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The Booms and Busts of Beta Arbitrage

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The Booms and Busts of Beta Arbitrage

Abstract

Historically, low-beta stocks deliver high average returns and low risk relative to high-beta stocks, offering a potentially profitable investment opportunity for professional money managers to "arbitrage" away. We argue that beta-arbitrage activity instead generates booms and busts in the strategy's abnormal trading profits. In times of relatively little activity, the beta-arbitrage strategy exhibits delayed correction, taking up to three years for abnormal returns to be realized. In stark contrast, in times of relatively-high activity, short-run abnormal returns are much larger and then revert in the long run for the stocks in question. Importantly, we document a novel positive-feedback channel operating through firm-level leverage that facilitates these boom and bust cycles. Namely, when arbitrage activity is relatively high and beta-arbitrage stocks are relatively more levered, the cross-sectional spread in betas widens, resulting in stocks remaining in beta-arbitrage positions significantly longer with short-run abnormal returns more than tripling in value. Our findings are exclusively in stocks with relatively low limits to arbitrage (large, liquid stocks with low idiosyncratic risk), consistent with excessive arbitrage activity destabilizing prices.

I. Introduction

The trade-off of risk and return is the key concept of modern finance. The simplest and most intuitive measure of risk is market beta, the slope in the regression of a security's return on the market return. In the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), market beta is the only risk needed to explain expected returns. More specifically, the CAPM predicts that the relation between expected return and beta, the security market line, has an intercept equal to the risk-free rate and a slope equal to the equity premium.

However, empirical evidence indicates that the security market line is too flat on average (Black 1972) and especially so during times of high expected inflation (Cohen, Polk, and Vuolteenaho 2005), disagreement (Hong and Sraer 2014) and market sentiment (Antoniou, Doukas, and Subrahmanyam 2013). These patterns are not explained by other well-known asset pricing anomalies such as size, value, and price momentum.

We study the response of arbitrageurs to this failure of the Sharpe-Lintner CAPM in order to identify booms and busts of beta arbitrage. In particular, we exploit the novel measure of arbitrage activity introduced by Lou and Polk (2014). They argue that traditional measures of such activity are flawed, poorly measuring a portion of the inputs to the arbitrage process, for a subset of arbitrageurs. Lou and Polk's innovation is to measure the outcome of the arbitrage process, namely, the correlated price impacts that previous research (Anton and Polk 2014 and others) has shown can generate excess return comovement in the spirit of Barberis and Shleifer (2003).

We first confirm that our measure of the excess comovement of beta-arbitrage stocks ($CoBAR$) relative to the three-factor model is correlated with existing measures of arbitrage activity. In particular, we find that time variation in the level of institutional holdings in low-beta stocks (i.e., stocks in the long leg of the beta strategy), the assets under management of long-short equity hedge funds, and aggregate liquidity together forecast roughly 38% of the time-series variation in $CoBAR$. These findings suggest that not only is our measure consistent with existing proxies for arbitrage activity but also that no one single existing proxy is sufficient for capturing time-series variation in arbitrage activity. Indeed, one could argue that perhaps much of the unexplained variation in $CoBAR$ represents variation in arbitrage activity missed by existing measures.

After validating our measure in this way, we then forecast the cumulative abnormal returns to beta arbitrage. We first find that when arbitrage activity is relatively high (as identified by the 20% of the sample with the highest values of $CoBAR$), abnormal returns to beta-arbitrage strategies occur relatively quickly, within the first six months of the trade. In contrast, when arbitrage activity is relatively low (as identified by the 20% of the sample with the lowest values of $CoBAR$), abnormal returns to beta-arbitrage strategies take much longer to materialize, appearing only two to three years after putting on the trade.

These effects are both economically and statistically significant. When beta-arbitrage activity is low, the abnormal four-factor returns on beta arbitrage are actually negative and statistically insignificant from zero in the six months after portfolio formation. For the patient arbitrageur, in year 3, the strategy earns abnormal four-factor returns of .50% per month with a t-statistic of 2.49. In stark contrast, for those periods when arbitrage activity is high, the abnormal four-factor returns to beta arbitrage average 1.04% per month with a t-statistic of 2.41 in the six months after the trade. Indeed, the return differential in the first six months between high and low $CoBAR$ periods is 1.25% per month with a t-statistic of 2.11.

We then show that the stronger performance of beta-arbitrage activities during periods of high beta-arbitrage activity can be linked to subsequent reversal of those profits. In particular, the year 3 abnormal four-factor returns are -0.92% with an associated t-statistic of -3.18. As a consequence, the long-run reversal of beta-arbitrage returns varies predictably through time in a striking fashion. The post-formation, year-3 spread in abnormal returns across periods of low arbitrage activity, when abnormal returns are predictably positive, and periods of high arbitrage activity, when abnormal returns are predictably negative, is -1.41%/month (t-statistic = -3.69) or more than 18% cumulative in that year.

This finding is the main result of the paper. 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. These results are consistent with time-varying arbitrage activity generating booms and busts in beta arbitrage.

We argue that these results are intuitive, as it is difficult to know how much arbitrage activity is pursuing beta arbitrage, and, in particular, the strategy is susceptible to positive-feedback trading. Specifically, successful bets on (against) low-beta (high-beta) stocks result in prices for those securities rising (falling). If the underlying firms are leveraged, this change in price will, all else equal, result in the security's beta falling (increasing) further. Thus, not only do arbitrageurs not know when to stop trading the low-beta strategy, their (collective) trades strengthen the signal. Consequently, beta arbitrageurs may increase their bets precisely when trading is more crowded.[1] Consistent with our novel positive-feedback story, we show that the cross-sectional spread in betas increases when beta-arbitrage activity is high and particularly so when beta-arbitrage stocks are relatively more levered. We document that, as a consequence, stocks remain in the extreme beta portfolios for a longer period of time.

A variety of robustness tests confirm our main findings. In particular, we show that controlling for other factors when either measuring $CoBAR$ or when predicting beta-arbitrage returns does not alter our primary conclusion that the excess comovement of beta-arbitrage stocks forecasts time-varying reversal to beta-arbitrage bets or that the beta spread varies with $CoBAR$.

Our findings can also be seen by estimating time variation in the short-run (months 1-6) and long-run (year 3) security market line, conditioning on $CoBAR$. Thus, the patterns we find are not just due to extreme-beta stocks, but reflect dynamic movements throughout the entire cross section. In particular, we find that during periods of high beta-arbitrage activity, the short-term security market line strongly slopes downward, indicating strong profits to the low-beta strategy, consistent with arbitrageurs expediting the correction of market misevaluation. However, this correction is excessive, as the long-run security market line dramatically slopes upwards. In

[1] Of course, crowded trading may or may not be profitable, depending on how long the arbitrageur holds the position and how long it takes for any subsequent correction to occur.

contrast, during periods of low beta-arbitrage activity, the short-term security market line is essentially flat. During these low-arbitrage periods, we do not find any downward slope to the security market line until the long-run.

A particularly compelling robustness test involves separating $CoBAR$ into excess comovement among low-beta stocks occurring when these stocks have relatively high returns (i.e., capital flowing into low beta stocks and pushing up the prices) vs. excess comovement occurring when low-beta stocks have relatively low returns–i.e., upside versus downside comovement. Under our interpretation of the key findings, it is the former that should track time-series variation in expected beta-arbitrage returns, as that particular direction of comovement is consistent with trading aiming to correct the beta anomaly. Our evidence confirms this indeed is the case: our main results are primarily driven by upside $CoBAR$.

Finally, Shleifer and Vishny (1997) link the extent of arbitrage activity to limits to arbitrage. Based on their logic, trading strategies that bet on firms that are cheaper to arbitrage (e.g., larger stocks, more liquid stocks, or stocks with lower idiosyncratic risk) should have more arbitrage activity. This idea of limits to arbitrage motivates tests examining cross-sectional heterogeneity in our findings. We show that our results primarily occur in those stocks that provide the *least* limits to arbitrage: large stocks, liquid stocks, and stocks with low idiosyncratic volatility. This cross-sectional heterogeneity in the effect is again consistent with the interpretation that arbitrage activity causes much of the time-varying patterns we document.

Our novel feedback channel also has implications for cross-sectional heterogeneity in abnormal returns. Consistent with our story, we show that the returns to beta-arbitrage are particularly strong among high-leverage stocks. The difference in four-factor alphas in the first six months between high and low $CoBAR$ periods is a striking 3.76% per month (t-statistic of 2.46) for high-leverage stocks.

The organization of our paper is as follows. Section II summarizes the related literature. Section III describes the data and empirical methodology. We detail our empirical findings in section IV, and present some additional results in Section V. Section VI concludes.

II. Related Literature

Our results shed new light on the risk-return trade-off, a cornerstone of modern asset pricing research. This trade-off was first established in the famous Sharpe-Lintner CAPM, which argues that the market portfolio is mean-variance-efficient. Consequently, a stock's expected return is a linear function of its market beta, with a slope equal to the equity premium and an intercept equal to the risk-free rate.

However, mounting empirical evidence is inconsistent with the CAPM. Black, Jensen, and Scholes (1972) were the first to show carefully that the security market line is too flat on average. Put differently, the risk-adjusted returns of high beta stocks are too low relative to those of low-beta stocks. This finding was subsequently confirmed in an influential study by Fama and French (1992). Blitz and van Vliet (2007) and Baker, Bradley, and Taliaferro (2013), Frazzini and Pedersen (2014), and Blitz, Pang, and van Vliet (2012) document that the low-beta anomaly is also present in both non-US developed markets as well as emerging markets.

Of course, the flat security market line is not the only failing of the CAPM (see Fama and French 1992, 1993, and 1996). Nevertheless, since this particular issue is so striking, a variety of explanations have been offered to explain the low-beta phenomenon. Black (1972) and more recently Frazzini and Pedersen (2014) argue that leverage-constrained investors, such as mutual funds, tend to deviate from the capital market line and invest in high beta stocks to pursue higher expected returns, thus causing these stocks to be overpriced relative to the CAPM benchmark.[2]

Cohen, Polk, and Vuolteenaho (2005) derive the cross-sectional implications of the CAPM in conjunction with the money illusion story of Modigliani and Cohn (1979). They show that money illusion implies that, when inflation is low or negative, the compensation for one unit of beta among stocks is larger (and the security market line steeper) than the rationally expected equity premium. Conversely, when inflation is high, the compensation for one unit of beta among stocks is lower (and the security market line shallower) than what the overall pricing of stocks relative to bills would suggest. Cohen, Polk, and Vuolteenaho provide empirical evidence in support of their theory.

Hong and Sraer (2014) provide an alternative explanation based on Miller's (1977) insights. In particular, they argue that investors disagree about the value of the market portfolio. This disagreement, coupled with short sales constraints, can lead to overvaluation, and particularly so for high-beta stocks, as these stocks allow optimistic investors to tilt towards the market. Further, Kumar (2009) and Bali, Cakici, and Whitelaw (2011) show that high risk stocks can indeed underperform low risk stocks, if some investors have a preference for volatile, skewed returns, in the spirit of the

[2] See also Baker, Bradley, and Wurgler (2011) and Buffa, Vayanos, and Woolley (2014) for related explanations based on benchmarking of institutional investors.

cumulative prospect theory as modeled by Barberis and Huang (2008). Related work also includes Antoniou, Doukas, and Subrahmanyam (2013).[3]

A natural question is why sophisticated investors, who can lever up and sell short securities at relatively low costs, do not take advantage of this anomaly and thus restore the theoretical relation between risk and returns. Our paper is aimed at addressing this exact question. Our premise is that professional investors indeed take advantage of this low-beta return pattern, often in dedicated strategies that buy low-beta stocks and sell high-beta stocks. However, the amount of capital that is dedicated to this low-beta strategy is both time varying and unpredictable from arbitrageurs' perspectives, thus resulting in periods where the security market line remains too flat–i.e., too little arbitrage capital, as well as periods where the security market line becomes overly steep–i.e., too much arbitrage capital.

Not all arbitrage strategies have these issues. Indeed, some strategies have a natural anchor that is relatively easily observed (Stein 2009). For example, it is straightforward to observe the extent to which an ADR is trading at a price premium (discount) relative to its local share. This ADR premium/discount is a clear signal to an arbitrageur of an opportunity and, in fact, arbitrage activity keeps any price differential small with deviations disappearing within minutes.[4] Importantly, if an unexpectedly large number of ADR arbitrageurs pursue a particular trade, the price differential narrows. An individual ADR arbitrageur can then adjust his or her demand accordingly.

