The Booms and Busts of Beta Arbitrage*

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This Draft, September 2014
First Draft: August 2013

* We would like to thank Andrea Frazzini, Lasse Pedersen, Dimitri Vayanos, Michela Verardo, Tuomo Vuolteenaho, and seminar participants at the London School of Economics for helpful comments and discussions. We are grateful for funding from the Europlace Institute of Finance, the Paul Woolley Center at the London School of Economics, and the QUANTVALLEY/FdR: Quantitative Management Initiative.

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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. 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. 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 2013) 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 (2013). 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 2013 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 1) the level of institutional holdings in low-beta stocks (i.e., stocks in the long leg of the beta strategy), 2) the extent of the shadow banking industry, and 3) the assets under management of long-short equity hedge funds together forecast roughly 48% 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 buy-and-hold 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. However, for those periods when arbitrage activity is high, the abnormal four-factor returns average 1.04% per month with a t-statistic of 2.41 in the six months after the trade. 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 these 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 beta arbitrage can be 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 affect the strength of 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.

Perhaps more interestingly, our findings can also be seen by estimating time variation in the short-run and long-run security market line, conditioning on $CoBAR$. 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. In contrast, during periods of low beta-arbitrage activity, the short-term security market line slopes upward, suggesting delayed correction of the beta anomaly. These patterns are completely reversed for the corresponding long-term security market line. Thus, the patterns we find are not just due to extreme-beta stocks, but reflect dynamic movements throughout the cross section.

[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.

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. 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 mostly 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.

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 (1972) and Black, Jensen, and Scholes (1972) were the first to show 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), 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.

Prior research has suggested a number of explanations for this low-beta phenomenon. Black (1972) and more recently Frazzini and Pedersen (2013) 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

[2] See also Baker, Bradley, and Wurgler (2011) and Buffa, Vayanos, and Woolley (2013) for a related explanation based on benchmarking of institutional investors.

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 (2013) provide an alternative explanation based on the insights of Miller (1977). 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 cumulative prospect theory as modeled by Barberis and Huang (2008). Related work also includes Antoniou, Doukas, and Subrahmanyam (2013).

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 arbitrageurs indeed take advantage of this low-beta return pattern by going long low-beta stocks and going short 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.

We argue that the difficulty in identifying the amount of beta-arbitrage capital is exacerbated by an indirect positive-feedback channel. 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 due to leverage effectively causes a 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) and total assets of the shadow banking sector from the Federal Reserve Board. Since the assets managed by hedge funds and held by the shadow banking sector grow substantially in our sample period, both variables are detrended.

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 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 (2012), we construct an aggregate disagreement proxy as the beta-weighted standard deviation of analysts' long-term growth rate forecasts; finally, following Frazzini and Pedersen (2012), 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. We operationalize this calculation by measuring the average correlation of the three-factor residual of every stock in the lowest beta decile with the rest of the stocks in the same decile:

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

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, 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 buy-and-hold 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 0.13 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 2013). $CoBAR$ 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, suggesting that arbitrage activity was initially slow to take advantage of this particular source of time-variation in beta-arbitrage profits.

Figure 1 plots $CoBAR$ as well as $CoBAR$ orthogonalized to contemporaneous variation in the two variables that are available for the full time period, the inflation and sentiment indices. The figure confirms that significant variation in arbitrage activity remains after purging $CoBAR$ of these two variables.[3]

Finally, Table A1 in the Internet Appendix documents that $CoBAR$ is 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. In year 0, the average excess correlation is 0.11. In years 1, 2, and 3, the average excess correlation of these same stocks remains around 0.07.

[3] We have also orthogonalized $CoBAR$ not only to the sentiment and inflation indexes but also to two different estimates of market return volatility. All of our results continue to hold.

IV.A. Determinants of *CoBAR*

To confirm that our measure of beta-arbitrage is sensible, we estimate regressions forecasting *CoBAR* with three variables that are often used to proxy for arbitrage activity. The first variable we use is the aggregate institutional ownership 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 additionally include a variable proposed by Adrian, Moench, and Shin (2010) as a proxy for the size of the shadow banking system (*shadow*). We further include the assets under management (*AUM*) of long-short equity hedge funds. All regressions in Table II include a trend to ensure that our results are not spurious as well as the two variables that the literature has shown forecast beta-arbitrage returns that are available over the entire sample, the inflation and sentiment indices.

All three variables forecast *CoBAR*, with R^2s as high as 50%.[4] This finding makes us comfortable in our interpretation that *CoBAR* is related to arbitrage activity. 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*. Panel A examines CAPM-

[4] 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.

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. Each panel also reports the result of a time-series regression forecasting the abnormal returns using $CoBAR$ ranks.

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.

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.[5]

However, as beta-arbitrage activity increases, the abnormal returns arrive sooner and stronger. 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). We also show these

[5] We also separately examine 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.

time-varying patterns using regression. In both Panel A and Panel B of Table 1, we regress the six-month beta-arbitrage return spread across high and low $CoBAR$ periods on the beginning of period rank-transformed $CoBAR$. Regardless of the risk adjustment, *CoBAR* ranks forecast time variation in expected returns in months one to six on the beta-arbitrage strategy.

