correlation (ρ=0.473, *p*-value<.0001) between decile 1 and 10 as opposed to strong correlation observed by Lou and Polk (2013) who found strong correlation. Furthermore, there is no evidence that decile 1 and decile 10 are more correlated with each other then with decile 5. There is also moderate though a bit weaker correlation between decile 1 and decile 5 equal to 0.323 with *p*-value<.0001, as well as moderate correlation between decile 10 and decile 5 equal to 0.399 and *p*-value<.0001. The obtained results suggest that decile 1 and 10 are not similar enough to be used as substitutes. Therefore, it is advisable to use Comom based on decile 1, because stocks in the highest momentum deciles can be subjected to the effects unrelated to long-short momentum strategy. The reason is that institutional investors generally tend to prefer momentum stocks from the highest decile, and this in turn can create additional price comovements in that decile.

Table 1 Panel B exhibits correlations between the Cobar measures based on different deciles. There is no significant correlation between Cobar based on decile 1 and decile 10 (ρ=0.045, *p*-value=0.316). In fact, there is relatively strong correlation of 0.552 between decile 5 and 10 with associated *p*-value of .0001. That means that two Cobars based on these two deciles are very different and will produce different result when used for further analysis of abnormal returns. Therefore, it is not possible to rely on Cobar constructed on the stocks in the lowest *or* highest portfolio. Therefore, it is better to compute Cobar based on decile 1. The explanation behind it can be that Cobar based on the highest decile capture the trend that is related not only to the long-short beta strategy but also to the more simple and widespread long-only strategy which is much easier to implement than a long-short strategy. The investor can simply go long on low volatility stocks and benefit from the higher Sharpe ratio than common equity indices. Further in this paper, I adhere the lowest decile for computing the arbitrage measures.

2.10.2 Asset-pricing model testing

I computed Comom and Cobar based on three- and six-factor model. Now I measure correlation between two specifications of each measure. Table 1 Panel C shows the results of correlation analysis for both Comom and Cobar.

I found that three- and six-factor model Cobars are strongly correlated (ρ=0.92787, *p*-value <.0001). The same is observed for two specifications of Comom (ρ=0.84061, *p*-value <.0001). It means that there is no need to adjust the three-factor model for computation of arbitrage measures for the other risk factors. In addition, I checked correlation between Comom and Cobar based on the same asset-pricing model. The results show that there is no correlation between two measures meaning that the periods of high (low) activity in momentum strategy do not correspond to high (low) activity in beta strategy. Consequently, two measures cannot be the substitutes for each other.

2.10.3 Stocks below $5 testing

I computed two specifications of Cobar and Comom. One is based on the sample that includes all the stocks and the other is based on the sample that excludes stocks below $5. Table 1 Panel D displays the results of correlation analysis for two specifications of Cobar and Comom. The correlation analysis shows that there is strong correlation between Comom based on the sample with stocks below $5 and Comom based on the sample without them equal to 0.86508 with associated *p*-value <.0001. Even stronger correlation is observed between two specifications of Cobar (ρ=0.92787, *p*-value <.0001). It means that an additional step of cheap stocks exclusion for Cobar and Comom computation is not necessary and both specifications of Cobar and Comom will show very similar trends.

Table 1: Correlation among specifications of Comom and Cobar

This table reports the time-series correlations among decile specifications of Comom and Cobar. At the end of each month, all momentum stocks are sorted into deciles based on their lagged-12-month cumulative returns (skipping the most recent month) and all beta stocks are sorted into deciles based on their lagged-12-month market beta computed using daily returns. Comom is computed as pair wise partial return correlations for all stocks in both the bottom momentum decile on weekly stock returns in the previous 12 months. Cobar is computed as pair wise partial return correlations for all stocks in the low beta decile based on weekly stock returns in the previous 12 months. Panel A reports time-series correlations among decile specifications of Comom. Panel B reports time-series correlations among decile specifications of Cobar. Panel C reports time-series correlations among asset-pricing model specifications of Comom and Cobar; *3f* is three-factor model, *6f* is six-factor model. Panel D reports time-series correlations among stocks below $5 specifications of Comom and Cobar. *P*-value is shown in parentheses.

Panel A: Comom

	Decile 1	Decile 5	Decile 10
Decile 1	1		
Decile 5	0.323 (<.0001)	1	
Decile 10	0.473 (<.0001)	0.399 (<.0001)	1

Panel B: Cobar

	Decile 1	Decile 5	Decile 10
Decile 1	1		
Decile 5	0.092 (0.039)	1	
Decile 10	0.045 (0.316)	0.552 (<.0001)	1

Panel C: Cobar & Comom

	3f model Cobar	6f model Cobar	3f model Comom	6f model Comom
3f model Cobar	1			–
6f model Cobar	0.92787 (<.0001)	1	–	
3f model Comom	0.02441 (0.5846)	–	1	
6f model Comom	–	0.06835 (0.1254)	0.84061 (<.0001)	1

Panel D: Cobar & Comom

	Cobar (without 5 $ stocks)	Comom (without 5 $ stocks)
Cobar (All stocks)	0.92787 (<.0001)	-
Comom (All stocks)	-	0.86508 (<.0001)

2.10.4 Summary statistics for Cobar and Comom

For further investigations I decide to use Cobar and Comom based on the three-factor model, decile 1, including stocks below $5. Table 2 provides simple characteristics of the arbitrage measures based on the chosen parameters. Figure 1 displays Cobar and Comom, based on the three-factor model and the lowest deciles of corresponding strategy.

The mean of Cobar is 0.109 what is actually very close to Cobar in the original paper, which is 0.108. The value varies from a low of 0.038 to a high of 0.301. This range is a bit bigger than in the study of Huang et al. (2014), where Cobar lies between 0.03 and 0.22.

As for Comom, the mean equals 0.104 and the range is from 0.015 to 0.291. In the original paper the mean is 0.118, the lowest value is 0.028 and the highest is 0.287. Overall, the obtained results are similar to the ones of Huang et al. (2014).

2.11 Intermediate Conclusion

The analysis of three specifications of Comom and Cobar showed that there is high correlation between Comoms based on the three- and the six-factor models, as well as high correlation between Comoms that include stocks below $5 and those that do not include them. Therefore, one can decide which specification to use for arbitrage measure construction as long as this decision will not change significantly the time series of Comom. The same applies for Cobar construction. However, decile used for Comom and Cobar computation should be carefully considered. Comoms based on top and bottom deciles are moderately correlated whereas Cobars based top and bottom deciles are not correlated at all. Therefore, two different specifications produce different time series of Comom and Cobar and, consequently, can affect the result when used for further analysis of abnormal returns. Thus, it is advisable to use only the lowest decile for Comom and Comom computation to avoid price comovements of the highest deciles, which can be subjected to effects unrelated to the investigated strategies. For further study I use Cobar and Comom based on the three-factor model, decile 1, including stocks below $5.