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[3] Of course, since all tests of market efficiency are joint tests of market efficiency and a particular model of market equilibrium (Fama 1970), one must always consider the possibility that a better model of market equilibrium can explain this and other failures of the Sharpe-Lintner CAPM. In fact, Campbell, Giglio, Polk, and Turley (2014) document that high-beta stocks hedge time-variation in the aggregate market's return volatility, offering a potential explanation for the low-beta anomaly.

[4] Rösch (2014) studies various properties of ADR arbitrage. For his sample of 72 ADR home stock stock pairs, the average time it takes until a ADR/home stock price deviation disappears is 252 seconds. For an institutional overview of this strategy, see J.P. Morgan (2014).

Similarly, value investors trading the book-to-market effect documented by Fama and French (1992) can rely on the cross-sectional spread in book-to-market ratios, dubbed the value spread by Cohen, Polk, and Vuolteenaho (2003). Those authors tie the profitability of value investing to the value spread both theoretically and empirically. In particular, Cohen, Polk, and Vuolteenaho (2003) derive an approximate log-linear model relating the spread in log book-to-market-equity ratios (θ) across high and low book-to-market portfolios to the spread in discounted expected future log returns (r) and log profitability (e) across those portfolios,

$$(B^{H}_{t-1} - B^{L}_{t-1}) \approx \sum_{j=0}^{oo} p^{j} E_{t-1} r^{HML}_{t+j} - \sum_{j=0}^{oo} p^{j} E_{t-1} e^{HML}_{t+j}.$$

Their model motivates a regression forecasting the return on a zero-cost portfolio similar to the HML factor of Fama and French (1993) using the value spread and the current spread in profitability,

$$R^{HML}_{t} = a + b(B^{H}_{t-1} - B^{L}_{t-1}) + c(e^{H}_{t-1} - e^{L}_{t-1}) + E_{t}$$

Their model is successful at predicting the returns on HML. Thus, value investors have a relatively straightforward anchor that is analogous to the ADR / home stock price gap. Buy value stocks and sell growth stocks until the value spread converges to the current profitability gap.[5] But there is no easy anchor for beta arbitrage.[6,7]

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[5] Asness, Friedman, Krail, and Liew (2000) suggest using projected earnings growth in such a comparison.

[6] Polk, Thompson, and Vuolteenaho (2006) use the Sharpe-Lintner CAPM to relate the cross-sectional beta premium to the equity premium. They show how the divergence of the two types of equity-premium measures implies a time-varying trading opportunity for beta arbitrage. Their methods are quite sophisticated and produce signals about the time-varying attractiveness of beta-arbitrage that, though useful in predicting beta-arbitrage returns, are still, of course, quite noisy.

[7] On average, low-beta (high-beta) stocks tend to be value (growth) stocks. As a consequence, the spread in book-to-market-equity ratios could potentially inform beta arbitrageurs about the relative attractiveness of the strategy. However, Frazzini and Pedersen (2014) document that beta-arbitrage strategies are not subsumed by value controls. Moreover, our analysis similarly controls for the value effect. Nevertheless, we confirm that our results are robust to controlling for the spread in book-to-market ratios across beta deciles in Table V.

We argue that the difficulty in identifying the amount of beta-arbitrage capital is exacerbated by an indirect positive-feedback channel.[8] Namely, beta-arbitrage trading can lead to the cross-sectional beta spread increasing when firms are levered. As a consequence, stocks in the extreme beta deciles are more likely to remain in these extreme groups when arbitrage trading becomes excessive. Given that beta arbitrageurs rely on realized beta as their trading signal, this beta expansion resulting from leverage effectively causes a potential feedback loop in the beta-arbitrage strategy.

III. Data and Methodology

The main dataset used in this study is the stock return data from the Center for Research in Security Prices (CRSP). Following prior studies on the beta-arbitrage strategy, we include in our study all common stocks on NYSE, Amex, and NASDAQ. We then augment this stock return data with institutional ownership in individual stocks provided by Thompson Financial. We further obtain information on assets under management of long-short equity hedge funds from Lipper's Trading Advisor Selection System (TASS). Since the assets managed by hedge funds grow substantially in our sample period, we detrend this variable.

We also construct, as controls, a list of variables that have been shown to predict future beta-arbitrage strategy returns. Specifically, a) following Cohen, Polk, and Vuolteenaho (2005), we construct an expected inflation index, defined as the exponential moving average CPI growth rate over the past 100 months (where the weight on month

[8] The idea that positive-feedback strategies are prone to destabilizing behaviour goes back to at least DeLong, Shleifer, Summers, and Waldmann (1990). In contrast, negative-feedback strategies like ADR arbitrage or value investing are less susceptible to destabilizing behaviour by arbitrageurs, as the price mechanism mediates any potential congestion. See Stein (2009) for a discussion of these issues.

N is given by 2/(n+1)); b) we also include in our study the sentiment index proposed by Baker and Wurgler (2006, 2007); c) following Hong and Sraer (2014), we construct an aggregate disagreement proxy as the beta-weighted standard deviation of analysts' long-term growth rate forecasts; finally, following Frazzini and Pedersen (2014), we use the Ted spread–the difference between the LIBOR rate and the US Treasury bill rate–as a measure of financial intermediaries' funding constraints.

At the end of each month, we sort all stocks into deciles (in some cases vigintiles) based on their pre-ranking market betas. Following prior literature, we calculate pre-ranking betas using daily returns in the past twelve months. (Our results are similar if we use monthly returns, or different pre-ranking periods.) To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression.

We then compute pairwise partial correlations using 52 weekly returns for all stocks in each decile in the portfolio ranking period. We control for the Fama-French three factors when computing these partial correlations to purge out any comovement in stocks induced by known risk factors. We measure the excess comovement of stocks involved in beta arbitrage ($CoBAR$) as the average pairwise partial correlation in the lowest market beta decile.[9] We operationalize this calculation by measuring the average

[9] We focus on the low-beta decile as these stocks tend to be larger and more liquid and, as a consequence, our measurement of excess comovement will be less susceptible to issues related to asynchronous trading. However, our results are robust to measuring CoBAR using the high-beta decile or combining both the high- and low-beta deciles together (with the appropriate sign change).

correlation of the three-factor residual of every stock in the lowest beta decile with the rest of the stocks in the same decile:

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

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. We have also measured $CoBAR$ using characteristics-adjusted stock returns (as in Daniel, Grinblatt, Titman, and Wermers, 1997), and returns that are orthogonalized not only to the Fama-French factors but also to each stock's industry return or to other empirical priced factors, and all our main results go through. We present these and many other robustness tests in Table IV.

In the following period, we then form a zero-cost portfolio that goes long the value-weight portfolio of stocks in the lowest market beta decile and short the value-weight portfolio of stocks in the highest market beta decile. We track the cumulative abnormal returns of this zero-cost long-short portfolio in months 1 through 36 after portfolio formation. To summarize the timing of our empirical exercise, year 0 is our portfolio formation year (during which we also measure $CoBAR$), year 1 is the holding year, and years 2 and 3 are our post-holding period, to detect any (conditional) long-run reversal to the beta-arbitrage strategy.

IV. Main Results

We first document simple characteristics of our arbitrage activity measure. Table I Panel A indicates that there is significant excess correlation among low-beta stocks on average and that this pairwise correlation varies through time. Specifically, the mean of *CoBAR* is .11 varying from a low of .03 to a high of .22.

Panel B of Table I examines *CoBAR*'s correlation with existing measures linked to time variation in the expected abnormal returns to beta-arbitrage strategies. We find that *CoBAR* is high when either disagreement or sentiment is high, with correlations of 0.34 and 0.12 respectively. *CoBAR* is also positively correlated with the Ted spread, consistent with a time-varying version of Black (1972), though the Ted spread does not forecast time-variation in expected abnormal returns to beta-arbitrage strategies (Frazzini and Pederson 2014). *CoBAR* is negatively correlated with the expected inflation measure of Cohen, Polk, and Vuolteenaho. However, in results not shown, the correlation between expected inflation and *CoBAR* becomes positive for the subsample from 1990-2010, consistent with arbitrage activity eventually taking advantage of this particular source of time-variation in beta-arbitrage profits.

Figure 1 plots *CoBAR as of the end of each December*. At the beginning of the sample, *CoBAR* exhibits some extreme swings, though these estimates are imprecisely measured. Note that we do not necessarily expect a trend in this measure. Though there is clearly more capital invested in beta-arbitrage strategies, in general, markets are also more liquid. Nevertheless, starting in 1974, *CoBAR* slowly trends slightly upward to the end of the sample. However, there are clear cycles around this trend. These cycles tend to peak before broad market declines. Also, note that *CoBAR* is essentially uncorrelated with market volatility. A regression of *CoBAR* on contemporaneous realized market volatility produces a loading of -0.023 with a *t*-statistic of -0.62.

Consistent with our measure tracking arbitrage activity, *CoBAR* is persistent through time. The autocorrelation of non-overlapping December observations is 0.1. Table A1 in the Internet Appendix documents that *CoBAR* is also persistent in event time. Specifically, the correlation between *CoBAR* measured in year 0 and year 1 for the same set of stocks is 0.24. In fact, year-0 *CoBAR* remains highly correlated with subsequent values of *CoBAR* for the same stocks all the way out to year 3. The average value of *CoBAR* remains high as well. Recall that in year 0, the average excess correlation is 0.11. We find that in years 1, 2, and 3, the average excess correlation of these same stocks remains around 0.07.[10]

IV.A. Determinants of *CoBAR*

To confirm that our measure of beta-arbitrage is sensible, we estimate regressions forecasting *CoBAR* with two variables that are often used to proxy for arbitrage activity. The first variable we use is the aggregate institutional ownership (*Inst Own*) of the low-beta decile–i.e., stocks in the long leg of the beta strategy–based on 13F filings. We include institutional ownership as these investors are typically considered smart money, at least relative to individuals, and we focus on their holdings in the low-beta decile as we do not observe their short positions in the high-beta decile. We also include the assets under management (*AUM*) of long-short equity hedge funds, the prototypical arbitrageur.

[10] *CoBAR* is essentially uncorrelated with a similar measure of excess comovement based on the fifth and sixth beta deciles.

All else equal, we expect *CoBAR* to be lower if markets are more liquid. However, as arbitrage activity is endogenous, times when markets are more liquid may also be times when arbitrageurs are more active. Indeed, Cao, Chen, Liang, and Lo (2013) show that hedge funds increase their activity in response to increases in aggregate liquidity. Following Cao, Chen, Liang, and Lo, we further include past market liquidity as proxied by the Pastor and Stambaugh (2003) liquidity factor (*PS liquidity*) in our regressions to measure which channel dominates.

All regressions in Table II include a trend to ensure that our results are not spurious. We also report specifications that include variables that arguably should forecast beta-arbitrage returns, the inflation, sentiment, and disagreement indices as well as the Ted spread. We measure these variables contemporaneously with *CoBAR* as we will be running horse races against these variables in our subsequent analysis.

Regression (2) in Table II documents that all three variables (*Inst Own, AUM,* and *PS liquidity*) forecast *CoBAR*, with an R^2 of approximately 38%.[11] Regressions (3) and (4) show that the extant predictors of beta-arbitrage returns are not highly correlated with *CoBAR*. Only one potential predictor of beta-arbitrage profitability, the Ted spread, adds some incremental explanatory power, with the sign of the coefficient consistent with arbitrageurs taking advantage of potential time-variation in beta-arbitrage returns linked to this channel. Indeed, as we show later, the Ted spread does a poor job forecasting beta-arbitrage returns in practice, perhaps because arbitrageurs have compensated appropriately for this potential departure from Sharpe-Lintner pricing.

[11] We choose to forecast *CoBAR* in predictive regressions rather than explain *CoBAR* in contemporaneous regressions simply to reduce the chance of a spurious fit. However, Table A2 in the Internet Appendix shows that R^2s remain high in contemporaneous versions of these regressions.

Overall, these findings make us comfortable in our interpretation that $CoBAR$ is related to arbitrage activity and distinct from existing measures of opportunities in beta arbitrage. As a consequence, we turn to the main analysis of the paper, the short- and long-run analysis of beta-arbitrage returns, conditional on $CoBAR$.