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). A regression approach confirms this result. In both Panel A and Panel B of Table 1, we regress the year-three abnormal return on the rank-transformed value of the formation-period $CoBAR$. The coefficient is statistically significant in both cases, with *t*-statistics over 3.

Figure 2 summarizes these patterns by plotting the buy-and-hold 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 argue that trading of the low-beta anomaly is initially stabilizing, then, as the trade becomes crowded, turns destabilizing, causing prices to overshoot.

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 are also robust to excluding the tech bubble crash (2000-2001) or the recent financial crisis (2007-2009).

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 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 volatility of beta-arbitrage returns, and measures of arbitrage activity in momentum and value (Lou and Polk 2013). In row 15, we include stock specific industry factors in the calculation of $CoBAR$. In row 16, we separate HML into its large cap and small cap components. In Row 17, we report DGTW-adjusted portfolio returns. Finally, in Row 18, we report six-factor-adjusted abnormal returns (including liquidity and reversal factors).

In all cases, $CoBAR$ continues to predict time-variation in the year 3 returns. The estimates are always very economically significant, with no point estimate smaller than 1%/month. 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.[6]

The last two rows in Table IV split $CoBAR$ into upside and downside components. Specifically, we measure the following

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

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

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 strategies selling low-beta stocks (such as leveraged-constrained investors modelled 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).

In Table V, we report the results of regressions forecasting the abnormal returns to beta-arbitrage spread bets for both the CAPM and the four-factor model. These

[6] Our results are essentially unchanged if also orthogonalize *CoBAR* topast market return variance. See Figure A1 in the Internet Appendix for related results.

regressions not only confirm that our findings are robust to how we orthogonalize $CoBAR$, they also document the relative extent to which existing measures forecast abnormal returns to beta-arbitrage strategies in the presence of $CoBAR$. Furthermore, these regressions, unlike those in Table III, do not rank our *CoBAR* measure.

Panel A of the table reports regressions forecasting time-series variation in months 1-6. $CoBAR$ strongly forecasts abnormal beta-arbitrage returns over the full sample, regardless of the risk-adjustment. The inflation and sentiment indexes also reliably describe time-variation in abnormal returns on the low-beta-minus-high-beta bet. 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.

Panel B of Table V presents regressions forecasting the returns on beta-arbitrage strategies in year 3. The message from this panel concerning the main result of the paper is clear; $CoBAR$ strongly forecasts a time-varying reversal regardless of the risk adjustment or 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 makes it clear 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.[7] 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 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 β_1^1, ..., β_{20}^1 and β_1^{25}, ..., β_{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 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 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

[7] 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.

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 slopes upward, and the beta-arbitrage strategy is substantially less profitable, suggesting 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, suggesting delayed profitability to the low beta strategy.

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. 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 VII, 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.

Panels A and B report results when the sample is split based on idiosyncratic variance. Among low idiosyncratic stocks, Panel A shows that $CoBAR$ strongly predicts higher returns to beta-arbitrage strategies in months 1-6. The spread in four-factor alpha is 1.58%/month with an associated *t*-statistic of 2.31. 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 -3.36. Turning to high idiosyncratic volatility stocks, Table VII Panel B shows that the corresponding point estimates are much lower and always statistically insignificant.

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 both months 1-6 and year 3. The spread in four-factor alpha across the high and low $CoBAR$ groups is 1.12%/month (t-statistic of 1.98) in the short run and -1.35%/month (t-statistic of -2.29) in the long-run. The corresponding t-statistics for the low liquidity sample are below 1.

Finally, Panels E and F split the sample based on market capitalization. Panel E documents that among large-cap stocks, $CoBAR$ positively forecasts differences in months 1-6 abnormal returns (1.36%/month with a t-statistic of 2.21) and negatively forecasts differences in year 3 abnormal returns (-1.45%/month with a t-statistic of -3.29). Corresponding differences among small stocks are insignificant at conventional levels.

In summary, Table VII confirms that our effect is stronger among those stocks where limits of arbitrage are weaker, where one expects arbitrageurs to play a larger role.

V.B. 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. Thus, not only do arbitrageurs not know 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 VIII. 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 ($Leverage$) 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 VIII 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 more than 5%. Regression (2) shows that this is particular true when $Leverage$ is also high. 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 a 2-3% increase in

$Fraction$. Regression (4) confirms that this effect is particularly strong when $Leverage$ is also high.

Taken together, these results are consistent with beta-arbitrage activity causing the cross-sectional spread in betas to expand. Table A4 in the Internet Appendix confirms that these results are robust to measuring $CoBAR$ in various ways.

V.B. 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 the staleness of beta.

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 shown in 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 (2013), 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 returns 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.