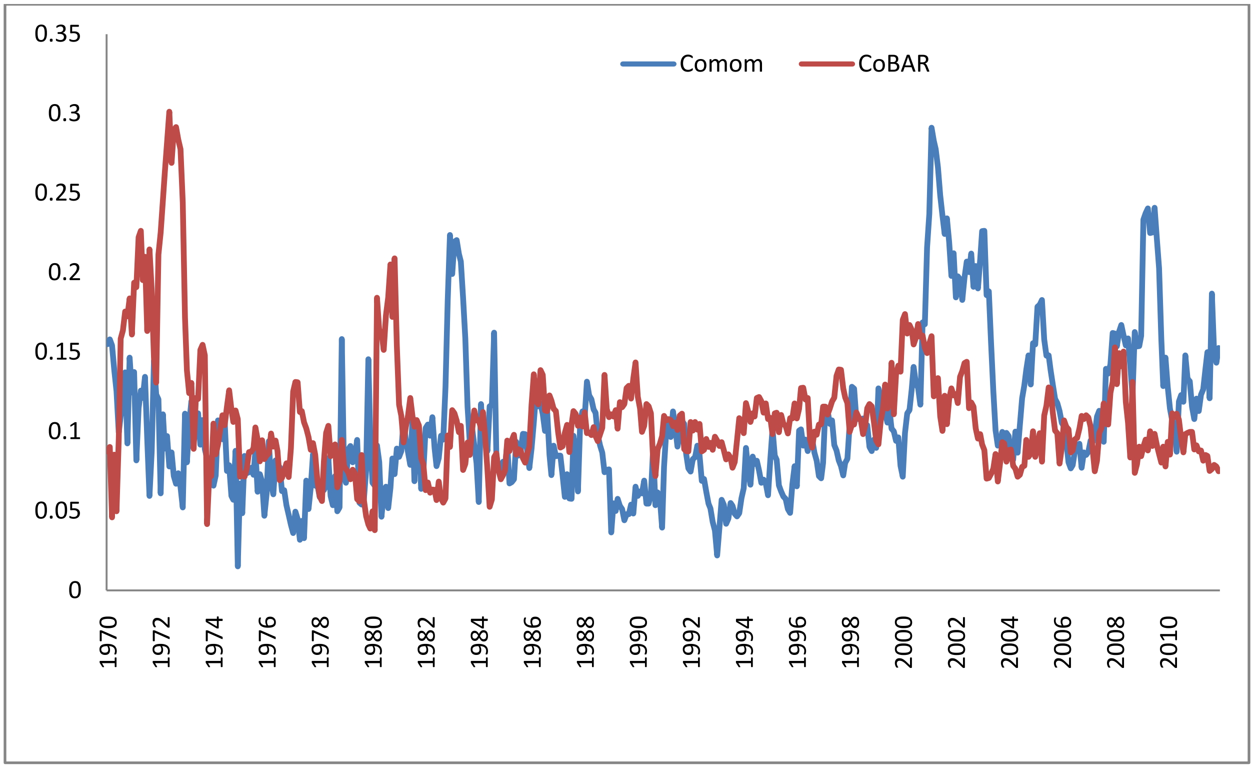
Table 2: Summary Statistics

This table provides the summary statistics of Comom and Cobar. Comom is the excess comovement of the momentum strategy over the period 1970-2011; Cobar is the excess comovement among low beta stocks over the period 1970-2011. To compute Comom, at the end of each month, all stocks are split into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Pair wise partial return correlations (after controlling for the Fama-French three factors) for all stocks in the bottom decile are computed based on weekly stock returns in the previous 12 months. To compute Cobar, at the end of each month, all stocks are split into deciles based on their lagged-12-month market beta computed using daily returns. Pair wise partial return correlations (after controlling for the Fama-French three factors) for all stocks in the low beta decile are computed based on weekly stock returns in the previous 12 months.

Summary Statistics					
Variable	N	Mean	Std. Dev.	Min	Max
Comom	504	0.104	0.047	0.015	0.291
Cobar	504	0.109	0.038	0.038	0.301

Figure 1: The time series of the Comom and Cobar

This figure shows the time series of the Comom and Cobar measures. Comom (shown in blue) is the average pair wise partial return correlation in the loser momentum decile measured in the ranking period. Cobar (shown in red) is the average pair wise partial return correlation in the lowest beta decile measured in the ranking period.



3. Portfolio Formation

In this chapter, I will provide details on portfolio construction. First, I will describe the original methodology of portfolio construction and the main results obtained by Lou and Polk (2013) and Huang et al. (2014). Then, I will present the procedure of portfolio construction explaining the main steps in SAS and the changes that I made in order to extend the original analysis.

3.1 Original portfolio construction and results

Lou and Polk (2013) use their constructed measure Comom to investigate abnormal returns in momentum strategy. More specifically, they look what happen with abnormal returns in momentum strategy when this strategy is crowded. For this purpose, they form a zero-cost portfolio that goes long a value-weight portfolio of the stocks in the top momentum decile and short a value-weight portfolio of stocks in the bottom momentum decile. The authors use CAPM and the four-factor model of Carhart to get portfolio returns. All months are then classified into five groups based on their Comom. The authors track the buy-and-hold returns of the zero-cost long-short portfolio in months 1 through 36 after portfolio formation. Year 0 is portfolio formation year (during which the authors also measure Comom), year 1 is the holding year, and years 2 and 3 are post-holding period[4], to detect any (conditional) long-run reversal to the momentum strategy.

As a result, Lou and Polk (2013) get abnormal portfolio returns for year 0, 1, 2 and 3. In every period, the abnormal returns are ranked into quintiles conditional on Comom. The authors have found that when comomentum is low, momentum strategies are profitable and stabilizing, reflecting an underreaction phenomenon that arbitrageurs correct. In contrast, during the periods of high comomentum, these strategies tend to crash and revert. To be more specific, in the lowest Comom group abnormal returns are positive in year 0 and 1 and become close to zero in the long run, while in the highest Comom group abnormal returns are high in year 0, become close to zero in year 1 and then significantly negative in year 2.

[4] Further in the paper year 2 and 3 are referred as holding periods.

Huang et al. (2014) following the same procedure as Lou and Polk (2013), form a zero-cost portfolio that goes long the value-weight portfolio of stocks in the lowest beta decile and short the value-weight portfolio of stocks in the highest beta decile. They track the buy-and-hold returns of this zero-cost long-short portfolio in months 1 through 36 after portfolio formation. Year 0 is portfolio formation year, year 1 is the holding year, and years 2 and 3 are post-holding period, to identify any (conditional) long-run reversal to the beta-arbitrage strategy.

The main finding of Huang et al. (2014) has been that "when beta-arbitrage activity is low, the returns to beta-arbitrage strategies exhibit significant delayed correction. In contrast, when beta-arbitrage activity is high, the returns to beta-arbitrage activities reflect strong over-correction due to crowded arbitrage trading" (Huang et al., 2014). Their results show that in the lowest Cobar group significant abnormal returns appear in year 2 and 3. In the highest Cobar group, significantly positive returns in year 1 and 2 revert in year 3 getting significantly negative.

3.2 Portfolio construction in momentum strategy

In this section, I will explain the procedure that I followed in order to form portfolios in momentum strategy. The steps will be explained in terms of operations in SAS.

At this point, I have a file that contains only stocks that belong to the lowest momentum decile. This file has only monthly dates, PERMNOs and portfolio id for every stock. In this case, portfolio id shows that a stock belongs to the portfolio that was formed in a particular month. Necessary to mention that every month from 1970 to 2011 I form a portfolio. Therefore, every month is a portfolio formation date and, as a result, I have 504 portfolios. I merge this file with data from CRSP. From CRSP I extract monthly returns, stock prices and number of shares outstanding. For every stock, I get the returns for 36 months after portfolio formation. It means that if, for example, portfolio was constructed in January 1970 I track the returns of this portfolio starting from February 1970.

Following the procedure of Lou and Polk (2013), I have to construct value-weight portfolios. I need to compute portfolios returns both for short and long positions in order to get returns of a portfolio that goes long in a value-weight portfolio of the stocks in the highest decile and short in value-weight portfolio of stocks in the lowest decile. Thus, the next steps are performed for stocks in both the lowest and the highest momentum deciles.

In order to get value weight for every stock, first, I compute market capitalization for each stock in the lowest (highest) decile by multiplying stock prices and number of shares outstanding. Then I sum the market capitalizations for all the stocks by month to find the total market capitalization in the lowest (highest) decile. After that, I divide market capitalizations of a stock by the total market capitalization and get the value weigh for every stock. Worth mentioning, that the weights for every stock starting from the first holding month are calculated based on the prices and shares outstanding of the preceding month.

After all the weights are obtained, I multiply the returns of the stocks in every portfolio by the value-weight and sum them up by month. The formula used for computation of value-weight return of the portfolio is:

$$R_P^{VW} = \sum\nolimits_{i=1}^{n} (w_i * R_i), \qquad w_i = \frac{MktCap_i}{\sum_{i=1}^{n} MktCap_i} \qquad (2)$$

where R_P^{VW} is the value-weight return of the portfolio, R_i is the return of a stock i, w_i is value weight of a stock i, $MktCap_i$ is market capitalization of a stock i, n is the number of stocks in the corresponding month.

As a result, I get portfolio returns for 36 months after portfolio is formed for long and short position. I merge obtained two files with portfolio returns in long and short position with the file with Fama-French factors and compute the excess return of each portfolio by subtracting risk-free rate from portfolio monthly return. Then, in order to find the excess return of the long-short portfolio I subtract excess returns of the portfolios in short position from the excess returns of the portfolios in the long position.

Now I need Comom values that I have already computed. I rank 504 Comoms into quintiles so that every monthly Comom belongs to one of the five groups, where group 1 is the group with the lowest Comoms, and group 5 – with the highest. The first group contains 100 observations, the rest have 101 observations each. Now every month from 1970 until 2011 belongs to one out of five Comom ranks. Then I distribute excess returns into five groups based on the rank of Comom. At this point, I can compute long-short portfolio abnormal returns. I do it by holding periods and Comom ranks.

