Aalto University
School of Business

CONSTRAINTS TO LEVERAGE AND MARKET CORRELATION

The Role of Systematic Risk and Margin Requirements in Driving the Low Risk Anomaly

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Juho Vapola
Aalto University School of Business
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Author Juho Vapola

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Abstract

High risk stocks tend to produce lower risk-adjusted returns than their lower risk counterparts. I take a novel look at leverage constraints as the primary driver of the anomaly, in exploring the impact of changing margin requirements on compensation for market correlation and volatility. Using a dataset from the US stock market between 1934 and 1974, I find that conditioned on volatility, correlation with the market reflects the additional risk investors seek to take on when access to additional leverage is hindered. On the other hand, higher volatility does not seem to play much of a role in investors adjusting for changing conditions for leverage. Additionally, I apply my results in the context of a Betting Against Correlation factor and find the returns to be largely related to leverage constraints as predicted by previous research.

Keywords Low Risk Anomaly, Betting Against Correlation, Leverage Constraints

Tekijä Juho Vapola

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Tiivistelmä

Korkeariskisten osakkeiden riskikorjatut tuotot ovat tavallisesti heikompia kuin matalariskisissä osakkeissa. Sovellan tutkielmassani uutta lähestymistapaa sijoittajien rajoitettuun velanottoon anomalian aiheuttajana sekä tarkastelen muuttuvien limiittivaatimusten vaikutusta markkinakorrelaation ja volatiliteetin tuottokompensaatioon. Tarkastelen tutkielmassani osakkeiden tuottoja Yhdysvalloissa vuosina 1934–1974 ja näytän empiirisesti, että tuottojen korrelaatio markkinatuoton kanssa heijastaa sijoittajien pyrkimyksiä kasvattaa portfolion riskiä, kun velkavivun käyttö on rajoitettua ja volatiliteetti pysyy vakiona. Toisaalta yksittäisten osakkeiden volatiliteetti ei vaikuta olevan keskeisessä asemassa, kun sijoittajat muuttavat omistuksiaan vastaamaan eri tasoisiin velkarajoitteisiin. Lisäksi tulokseni osoittavat, että niin sanotun BAC-faktorin ("Betting Against Correlation") tuotot liittyvät suurilta osin sijoittajien velanoton rajoitteisiin, yhteensopivasti aikaisemman kirjallisuuden kanssa.

Avainsanat Matalan riskin anomalia, BAC, Velkarajoitteet

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1 Introduction

1.1 Low Risk Anomaly

The low risk effect represents one of the most persistent anomalies and unsolved puzzles in asset pricing research. Early literature by e.g. Sharpe (1964), Lintner (1965) and Mossin (1966) suggests that investors seeking mean variance efficient portfolios should in equilibrium produce some form of the security market line captured by the Capital Asset Pricing Model. Empirical findings however have been quite on the contrary since the inception of the early models and still remarkably persist today. The security market line turns out to be empirically flatter than implied by the CAPM with a variety of candidate explanations ranging from explanations based on systemic risk[1] to pure behavioral biases[2].

The most commonplace explanations stem from two main categories: investors' leverage constraints and behavioral biases or hindrances such as the investors' inclination for lottery-like payoffs or the asymmetric impact of idiosyncratic volatility. The framework of leverage constrained investors echoes a risk-based view on the anomaly. In the presence of binding constraints to leverage, investors are not fully able to take on the level of risk they desire on their optimal portfolios but are forced to resort to changing the composition of their holdings rather than taking on debt. The new equilibrium for leverage constrained investors causes increased price pressure on high risk securities, i.e. stocks with high betas, and is then materialized by the flattening of the empirical security market line. Not only does the new equilibrium put pressure on the higher beta assets but also reduces the demand for assets with low betas, as most investors cannot reach their target returns by levering up low risk stocks. The simultaneous decrease in the slope and the increase in the intercept as leverage constraints tighten should then manifest itself as the low risk anomaly. Recent research, most prominently (Jylhä, 2018) sheds increasing light on the various forms the security market line takes under changing exogenous margin constraints.

Behavioral explanations however provide a very contrarian view on the empirical failures of the model with a spectrum of different takes. Liu et al. (2018) argue that the low risk anomaly is a product of guilt association to beta and is in fact caused by the negative return relation of idiosyncratic risk and limits to arbitrage. Alternatively one can take a

[1] see e.g. (Frazzini & Pedersen, 2014), (Asness, Frazzini, Gormsen, & Pedersen, 2016), (Jylhä, 2018) and (Boguth & Simutin, 2018) for a recent perspective on risk and leverage constraints based explanations.