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 Fisher Black's famous 1972 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 lagged-12-month market beta computed using daily returns. Pairwise partial return correlations (after controlling for the Fama-French three factors) for all stocks in the low beta decile are computed based on weekly stock returns in the previous 12 months. $CoBAR$ 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
$CoBAR$	546	0.108	0.029	0.034	0.215
Inflation	546	0.004	0.002	0.001	0.007
Sentiment	546	0.000	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	Disagrmnt	Ted Spread
$CoBAR$	1.000				
Inflation	-0.311	1.000			
Sentiment	0.126	0.075	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 related to arbitrage capital. 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 in the regressions, $CoBAR$, is the average pairwise partial weekly return correlation in the low-beta decile over the past 12 months. pih_{t-1} is the aggregate institutional ownership of the low-beta decile, $shadow_{t-1}$ is the percentage flow to the shadow banking system, AUM_{t-1} is the logarithm of the total assets under management of long-short equity hedge funds, $Inflation_{t-1}$ 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)), and $Sentiment_{t-1}$ is the investor sentiment index, all measured at the end of year t-1. We also include in the regression the average Pastor-Stambaugh liquidity factor in year t-1, as well as $mktret36_{t-1}$ and $mktvol36_{t-1}$, which are, respectively, the three-year return and the monthly return volatility of the CRSP market portfolio. A trend dummy is included in all regression specifications. All the independent variables are standardized by the corresponding standard deviation, so the coefficient represents the effect of a one-standard-deviation change in the independent variable on $CoBAR$. Standard errors, shown in brackets, are corrected for serial-dependence with 12 lags. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

Dependent Variable	$CoBAR_t$					
	[1]	[2]	[3]	[4]	[5]	[6]
pih_{t-1}	0.008***	0.007***	0.018***	0.017***	0.016***	0.009***
	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]	[0.004]
$shadow_{t-1}$		0.003***	0.003***		0.002*	0.004**
		[0.001]	[0.001]		[0.001]	[0.001]
AUM_{t-1}			0.005***			0.004**
			[0.002]			[0.002]
$Inflation_{t-1}$				-0.019***	-0.018***	0.020
				[0.004]	[0.004]	[0.014]
$Sentiment_{t-1}$				0.001	0.001	0.009**
				[0.002]	[0.002]	[0.004]
TREND	YES	YES	YES	YES	YES	YES
Adj-R^2	0.24	0.25	0.48	0.32	0.32	0.50
No. Obs.	357	357	180	357	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. 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. We also orthogonalize $CoBAR$ with regard to both the sentiment index and inflation index to focus on the residual effect. 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 $CoBAR$; "OLS" is the slope coefficient from the regression of monthly long-short strategy returns on ranks of $CoBAR$. 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)**
OLS		**0.32%**	**(1.97)**	0.15%	(0.99)	-0.09%	(-0.82)	**-0.32%**	**(-3.27)**

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)**
OLS		**0.27%**	**(2.04)**	0.09%	(0.81)	-0.14%	(-1.26)	**-0.29%**	**(-3.21)**

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. 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, 2012), and Ted Spread. 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, 2013). In Row 15, we further control for industry factors in the calculation of $CoBAR$. In Row 16, we control for both large- and small-cap HML in computing $CoBAR$. In Row 17, we report DGTW-adjusted portfolio returns. Finally, in Row 18, we report the six-factor adjusted holding period returns (including liquidity and reversal factors). In Rows 19 and 20, we examine the upside and downside $CoBAR$, calculated based on the median low-beta portfolio return. 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.

	Months 1-6		Year 3	
	Estimate	t-stat	Estimate	t-stat
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)**
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)
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(BetaArb)	**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 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)**
Upside CoBAR	**1.09%**	**(2.08)**	**-0.80%**	**(-2.32)**
Downside CoBAR	0.04%	(0.08)	-0.30%	(-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. The dependent variable is the return to the beta arbitrage strategy (i.e., to go 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 return correlation in 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), and Ted Spread. Panel A examines returns to the beta arbitrage strategy in months 1-6, while Panel B examines the returns in year 3 after portfolio formation. We report results based on both CAPM and 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 90%, 95%, and 99% level, respectively.

Panel A: Beta-Arbitrage Returns in Months 1-6

DepVar	CAPM Alpha			Four-Factor Alpha		
$CoBAR$	0.193***	0.221***	0.112	0.179***	0.203***	0.097
	[0.088]	[0.094]	[0.123]	[0.069]	[0.070]	[0.108]
Inflation		0.029*	0.128**		0.024*	0.118***
		[0.016]	[0.060]		[0.013]	[0.045]
Sentiment		0.008***	0.013		0.006**	0.006
		[0.002]	[0.010]		[0.002]	[0.007]
Disagreement			0.010			0.012**
			[0.009]			[0.006]
Ted Spread			-0.019***			-0.006
			[0.006]			[0.006]
Adj-R^2	0.043	0.141	0.258	0.054	0.142	0.223
N of Obs	545	545	312	545	545	312