IV.B. Forecasting Beta-Arbitrage Returns

Table III forecasts the abnormal returns on the standard beta-arbitrage strategy as a function of investment horizon, conditional on $CoBAR$.[12] Panel A examines CAPM-adjusted returns while Panel B studies abnormal returns relative to the four-factor model of Carhart (1997). In each panel, we measure the average abnormal returns in the first six months subsequent to the beta-arbitrage trade, and those occurring in years one, two, and three. These returns are measured conditional on the value of $CoBAR$ as of the end of the beta formation period. In particular, we split the sample into five equal $CoBAR$ groups.

Pursuing beta arbitrage when arbitrage activity is low takes patience. Abnormal CAPM returns are statistically insignificant in the first year for the bottom three $CoBAR$ groups. Only in the second year do abnormal returns become statistically significant for the two lowest $CoBAR$ groups. This statistical significance continues through year 3 for the 20% of the sample where beta-arbitrage activity is at its lowest values.

[12] To ensure that our results do not repackage any existing predictability findings, our non-parametric portfolio analysis in Tables III, IV, and IX first orthogonalizes $CoBAR$ to the two extant beta-arbitrage predictors available for the entire sample, the sentiment and inflation indices. The resulting residual $CoBAR$ is highly correlated (0.93) with the original series and results are quite similar regardless of which series we use.

These findings are strengthened once returns are adjusted for size, value, and momentum effects. In Panel B, four-factor beta-arbitrage alphas are indistinguishable from zero except in year 3 for the lowest $CoBAR$ group. In that period, the four-factor alpha is 0.50%/month with an associated t-statistic of 2.49.[13]

However, as beta-arbitrage activity increases, the abnormal returns arrive sooner and stronger. For the highest $CoBAR$ group, the abnormal four-factor returns average 1.04%/month in the six months immediately subsequent to the beta-arbitrage trade. This finding is statistically significant with a t-statistic of 2.41. Moreover, the difference between abnormal returns in high and low $CoBAR$ periods is 1.25%/month (t-statistic of 2.11).

The key finding of our paper is that these quicker and stronger beta-arbitrage returns can be linked to subsequent reversal in the long run. Specifically, in year three, the abnormal four-factor return to beta arbitrage when $CoBAR$ is high is -0.92%/month, with a t-statistic of -3.18. These abnormal returns are dramatically different from their corresponding values when $CoBAR$ is low; the difference in year 3 abnormal four-factor returns is a gigantic -1.41%/month (t-statistic: -3.69).

The top plot of Figure 2 summarizes these patterns by plotting the cumulative abnormal four-factor returns to beta arbitrage during periods of high and low $CoBAR$. This figure clearly shows that there is a significant delay in abnormal trading profits to beta arbitrage when beta-arbitrage activity is low. However, when beta-arbitrage activity is high, beta arbitrage results in prices overshooting, as evidenced by the long-run reversal we document. We argue that trading of the low-beta anomaly is initially

[13] We have also separately examined the long and short legs of beta arbitrage (i.e., low-beta vs. high-beta stocks). Around 40% of our return effect comes from the long leg, and the remaining 60% from the short leg.

stabilizing, then, as the trade becomes crowded, turns destabilizing, causing prices to overshoot.[14]

IV.C. Robustness of Key Results

Table IV examines variations to our methodology to ensure that our finding of time-varying reversal of beta-arbitrage profits is robust. For simplicity, we only report the difference in returns to the beta strategy between the high and low $CoBAR$ groups in the short run (months 1-6) and the long-run (year 3). For comparison, the first row of Table IV reports the baseline results from Table III Panel B.

In rows two and three, we conduct the same analysis for two subperiods (1965-1980 and 1981-2010). Our finding is stronger in the second subsample, consistent with the intuition that beta arbitrage has dramatically increased in popularity over the last thirty years. The second subsample has an average monthly return differential in year 3 across the high and low $CoBAR$ groups of -1.78%, with an associated *t*-statistic of -4.99. This point estimate is more than twice as large as the corresponding estimate for the earlier period. Our results remain robust if we exclude the tech bubble crash (2000-2001) or the recent financial crisis (2007-2009) from our sample.

In rows six through nine, we report the results from similar tests using extant variables linked to potential time variation in beta-arbitrage profits. None of the four variables are associated with time variation in long-run abnormal returns.

In the tenth row, we control for UMD when computing $CoBAR$. In rows 11 through 14, we orthogonalize $CoBAR$ not only to the inflation and sentiment indices but also to the average correlation in the market (Pollet and Wilson 2010), the past

[14] We discuss the bottom plot of Figure 2 as well as the 5-1 (conditional) rows in Table II in Section V.C.

volatility of beta-arbitrage returns, and measures of arbitrage activity in momentum and value (Lou and Polk 2013). In row 15, we control for a trend in *CoBAR*. In row 16, we include stock specific industry factors in the calculation of *CoBAR*. In row 17, we separate HML into its large cap and small cap components. In Row 18, we report results based on DGTW-adjusted portfolio returns. In Row 19, we report six-factor-adjusted abnormal returns (including liquidity and reversal factors). Row 20 documents that our results are robust to orthogonalizing *CoBAR* to the volatility of market returns over the twelve-month period corresponding to the measurement of *CoBAR*.

In all cases, *CoBAR* continues to predict time-variation in year 3 returns. The estimates are always very economically significant, with no point estimate smaller than 1%/month.[15] Statistical significance is always strong as well, with no *t*-statistic less than 2.44. Taken together, these results confirm that our measure of crowded beta arbitrage robustly forecasts times of strong reversal to beta-arbitrage strategies.

Rows 21 and 22 split *CoBAR* into upside and downside components. Specifically, we measure the following

$$CoBAR^U = \frac{1}{N}\sum_{i=1}^{N} partialCorr(retrf_i^L, retrf_{-i}^L \mid mktrf, smb, hml, retrf^L > median(retrf^L))$$

$$CoBAR^D = \frac{1}{N}\sum_{i=1}^{N} partialCorr(retrf_i^L, retrf_{-i}^L \mid mktrf, smb, hml, retrf^L < median(retrf^L))$$

Separating *CoBAR* in this way allows us to distinguish between excess comovement tied to strategies buying low-beta stocks (such as those followed by beta arbitrageurs) and

[15] Though in some instances, difference in short-run abnormal returns across high and low *CoBAR* periods are no longer statistically significant; the point estimates are always economically large. Moreover, some of the overcorrection corresponding to the long-run reversal may accrue in our formation period as the timing of our empirical exercise is somewhat arbitrary. It is certainly possible that the beta arbitrageurs we are interested in may use shorter formation periods when pursuing their particular version of the strategy.

strategies selling low-beta stocks (such as leveraged-constrained investors modeled by Black (1972)). Consistent with our interpretation, we find that only $CoBAR^U$ forecasts time variation in the short- and long-run expected returns to beta arbitrage (whereas $CoBAR^D$ does not).

Finally, in rows 23 and 24, we report the results of AUM (as the only proxy for arbitrage activity available for the full sample) as well as the linear combination of the three variables implied by regression (2) in Table II. AUM is unable to pick up the long-run reversal we have linked to $CoBAR$. Interestingly, the fitted value of $CoBAR$ from regression (2) in Table II is able to pick up some of this reversal, though the effect is not statistically significant.

In Table V, we report the results of regressions forecasting the abnormal four-factor returns to beta-arbitrage spread bets. Unlike Table II, these regressions exploit not just the ordinal but also the cardinal aspect of $CoBAR$. Moreover, these regressions not only confirm that our findings are robust to existing measures of the profitability of beta arbitrage, they also document the relative extent to which existing measures forecast abnormal returns to beta-arbitrage strategies in the presence of $CoBAR$.

Regressions (1)-(3) in Table V forecast time-series variation in abnormal beta-arbitrage returns in months 1-6. Regression (1) confirms that $CoBAR$ strongly forecasts beta-arbitrage four-factor alphas over the full sample. Regression (2) then includes controls that are available over the entire sample. These include the inflation and sentiment indices, market volatility, and a version of Cohen, Polk, and Vuolteenaho's (2003) value spread for the beta deciles in question. $CoBAR$ continues to reliably describe time-variation in abnormal four-factor returns on the low-beta-minus-high-beta strategy, with only the sentiment index providing any additional explanatory power. Over the shorter period where both aggregate disagreement and the Ted spread are available, $CoBAR$ does not independently forecast time-variation in the abnormal returns to a standard beta-arbitrage strategy.

Regressions (4)-(6) of Table V forecast the returns on beta-arbitrage strategies in year 3. The message from these regressions concerning the main result of the paper is clear; $CoBAR$ strongly forecasts a time-varying reversal regardless of the other forecasting variables included in the regression.

IV.D. Predicting the Security Market Line

Our results can also be seen from the time variation in the shape of the security market line (SML) as a function of lagged $CoBAR$. Such an approach documents that the time-variation we document is not restricted to a small subset of extreme betas stocks, but instead is a robust feature of the cross-section. At the end of each month, we sort all stocks into 20 value-weighted portfolios by their pre-ranking betas.[16] We track these 20 portfolio returns both in months 1-6 and months 25-36 after portfolio formation to compute short-term and long-term post-ranking betas, and, in turn, to construct our short-term and long-term security market lines.

For the months 1-6 portfolio returns, we then compute the post-ranking betas by regressing each of the 20 portfolios' value-weighted monthly returns on market excess returns. Following Fama and French (1992), we use the entire sample to compute post-ranking betas. That is, we pool together these six monthly returns across all calendar

[16] We sort stocks into vigintiles in order to increase the statistical precision of our cross-sectional estimate. However, Table A3 in the Internet Appendix confirms that our results are qualitatively the same if we instead sort stocks into deciles.

months to estimate the portfolio beta. We estimate post-ranking betas for months 25-36 in a similar fashion. The two sets of post-ranking betas are then labelled $\beta_1^1, \ldots, \beta_{20}^1$ and $\beta_1^{25}, \ldots, \beta_{20}^{25}$.

To calculate the intercept and slope of the short-term and long-term security market lines, we estimate the following cross-sectional regressions:

$$\text{short-term SML: } XRet_{i,t}^1 = intercept_t^1 + slope_t^1 \beta_i^1,$$

$$\text{long-term SML: } XRet_{i,t}^{25} = intercept_t^{25} + slope_t^{25} \beta_i^{25},$$

where $XRet_{i,t}^1$ is portfolio i's monthly excess returns in months 1 through 6, and $XRet_{i,t}^{25}$ is portfolio i's monthly returns in months 25 through 36. These two regressions then give us two time-series of coefficient estimates of the intercept and slope of the short-term and long-term security market lines: $(intercept_t^1, slope_t^1)$ and $(intercept_t^{25}, slope_t^{25})$, respectively. As the average excess returns and post-ranking betas are always measured at the same point in time, the pair $(intercept_t^1, slope_t^1)$ fully describes the security market line in the short run, while $(intercept_t^{25}, slope_t^{25})$ captures the security market line two years down the road.

We then examine how these intercepts and slopes vary as a function of our measure of beta-arbitrage capital. In particular, we conduct an OLS regression of the intercept and slope measured in each month on lagged $CoBAR$. As can be seen from Table VI, the intercept of the short-term security market line significantly increases in $CoBAR$, and its slope significantly decreases in $CoBAR$. The top panel of Figure 3 shows this fact clearly. During high $CoBAR$–i.e., high beta-arbitrage capital–periods, the short-term security market line strongly slopes downward, indicating strong profits to the low-beta strategy, consistent with arbitrageurs expediting the correction of market misevaluation. In contrast, during low $CoBAR$–i.e., low beta-arbitrage capital–periods, the short-term security market line is essentially flat and the beta-arbitrage strategy, as a consequence, unprofitable, consistent with delayed correction of the beta anomaly.

The pattern is completely reversed for the long-term security market line. The intercept of the long-term security market line is significantly negatively related to $CoBAR$, whereas its slope is significantly positively related to $CoBAR$. As can be seen from the bottom panel of Figure 3, two years after high $CoBAR$ periods, the long-term security market line turns upward sloping; indeed, the slope is so steep that the beta strategy loses money, consistent with over-correction of the low beta anomaly by crowded arbitrage trading. In contrast, after low $CoBAR$ periods, the long-term security market line turns downward sloping, reflecting eventual profitability of the low-beta strategy in the long run.

V. Additional Analyses

We perform a number of further analyses to provide additional support to our thesis that crowded arbitrage trading can potentially destabilize prices.