In original methodology, abnormal returns are computed with CAPM and the Carhart four-factor model. Instead, I use the Fama-French three-factor model, the Carhart four-factor model, the five- and the six-factor models. The alphas obtained from the regression models are sought-for abnormal returns.

To control for heteroscedasticity and autocorrelation induced by overlapping observations in portfolios' abnormal returns I run all the regressions using the Newey-West standard error correction. In SAS the Newey-West estimator corresponds to the Bartlett kernel with bandwidth parameter L+1, where L is the maximum lag length. Therefore, for the periods year 1, year 2, and year 3 I use kernel = (BART, 13, 0), for 3 and 6 months I use kernel = (BART, 4, 0) and kernel = (BART, 7, 0), respectively.

3.3 Portfolio construction in beta strategy

The portfolio construction in beta strategy largely repeats the procedure in momentum strategy. However, several steps are different. For this reason, in this section I will explain the whole procedure for portfolio construction in beta strategy.

When calculating Cobars I saved a file with stocks that belong to the lowest beta decile. This file has only monthly dates, PERMNOs and portfolio id for every stock. Portfolios are identified by the month when they are formed. I form a portfolio every month from 1970 to 2010. Therefore, every month is a portfolio formation date and, as a result, I have 504 portfolios. I merge this file with monthly returns, stock prices and number of shares outstanding that I get from CRSP. For every stock, I obtain the returns for 36 months after portfolio formation.

Following the procedure of Huang et al. (2014), I have to construct value-weight portfolios. I need to compute portfolios returns both for short and long positions in order to get returns of a portfolio that goes long in a value-weight portfolio of the stocks in the lowest beta decile and short in value-weight portfolio of stocks in the highest beta decile. Thus, the next steps are executed for stocks in both the lowest and the highest beta deciles.

In order to get value weight for every stock, first, I compute market capitalization for each stock in the lowest (highest) decile by multiplying stock prices and number of shares outstanding. Then I sum the market capitalizations for all the stocks by month to find the total market capitalization in the lowest (highest) decile. After that, I divide market capitalizations of a stock by the total market capitalization and get the value weigh for every stock. The same as in momentum strategy, the weights for every stock starting from the first holding month are calculated based on the prices and shares outstanding of the preceding month.

After all the weights are computed, I multiply the returns of the stocks in every portfolio by the value-weight and sum them up by month. The same formula (2) is used for computation of value-weight return of the portfolio.

As a result, I get portfolio returns for 36 months after portfolio is formed for long and short position. I merge obtained two files with portfolio returns in long and short position with the file that contains Fama-French factors and compute the excess return of each portfolio by subtracting risk-free rate from portfolio monthly return. In order to find the excess return of the long-short portfolio I subtract excess returns of the portfolios in short position from the excess returns of the portfolios in the long position.

Now I need Cobar values that I have already computed. I rank 504 Cobars into quintiles so that every monthly Cobar belongs to one of the five groups, where group 1 is the group with the lowest Cobars, and group 5 – with the highest. The first group contains 100 observations, the rest have 101 observations each. I merge the data with excess returns with ranked Cobars. It means that now all monthly excess returns are distributed to one of the five Cobar ranks. Now I can compute long-short portfolio abnormal returns. I do it by holding periods and Cobar ranks.

I use the Fama-French three-factor model, the Carhart four-factor model, the five- and the six-factor models to compute portfolio abnormal returns while in original methodology the authors use CAPM and the Carhart four-factor model.

I run all the regressions using the Newey-West standard error correction to control for heteroscedasticity and autocorrelation, induced by overlapping observations in portfolios' abnormal returns.

3.4 Combined measure Comom/Cobar

The major contribution of this paper is to construct and investigate the measure based on combination of Comom and Cobar that has not been done in the original papers. I combine these measures in two ways: First, I analyze *beta strategy* using *Comom* and *momentum strategy* using *Cobar*. Second, I create an additional measure that combines Comom and Cobar and then apply this measure to evaluate beta and momentum strategies.

As long as the combined measures are based on Comom and Cobar, I do not need to explain the whole process of their construction. The changes occur only during the process of portfolio excess returns ranking. In the first method of combining measures, in the process of returns ranking conditional on arbitrage measure, I do the following. I rank portfolio excess returns in *momentum strategy* (both in long and short positions) based on *Cobar* measure; I also rank portfolio excess returns in *beta strategy* (both in long and short positions) based on *Comom* measure.

The rest of the process of abnormal returns calculation is the same as described in the section 3.2 and 3.3.

The second method is to create a new measure Comom/Cobar. I sum the rankings of both measures and then distribute them into quintiles. The procedure looks as follows:

If sum of ranks < = 2 then quintile=1;

If 2 < sum of ranks <= 4 then quintile=2;

If 4 < sum of ranks <= 6 then quintile=3;

If 6 < sum of ranks <= 8 then quintile=4;

If 8< sum of ranks <= 10 then quintile=5;

Then I repeat the procedure of portfolio excess return ranking using the constructed measure. I apply the Comom/Cobar measure for both beta and momentum strategies.

4. Abnormal returns analysis

In this chapter, I focus on investigation of the arbitrage effect on the stock prices. I am going to analyze the short- and long-run returns, conditional on arbitrage measures. I will investigate the effect of crowded trading in momentum strategy on the prices of stocks involved in momentum strategy. For this purpose, I use Comom measure. I do the same for beta strategy: I explore prices of stocks involved in beta strategy conditional on Cobar. Then I will explore the effect of arbitrage activity in momentum strategy on abnormal returns in *beta strategy* using *Comom* and the effect of arbitrage activity in beta strategy on abnormal returns in *momentum strategy* using *Cobar*. Finally, I will investigate abnormal returns in beta strategy when activity in both momentum and beta strategies is high. The same I will do for abnormal returns in momentum strategy. For this purpose, I will use the Comom/Cobar measure.

As mentioned in the previous chapter, four asset-pricing models are used to evaluate abnormal returns: the Fama-French three-factor model, the Carhart four-factor model, the five- and the six-factor models. In my analysis, the conclusions will be based on the Carhart four-factor model in order to be consistent in my comparison of the results with the findings in original papers that also use the four-factor returns. After every section, I present the corresponding table that tracks the profits on investigated strategies over the three years subsequent to portfolio formation. Such an event time approach allows making statements about variations in abnormal returns.

4.1.1 Momentum strategy conditional on Comom

Table 3 Panel A, B, C and D exhibit three-, four-, five and six-factor adjusted returns in momentum strategy conditional on Comom, respectively. According to the three-factor model, during the first year abnormal returns present in all the Comom groups except for the highest one. The highest abnormal returns are observed in the first 3 months of the holding period in the lowest Comom group. In the second year, abnormal returns revert in the third and fourth group.

The five-factor model shows the similar results – all groups except for the group 5 provide significant positive returns. However, the highest returns are in the fourth group (α= 2.64%, *t*-statistic=6.23). These returns are decreasing towards the end of the first year and then become close to zero. The fifth group shows significantly negative returns during the first year but in year 3 they turn to 0.94%/month with a strong associated *t*-statistic of 7.85.

When the model is adjusted for momentum factor (four- and six-factor models), middle Comom do not show significant positive results except for the second Comom group in year 1 in both models, and the group 4 in the first three months of holding period in the six-factor model. In the group 5, significant positive returns appear only in year 3 in four- and six-factor models and are equal to 1.01%/month with *t*-statistic of 8.14 and 0.88%/month with *t*-statistic 7.24, respectively.

If we compare abnormal returns in high and low Comom groups in the four-factor model, the difference in year 3 abnormal four-factor returns is quite big and equal 1.06%/month with *t*-statistic of 5.6.

Thus, according to the four-factor model, momentum strategies are profitable in the short run during periods of low Comom supporting the findings of Lou and Polk (2013). However, an overreaction phenomenon with a reversal pattern in the long run when Comom is high found by the authors is not observed.