Panel B: Beta-Arbitrage Returns in Year 3

DepVar	CAPM Alpha			Four-Factor Alpha		
$CoBAR$	-0.179***	-0.182***	-0.160**	-0.146***	-0.153***	-0.238***
	[0.049]	[0.045]	[0.070]	[0.046]	[0.042]	[0.069]
Inflation		0.003	-0.022		0.000	0.007
		[0.012]	[0.057]		[0.011]	[0.050]
Sentiment		0.003	-0.005		0.002	-0.007
		[0.002]	[0.008]		[0.001]	[0.007]
Disagreement			0.001			0.007
			[0.007]			[0.006]
Ted Spread			0.003			0.006
			[0.004]			[0.004]
Adj-R^2	0.102	0.125	0.112	0.078	0.090	0.143
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 20 portfolios based on their market beta calculated using daily returns in the past 12 months. 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 post-ranking betas are calculated 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. 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. 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 90%, 95%, and 99% level, respectively.

Panel A: Dependent Variable = Intercept of SML

	Months 1-6				Year3			
$CoBAR$	0.149**	0.183***	0.194***	0.119	-0.176***	-0.187***	-0.192***	-0.169***
	[0.078]	[0.073]	[0.054]	[0.085]	[0.052]	[0.049]	[0.048]	[0.072]
Inflation		0.029***	0.026***	0.060		0.002	0.003	0.002
		[0.011]	[0.009]	[0.032]		[0.012]	[0.012]	[0.057]
Sentiment		0.004**	0.003***	0.004		0.004	0.004	-0.005
		[0.002]	[0.001]	[0.005]		[0.002]	[0.002]	[0.008]
Disagreement				0.003				0.010
				[0.004]				[0.007]
Ted Spread				-0.011***				0.001
				[0.005]				[0.004]
Control	No	No	Yes	Yes	No	No	Yes	Yes
Adj-R^2	0.037	0.120	0.384	0.494	0.071	0.111	0.132	0.173
N of Obs	545	545	545	312	545	545	545	312

Panel B: Dependent Variable = Slope of SML

	Months 1-6				Year3			
$CoBAR$	-0.314***	-0.349***	-0.179***	-0.084	0.201***	0.226***	0.224***	0.245***
	[0.086]	[0.088]	[0.051]	[0.089]	[0.063]	[0.063]	[0.060]	[0.078]
Inflation		-0.035**	-0.026***	-0.065		0.008	0.006	-0.007
		[0.014]	[0.010]	[0.032]		[0.016]	[0.016]	[0.067]
Sentiment		-0.007***	-0.003***	-0.005		-0.003	-0.003	0.007
		[0.002]	[0.001]	[0.005]		[0.002]	[0.002]	[0.010]
Disagreement				-0.002				-0.007
				[0.004]				[0.008]
Ted Spread				0.013***				-0.004
				[0.005]				[0.004]
Control	No	No	Yes	Yes	No	No	Yes	Yes
Adj-R^2	0.093	0.180	0.663	0.708	0.065	0.080	0.117	0.164
N of Obs	545	545	545	312	545	545	545	312

Table VII: Limits to Arbitrage

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. 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 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 $CoBAR$; "OLS" is the slope coefficient from the regression of monthly long-short strategy returns on ranks of $CoBAR$. Panels A and B report the average monthly returns to the beta-arbitrage strategy constructed solely based on stocks with low or high idiosyncratic volatilities (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 large or small market capitalization (as of the beginning of the holding period), respectively. Across all Panels, splits are based on the median value of the firm characteristic 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: Low Idiosyncratic Volatility

		Month1-6		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	109	-0.36%	(-0.75)	-0.11%	(-0.27)	0.62%	(2.11)	0.42%	(1.80)
2	109	-0.40%	(-1.24)	-0.12%	(-0.43)	0.30%	(0.85)	0.24%	(0.90)
3	109	-0.31%	(-0.93)	-0.01%	(-0.03)	-0.09%	(-0.32)	-0.18%	(-0.52)
4	109	-0.20%	(-0.80)	-0.25%	(-1.94)	-0.15%	(-0.42)	-0.08%	(-0.26)
5	109	**1.22%**	**(2.52)**	0.56%	(1.78)	0.14%	(0.36)	**-0.87%**	**(-3.26)**
5–1		**1.58%**	**(2.31)**	0.67%	(1.30)	-0.48%	(-1.00)	**-1.30%**	**(-3.36)**
OLS		**0.34%**	**(2.30)**	0.12%	(1.02)	-0.14%	(-1.25)	**-0.29%**	**(-3.18)**