V.A. Beta Expansion

Beta arbitrage can be susceptible to positive-feedback trading. Successful bets on (against) low-beta (high-beta) stocks result in prices for those securities rising (falling). If the underlying firms are leveraged, this change in price will, all else equal, result in the security's beta falling (increasing) further.[17] Thus, not only do arbitrageurs not know

[17] The idea that, all else equal, changes in leverage drive changes in equity beta is, of course, the key insight behind Proposition II of Modigiliani and Miller (1958).

when to stop trading the low-beta strategy, their (collective) trades also affect the strength of the signal. Consequently, beta arbitrageurs may increase their bets precisely when trading becomes crowded and the profitability of the strategy has decreased.

We test this prediction in Table VII. The dependent variable in columns (1) and (2) is the spread in betas across the high and low value-weight beta decile portfolios, denoted *BetaSpread*, as of the end of year 1. The independent variables include lagged *CoBAR*, the beta-formation-period value of *BetaSpread*, the average book leverage quintile (*Leverage*) across the high and low beta decile portfolios, and an interaction between *CoBAR* and *Leverage*.

The dependent variable in columns (3) and (4) is the fraction of the stocks in the high and low beta decile portfolios that continue to be in these portfolios when stocks are resorted into beta deciles at the end of year 1 (denoted *Fraction*). Note that since we estimate beta using 52 weeks of stock returns, the two periods of beta estimation that determine the change in *BetaSpread* and *Fraction* do not overlap. We include a trend in all regressions, but our results are robust to not including the trend dummy.

Regression (1) in Table VII shows that when *CoBAR* is relatively high, future *BetaSpread* is also high, controlling for lagged *BetaSpread*. A one-standard-deviation increase in *CoBAR* forecasts an increase in *BetaSpread* of roughly 6%. Regression (2) shows that this is particular true when *Leverage* is also high. If beta-arbitrage bets were to contain the highest book-leverage quintile stocks, a one-standard deviation increase in *CoBAR* would increase *BetaSpread* by nearly 9.5%. These two facts are consistent with a positive feedback channel for the beta-arbitrage strategy that works through firm-level leverage.

Regressions (3) and (4) replace the dependent variable, *BetaSpread*, with *Fraction*. Regression (3) shows that a larger fraction of the stocks in the extreme beta portfolio remain in these extreme portfolios when *CoBAR* is relatively high. Specifically, a one-standard-deviation increase in *CoBAR* is associated with the level of *Fraction* increasing by almost 7.8%. Regression (4) confirms that this effect is particularly strong when *Leverage* is also high. If beta-arbitrage bets were to contain the highest book-leverage quintile stocks, a one-standard deviation increase in *CoBAR* would increase *Fraction* by more than 9.3%. Table VII Panel B confirms that these results are robust to the same methodological variations as in Table IV.

Table VIII turns to firm-level regressions to document the beta expansion our story predicts. In particular, we estimate panel regressions of subsequent changes in stock beta on lagged *CoBAR* . At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. The dependent variable is *BetaChange*, the change in stock beta from year t to t+1 (again, we use non-overlapping periods). In addition to *CoBAR*, we also include *Distance*, the difference between a stock's beta decile rank and the average rank of 5.5 in year t. *Leverage* is the book leverage of the firm, measured in year t. We also include all double and triple interaction terms of *CoBAR*, *Distance*, and *Leverage*. Other control variables include the lagged firm size, book-to-market ratio, lagged one-month and one-year stock return, and the prior-year idiosyncratic volatility. Time-fixed effects are included in Columns 3 and 4. Note that since *CoBAR* is a time-series variable, it is subsumed by the time dummies in those regressions.

In all four regresisons, stocks with higher *Distance* have a lower *BetaChange*, consistent with mean reversion. Our main focus is on the triple interaction among *CoBAR*, *Distance*, and *Leverage*. This mean reversion effect is significantly dampened when *CoBAR* and *Leverage* are high.

Taken together, these results are consistent with beta-arbitrage activity causing the cross-sectional spread in betas to expand.

V.B. *Low* Limits to Arbitrage

We interpret our findings as consistent with arbitrage activity facilitating the correction of the slope of the security market line in the short run. However, in periods of crowded trading, arbitrageurs can cause price overshooting. In Table IX, we exploit cross-sectional heterogeneity to provide additional support for our interpretation. All else equal, arbitrageurs prefer to trade stocks with low idiosyncratic volatility (to reduce tracking error), high liquidity (to facilitate opening/closing of the position), and large capitalization (to increase strategy capacity). As a consequence, we split our sample each period into two subgroups along each of these dimensions.[18] Our focus is on the long-run reversal associated with periods of high *CoBAR*.

Panels A and B split the sample based on market capitalization. Panel A documents that among large-cap stocks, *CoBAR* negatively forecasts differences in year 3 abnormal returns (-1.86%/month with a *t*-statistic of -3.97). Corresponding differences among small stocks are insignificant at conventional levels.

[18] To ensure that our findings from these double-sorted portfolios are not driven by small stocks, we exclude stocks that are microcaps (stocks below the NYSE 20th size percentile) or have stock prices below five dollars. However, if we include these stocks, our results are stronger.

Panels C and D examine time variation in the abnormal four-factor returns as a function of liquidity. For relatively high liquidity stocks, we continue to find that *CoBAR* has information about time-series variation in expected abnormal returns in year 3. The spread in four-factor alpha across the high and low *CoBAR* groups is -1.97%/month (*t*-statistic of -3.45) in the long-run. The corresponding estimates for the low liquidity sample are statistically insignificant.

Panels E and F report results when the sample is split based on idiosyncratic variance. Among low idiosyncratic stocks, Panel E shows that, in year 3, *CoBAR* strongly predicts a reversal in trading profits of 1.3%/month. This predictability is very statistically significant as the *t*-statistic is -3.60. Turning to high idiosyncratic volatility stocks, Table VII Panel F shows that the corresponding point estimate is much lower and statistically insignificant.

Finally, our feedback channel suggests that booms and busts of beta arbitrage should be especially strong among levered stocks. Thus, Panels G and H of Table IX report results when the sample is split based on leverage. Among high-leverage stocks, Panel G shows that for the highest *CoBAR* group, the abnormal four-factor returns average a striking 3.53%/month in the six months immediately subsequent to the beta-arbitrage trade. This finding is statistically significant with a *t*-statistic of 2.39. Moreover, the difference between abnormal returns in high and low *CoBAR* periods among high-leverage stocks is 3.76%/month (*t*-statistic of 2.46).

Again, these stronger beta-arbitrage returns can be linked to subsequent reversal in the long run. Specifically, in year three, the abnormal four-factor return to beta arbitrage when *CoBAR* is high is -1.11%/month, with a *t*-statistic of -2.79. These abnormal returns are dramatically different from their corresponding values when *CoBAR* is low; the difference in year 3 abnormal four-factor returns is -1.27%/month (*t*-statistic: -2.49).

Panel H of Table IX reports the patterns among low-leverage stocks. Consistent with our story, differences across *CoBAR* groups among stocks where our positive-feedback channel cannot play a role are much smaller and, in every case, are statistically insignificant.

In summary, Table IX confirms that our effect is stronger among those stocks where limits of arbitrage are weaker, where one expects arbitrageurs to play a larger role, and among high-leverage stocks, where our feedback channel is relevant.

V.C. Conditional Attribution

Of course, if beta is moving with *CoBAR,* we must estimate conditional performance attribution regressions. The last rows of Table II Panel A and Table II Panel B report the results of those regressions. We find that the long-run reversal of beta-arbitrage profits remains. The bottom plot in Figure 2 shows the corresponding cumulative abnormal four-factor returns to beta arbitrage during periods of high and low *CoBAR*. We continue to find an economically large reversal of beta-arbitrage profits when *CoBAR* is high. Figure 4 plots the conditional security market line in the short and long-run as a function of lagged *CoBAR*. The fact that beta expansion and destabilization go hand-in-hand is easy to see.

V.D. Fresh versus Stale Beta

Though beta-arbitrage activity may cause the beta spread to vary through time, for a feedback loop to occur, beta arbitrageurs must base their strategies on fresh estimates of beta rather than on stale estimates. Consistent with this claim, we show that our predictability results decay as a function of beta staleness.

We repeat the previous analysis of section IV.B, but replacing our fresh beta estimates (measured over the most recent year) with progressively staler ones. In particular, we estimate betas in each of the five years prior to the formation year. As a consequence, both the resulting beta strategy and the associated $CoBAR$ are different for each degree of beta staleness. For each of these six beta strategies, we regress the four-factor alpha of the strategy in months one-six and year three on its corresponding $CoBAR$.

Figure 4 plots the resulting regression coefficients (results for months 1-6 plotted with a blue square and results for year 3 plotted with a red circle) as a function of the degree of staleness of beta. The baseline results with the most recent beta are simply the corresponding results from Table V. We find that both the short-run and long-run predictability documented in section IV.B decays as the beta signal becomes more and more stale. Indeed, strategies using beta estimates that are five years old display no predictability. These results are consistent with the feedback loop we propose.

VI. Conclusion

We study the response of arbitrageurs to the flatness of the security market line. Using an approach to measuring arbitrage activity first introduced by Lou and Polk (2014), we document booms and busts in beta arbitrage. Specifically, we find that when arbitrage activity is relatively low, abnormal returns on beta-arbitrage strategies take much longer to materialize, appearing only two to three years after putting on the trade. In sharp contrast, when arbitrage activity is relatively high, abnormal returns on beta-arbitrage strategies occur relatively quickly, within the first six months of the trade. These strong abnormal returns then revert over the next three years. Thus, our findings are consistent with arbitrageurs exacerbating this time-variation in the expected return to beta arbitrage.

We provide evidence on a novel positive feedback channel for beta-arbitrage activity. Welch (2004) shows that firms do not issue and repurchase debt and equity to counteract the mechanical effect that stock returns have on their market leverage ratio. Since the typical firm is levered and given the benign effects of leverage on equity beta (Modigliani and Miller 1958), buying low-beta stocks and selling high-beta stocks may cause the cross-sectional spread in betas to increase. We show that this beta expansion occurs when beta-arbitrage activity is high and particularly so when stocks typically traded by beta arbitrageurs are particularly levered. Thus, beta arbitrageurs may actually increase their bets when the profitability of the strategy has decreased. Indeed, we find that the short-run abnormal returns to high-leverage beta-arbitrage stocks more than triples before reverting in the long run.

Interestingly, the *unconditional* four-factor alpha of beta arbitrage over typical holding periods for our 1965-2010 sample is close to zero, much lower than the positive value one finds for earlier samples. Thus, it seems that the response to Black, Jensen, and Scholes's (1972) famous finding is right *on average*. However, our conditional analysis reveals rich time-series variation that is consistent with the general message of

Stein (2010): Arbitrage activity faces a significant coordination problem for unanchored strategies that have positive feedback characteristics.

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Table I: Summary Statistics

This table provides characteristics of "*CoBAR*," the *excess* comovement among low beta stocks over the period 1964 to 2010. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. Pairwise partial return correlations (controlling for the Fama-French three factors) for all stocks in the bottom beta decile are computed based on weekly stock returns in the previous 12 months. *CoBAR* is the average pair-wise correlation between any two stocks in the low-beta decile in year *t*. *Inflation* is the exponential moving average CPI growth rate over the past 100 months (where the weight on month N is given by 2/(n+1)), as constructed by Cohen, Polk, and Vuolteenaho (2005). *Sentiment* is the sentiment index proposed by Wurgler and Baker (2006, 2007). *Disagreement* is the beta-weighted standard deviation of analysts' long-term growth rate forecasts, as used in Hong and Sraer (2012). *Ted Spread* is the difference between the LIBOR rate and the US Treasury bill rate. Panel A reports the summary statistics of these variables. Panel B shows the time-series correlations among these key variables for the entire sample period.