Table 3: Forecasting Momentum Returns with Comom

The table reports returns to the momentum strategy as a function of lagged Comom. At the end of each month, all stocks are ranked into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). All months are then classified into five groups conditional on Comom, the average pair wise partial return correlation in the loser decile ranked in the previous 12 months. Reported below are the returns to the momentum strategy (long the value-weight winner decile and short the value-weight loser decile) in each of the three years after portfolio formation during 1970 to 2011, following low to high Comom. Panels A, B, C, and D report, respectively, the average monthly Fama-French Three-Factor alpha, Carhart Four-Factor alpha, Five- and Six-factor alphas of the momentum strategy. "5-1" is the difference in monthly returns to the momentum strategy following high vs. low Comom; returns with 5% statistical significance are indicated in bold. Significant positive returns are marked with red color; significant negative returns are in blue color. Decile 1 means that Comom is based on the lowest decile.

Panel A: Three-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	**2.72%**	8.07	**2.26%**	9.81	**1.38%**	8.76	**0.28%**	2.21	0.12%	0.95
2	101	**1.23%**	3.24	**1.38%**	5.68	**1.45%**	8.94	0.23%	1.55	**-0.34%**	-2.34
3	101	**1.40%**	3.85	**1.42%**	5.41	**0.91%**	5.27	**-0.35%**	-2.07	-0.13%	-0.85
4	101	**2.33%**	5.61	**1.34%**	4.73	**0.51%**	2.70	**-0.50%**	-3.13	-0.04%	-0.23
5	101	0.14%	0.21	0.42%	0.96	0.18%	0.68	**0.46%**	2.59	**1.12%**	9.17
5-1		**-2.59%**	-3.43	**-1.84%**	-3.71	**-1.19%**	-3.79	0.18%	0.84	**1.00%**	5.59

Panel B: Four-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	**0.91%**	3.84	**0.80%**	4.57	**0.36%**	2.83	-0.03%	-0.27	-0.05%	-0.32
2	101	0.09%	0.41	0.25%	1.50	**0.57%**	4.08	0.09%	0.58	-0.21%	-1.40
3	101	0.28%	1.31	0.11%	0.58	-0.06%	-0.36	-0.05%	-0.31	-0.10%	-0.65
4	101	0.43%	1.83	0.23%	1.10	0.01%	0.02	-0.18%	-1.14	0.05%	0.33
5	101	0.44%	1.16	0.52%	1.86	0.24%	1.15	0.32%	1.85	**1.01%**	8.14
5-1		-0.47%	-1.06	-0.28%	-0.84	-0.12%	-0.50	0.35%	1.65	**1.06%**	5.60

Panel C: Five-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	**2.25%**	6.18	**1.84%**	7.44	**1.03%**	6.19	-0.01%	-0.08	0.08%	0.57
2	101	**1.24%**	3.18	**1.41%**	5.63	**1.58%**	9.52	**0.34%**	2.26	**-0.40%**	-2.68
3	101	**1.41%**	4.06	**1.43%**	5.55	**1.05%**	6.01	-0.31%	-1.86	-0.19%	-1.20
4	101	**2.64%**	6.23	**1.42%**	4.95	**0.64%**	3.29	-0.18%	-1.16	-0.26%	-1.71
5	101	**-1.27%**	-2.00	**-0.97%**	-2.28	**-1.12%**	-4.27	-0.10%	-0.63	**0.94%**	7.85
5-1		**-3.52%**	-4.81	**-2.81%**	-5.71	**-2.15%**	-6.92	-0.09%	-0.42	**0.86%**	4.73

Panel D: Six-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	**0.88%**	3.57	**0.67%**	3.74	**0.28%**	2.12	**-0.31%**	-2.29	-0.11%	-0.74
2	101	0.10%	0.45	0.24%	1.34	**0.68%**	4.77	0.20%	1.28	**-0.30%**	-2.01
3	101	0.28%	1.30	0.09%	0.48	0.04%	0.27	-0.14%	-0.82	-0.18%	-1.14
4	101	**0.55%**	2.22	0.40%	1.85	0.21%	1.15	-0.05%	-0.35	-0.19%	-1.24
5	101	0.14%	0.36	0.16%	0.55	-0.21%	-0.95	-0.05%	-0.31	**0.88%**	7.24
5-1		-0.74%	-1.59	-0.51%	-1.48	-0.49%	-1.91	0.26%	1.28	**0.98%**	5.23

4.1.2 Beta strategy conditional on Cobar

Table 4 shows abnormal returns in beta strategy based on Cobar. The table shows the average abnormal returns in the first three and six months subsequent to the beta-arbitrage trade, and those occurring in year 1, 2, and 3. Rank represents the group of abnormal returns conditional on Cobar.

The four-factor model shows that during little activity in beta arbitrage, that is, when Cobar is low, abnormal returns are observed in all the periods, except for the first three months, with the highest ones in year 3 (α=0.51, *t*-statistic=4.33). The results are not monotonic through holding periods. In year 3, the returns monotonically decrease cross section from the group 1 to the group 5. When Cobar is high, it does not generate abnormal returns. In the last holding year, abnormal returns become significantly negative and on average equal -0.99% per month with associated *t*-statistic -6.03.

These results are contrary to the findings of the original paper, which suggests that abnormal returns to beta-arbitrage strategies occur relatively quickly when arbitrage activity is relatively high and take much longer to materialize when arbitrage activity is relatively low.

In fact, the idea of the main article is supported by the results of the three-factor and five-factor models in the highest Cobar group. In the three-factor model, the average return of 0.6%/month (t-statistic of 2.48) in the first six months is immediately arbitraged away. In year 3, the strategy generates negative returns of -0.46%/month with a t-statistic of -2.66. In the five factor model the returns are already realized in year 2 (α=0.26, *t*-statistic=2.05) and increase by year 3 (α=0.40, *t*-statistic=3.29).

The reason why the three-factor and the five-factor models provide the result different from the results of the Carhart model is that they do not capture the momentum factor and therefore inflate the corresponding abnormal returns.

After adjusting the model for profitability, investment and momentum effects, we can see that abnormal profits appear only in year 3 when beta arbitrage is low. However, in the highest Cobar group the six-factor model does not show significant abnormal returns in any of the periods.

One of the explanations of the conflicting results in this paper with the findings of Huang et al. (2014) could be the different dataset used in this paper. The reason is that I did not have access to some of the information sources used by the authors. Furthermore, lack of detailed information regarding the sample construction process in the main article allows for different interpretation of the steps for data construction. That could also cause some changes in abnormal returns patterns.

Abnormal returns in the lowest Cobar group in year 1, 2 and 3 are significantly bigger than the returns in the highest Cobar group, with the biggest difference in year 3 equal to 1.52% (*t*-statistic: -7.42)

To summarize the results of the four-factor model, when Cobar is low, beta arbitrage strategy is profitable in all the holding periods starting from the sixth month after portfolio formation. During crowded trading in beta strategy, that is, when Cobar is high, the strategy does not produce significant positive results.

Table 4: Forecasting Beta-arbitrage Returns with Cobar

The table reports returns to the beta arbitrage strategy as a function of lagged Cobar. At the end of each month, all stocks are ranked into deciles based on their market beta calculated using daily returns in the past 12 months. All months are then classified into five groups conditional on Cobar, the average pair wise partial weekly return correlation in the low-beta decile over the past 12 months. Reported below are the returns to the beta arbitrage strategy (i.e., to go long the value-weight low-beta decile and short the value-weighted high-beta decile) in each of the three years after portfolio formation during 1970 to 2011, following low to high Cobar. Panels A, B, C, and D report, respectively, the average monthly Fama-French Three-Factor alpha, Carhart Four-Factor alpha, Five- and Six-factor alphas of the beta arbitrage strategy. "5-1" is the difference in monthly returns to the long-short strategy following high vs. low Cobar; returns with 5% statistical significance are indicated in bold. Significant positive returns are marked with red color; significant negative returns are in blue color. Decile 1 means that Cobar is based on the lowest decile.