Panel B: High Idiosyncratic Volatility

		Month1-6		Year 1		Year 2		Year 3	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
1	109	0.22%	(0.46)	0.38%	(1.14)	0.25%	(0.84)	0.36%	(1.12)
2	109	-0.56%	(-1.74)	-0.08%	(-0.25)	0.18%	(0.51)	-0.17%	(-0.40)
3	109	-0.40%	(-0.81)	-0.03%	(-0.08)	0.11%	(0.24)	-0.03%	(-0.07)
4	109	-0.38%	(-0.85)	-0.26%	(-0.95)	-0.26%	(-0.91)	-0.20%	(-0.53)
5	109	**1.10%**	**(2.15)**	0.60%	(1.19)	0.05%	(0.13)	-0.54%	(-1.22)
5–1		0.88%	(1.29)	0.22%	(0.37)	-0.19%	(-0.39)	-0.90%	(-1.53)
OLS		0.19%	(1.22)	0.03%	(0.18)	-0.08%	(-0.74)	-0.18%	(-1.43)

Panel C: High Liquidity									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	99	-0.21%	(-0.50)	-0.07%	(-0.26)	0.04%	(0.16)	0.36%	(1.03)
2	100	-0.51%	(-1.58)	-0.29%	(-1.01)	0.05%	(0.23)	-0.07%	(-0.18)
3	99	-0.22%	(-0.86)	0.03%	(0.12)	-0.11%	(-0.30)	-0.25%	(-0.73)
4	100	**-0.76%**	**(-2.20)**	**-0.50%**	**(-2.28)**	-0.43%	(-1.01)	-0.09%	(-0.28)
5	99	**0.91%**	**(2.52)**	0.36%	(0.98)	-0.11%	(-0.25)	**-1.00%**	**(-2.41)**
5--1		**1.12%**	**(1.98)**	0.43%	(0.96)	-0.15%	(-0.30)	**-1.35%**	**(-2.29)**
OLS		0.20%	(1.51)	0.06%	(0.53)	-0.08%	(-0.69)	**-0.27%**	**(-2.17)**

Panel D: Low Liquidity									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	99	0.67%	(1.48)	0.44%	(1.02)	0.05%	(0.22)	-0.03%	(-0.11)
2	100	-0.16%	(-0.53)	-0.02%	(-0.07)	-0.10%	(-0.55)	-0.41%	(-1.89)
3	99	-0.15%	(-0.46)	0.17%	(0.65)	-0.03%	(-0.10)	-0.36%	(-1.95)
4	100	0.69%	(1.86)	0.32%	(0.89)	-0.06%	(-0.23)	-0.07%	(-0.19)
5	99	0.74%	(1.33)	0.63%	(1.35)	0.15%	(0.25)	-0.31%	(-0.68)
5--1		0.07%	(0.10)	0.19%	(0.31)	0.09%	(0.15)	-0.28%	(-0.46)
OLS		0.10%	(0.61)	0.07%	(0.46)	0.02%	(0.17)	-0.02%	(-0.17)

Panel E: Large Market Capitalization									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	-0.28%	(-0.68)	-0.04%	(-0.13)	0.48%	(1.57)	**0.50%**	**(2.24)**
2	109	-0.56%	(-1.81)	-0.16%	(-0.52)	0.20%	(0.67)	0.02%	(0.06)
3	109	-0.41%	(-1.40)	-0.04%	(-0.15)	-0.11%	(-0.31)	-0.07%	(-0.20)
4	109	-0.45%	(-1.52)	**-0.36%**	**(-2.12)**	-0.33%	(-0.89)	-0.09%	(-0.29)
5	109	**1.08%**	**(2.29)**	0.60%	(1.67)	-0.08%	(-0.20)	**-0.95%**	**(-2.92)**
5--1		**1.36%**	**(2.21)**	0.64%	(1.34)	-0.56%	(-1.11)	**-1.45%**	**(-3.29)**
OLS		**0.28%**	**(2.06)**	0.11%	(0.92)	-0.17%	(-1.43)	**-0.30%**	**(-2.92)**

Panel F: Small Market Capitalization									
		Month1-6		Year 1		Year 2		Year3	
Rank	No Obs	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	109	0.64%	(1.54)	**0.90%**	**(2.18)**	0.64%	(1.62)	0.29%	(1.00)
2	109	-0.11%	(-0.33)	0.20%	(0.89)	-0.13%	(-0.55)	0.10%	(0.29)
3	109	0.18%	(0.62)	0.20%	(1.02)	-0.01%	(-0.02)	0.55%	(1.71)
4	109	**0.69%**	**(2.59)**	**0.44%**	**(2.28)**	-0.11%	(-0.44)	0.19%	(0.72)
5	109	**0.94%**	**(3.03)**	0.39%	(1.54)	0.42%	(1.01)	-0.44%	(-1.00)
5--1		0.30%	(0.58)	-0.51%	(-1.10)	-0.22%	(-0.40)	-0.73%	(-1.47)
OLS		0.14%	(1.19)	-0.08%	(-0.72)	-0.04%	(-0.34)	-0.14%	(-1.16)

Table VIII: Beta Spread

This table reports the beta expansion associated with arbitrage trading. The dependent variable in columns 1 and 2, $BetaSpread$, is the beta spread between the high-beta stocks and low-beta portfolio from year t-1 to t. The dependent variable in columns 3 and 4, $Fraction$, is the fraction of stocks in the bottom beta decile ranked in year t-1 remains in the bottom beta decile in year t (the two beta ranking periods are non-overlapping). $CoBAR$ is the average pairwise excess weekly return correlation in the low-beta decile over the past 12 months. $Leverage$ is the average of the value-weighted book leverage of the bottom and top beta deciles. We also include in the regression an interaction term between $CoBAR$ and $Leverage$. Other control variables include the lagged $BetaSpread$. Standard errors, shown in brackets, are corrected for serial-dependence with 12 lags. *, **, *** denote significance at the 90%, 95%, and 99% level, respectively.