Panel A: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
CoBAR	545	0.108	0.029	0.034	0.215
Inflation	545	0.004	0.002	0.001	0.007
Sentiment	545	0.003	1.000	-2.578	2.691
Disagreement	349	4.426	0.897	3.266	7.338
Ted Spread	313	0.566	0.412	0.127	3.443

Panel B: Correlation

	CoBAR	Inflation	Sentiment	Disagreemt	Ted Spread
CoBAR	1.000				
Inflation	-0.315	1.000			
Sentiment	0.123	0.071	1.000		
Disagreement	0.338	-0.384	0.388	1.000	
Ted Spread	0.174	0.254	0.080	-0.137	1.000

Table II: Determinants of *CoBAR*

This table reports regressions of *CoBAR*, described in Table I, on variables plausibly linked to arbitrage activity. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. The dependent variable in the regressions, *CoBAR*, is the average pairwise partial weekly return correlation in the low-beta decile over the past 12 months. *Inst Own* is the aggregate institutional ownership of the low-beta decile, *AUM* is the logarithm of the total assets under management of long-short equity hedge funds. *Inflation* is the exponential moving average CPI growth rate over the past 100 months (where the weight on month N is given by 2/(n+1)), as constructed by Cohen, Polk, and Vuolteenaho (2005). *Sentiment* is the sentiment index proposed by Wurgler and Baker (2006, 2007). *Disagreement* is the beta-weighted standard deviation of analysts' long-term growth rate forecasts, as used in Hong and Sraer (2012). *Ted Spread* is the difference between the LIBOR rate and the US Treasury bill rate. We also include in the regression the Pastor-Stambaugh liquidity factor (*PS Liquidity*). A trend dummy is included in all regression specifications. All independent variables are divided by their corresponding standard deviation, so that the coefficient represents the effect of a one-standard-deviation change in the independent variable on *CoBAR*. Standard errors are shown in brackets. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

DepVar	$CoBAR_t$			
	[1]	[2]	[3]	[4]
$Inst\ Own_{t-1}$	0.018***	0.025***	0.014***	0.012**
	[0.007]	[0.006]	[0.005]	[0.006]
AUM_{t-1}		0.008***		0.005**
		[0.002]		[0.002]
$Inflation_t$			-0.016*	-0.005
			[0.009]	[0.004]
$Sentiment_t$			0.003	0.004
			[0.008]	[0.021]
$Disagreement_t$			0.007	0.006
			[0.005]	[0.013]
$Ted\ Spread_t$			0.010***	0.011**
			[0.003]	[0.005]
$PS\ Liquidity_t$	0.007**	0.008***	0.010***	0.010***
	[0.003]	[0.003]	[0.002]	[0.003]
TREND	YES	YES	YES	YES
Adj-R^2	0.152	0.382	0.372	0.441
No. Obs.	357	180	357	180

Table III: Forecasting Beta-arbitrage Returns with *CoBAR*

This table reports returns to the beta arbitrage strategy as a function of lagged *CoBAR*. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. All months are then classified into five groups based on *CoBAR*, the average pairwise 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 1965 to 2010, following low to high *CoBAR*. Panels A and B report, respectively, the average monthly CAPM alpha and Carhart four-factor alpha of the beta arbitrage strategy. "5-1" is the difference in monthly returns to the long-short strategy following high vs. low *CoBAR*; "5-1 Conditional" is the difference in conditional abnormal returns (i.e., allowing for risk loadings to vary as a function of *CoBAR*) following high vs. low *CoBAR*. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: CAPM Adjusted Beta-arbitrage Returns

		Months 1-6		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	109	0.19%	(0.38)	0.38%	(1.01)	**0.93%**	**(3.18)**	**0.93%**	**(4.30)**
2	109	0.04%	(0.12)	0.43%	(1.31)	**0.63%**	**(2.07)**	0.41%	(1.34)
3	109	-0.08%	(-0.20)	0.47%	(1.37)	0.36%	(1.05)	0.43%	(1.31)
4	109	0.37%	(1.25)	**0.48%**	**(2.43)**	0.29%	(0.78)	0.29%	(0.93)
5	109	**1.64%**	**(2.85)**	**1.11%**	**(2.02)**	0.63%	(1.54)	**-0.60%**	**(-2.03)**
5-1		1.45%	(1.93)	0.73%	(1.10)	-0.30%	(-0.61)	**-1.52%**	**(-3.86)**
5-1(Conditional)		1.39%	**(1.98)**	0.66%	(1.04)	-0.29%	(-0.59)	**-1.48%**	**(-3.77)**

Panel B: Four-Factor Adjusted Beta-arbitrage Returns

		Months 1-6		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	109	-0.21%	(-0.49)	0.05%	(0.16)	0.47%	(1.74)	**0.50%**	**(2.49)**
2	109	-0.57%	(-1.91)	-0.15%	(-0.53)	0.19%	(0.68)	-0.03%	(-0.09)
3	109	-0.42%	(-1.46)	-0.05%	(-0.19)	-0.11%	(-0.34)	-0.04%	(-0.13)
4	109	-0.35%	(-1.21)	**-0.29%**	**(-1.96)**	-0.27%	(-0.83)	-0.13%	(-0.42)
5	109	**1.04%**	**(2.41)**	0.58%	(1.67)	0.01%	(0.01)	**-0.92%**	**(-3.18)**
5-1		**1.25%**	**(2.11)**	0.53%	(1.17)	-0.46%	(-0.96)	**-1.41%**	**(-3.69)**
5-1(Conditional)		0.62%	(1.24)	-0.01%	(-0.04)	-0.88%	(-1.92)	**-1.40%**	**(-3.78)**

Table IV: Robustness Checks

This table reports returns to the beta arbitrage strategy as a function of lagged *CoBAR*. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. All months are then classified into five groups based on *CoBAR*, the average pairwise partial weekly return correlation in the low-beta decile over the past 12 months. Reported below is the difference in four-factor alpha to the beta arbitrage strategy between high *CoBAR* periods and low *CoBAR* periods. Year zero is the beta portfolio ranking period. Row 1 shows the baseline results which are also reported in Table III. In Rows 2 and 3, we conduct the same analysis for two sub periods. In Rows 4 and 5, we exclude the tech bubble crash and the recent financial crisis from our sample. In Rows 6-9, we rank all months based on the inflation index (Cohen, Polk, and Vuolteenaho, 2005), sentiment index (Wurgler and Baker, 2006), aggregate analyst forecast dispersion (Hong and Sraer, 2014), and Ted Spread (Frazzini and Pedersen, 2014), respectively. In Row 10, we also control for the UMD factor in computing *CoBAR*. In Rows 11-14, we take the residual *CoBAR* after purging out, respectively, the average pair-wise correlation in the market, the lagged 36-month volatility of the BAB factor (Frazzini and Pedersen, 2013), and *CoMomentum* and *CoValue* (Lou and Polk, 2014). In Row 15, we use de-trended *CoBAR*. In Row 16, we further control for industry factors in the calculation of *CoBAR*. In Row 17, we control for both large- and small-cap HML in computing *CoBAR*. In Row 18, we report DGTW-adjusted portfolio returns. In Row 19, we report results using a six-factor model (including liquidity and reversal factors) when measuring *CoBAR* and benchmarking abnormal returns. In Row 20, we orthogonalize *CoBAR* with regard to market volatility over the past 12 months. In Rows 21 and 22, we examine upside and downside *CoBAR*, as distinguished by the median low-beta portfolio return. Finally in Rows 23 to 24, we rank all months based on aggregate institutional ownership of the low-beta decile and the fitted value of *CoBAR* on these two variables. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Four-Factor Adjusted Beta-arbitrage Returns				
	Months 1-6		Year 3	
	Estimate	t-stat	Estimate	t-stat
Subsamples				
Full Sample: 1965-2010	**1.25%**	**(2.11)**	**-1.41%**	**(-3.69)**
Subsample: 1965-1980	**1.45%**	**(2.14)**	-0.73%	(-0.89)
Subsample: 1981-2010	0.68%	(0.85)	**-1.78%**	**(-4.99)**
Excluding 2000-2001	0.83%	(1.66)	**-1.25%**	**(-3.05)**
Excluding 2007-2009	0.68%	(1.38)	**-1.19%**	**(-2.64)**
Other predictors of beta-arbitrage returns				
Inflation	0.56%	(1.08)	0.01%	(0.03)
Sentiment	**1.63%**	**(2.90)**	0.55%	(1.18)
Disagreement	0.81%	(1.14)	0.29%	(0.37)
Ted Spread	-0.50%	(-0.64)	-0.60%	(-1.24)
Alternative definitions of CoBAR				
Controlling for UMD	0.87%	(1.58)	**-1.47%**	**(-3.61)**
Controlling for MKT CORR	1.14%	(1.94)	**-1.60%**	**(-4.01)**
Controlling for Vol(BAB)	**1.11%**	**(1.99)**	**-1.40%**	**(-3.53)**
Controlling for Comomentum	1.02%	(1.82)	**-1.37%**	**(-3.47)**
Controlling for Covalue	1.02%	(1.85)	**-1.46%**	**(-3.60)**
Controlling for Trend	**1.20%**	**(2.01)**	**-1.29%**	**(-3.39)**
Controlling for Industry Return	0.62%	(0.95)	**-1.04%**	**(-2.44)**
Controlling for Large/Small-Cap HML	**1.29%**	**(2.19)**	**-1.40%**	**(-3.46)**
Controlling for DGTW Adjustments	**2.04%**	**(2.85)**	**-1.20%**	**(-2.70)**
Controlling for Six Factors	**1.12%**	**(1.96)**	**-1.35%**	**(-3.47)**
Controlling for Mktvol12	**1.24%**	**(2.11)**	**-1.38%**	**(-3.54)**
Upside CoBAR	**1.09%**	**(2.08)**	**-0.80%**	**(-2.32)**
Downside CoBAR	0.04%	(0.08)	-0.30%	(-0.65)
Fitted CoBAR				
Institutional Ownership	0.81%	(0.89)	0.46%	(0.71)
Fitted CoBAR	0.72%	(0.81)	-0.38%	(-0.65)

Table V: Regression Analysis

This table reports returns to the beta arbitrage strategy as a function of lagged *CoBAR*. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. The dependent variable is the four-factor alpha of the beta arbitrage strategy (i.e., a portfolio that is long the value-weight low-beta decile and short the value-weighted high-beta decile). The main independent variable is *CoBAR*, the average pairwise partial weekly three-factor residual correlation within the low-beta decile over the past 12 months. We also include in the regression the inflation index (Cohen, Polk, and Vuolteenaho, 2005), sentiment index (Wurgler and Baker, 2006), aggregate analyst forecast dispersion (Hong and Sraer, 2012), Ted Spread–the difference between the LIBOR rate and the US Treasury bill rate, the *ValueSpread*–the spread in log book-to-market-ratios across the low-beta and high-beta deciles, and the market volatility over the past 12 months. The first three columns examine returns to the beta arbitrage strategy in months 1-6, and the next three columns examine the returns in year 3 after portfolio formation. We report results based on Carhart four-factor adjustments. T-statistics, shown in brackets, are computed based on standard errors corrected for serial-dependence with 12 lags. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

DepVar	Four-Factor Alpha to the Beta Arbitrage Strategy					
	Months 1-6			Year 3		
	[1]	[2]	[3]	[4]	[5]	[6]
CoBAR	0.174***	0.176**	0.035	-0.148***	-0.134***	-0.187***
	[0.069]	[0.071]	[0.144]	[0.045]	[0.047]	[0.072]
Inflation		0.014	0.069*		0.003	-0.009
		[0.013]	[0.043]		[0.012]	[0.050]
Sentiment		0.005***	0.006		0.002	-0.004
		[0.002]	[0.007]		[0.001]	[0.007]
Disagreement			0.011*			0.005
			[0.006]			[0.006]
Ted Spread			-0.005			0.006*
			[0.006]			[0.003]
ValueSpread		0.001	0.002		-0.004	-0.004
		[0.003]	[0.004]		[0.003]	[0.003]
Mktvol12		0.002	-0.221		-0.01	-0.087
		[0.102]	[0150]		[0.100]	[0.139]
Adj-R^2	0.045	0.099	0.153	0.069	0.095	0.154
N of Obs	545	545	312	545	545	312

Table VI: Predicting the Security Market Line

This table reports regressions of the intercept and slope of the security market line on lagged *CoBAR*. At the end of each month, all stocks are sorted into vigintiles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. We then estimate two security market lines based on these 20 portfolios formed in each period: one SML using monthly portfolio returns in months 1-6, and the other using monthly portfolio returns in year 3 after portfolio formation. The post-ranking betas are calculated by regressing each of the 20 portfolios' value-weighted monthly returns on the corresponding market return. Following Fama and French (1992), we use the entire sample to compute post-ranking betas. The dependent variable in Panel A is the intercept of the SML, while that in Panel B is the slope of the SML. We also include in the regressions the inflation index (Cohen, Polk, and Vuolteenaho, 2005), sentiment index (Wurgler and Baker, 2006), aggregate analyst forecast dispersion (Hong and Sraer, 2012), and Ted Spread, the difference between the LIBOR rate and the US Treasury bill rate. Other (unreported) control variables include the contemporaneous market excess return, SMB return, and HML return. Standard errors, shown in brackets, are computed based on standard errors corrected for serial-dependence with 6 or 12 lags, as appropriate. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: $DepVar =$ Intercept of SML