[2] see e.g. (Stambaugh & Yuan, 2017), (Liu, Stambaugh, & Yuan, 2018) and (Bali, Brown, Murray, & Yi Tang, 2017) for takes on the role of residual volatility and positive skewness.

positive view on volatility in excess of the systematic risk and tie the anomalous returns to the chase of lottery payoffs. In fact, Bali et al. (2017) show that the anomaly manifests itself during times when high beta assets display lottery like features. Nonetheless, one common denominator for many of the behavioral explanations is their inherent linkage to volatility, be it idiosyncratic volatility in itself or patterns of positive skewness in returns. Explanations related to volatility however should not particularly arise in conjunction with changing leverage constraints.

1.2 Contribution to Existing Research

As persistent the low risk effect has been, the literature has taken quite a while to focus on exploiting it compared to e.g. momentum by Jegadeesh and Titman (1993) or investing on the Fama and French (1993) factors. Frazzini and Pedersen (2014) present a way of taking advantage of the anomaly through their Betting Against Beta factor that goes long in low beta and short in high beta assets. Their approach produces robust alphas on the most common factor models both in the US and International equities. Consequently the BAB factor also serves as a useful benchmark for further research in testing and validating new candidate explanations. Asness et al. (2016) divide the BAB factor further and run horse races between many of the common candidate variables. They come up with factors combining in the BAB profit: Betting Against Correlation or BAC and Betting Against Volatility or BAV. The new factors are built analogously to the BAB factor but are relatively uncorrelated with each other allowing one to frame the source of BAB alphas into an alias for behavioral explanations, BAV and the candidate for proxying systematic risk, BAC.

The competing branches of explanations provide fruitful ground for further research and bridging the gap. In my approach I provide a novel take on the phenomenon by decomposing the anomaly, a stock's beta into its two components, correlation and volatility. The alternative decomposition allows one to examine the impact of leverage constraints in generating the low risk anomaly by distinctively different beta components. To test the effects, I use daily and monthly stock return data from CRSP between January 1934 and December 1974 in addition to data on changes in the FED initial margin requirement also used by Jylhä (2018).

To the best of my knowledge, none of the previous research addresses the margin impact of the return compensation for volatility and correlation as beta determinants. The approach by Jylhä (2018) serves as an inspiration for much of my approach but stops short in detailing the shape of the security market line. Frazzini and Pedersen (2014) also proxy margin constraints in the research by TED spread but end up with findings inconsistent with their model. Asness et al. (2016) include a measure of margin debt in their factor horse races but only report the impact on their rank weighted portfolios that hardly represent the properties of the full universe of stocks.

I methodologically track the roots to the anomaly from the return relation of the distinctive beta components, correlation and volatility to the shape of their analogous security market line mockups. Finally, I link the findings across all stocks to the more specific case of the BAB, BAC and BAV factors.

My thesis holds three main contributions to the existing body of research:

1) I decompose the effects of leverage constraints on risk compensation

I apply the logic introduced by e.g. Frazzini and Pedersen (2014) and Asness et al. (2016) in attributing the effects of exogenous leverage constraints separately to systematic and behavioral components. Instead of using the correlation and volatility components solely for beta- or portfolio construction, I treat them as separate positive return drivers and construct mockups of the security market line analogously to Jylhä (2018). The construction of the separate security market line mockups allows for closer examination of the link between leverage constraints and the systematic as well as behavioral candidate explanations.

2) I find that conditioned on volatility, the slope of the return compensation to market correlation is negatively affected by tighter margin constraints

The more granular look on the beta determinants allows for studying the effects of increasing either correlation or volatility while holding the other one constant. I find that conditioned on volatility, the slope of the return compensation to market correlation is negatively affected by tighter margin constraints entailing that market correlation reflects the implicit leverage investors take on in lieu of financial leverage.

My findings are consistent with the ones by Jylhä (2018) to the extent that a similar, albeit weaker, relation between market correlation and initial margin requirement persists when controlling for volatility. To amend this view, I also find that (residual) volatility holds no significant connection to initial margin requirements when conditioned on correlation. Finally, the use of security market line mockups allows for a more general look at the phenomenon as opposed to the factor approach by Asness et al. (2016).

3) I provide additional support to returns to a Betting Against Correlation factor being related to lagged changes in leverage constraints

I find that the Asness et al. (2016) BAC factor returns between 1934 and 1974 are to a large extent related to lagged changes in the initial margin requirement. However, I cannot rule out the margin constraint relation in the variance portion of Betting Against Beta or the BAB factor.

My results on the BAC factor are consistent with Asness et al. (2016), but also provide a second view with exogenous leverage constraints imposed by the regulator as opposed to using broker-dealer margin debt as an endogenous proxy for leverage constraints.

2 Theoretical Motivation and Hypotheses

2.1 Systematic Risk in the Context of the Low Risk Anomaly

The low risk effect is typically attributed to either systematic (e.g. leverage constraints) or behavioral (e.g. lottery preferences, barriers to arbitrage) explanations. While economically intuitive, leverage constraints as the primary driver has had little success in the existing literature, in ruling out other explanations from the mix. Jylhä (2018) finds that in a period ranging from 1934 to 1974, exogenous changes in US Federal Reserve's margin requirement have an expected effect on the shape of the Security Market Line – that is, a flatter SML in the times of high margin requirements and a steeper slope in the times of low margin requirements, much alike its CAPM prediction by Jylhä (2018).