Dependent Variable	$BetaSpread_t$		$Fraction_t$	
	[1]	[2]	[3]	[4]
$BetaSpread_{t-1}$	0.282***	0.276***		
	[0.061]	[0.059]		
$CoBAR_{t-1}$	1.253***	0.129	2.681*	0.388
	[0.411]	[0.498]	[1.533]	[1.714]
$Leverage_{t-1}$		-0.047***		-0.250***
		[0.011]		[0.040]
$CoBAR_{t-1} * Leverage_{t-1}$		0.456***		0.766**
		[0.117]		[0.279]
Adj-R^2	0.12	0.15	0.01	0.09
No. Obs.	545	545	545	545

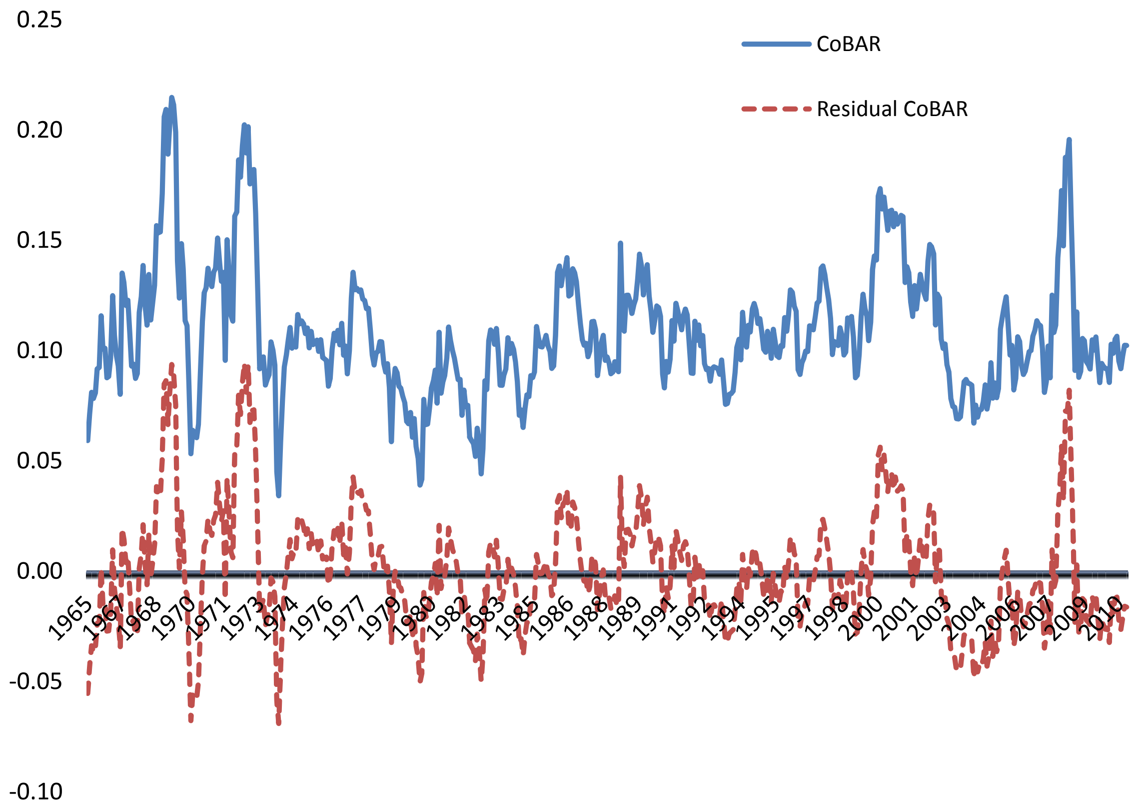

Figure 1: This figure shows the time series of the $CoBAR$ measure. At the end of each month, all stocks are sorted into decile portfolios based on their market beta calculated using lagged 12-month daily returns. $CoBAR$ (shown in blue) is the average pairwise partial return correlation in the low-beta decile measured in the ranking period. Residual $CoBAR$ (shown in dotted red) is the residual from the regression of $CoBAR$ on the contemporaneous sentiment index and inflation index.