	Months 1-6			Year3		
CoBAR	0.149**	0.194***	0.119	-0.176***	-0.192***	-0.169***
	[0.078]	[0.054]	[0.085]	[0.052]	[0.048]	[0.072]
Inflation		0.026***	0.060		0.003	0.002
		[0.009]	[0.032]		[0.012]	[0.057]
Sentiment		0.003***	0.004		0.004	-0.005
		[0.001]	[0.005]		[0.002]	[0.008]
Disagreement			0.003			0.010
			[0.004]			[0.007]
Ted Spread			-0.011***			0.001
			[0.005]			[0.004]
Adj-R^2	0.037	0.384	0.494	0.071	0.132	0.173
N of Obs	545	545	312	545	545	312

Panel B: $DepVar =$ Slope of SML

	Months 1-6			Year3		
CoBAR	-0.314***	-0.179***	-0.084	0.201***	0.224***	0.245***
	[0.086]	[0.051]	[0.089]	[0.063]	[0.060]	[0.078]
Inflation		-0.026***	-0.065		0.006	-0.007
		[0.010]	[0.032]		[0.016]	[0.067]
Sentiment		-0.003***	-0.005		-0.003	0.007
		[0.001]	[0.005]		[0.002]	[0.010]
Disagreement			-0.002			-0.007
			[0.004]			[0.008]
Ted Spread			0.013***			-0.004
			[0.005]			[0.004]
Adj-R^2	0.093	0.663	0.708	0.065	0.117	0.164
N of Obs	545	545	312	545	545	312

Table VII: Beta Expansion, Time-Series Analysis

This table examines time-series beta expansion associated with arbitrage trading. Panel A reports the baseline regression. The dependent variable in columns 1 and 2 is the beta spread between the high-beta and low-beta deciles (ranked in year t) in year t+1. The dependent variable in columns 3 and 4 is the fraction of stocks in the bottom beta decile ranked in year t that remain in the bottom beta decile in year t+1 (the two periods are non-overlapping). *CoBAR* is the average pairwise weekly three-factor residual correlation in the low-beta decile over the past 12 months. *Leverage* is a quintile dummy based on the average value-weighted book leverage of the bottom and top beta deciles. We also include in the regression an interaction term between *CoBAR* and *Leverage*. Panel B reports a battery of robustness checks. The dependent variable in all rows is the beta spread between the high-beta and low-beta deciles in year t+1. Reported below is the coefficient on the interaction of *CoBAR* and *Leverage*. Row 1 shows the baseline results which are also reported in Panel A. In Rows 2 and 3, we conduct the same analysis for two sub-periods. In Rows 4 and 5, we exclude the tech bubble crash and the recent financial crisis from our sample. In Row 6, we also control for the UMD factor in computing *CoBAR*. In Rows 7-10, we take the residual *CoBAR* after purging out, respectively, the average pair-wise correlation in the market, the lagged 36-month volatility of the BAB factor (Frazzini and Pedersen, 2014), and CoMomentum and CoValue (Lou and Polk, 2014). In Row 11, we further control for industry factors in the calculation of *CoBAR*. In Row 12, we control for both large- and small-cap HML in computing *CoBAR*. In Rows 13 and 14, we control for sentiment and inflation indices, and the prior 36-month market return and market volatility. In Row 15, we use de-trended *CoBAR*. In Rows 16 and 17, we examine the upside and downside *CoBAR*, as distinguished by the median low-beta portfolio return. Standard errors are shown in brackets. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Baseline Regression

DepVar	$BetaSpread_{t+1}$		$Fraction_{t+1}$	
	[1]	[2]	[3]	[4]
BetaSpread	0.282***	0.276***		
	[0.061]	[0.059]		
CoBAR	1.253***	0.129	2.681*	0.388
	[0.411]	[0.498]	[1.533]	[1.714]
Leverage		-0.047***		-0.250***
		[0.011]		[0.040]
*CoBAR * Leverage*		0.456***		0.766**
		[0.117]		[0.279]
Adj-R^2	0.12	0.15	0.01	0.09
No. Obs.	533	533	533	533

Panel B: Robustness Checks		
$DepVar = BetaSpread_{t+1}$		
	Estimate	Std Dev
Subsamples		
Full Sample:1965-2010	0.456***	[0.117]
Subsample: 1965-1980	0.064	[0.391]
Subsample: 1980-2010	0.510***	[0.151]
Excluding 2000-2001	0.509***	[0.099]
Excluding 2007-2009	0.305**	[0.140]
Alternative definitions of CoBAR		
Controlling for UMD	0.511***	[0.114]
Controlling for MKT CORR	0.283**	[0.123]
Controlling for Vol(BAB)	0.417***	[0.117]
Controlling for CoMomentum	0.249**	[0.119]
Controlling for CoValue	0.427***	[0.117]
Controlling for Industry Return	0.567***	[0.120]
Controlling for Large/Small-Cap HML	0.460***	[0.121]
Controlling for Sentiment and Inflation	0.324***	[0.118]
Controlling for *mktvol12*	0.466***	[0.113]
Controlling for Trend	0.365***	[0.121]
Upside *CoBAR*	0.567***	[0.158]
Downside *CoBAR*	0.384***	[0.123]

Table VIII: Beta Expansion, Cross-Sectional Analysis

This table reports panel regressions of subsequent changes in stock beta on lagged *CoBAR*. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. The dependent variable is the change in stock beta from year t to $t+1$ (non-overlapping periods). The main independent variable is lagged *CoBAR*, the average pairwise excess weekly return correlation in the low-beta decile over the past 12 months. *Distance* is the difference between a stock's beta decile rank and the average rank of 5.5 in year t. *Leverage* is the book leverage of the firm, measured in year t. We also include all double and triple interaction terms of *CoBAR*, *Distance*, and *Leverage*. Other control variables include lagged firm size, book-to-market ratio, momentum, idiosyncratic volatility (over the prior year), and the past one-month return. Time-fixed effects are included in Columns 3 and 4. (Since *CoBAR* is a time-series variable, it is subsumed by the time dummies.) Standard errors, shown in brackets, are double clustered at both the firm and year-month levels. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

DepVar	*Beta Change*$_{t+1}$			
	[1]	[2]	[3]	[4]
CoBAR	0.295**	0.172		
	[0.136]	[0.134]		
Distance	-0.077***	-0.079***	-0.077***	-0.079***
	[0.004]	[0.005]	[0.004]	[0.005]
*CoBAR * Distance*	0.071**	0.053	0.029	0.012
	[0.036]	[0.042]	[0.036]	[0.042]
Leverage		-0.008***		-0.006***
		[0.002]		[0.002]
*CoBAR * Leverage*		0.054***		0.032**
		[0.016]		[0.016]
*Leverage * Distance*		0.000		0.000
		[0.001]		[0.001]
*CoBAR * Leverage * Distance*		0.015***		0.013***
		[0.005]		[0.004]
Size	0.005***	0.004***	0.009***	0.008***
	[0.002]	[0.002]	[0.002]	[0.002]
BM	-0.018***	-0.019***	-0.031***	-0.031***
	[0.003]	[0.003]	[0.003]	[0.003]
Ret_{-1}	0.059***	0.059***	0.053***	0.054***
	[0.023]	[0.023]	[0.019]	[0.019]
$Ret_{-2,-12}$	0.723***	0.731***	0.545***	0.551***
	[0.084]	[0.083]	[0.070]	[0.070]
IVOL	0.154***	0.152***	0.210***	0.205***
	[0.015]	[0.014]	[0.009]	[0.009]
Time Fixed Effect	No	No	Yes	Yes
Adj-R2	0.217	0.219	0.279	0.281
No. Obs.	1,105,815	1,105,815	1,105,815	1,105,815

Table IX: *Low* Limits to Arbitrage

This table reports returns to the beta arbitrage strategy as a function of lagged *CoBAR* in various subsamples. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. All months are then classified into five groups based on *CoBAR*, the average pairwise weekly three-factor residual correlation in the low-beta decile over the past 12 months. Reported below are the Carhart four-factor alpha 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 1965 to 2010, following low to high *CoBAR*. "5-1" is the difference in monthly returns to the long-short strategy following high vs. low *CoBAR*. To ensure that our findings from these double-sorted portfolios are not driven by small stocks, we exclude stocks that are microcaps (stocks below the NYSE 20th size percentile) or have stock prices below five dollars. Panels A and B report the average monthly returns to the beta-arbitrage strategy constructed solely based on stocks with large size or small market capitalization (as of the beginning of the holding period), respectively. Panels C and D report the average monthly returns to the beta-arbitrage strategy constructed solely based on stocks with high or low liquidity (as of the beginning of the holding period), respectively. Panels E and F report the average monthly returns to the beta-arbitrage strategy constructed solely based on stocks with high or low idiosyncratic volatilities (as of the beginning of the holding period), respectively. Panels G and H report the average monthly returns to the beta-arbitrage strategy constructed solely based on stocks with high or low leverage (as of the beginning of the holding period), respectively. Across all Panels, splits are based on the median value of the firm characteristic in each month. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Large Stocks

		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	-0.27%	(-0.54)	-0.17%	(-0.34)	0.69%	(1.54)	0.40%	(1.38)
2	109	-0.73%	(-1.62)	-0.37%	(-0.88)	0.06%	(0.13)	-0.11%	(-0.19)
3	109	-0.35%	(-0.66)	-0.15%	(-0.36)	-0.84%	(-1.81)	-0.48%	(-0.81)
4	109	-0.08%	(-0.17)	-0.34%	(-1.59)	**-1.57%**	**(-5.45)**	-0.43%	(-0.87)
5	109	1.84%	(1.83)	0.94%	(1.26)	0.52%	(1.00)	**-1.46%**	**(-4.20)**
5-1		**2.11%**	**(2.00)**	1.11%	(1.27)	-0.17%	(-0.23)	**-1.86%**	**(-3.97)**

Panel B: Small Stocks

		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	0.75%	(1.35)	0.92%	(1.88)	0.19%	(1.14)	-0.29%	(-0.86)
2	109	0.06%	(0.13)	-0.15%	-(0.59)	-0.06%	(-0.14)	-0.46%	(-1.49)
3	109	0.28%	(0.62)	0.39%	(1.64)	-0.44%	(-1.22)	-0.06%	(-0.09)
4	109	1.06%	(1.55)	0.94%	(1.35)	-0.75%	(-1.78)	**-1.00%**	**(-2.10)**
5	109	1.17%	(1.59)	0.75%	(1.56)	1.05%	(1.23)	-0.11%	(-0.23)
5-1		0.41%	(0.45)	-0.16%	(-0.25)	0.86%	(0.99)	0.18%	(0.37)

Panel C: Liquid Stocks									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	0.02%	(0.03)	-0.16%	(-0.27)	0.17%	(0.49)	-0.03%	(-0.10)
2	109	-0.71%	(-1.33)	-0.53%	(-1.29)	-0.13%	(-0.49)	-0.41%	(-0.84)
3	109	-0.13%	(-0.25)	-0.13%	(-0.29)	**-1.08%**	**(-2.26)**	-0.61%	(-1.11)
4	109	-0.09%	(-0.20)	-0.36%	(-1.66)	**-1.61%**	**(-3.80)**	-0.71%	(-1.37)
5	109	1.06%	(1.41)	0.44%	(0.57)	0.53%	(0.81)	**-1.99%**	**(-5.08)**
5-1		1.04%	(1.18)	0.60%	(0.60)	0.35%	(0.42)	**-1.97%**	**(-3.45)**

Panel D: Illiquid Stocks									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	**0.95%**	**(4.13)**	0.34%	(1.23)	-0.23%	(-0.33)	-0.27%	(-0.67)
2	109	-0.91%	(-1.10)	-0.75%	(-1.61)	-0.43%	(-1.16)	-0.26%	(-0.74)
3	109	-1.68%	(-1.34)	-0.58%	(-1.22)	-0.84%	(-1.10)	-0.12%	(-0.25)
4	109	0.35%	(0.57)	0.00%	(0.01)	-0.65%	(-1.18)	**-0.65%**	**(-2.88)**
5	109	1.87%	(1.13)	0.99%	(1.46)	0.79%	(2.04)	**-1.25%**	**(-4.58)**
5-1		0.92%	(0.55)	0.64%	(0.87)	1.02%	(1.01)	-0.98%	(-1.78)