Panel A: Three-Factor Model											
Decile 1											
		3 months		6 months		Year 1		Years 2		Years 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	**0.64%**	2.15	**0.55%**	2.76	**0.53%**	4.10	**0.45%**	3.83	**0.64%**	5.50
2	101	0.54%	1.84	**0.71%**	3.47	**0.65%**	4.75	**0.60%**	4.89	**0.46%**	3.65
3	101	0.01%	0.02	-0.04%	-0.19	0.17%	1.15	**0.28%**	2.02	0.11%	0.73
4	101	-0.18%	-0.52	0.04%	0.18	0.16%	0.98	**-0.41%**	-2.53	-0.10%	-0.70
5	101	0.52%	1.58	**0.60%**	2.48	0.14%	0.77	0.03%	0.15	**-0.46%**	-2.65
5-1		-0.12%	-0.27	0.05%	0.15	-0.39%	-1.76	**-0.42%**	-2.00	**-1.10%**	-5.27

Panel B: Four-Factor Model											
Decile 1											
		3 months		6 months		Year 1		Years 2		Years 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.57%	1.88	**0.42%**	2.13	**0.41%**	3.19	**0.42%**	3.47	**0.51%**	4.33
2	101	0.45%	1.74	**0.56%**	2.95	**0.45%**	3.39	**0.50%**	3.95	**0.26%**	2.17
3	101	-0.38%	-1.15	-0.26%	-1.23	0.03%	0.22	0.14%	0.98	-0.15%	-1.04
4	101	-0.58%	-1.70	-0.38%	-1.60	-0.23%	-1.48	**-0.66%**	-4.12	**-0.31%**	-2.13
5	101	0.56%	1.61	0.43%	1.75	-0.10%	-0.58	-0.31%	-1.93	**-0.99%**	-6.03
5-1		-0.01%	-0.01	0.01%	0.03	**-0.52%**	-2.35	**-0.73%**	-3.61	**-1.51%**	-7.42

Panel C: Five-Factor Model											
Decile 1											
		3 months		6 months		Year 1		Years 2		Years 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.15%	0.50	0.17%	0.84	0.19%	1.43	**0.26%**	2.05	**0.40%**	3.29
2	101	-0.08%	-0.26	0.15%	0.75	**0.27%**	1.99	0.25%	1.95	0.08%	0.66
3	101	-0.63%	-1.90	**-0.71%**	-3.40	**-0.42%**	-2.94	-0.03%	-0.25	**-0.36%**	-2.41
4	101	**-0.84%**	-2.60	**-0.65%**	-2.97	**-0.47%**	-3.10	**-0.97%**	-6.35	**-0.42%**	-2.87
5	101	-0.27%	-0.92	-0.09%	-0.38	**-0.43%**	-2.52	**-0.40%**	-2.54	-0.25%	-1.43
5-1		-0.42%	-1.00	-0.26%	-0.84	**-0.62%**	-2.86	**-0.66%**	-3.27	**-0.65%**	-3.04

Panel D: Six-Factor Model											
Decile 1											
		3 months		6 months		Year 1		Years 2		Years 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.14%	0.47	0.13%	0.65	0.15%	1.11	0.24%	1.95	**0.34%**	2.79
2	101	0.04%	0.14	0.16%	0.83	0.13%	0.96	0.18%	1.41	0.02%	0.13
3	101	**-0.84%**	-2.62	**-0.82%**	-3.94	**-0.48%**	-3.29	-0.17%	-1.16	**-0.48%**	-3.32
4	101	**-1.02%**	-3.13	**-0.88%**	-3.99	**-0.74%**	-4.96	**-1.12%**	-7.36	**-0.55%**	-3.75
5	101	-0.05%	-0.17	-0.16%	-0.69	**-0.58%**	-3.45	**-0.52%**	-3.52	**-0.81%**	-4.78
5-1		-0.19%	-0.45	-0.29%	-0.94	**-0.73%**	-3.39	**-0.77%**	-3.95	**-1.15%**	-5.51

4.1.3 Beta strategy conditional on Comom

In this section, I investigate abnormal returns generated in beta-arbitrage strategy during peaks and downs of momentum strategy. Table 5 reports abnormal returns in beta-arbitrage strategy conditional on Comom. I am going to investigate the patterns in abnormal returns in beta strategy when investors actively trade in momentum strategy.

The three-factor model shows that when Comom is high the highest abnormal returns appear in the second year and equal 0.88%/month with associated *t*-statistic 5.74. In the third year, abnormal returns decrease but still are 0.74%/month with associated *t*-statistic 5.4. These values are higher than the one generated during the booms and busts of beta strategy. When Comom is low, no significant positive results are observed.

When adjusted for momentum, returns look different. The second Comom group shows significant positive returns from the first three months that decrease towards the first year and become negative in year 2. Group 4 also shows significant returns after three months and in year 1. As for the highest Comom group, significant positive results occur in the long run: 0.7%/month with t-statistic 4.95 in year 2 and 0.61%/month in year 3.

After adjusting returns for all six risk factors, the significant abnormal returns occur in the second year in the lowest Comom group, and in the third year in the highest Comom group. Significant positive returns are also found in the second group in three and six months of holding periods.

When comparing the four-factor alphas in the lowest and highest Comom groups we see that the difference in year 2 and 3 is significant and equal 0.64% (*t*-statistic 3.49) and 0.90% (*t*-statistic 4.78), respectively.

To sum up the results, according to the four-factor model, when activity in momentum strategy is high it takes time for returns in beta strategy to be realized, that is, the significant positive results appear only in the long run. When there is little activity in momentum, beta strategy does not produce significant positive returns, furthermore, in the long run abnormal returns become even negative.

Table 5: Forecasting Beta-arbitrage Returns with Comom

The table reports returns to the beta arbitrage strategy as a function of lagged Comom. At the end of each month, all stocks are ranked into deciles based on their market beta calculated using daily returns in the past 12 months. All months are then classified into five groups conditional on Comom, the average pair wise partial return correlation in the loser momentum decile ranked in the previous 12 months. Reported below are the returns to the beta arbitrage strategy (i.e., to go long the value-weight low-beta decile and short the value-weighted high-beta decile) in each of the three years after portfolio formation during 1970 to 2011, following low to high Comom. Panels A, B, C, and D report, respectively, the average monthly Fama-French Three-Factor alpha, Carhart Four-Factor alpha, Five- and Six-factor alphas of the beta arbitrage strategy. "5-1" is the difference in monthly returns to the long-short strategy following high vs. low Comom; returns with 5% statistical significance are indicated in bold. Significant positive returns are marked with red color; significant negative returns are in blue color.

Panel A: Three-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	-0.04%	-0.18	-0.14%	-0.87	-0.07%	-0.65	0.10%	0.87	**-0.29%**	-2.41
2	101	**0.50%**	2.00	**0.55%**	3.267	**0.28%**	2.18	-0.20%	-1.52	-0.16%	-1.16
3	101	-0.51%	-1.72	-0.22%	-1.04	0.18%	1.31	0.23%	1.55	-0.29%	-1.92
4	101	0.23%	0.72	0.04%	0.16	**0.37%**	2.35	0.16%	0.95	0.21%	1.39
5	101	0.14%	0.34	0.31%	1.08	0.32%	1.63	**0.88%**	5.74	**0.74%**	5.40
5-1		0.18%	0.38	0.45%	1.36	0.39%	1.74	**0.78%**	4.13	**1.03%**	5.66

Panel B: Four-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.29%	1.25	0.00%	0.02	-0.03%	-0.25	0.06%	0.54	**-0.29%**	-2.29
2	101	**0.82%**	3.38	**0.78%**	4.56	**0.35%**	2.63	**-0.32%**	-2.40	**-0.33%**	-2.46
3	101	-0.45%	-1.49	-0.10%	-0.45	0.30%	2.07	0.07%	0.44	**-0.46%**	-3.24
4	101	**0.70%**	2.20	0.23%	0.98	**0.33%**	2.00	-0.20%	-1.22	-0.11%	-0.79
5	101	0.25%	0.66	0.35%	1.36	0.34%	1.94	**0.70%**	4.95	**0.61%**	4.39
5-1		-0.04%	-0.08	0.35%	1.13	0.37%	1.76	**0.64%**	3.49	**0.90%**	4.78

Panel C: Five-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	-0.16%	-0.69	**-0.34%**	-2.06	-0.20%	-1.79	**0.31%**	2.59	-0.22%	-1.73
2	101	0.31%	1.22	**0.41%**	2.40	0.11%	0.88	**-0.39%**	-2.96	-0.22%	-1.61
3	101	-0.56%	-1.99	-0.39%	-1.92	-0.05%	-0.35	-0.21%	-1.49	**-0.68%**	-4.56
4	101	-0.48%	-1.60	**-0.50%**	-2.43	-0.21%	-1.41	**-0.52%**	-3.34	-0.15%	-1.03
5	101	**-0.87%**	-2.21	**-0.82%**	-3.03	**-0.83%**	-4.57	-0.01%	-0.06	**0.39%**	3.06
5-1		-0.71%	-1.57	-0.47%	-1.49	**-0.62%**	-2.91	-0.32%	-1.77	**0.60%**	3.39