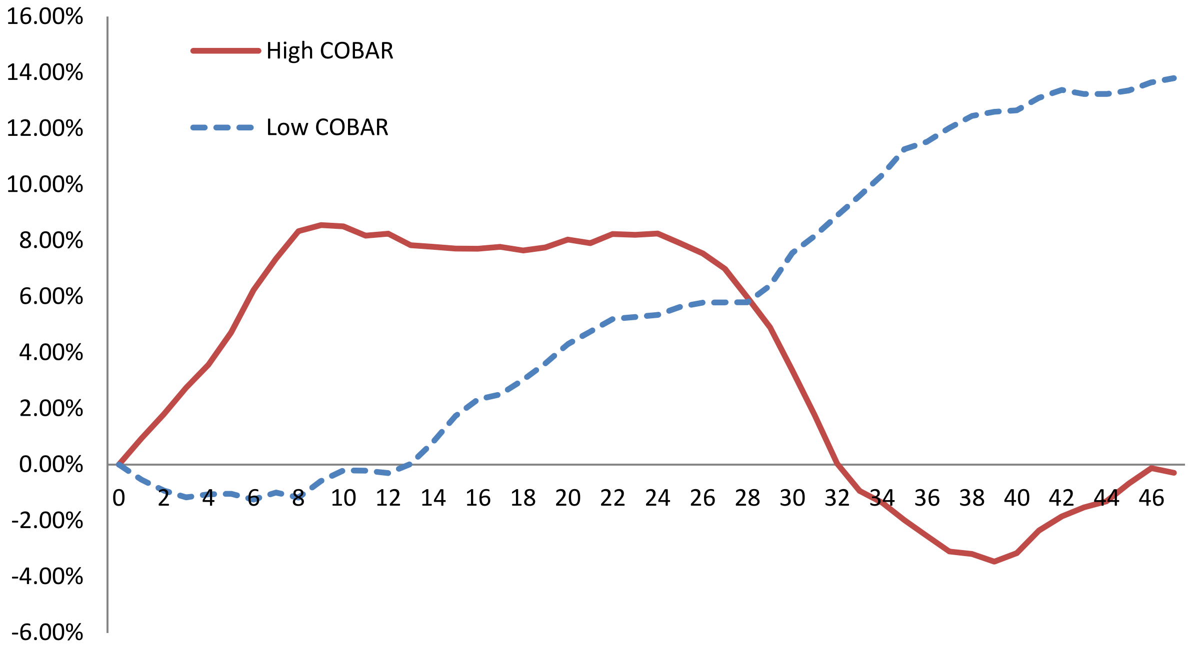

Figure 2: This figure shows returns to the beta arbitrage strategy as a function of lagged $CoBAR$,. At the end of each month, all stocks are sorted into deciles based on their market beta calculated using daily returns in the past 12 months. Stocks with prices below $5 a share and/or are in the bottom NYSE size decile are excluded from the sample. All months are then sorted into five groups based on $CoBAR$, the average pairwise partial weekly return correlation in 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., to go 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 $CoBAR$.