Panel E: Low Idiosyncratic Volatility Stocks									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	-0.18%	(-0.33)	0.04%	(0.08)	0.80%	(1.82)	0.17%	(0.50)
2	109	-0.34%	(-1.04)	0.08%	(0.23)	0.27%	(0.62)	0.06%	(0.16)
3	109	-0.45%	(-1.20)	-0.20%	(-0.75)	-0.46%	(-1.06)	-0.40%	(-0.77)
4	109	0.31%	(0.74)	-0.25%	(-1.41)	**-0.92%**	**(-2.10)**	-0.38%	(-0.76)
5	109	1.24%	(1.34)	0.59%	(1.01)	0.70%	(1.68)	**-1.25%**	**(-4.37)**
5-1		1.42%	(1.35)	0.55%	(0.72)	-0.10%	(-0.15	**-1.41%**	**(-3.60)**

Panel F: High Idiosyncratic Volatility Stocks									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	0.36%	(0.80)	0.19%	(0.64)	0.14%	(0.46)	-0.25%	(-0.85)
2	109	-0.67%	(-0.98)	-0.35%	(-0.65)	0.12%	(0.37)	-0.34%	(-0.54)
3	109	-0.70%	(-0.69)	-0.32%	(-0.43)	-0.29%	(-0.55)	0.20%	(0.26)
4	109	0.43%	(0.46)	0.33%	(0.58)	-0.42%	(-1.49)	**-1.09%**	**(-2.20)**
5	109	1.43%	(1.60)	1.47%	(1.85)	0.77%	(1.00)	-0.78%	(-1.48)
5-1		1.07%	(1.12)	1.28%	(1.55)	0.63%	(0.72)	-0.53%	(-1.02)

Panel G: High Leverage									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	-0.23%	(-0.44)	-0.36%	(-0.60)	0.56%	(1.00)	0.16%	(0.47)
2	109	-0.47%	(-0.73)	-0.06%	(-0.11)	0.43%	(0.99)	0.49%	(0.75)
3	109	-0.28%	(-0.47)	0.01%	(0.02)	-0.56%	(-0.99)	-0.33%	(-0.46)
4	109	1.05%	(1.77)	0.37%	(0.75)	**-1.32%**	**(-2.89)**	-0.49%	(-1.20)
5	109	**3.53%**	**(2.39)**	**2.38%**	**(2.47)**	0.19%	(0.35)	**-1.11%**	**(-2.79)**
5-1		**3.76%**	**(2.46)**	**2.74%**	**(2.51)**	-0.37%	(-0.47)	**-1.27%**	**(-2.49)**

Panel H: Low Leverage									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	0.60%	(1.43)	0.71%	(1.73)	0.56%	(1.53)	-0.08%	(-0.22)
2	109	-0.51%	(-1.02)	-0.23%	(-0.62)	-0.16%	(-0.37)	-0.50%	(-0.77)
3	109	-0.51%	(-0.86)	-0.59%	(-1.08)	-0.67%	(-1.13)	0.22%	(0.31)
4	109	-0.14%	(-0.21)	0.05%	(0.10)	**-1.08%**	**(-2.53)**	0.28%	(0.62)
5	109	1.11%	(1.36)	0.72%	(0.72)	**1.17%**	(3.05)	-1.11%	(-1.86)
5-1		0.51%	(0.57)	0.01%	(0.01)	0.61%	(1.07)	-1.03%	(-1.60)

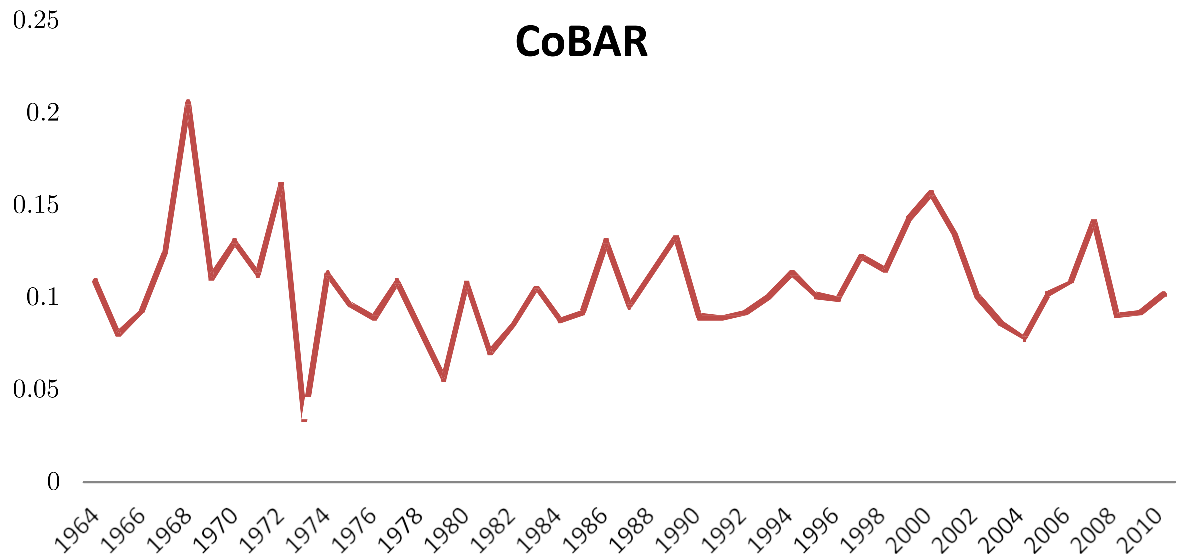

Figure 1: This figure shows the time series of the *CoBAR* measure. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. *CoBAR* is the average pairwise partial return correlation in the low-beta decile measured in the ranking period.

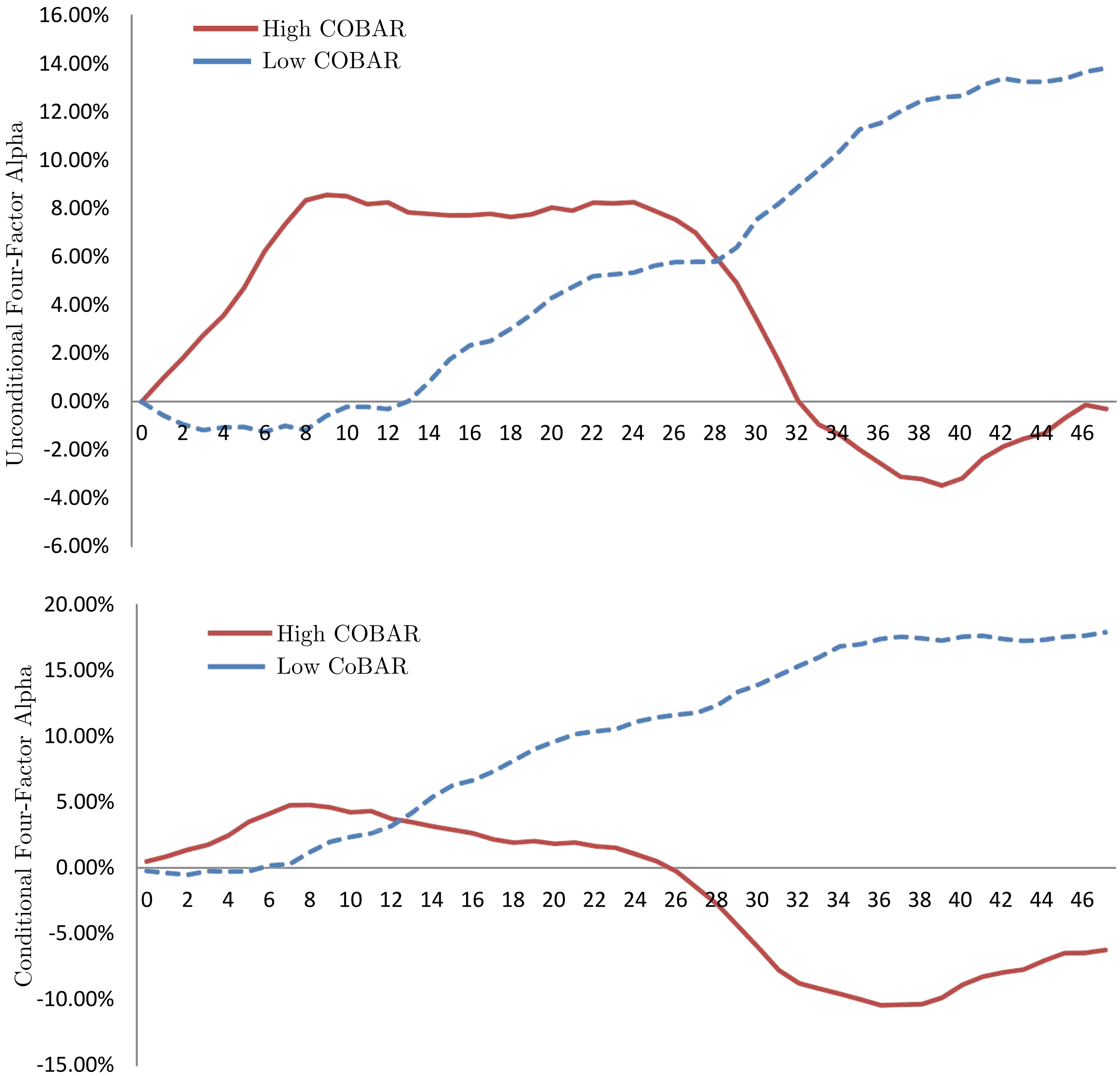

Figure 2: This figure shows returns to the beta arbitrage strategy as a function of lagged *CoBAR*. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. All months are then sorted into five groups based on *CoBAR*, the average pairwise weekly three-factor residual correlation within the low-beta decile over the previous 12 months. The red curve shows the cumulative Carhart four-factor alpha to the beta arbitrage strategy (i.e., a portfolio that is long the value-weight low-beta decile and short the value-weighted high-beta decile) formed in high *CoBAR* periods, whereas the dotted blue curve shows the cumulative Carhart four-factor alpha to the beta arbitrage strategy formed in periods of low *CoBAR*. The top panel shows the unconditional four-factor alpha and the bottom panel shows the conditional four-factor alpha (i.e., where betas are allowed to vary with *CoBAR*).