Panel D: Six-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.19%	0.84	-0.13%	-0.78	-0.12%	-1.00	**0.30%**	2.49	-0.21%	-1.56
2	101	**0.61%**	2.48	**0.62%**	3.55	0.17%	1.26	**-0.48%**	-3.52	**-0.36%**	-2.57
3	101	-0.57%	-1.97	-0.33%	-1.56	0.04%	0.25	**-0.29%**	-2.04	**-0.71%**	-5.00
4	101	-0.07%	-0.23	-0.35%	-1.67	-0.23%	-1.55	**-0.67%**	-4.38	**-0.37%**	-2.65
5	101	-0.51%	-1.36	-0.49%	-1.91	**-0.54%**	-3.05	0.06%	0.46	**0.34%**	2.65
5-1		-0.70%	-1.60	-0.36%	-1.16	**-0.43%**	-2.01	-0.24%	-1.37	**0.55%**	2.96

4.1.4 Momentum strategy conditional on Cobar

In this section, I investigate abnormal returns generated by momentum strategy during peaks and downs of beta strategy. Table 6 shows abnormal returns in momentum strategy conditional on Cobar

The three-factor model shows that abnormal returns are significantly positive in all Cobar groups after 3 and 6 months and in year 1. In the lowest Cobar group, the returns are significant through all periods and monotonically decrease. Abnormal returns are the highest in the fifth Cobar group within the first three months and equal 3.43%/month with associated *t*-statistic of 6.04. During high Cobar, returns are significant only within three and six months after portfolio formation, and in the first year. After that, the returns are close to zero.

In the four-factor model, much less groups and holding periods produce positive returns. In the lowest Cobar group, the positive returns are found in the first six months (α=0.42%, *t*-statistic=2.33), year 2 (α= 0.47%, *t*-statistic=3.58) and year 3 (α= 0.28%, *t*-statistic=2.29). In the highest Cobar group, significant positive returns occur only in year 3 and equal 0.47% with associated *t*-statistic 2.93. Significant positive returns are also present in the second Cobar group after three and six months.

The five-factor model shows to some extent similar results to the three-factor model but with less positive abnormal returns in the lowest Cobar group. The six-factor model suggests that the lowest Cobar group is profitable only in the second year. In the highest Cobar group, the significant returns appear in period of 6 months, year 1 and year 3. The highest return is in the top Cobar group in the first six months and is equal to 0.63%/month with associated t-statistic of 2.29.

The four-factor model predicts the significant difference in returns between the highest and the lowest Cobar group only in the year 2 which is equal to -0.70% with *t*-statistic -3.13. Overall, according to the four-factor model when activity in beta strategy is high it takes three years for abnormal returns in momentum strategy to be realized. During low activity in beta, positive abnormal returns occur both in the short and in the long run.

Table 6: Forecasting Momentum Returns with Cobar

The table reports returns to the momentum strategy as a function of lagged Cobar. At the end of each month, all stocks are ranked into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). All months are then classified into five groups conditional on Cobar, the average pair wise partial weekly return correlation in the low-beta decile over the past 12 months. Reported below are the returns to the momentum strategy (i.e., long the value-weight winner decile and short the value-weight loser decile) in each of the three years after portfolio formation during 1970 to 2011, following low to high Cobar. Panels A, B, C, and D report, respectively, the average monthly Fama-French Three-Factor alpha, Carhart Four-Factor alpha, Five- and Six-factor alphas of the momentum strategy. "5-1" is the difference in monthly returns to the momentum strategy following high vs. low Cobar; returns with 5% statistical significance are indicated in bold. Significant positive returns are marked with red color; significant negative returns are in blue color.

Panel A: Three-Factor Model											
		Decile 1									
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	**1.31%**	3.06	**1.21%**	4.21	**0.85%**	4.61	**0.70%**	5.32	**0.47%**	3.83
2	101	**0.95%**	2.01	**0.99%**	3.19	**0.90%**	4.75	**0.31%**	2.311	**0.31%**	2.37
3	101	**1.42%**	3.54	**1.31%**	5.07	**0.99%**	5.57	-0.26%	-1.56	0.10%	0.69
4	101	**1.60%**	3.60	**1.61%**	5.35	**0.97%**	4.90	-0.24%	-1.35	0.12%	0.80
5	101	**3.43%**	6.04	**2.34%**	6.03	**1.07%**	4.25	-0.24%	-1.32	0.12%	0.73
5-1		**2.12%**	2.99	**1.13%**	2.34	0.22%	0.72	**-0.94%**	-4.22	-0.35%	-1.74

Panel B: Four-Factor Model											
		Decile 1									
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.40%	1.71	**0.42%**	2.33	0.10%	0.71	**0.47%**	3.58	**0.28%**	2.29
2	101	**0.70%**	2.79	**0.51%**	2.84	0.28%	1.93	0.23%	1.69	0.25%	1.95
3	101	0.25%	0.92	0.37%	1.95	0.25%	1.55	-0.33%	-1.97	0.04%	0.29
4	101	-0.01%	-0.05	0.05%	0.27	-0.04%	-0.25	-0.32%	-1.76	0.13%	0.84
5	101	0.56%	1.90	0.52%	1.95	0.34%	1.56	-0.23%	-1.27	**0.47%**	2.93
5-1		0.15%	0.41	0.11%	0.33	0.25%	0.96	**-0.70%**	-3.13	0.19%	0.92

Panel C: Five-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.67%	1.56	**0.65%**	2.22	0.32%	1.68	**0.42%**	3.05	0.08%	0.68
2	101	0.10%	0.21	0.40%	1.26	**0.56%**	2.92	0.18%	1.41	0.24%	1.81
3	101	**1.07%**	2.57	**0.92%**	3.48	**0.64%**	3.54	-0.18%	-1.24	**-0.33%**	-2.28
4	101	**1.10%**	2.63	**1.16%**	3.94	**0.67%**	3.46	-0.15%	-0.91	0.02%	0.14
5	101	**2.96%**	5.29	**2.17%**	5.41	**1.13%**	4.34	-0.01%	-0.07	0.22%	1.32
5-1		**2.29%**	3.24	**1.52%**	3.07	**0.81%**	2.53	-0.43%	-1.93	0.14%	0.67

Panel D: Six-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.31%	1.26	0.30%	1.60	-0.06%	-0.42	**0.28%**	2.04	0.00%	0.03
2	101	0.51%	1.92	**0.41%**	2.19	0.09%	0.60	0.10%	0.75	0.22%	1.62
3	101	0.24%	0.84	0.24%	1.24	0.03%	0.21	**-0.34%**	-2.31	**-0.36%**	-2.51
4	101	-0.08%	-0.35	-0.05%	-0.24	-0.15%	-0.96	-0.24%	-1.48	-0.04%	-0.27
5	101	0.59%	1.95	**0.63%**	2.29	**0.56%**	2.53	-0.01%	-0.06	**0.61%**	3.60
5-1		0.28%	0.72	0.33%	1.01	**0.61%**	2.36	-0.29%	-1.29	**0.60%**	2.89

4.1.5 Beta strategy conditional on Comom/Cobar

In this and the next section, I want to explore abnormal returns during the periods when both Cobar and Comom are high, that is, when investors are active in both momentum and beta strategies. Table 7 reports abnormal returns in beta strategy conditional on combined measure Comom/Cobar.

The three- and the four-factor models show no significant returns when Comom/Cobar measure is high. However, there are significant abnormal returns in some of the periods in the second, third and fourth group in the three-factor model, and in the second and third group in the four-factor model. The five-factor model shows no significant positive abnormal returns in any of the groups and periods.

If we look at six-factor model, abnormal returns occur only in year 3 in the lowest Cobar and Comom group (α=0.30%/month, *t*-statistic= 2.01). The highest Comom/Cobar group produces significantly negative results from first three month up to year 2 and turn zero at year 3.

Therefore, none of the models shows positive significant profits in beta strategy during peaks of activity in both beta and momentum strategy. In fact, models adjusted for CMA and RMW factors, in the top Comom/Cobar group produce significantly negative results during most of the holding periods.

It is interesting that the six-factor model shows similar trends of abnormal returns based on just Cobar and Comom/Cobar. In both situations, the significant returns appear only in the third year after the portfolio formation and only in the lowest group. The returns are close and equal 0.34%/month (t-statistic=2.79) during the lowest Cobar and 0.30%/month (t-statistic =2.01) during the lowest Comom/Cobar. The significantly negative returns shift towards the highest Comom/Cobar group during the first two years and are concentrated in the middle groups in year 3.