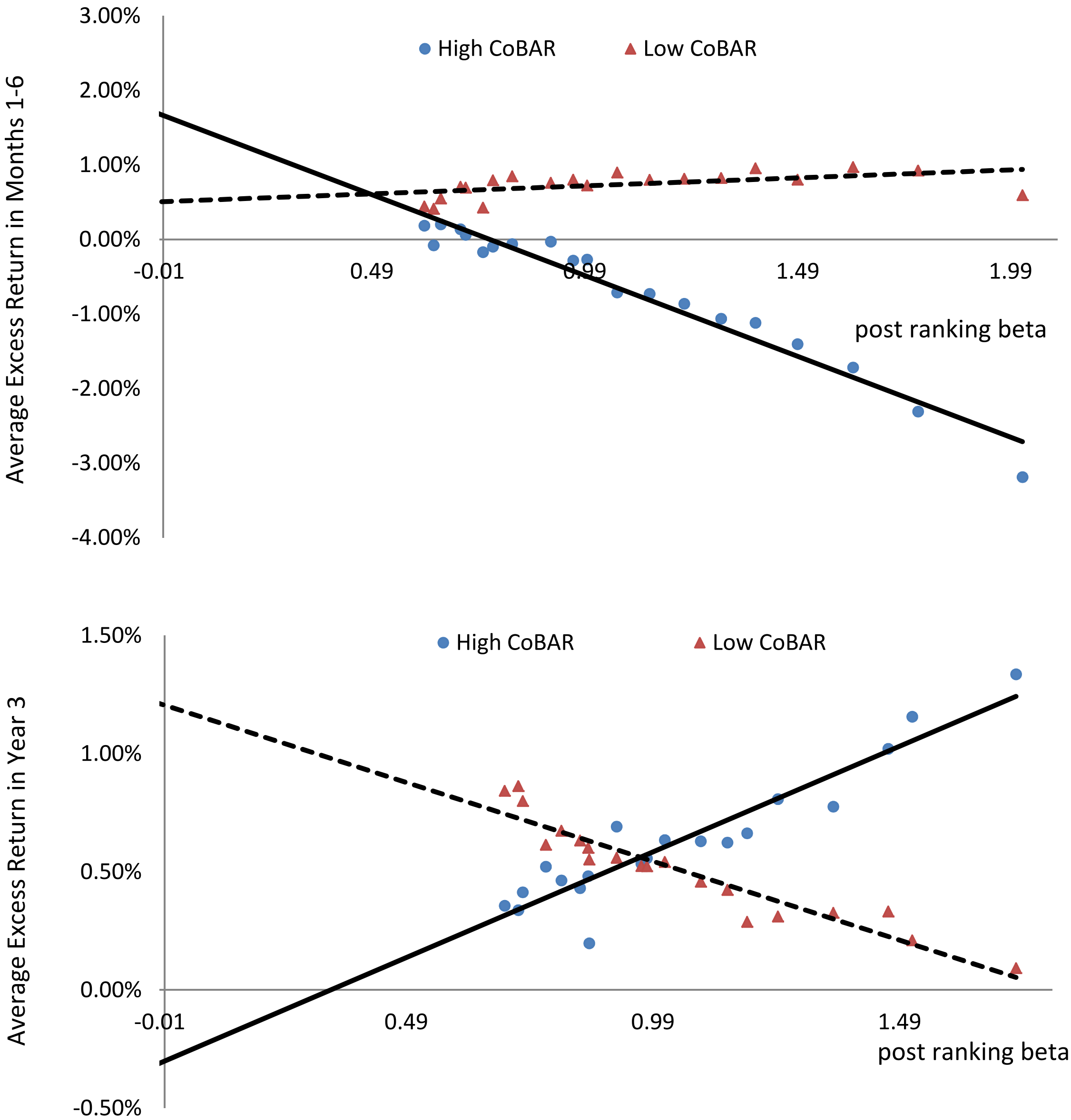

Figure 3: This figure shows the security market line as a function of lagged $CoBAR$. At the end of each month, all stocks are sorted into 20 portfolios based on their market beta calculated using daily returns in the past 12 months. We then estimate two security market lines based on these 20 portfolios 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 most recent betas. The Y-axis is the average monthly excess returns to these 20 portfolios, and the X-axis is 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 returns to the beta arbitrage strategy in months 1-6, while the bottom Panel shows the returns in year 3 after portfolio formation.

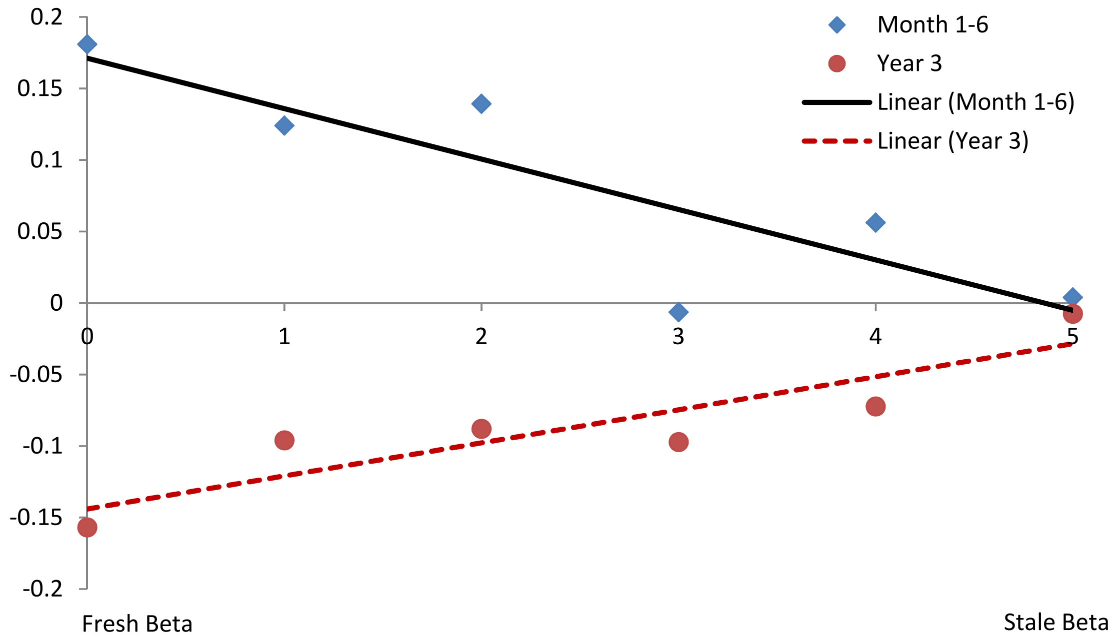

Figure 4: This figure shows how the information in $CoBAR$ about time-variation in the expected holding and post-holding return to beta-arbitrage strategies decays as staler estimates of beta are used to form the beta-arbitrage strategy. At the end of each month, all stocks are sorted into deciles based on their market beta. 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 four-factor alpha 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.