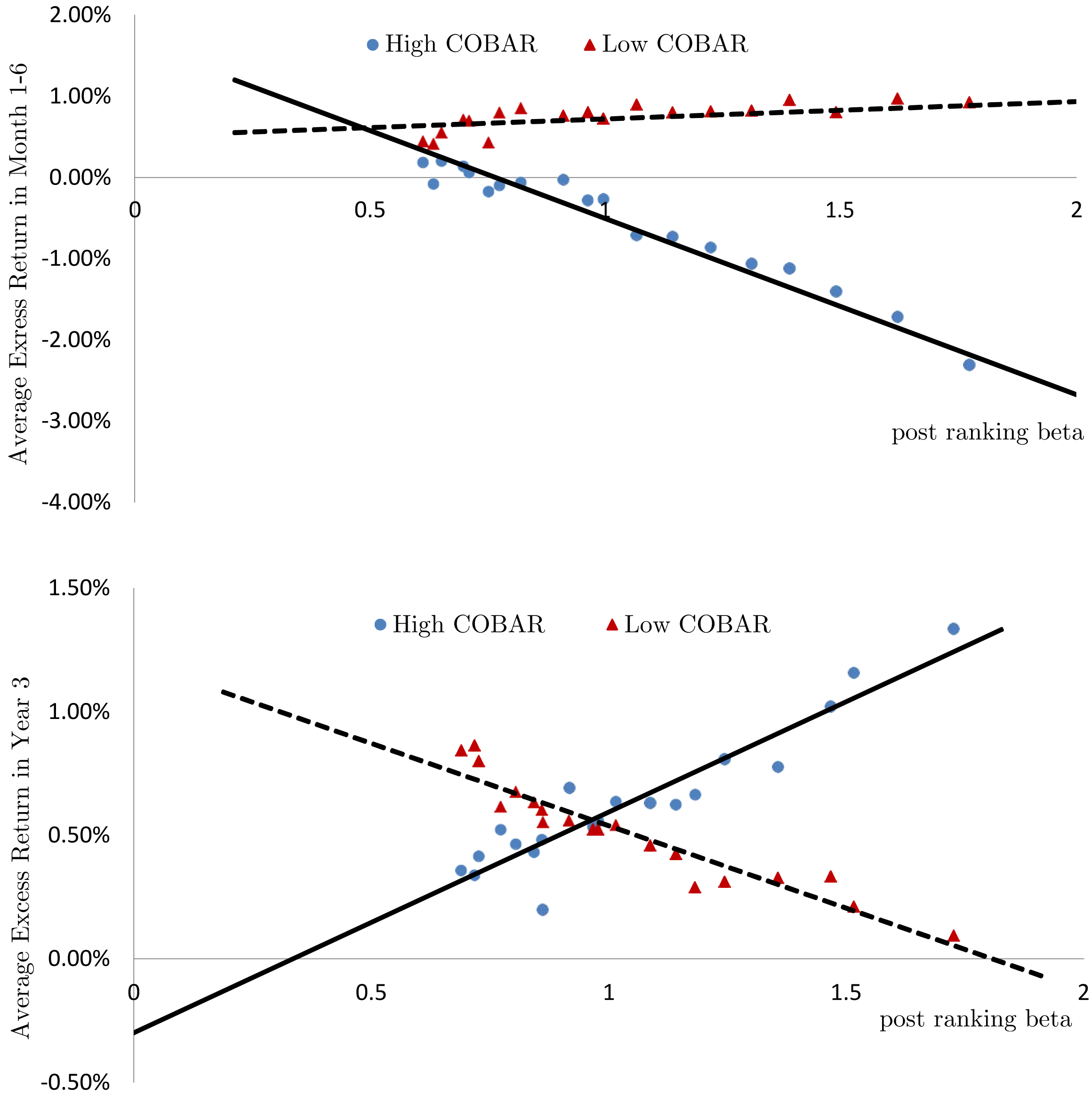

Figure 3: This figure shows the security market line as a function of lagged *CoBAR*. At the end of each month, all stocks are sorted into vigintiles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. We then estimate two security market lines based on these 20 portfolios formed in each period: one SML using portfolio returns in months 1-6, and the other using portfolio returns in year 3 after portfolio formation; the betas used in these SML regressions are the corresponding post-ranking betas. The Y-axis reports the average monthly excess returns to these 20 portfolios, and the X-axis reports the post-ranking betas of these portfolios. Beta portfolios formed in high *CoBAR* periods are depicted with a blue circle and fitted with a solid line, and those formed in low *CoBAR* periods are depicted with a red triangle and fitted with a dotted line. The top panel shows average excess returns and betas to the beta-arbitrage strategy in months 1-6 after portfolio formation, while the bottom panel shows average excess returns and betas in year 3 after portfolio formation.

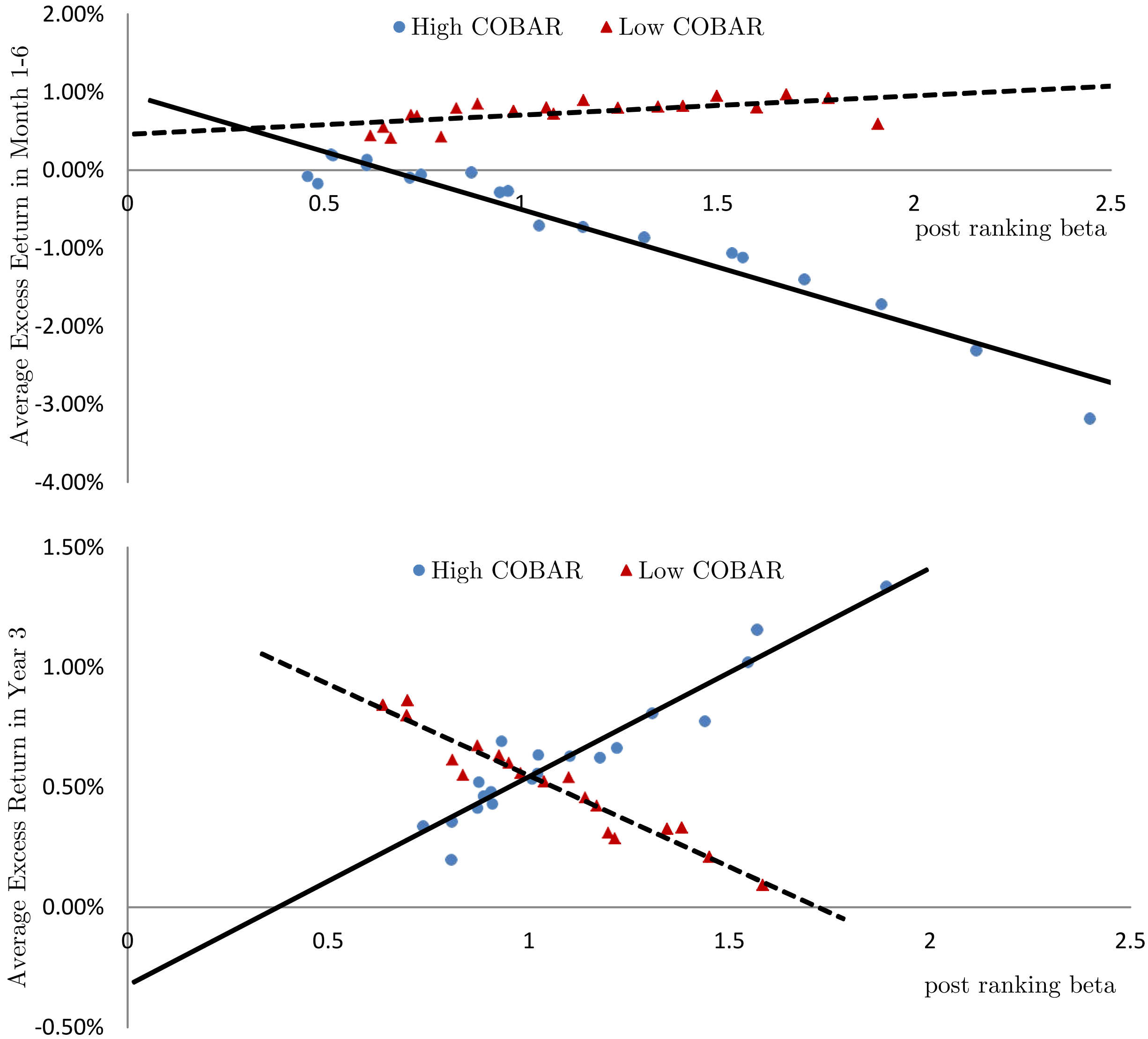

Figure 4: This figure shows the conditional security market line as a function of lagged $CoBAR$ (i.e., where betas are allowed to vary with $CoBAR$). At the end of each month, all stocks are sorted into vigintiles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. We then estimate two security market lines based on these 20 portfolios: one SML using portfolio returns in months 1-6, and the other using portfolio returns in year 3 after portfolio formation; the betas used in these SML regressions are the corresponding post-ranking betas. The Y-axis reports the average monthly excess returns to these 20 portfolios, and the X-axis reports the post-ranking beta of these portfolios. Beta portfolios formed in high $CoBAR$ periods are depicted with a blue circle and fitted with a solid line, and those formed in low $CoBAR$ periods are depicted with a red triangle and fitted with a dotted line. The top panel shows average excess returns and betas to the beta arbitrage strategy in months 1-6 after portfolio formation, while the bottom panel shows average excess returns and betas in year 3 after portfolio formation.

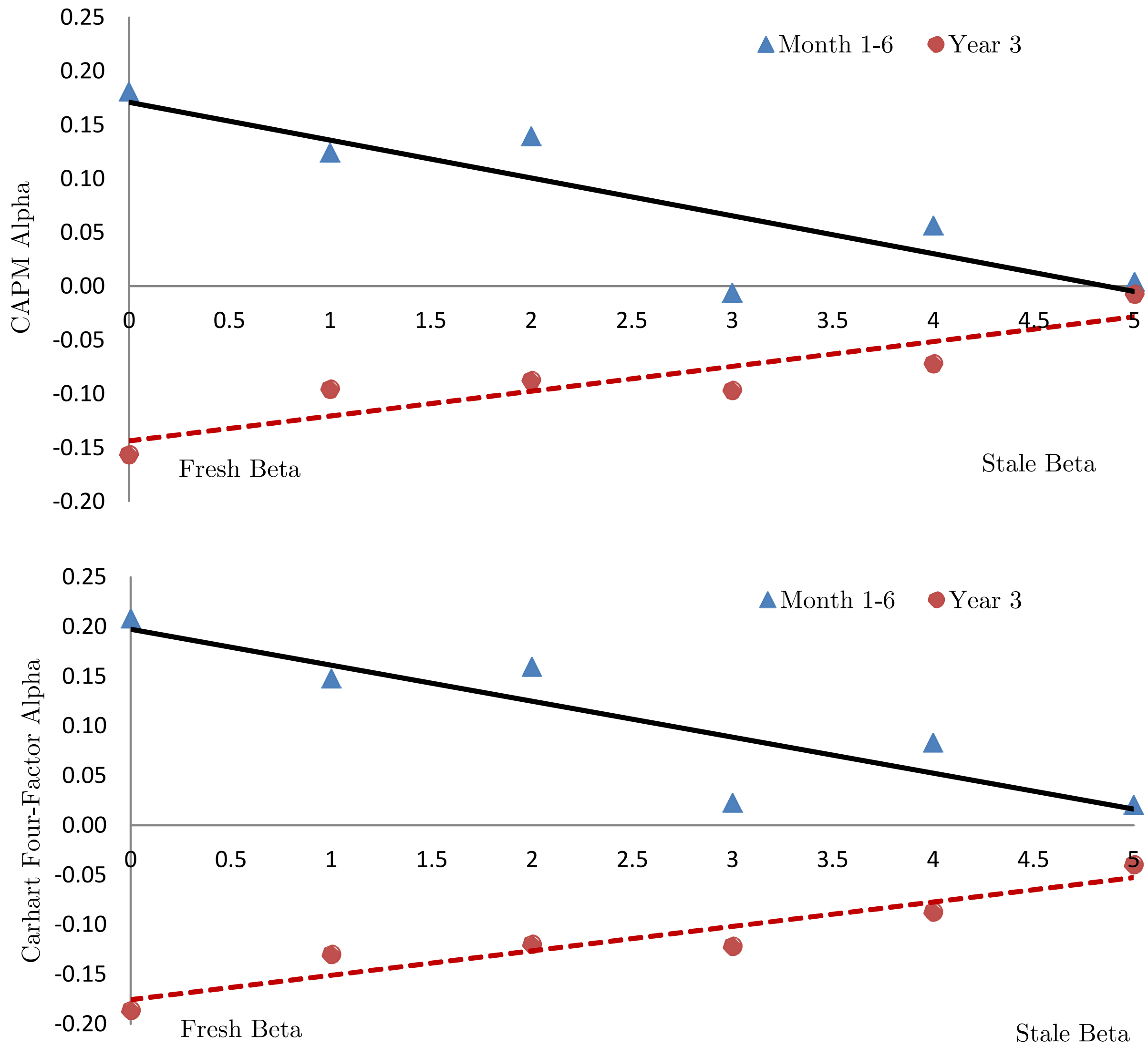

Figure 5: This figure shows how the information in *CoBAR* about time-variation in the expected holding and post-holding return to beta-arbitrage strategies decays as staler estimates of beta are used to form the beta-arbitrage strategy. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. To account for illiquidity and non-synchronous trading, we include on the right hand side of the regression equation five lags of the excess market return, in addition to the contemporaneous excess market return. The pre-ranking beta is simply the sum of the six coefficients from the OLS regression. We then compute the strategy return as the value-weight low-beta decile return minus the value-weight high-beta decile return. We separately regress the abnormal return of the beta-arbitrage strategy in months one-six and year three on *CoBAR*. In this process, we first use a fresh estimate of beta, calculated using daily returns in the past 12 months. We then repeat the analysis using stale betas, computed from daily returns in each of the prior 5 years (thus having different beta portfolios as of time zero for each degree of beta staleness). We plot the corresponding regression coefficients (results for months 1-6 plotted with a blue square and results for year 3 plotted with a red circle) for each of the six beta-arbitrage strategies, ranging from fresh beta to five years stale beta. The top panel reports the CAPM alpha, and the bottom panel shows the Carhart four-factor alpha to the beta arbitrage strategy.