To summarize the results based on the four-factor model, neither the lowest nor the highest Comom/Cobar groups produce significant positive abnormal returns after portfolio formation.

Table 7: Forecasting Beta-arbitrage Returns with Comom/Cobar

The table reports returns to the beta arbitrage strategy as a function of lagged Comom/Cobar. At the end of each month, all stocks are ranked into deciles based on their market beta calculated using daily returns in the past 12 months. All months are then classified into five groups conditional on Comom/Cobar, the simple combination of Comom and Cobar measures. Reported below are the returns to the beta arbitrage strategy (i.e., to go long the value-weight low-beta decile and short the value-weighted high-beta decile) in each of the three years after portfolio formation during 1970 to 2011, following low to high Comom/Cobar. Panels A, B, C, and D report, respectively, the average monthly Fama-French Three-Factor alpha, Carhart Four-Factor alpha, Five- and Six-factor alphas of the beta arbitrage strategy. "5-1" is the difference in monthly returns to the long-short strategy following high vs. low Comom/Cobar; returns with 5% statistical significance are indicated in bold. Significant positive returns are marked with red color; significant negative returns are in blue color.

Panel A: Three-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	-0.14%	-0.47	-0.21%	-1.04	-0.11%	-0.82	0.15%	1.14	0.19%	1.37
2	101	**0.47%**	2.05	**0.41%**	2.59	**0.39%**	3.68	0.05%	0.47	-0.04%	-0.37
3	101	0.49%	1.71	0.39%	1.98	**0.45%**	3.11	**0.60%**	4.32	0.21%	1.54
4	101	-0.48%	-1.53	-0.27%	-1.28	0.04%	0.26	0.01%	0.10	**0.28%**	2.14
5	101	-0.03%	-0.05	0.12%	0.35	0.02%	0.10	0.15%	0.65	-0.22%	-1.11
5-1		0.11%	0.19	0.33%	0.84	0.13%	0.47	0.00%	0.02	-0.41%	-1.69

Panel B: Four-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	-0.02%	-0.08	-0.09%	-0.43	0.04%	0.30	0.12%	0.92	0.22%	1.56
2	101	**0.54%**	2.32	**0.34%**	2.11	**0.34%**	3.09	0.01%	0.12	-0.21%	-1.92
3	101	0.33%	1.18	0.31%	1.57	**0.31%**	2.09	**0.63%**	4.34	-0.07%	-0.55
4	101	**-0.63%**	-2.03	-0.40%	-1.92	-0.09%	-0.60	-0.24%	-1.78	-0.07%	-0.57
5	101	-0.16%	-0.33	0.00%	0.01	0.00%	-0.02	-0.08%	-0.41	-0.37%	-1.88
5-1		-0.14%	-0.24	0.09%	0.23	-0.04%	-0.17	-0.21%	-0.84	-0.59%	-2.43

Panel C: Five-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	-0.20%	-0.69	-0.27%	-1.27	-0.11%	-0.8196	0.16%	1.15	0.29%	1.97
2	101	0.02%	0.06	-0.12%	-0.71	-0.03%	-0.2789	-0.14%	-1.23	**-0.35%**	-3.08
3	101	-0.10%	-0.33	-0.08%	-0.39	0.07%	0.5112	0.19%	1.36	-0.19%	-1.38
4	101	**-0.67%**	-2.19	**-0.51%**	-2.51	**-0.31%**	-2.29	**-0.36%**	-2.72	-0.16%	-1.21
5	101	**-1.22%**	-2.73	**-1.08%**	-3.44	**-0.99%**	-4.39	**-0.56%**	-2.97	-0.13%	-0.79
5-1		-1.02%	-1.92	**-0.81%**	-2.14	**-0.88%**	-3.34	**-0.73%**	-3.08	-0.42%	-1.90

Panel D: Six-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	-0.05%	-0.18	-0.14%	-0.66	0.02%	0.14	0.15%	1.01	**0.30%**	2.01
2	101	0.09%	0.34	-0.12%	-0.74	-0.04%	-0.39	-0.15%	-1.33	**-0.45%**	-3.99
3	101	-0.14%	-0.47	-0.09%	-0.4578	0.00%	-0.01	0.23%	1.55	**-0.35%**	-2.57
4	101	**-0.81%**	-2.71	**-0.67%**	-3.2850	**-0.42%**	-3.11	**-0.52%**	-3.98	**-0.36%**	-2.78
5	101	**-1.28%**	-2.85	**-1.11%**	-3.5650	**-0.91%**	-4.14	**-0.52%**	-2.93	-0.17%	-1.02
5-1		**-1.23%**	-2.31	**-0.97%**	-2.58	**-0.93%**	-3.60	**-0.67%**	-2.91	**-0.47%**	-2.10

4.1.6 Momentum strategy conditional on Comom/Cobar

Table 8 reports abnormal returns in momentum strategy conditional on Comom/Cobar measure. The three-factor model shows that the middle Comom/Cobar groups are profitable in the short run, that is, up to year 1. The second Comom/Cobar group shows positive alpha also in year 2. In the lowest Comom/Cobar group, abnormal returns are significant for the periods of 6 month, year 1 and year 2 and monotonically decrease. In the highest groups, significant abnormal returns are observed in the first three and six months and then in year 3 with the highest alpha in the first three months (α=1.89%/month with *t*-statistic=2.07).

After adjustment for momentum factor, the middle groups show positive alpha after three and six months. Abnormal returns in the second group are also found in year 2 and monotonically decrease through time. The significant positive returns are not observed when activity in momentum and beta-arbitrage is low. During high Comom/Cobar positive alpha is found only in year 3 (α=0.96%/month, *t*-statistic= -2.24). The difference between the returns in the lowest and the highest Comom/Cobar groups in the year 3 is significant and equal 1.14%/month with associated *t*-statistic 4.85.

The five-factor model produces similar results to the three-factor model. When adjusting the model for all six factors, the lowest Comom/Cobar group does not produce any positive significant results, while in the highest group abnormal returns are significantly positive in year 3 and equal 1.03% per month with associated *t*-statistic 5.71. Significant positive results appear also in the second group in the short run and in the third group in the first three months.

To sum up the findings, using the four-factor model, during low activity in momentum and beta arbitrage momentum strategy is not profitable, while during the periods of high Comom/Cobar abnormal returns are realized only in the long run appearing in year 3.

Table 8: Forecasting Momentum Returns with Comom/Cobar

The table reports returns to the momentum strategy as a function of lagged Comom/Cobar. At the end of each month, all stocks are ranked into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). All months are then classified into five groups conditional on Comom/Cobar, the simple combination of Comom and Cobar measures. Reported below are the returns to the momentum strategy (i.e., long the value-weight winner decile and short the value-weight loser decile) in each of the three years after portfolio formation during 1970 to 2011, following low to high Comom/Cobar. Panels A, B, C, and D report, respectively, the average monthly Fama-French Three-Factor alpha, Carhart Four-Factor alpha, Five- and Six-factor alphas of the momentum strategy. "5-1" is the difference in monthly returns to the momentum strategy following high vs. low Comom/Cobar; returns with 5% statistical significance are indicated in bold. Significant positive returns are marked with red color; significant negative returns are in blue color.

Panel A: Three-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.86%	1.65	**1.24%**	3.85	**0.86%**	4.41	**0.54%**	3.36	-0.07%	-0.49
2	101	**1.74%**	6.01	**1.52%**	7.45	**1.20%**	8.48	**0.34%**	2.77	0.20%	1.73
3	101	**1.50%**	4.02	**0.97%**	3.75	**0.78%**	4.70	-0.12%	-0.89	0.18%	1.37
4	101	**1.37%**	3.33	**1.52%**	5.70	**0.87%**	5.17	**-0.52%**	-3.50	-0.02%	-0.15
5	101	**1.89%**	2.07	**1.21%**	2.00	0.13%	0.34	-0.29%	-1.13	**0.87%**	4.94
5-1		**1.02%**	0.97	-0.03%	-0.04	-0.73%	-1.67	**-0.83%**	-2.72	**0.95%**	4.10

Panel B: Four-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	-0.17%	-0.56	0.16%	0.73	-0.02%	-0.13	0.15%	0.96	-0.18%	-1.15
2	101	**0.68%**	3.61	**0.55%**	3.79	**0.37%**	3.16	0.11%	0.90	0.13%	1.16
3	101	**0.63%**	2.65	**0.36%**	2.01	0.18%	1.26	0.03%	0.18	0.15%	1.07
4	101	**0.49%**	2.14	**0.39%**	2.21	0.07%	0.45	-0.28%	-1.91	0.10%	0.71
5	101	-0.13%	-0.29	0.15%	0.37	0.05%	0.14	-0.37%	-1.43	**0.96%**	5.45
5-1		0.04%	0.07	-0.01%	-0.02	0.07%	0.18	-0.52%	-1.72	**1.14%**	4.85

Panel C: Five-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	0.72%	1.38	**0.96%**	2.93	**0.64%**	3.16	**0.39%**	2.26	-0.31%	-1.99
2	101	**1.42%**	4.41	**1.16%**	5.25	**0.98%**	6.41	0.10%	0.78	0.11%	0.94
3	101	**1.03%**	2.74	**0.54%**	2.07	**0.53%**	3.18	-0.25%	-1.84	-0.04%	-0.31
4	101	**1.13%**	2.73	**1.37%**	5.05	**0.86%**	4.94	-0.13%	-0.95	-0.10%	-0.69
5	101	1.25%	1.31	0.61%	0.95	-0.17%	-0.42	-0.08%	-0.35	**0.94%**	5.26
5-1		0.53%	0.49	-0.35%	-0.49	-0.81%	-1.78	-0.48%	-1.63	**1.26%**	5.27

Panel D: Six-Factor Model											
Decile 1											
		3 months		6 months		1 Year		2 Years		3 Years	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	100	-0.23%	-0.82	0.01%	0.06	-0.10%	-0.68	-0.02%	-0.12	**-0.36%**	-2.26
2	101	**0.74%**	3.60	**0.57%**	3.65	**0.30%**	2.38	-0.12%	-0.96	0.07%	0.58
3	101	**0.64%**	2.60	0.31%	1.71	0.07%	0.51	-0.21%	-1.54	-0.09%	-0.69
4	101	0.38%	1.62	0.30%	1.66	0.12%	0.78	-0.05%	-0.38	-0.04%	-0.25
5	101	-0.31%	-0.68	0.07%	0.16	0.17%	0.50	-0.07%	-0.30	**1.03%**	5.71
5-1		-0.08%	-0.14	0.06%	0.12	0.28%	0.74	-0.05%	-0.17	**1.38%**	5.78

4.2 Intermediate conclusion

The conclusion on abnormal returns is made based on the Carhart four-factor model to be in line with the original papers of Lou and Polk (2014) and Huang et al. (2014). Therefore, the analysis of the influence of beta arbitrage activity in momentum and beta stocks on abnormal trading profits in momentum and beta-arbitrage strategies showed that there is no common effect on abnormal returns across the investigated strategies. In every strategy, there are specific price reactions on different arbitrage activities (i.e., arbitrage in momentum, beta strategy or both). In particular, I observed that i) momentum strategies are profitable and stabilizing during periods of low Comom, supporting the finding of Lou and Polk (2013), while in the periods of high Comom returns are realized only in the third year after portfolio formation; ii) when Cobar is low, beta arbitrage strategy is profitable from the sixth month through year 3, but unprofitable during observed periods when Cobar is high; iii) during low Comom, beta strategy is not profitable, while during high Comom, the significant positive results in beta strategy occur only in the long run; iv) during low Cobar, positive abnormal returns appear both in the short and in the long run, however, when Cobar is high, it takes three years for abnormal returns in momentum strategy to be realized; v) neither the lowest nor the highest Comom/Cobar groups show significant positive returns in beta strategy after portfolio formation; vi) when Comom/Cobar is low, momentum strategy is not profitable, while during the periods of high Comom/Cobar abnormal returns occur in the long run.

The findings of this paper regarding abnormal returns in momentum stock during high Comom differs from the findings of Lou and Polk (2013). There is also discrepancy between my results and those of Huang et al. (2014) regarding the abnormal returns in beta strategy during high and low Cobar. More specifically in this study, I did not observe destabilizing effect of crowded arbitrage on abnormal returns that was found in the main articles. The discrepancies could arise because of the difference between the datasets in the main article and this paper, as well as difference in the methods of data construction caused by a lack of detailed methodology description in the original papers.

5. Limitations and Suggestions for Further Research

There are several potential weaknesses in the present study. One of the limitations is related to data availability. I obtained the data solely from CRSP due to lack of access to other sources of information used in the main articles. That could be one of the explanations of the differences in my results from the main findings of Lou and Polk (2013) and Huang et al. (2014).

Another weakness is the process of data construction that may be different from the one applied in the main articles. The limited description of data construction process urged me to use methods that reflect the main idea of the original articles but are not necessarily identical to the ones used by the authors.

To avoid the problem of inadequately measured risk in my study I observed several asset-pricing models. However, according to the obtained results, the asset-pricing models used for calculations of abnormal returns may significantly affect the outcome of the research. Hence, it is important to consider carefully the choice of the model for further investigations.

In this paper, I investigate only two strategies using the novel measures of Huang et al. (2014), and Lou and Polk (2013); but the new method measuring arbitrage activity in fact can be applied for any other strategy. Therefore, it would be worthwhile examining the effect of arbitrage activity in different strategies on abnormal returns in the same or other strategies. Furthermore, combined measures other than Comom and Cobar can be created and tested.

6. Conclusion

This paper investigates the effect of arbitrage activity in beta and momentum strategies on abnormal trading profits generated in the same strategies. It has been always difficult to measure arbitrage activity due to unavailability of information necessary for its evaluation. In this study, I used a new measure of arbitrage activity proposed by Lou and Polk (2013) and Huang et al. (2014), called Comom and Cobar. Following the method of the main articles, I replicated these measures based on the past degree of abnormal return correlations among those stocks on which investors would speculate. I investigated several specifications of the arbitrage measures and found that such parameters as asset-pricing model (three- or six-factor model) and inclusion of penny stocks do not affect the result. However, the choice of decile (decile 1 or 10) may affect the outcome. The measures, based on the decile 1 should produce the result different from the result of the measures, based on decile 10. Therefore, I suggest using the lowest deciles for both beta and momentum strategies because abnormal price correlations in these deciles should be indeed caused by the activity of arbitrageurs in the investigated strategies, while stocks in the highest deciles can be subjected to the effects unrelated to long-short beta or momentum strategies. The result also showed that Comom and Cobar cannot be used as substitutes for each other.

In the second part of the study, I focused on the effect of arbitrage activity in beta and momentum strategies using Cobar and Comom measures. I evaluated abnormal returns in momentum strategy through Comom and returns in beta-arbitrage strategy through Cobar. I also explored abnormal returns in one strategy during high and low activity in the other strategy. Furthermore, I made a simple combined measure Comom/Cobar to evaluate abnormal returns when activity in both strategies is high.

The main result of the paper indicates that arbitrage activity does not have one clearly defined effect on abnormal returns in beta and momentum strategy but rather generates specific price reactions in each strategy. In particular, I found that momentum strategies are profitable and stabilizing during periods of low Comom, supporting the finding of Lou and Polk (2013). However, another finding, which shows that during high Comom it takes three years for abnormal returns to materialize, is different from the finding of the original paper.

I also found that when Cobar is low, beta arbitrage strategy is profitable from the sixth month through year 3. During crowded trading in beta strategy no significant positive results are observed. However, these results are different from the results of Huang et al. (2014) who found that abnormal returns in beta-arbitrage strategies occur relatively quickly when arbitrage activity is high and take much longer to materialize when arbitrage activity is low. The differences between my results and those of Lou and Polk (2013) and Huang et al. (2014) could occur due to unavailability some of the originally used data that I consequently could not include into the dataset. Another reason could be different construction methods used in this study due to a lack of detailed descriptions of the methodology in the original articles.

My results also indicate that when activity in momentum strategy is high, the significant positive results in beta strategy occur only in the long run, while during low activity in momentum, beta strategy does not produce significant positive returns and in the long run abnormal returns become even negative.

When activity in beta strategy is high, it takes three years for abnormal returns in momentum strategy to be realized. However, during low activity in beta strategy, positive abnormal returns appear both in the short and in the long run.

Neither the lowest nor the highest Comom/Cobar groups produce significant positive abnormal returns in beta strategy after portfolio formation. Finally, when activity in momentum and beta arbitrage is low, momentum strategy is not profitable, whereas during the periods of high Comom/Cobar abnormal returns occur in the third year.

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