Adrian, Etula, and Muir (2014) back a similar sentiment by tying their financial intermediary leverage factor to a betting against beta factor and showing that the returns comove with changing funding conditions. Additionally, Asness et al. (2016) find that change in total margin debt held by NYSE broker dealers has a statistically significant effect on the return to their factor mimicking poor returns when betting on systematic risk. An inverted approach by Boguth and Simutin (2018) provides a similar conclusion. Assuming that mutual funds are for the most part particularly constrained for leverage, they show that high beta assets seen as instruments with a high payoff in a leverage constrained environment, should be priced higher by constrained investors. This then leads to the same assets delivering weaker consequent returns. Simultaneously mutual fund managers focusing on low beta assets end up taking on leverage constraint risk but earning abnormal returns in relation to a standard CAPM.

Mutual fund incentivization in general seems to be another amplifying factor in the return impact of leverage constraints. As fund managers are typically evaluated against a fixed benchmark not their risk adjusted performance, the leverage constrained managers resort to higher beta. Karceski (2002) shows that mutual fund inflows seem to follow dramatic market runups and returns are chased cross-sectionally to best performing funds. The consequential incentive for mutual funds is therefore to shift their holdings towards higher beta than indicated by e.g. the CAPM equilibrium. On a similar note, Baker, Bradley, and Wurgler (2011) propose that institutional investors' mandates prevent the high-resource, smart investors from correcting prices in the market, but in fact encourage them to invest in high-beta securities without much leverage. They also suggest that institutional investors are incentivized by a fixed benchmark causing them to chase high benchmark adjusted returns, particularly when the market is on the rise. The potential implicit limitations to access to leverage drives up the demand for high risk or high beta stocks. The smart money therefore ends up passing on superior return opportunities in the low-beta end of the security market line (Baker et al., 2011). Christoffersen and Simutin (2017) report a similar conclusion among “defined contribution” mutual funds. They show empirically that benchmarking seems to alter the behavior of leverage constrained fund managers and increase the demand of high beta assets in lieu of low beta alternatives.

Addressing the leverage constraints and the systematic risk based explanation somewhat disregards the potential behavioral and micro market hindrances at play in generating the anomaly. Stambaugh, Yu, and Yuan (2015) argue that the poor return compensation of high risk stocks is due to idiosyncratic volatility and primarily driven by impediments to arbitrage. Additionally, Liu et al. (2018) set their sights on the low risk anomaly and betting against beta. They find that controlling for idiosyncratic volatility and mispricing makes the beta anomaly disappear, arguing that rather than being the de facto driver of the phenomenon, beta suffers from “guilt association” in being positively correlated with idiosyncratic volatility and therefore negatively correlated with alpha. They conclude that the anomaly seems to be driven by short-sale frictions and mispricing caused by idiosyncratic volatility, not by the investors seeking to bet on higher systematic risk per se. Bali, Cakici, and Whitelaw (2011) and Bali et al. (2017) on the other hand suggest that as market participants select a sub-optimal number of securities in their portfolios[1] the poor returns to high beta assets seem to be due to the prospect of lottery-like payoffs being correlated with market beta.

As Liu et al. (2018) also concede, leverage constraints may co-exist with other behavioral explanations when considering alternate measures of risk such as market correlation reported by Asness et al. (2016). Indeed, e.g. idiosyncratic risk as a barrier to selling short should have little to do with changing margin requirements and vice versa. In addition to Jylhä (2018) reporting the changing shape of the Security Market Line without distinguishing between the behavioral explanations, it is relevant to address the theories in the context of the different beta determinants. The two positive beta drivers in market correlation and volatility may well exhibit different return phenomena without completely ruling each other out. While I focus on the effect of exogenous leverage constraints, a similar approach to the behavioral explanations could benefit our understanding of the beta-return relation and its causes.

2.2 Theoretical Framework

In a leverage constrained CAPM setting a shadow price for margin is added to the standard equation [e.g. Frazzini and Pedersen (2014); Jylhä (2018)]. The shadow price,

[1] For additional perspective on investors’ lottery preferences and under-diversification see e.g. Odean (1999), Blume and Friend (1975), Mitton and Vorkink (2007)]

measuring the tightness of leverage or funding constraints flattens the security market line by increasing the intercept and reducing the slope as the margin constraints increase. I follow the approach by Jylhä (2018), in which the margin requirement m is constant for all market participants and driven by the explicit changes in market wide margin requirement. In this case the demand for high beta securities will be higher due to the investors being forced to take implicit leverage through high beta assets. Simultaneously the demand for low beta stocks becomes lower translating to higher expected returns in the low end of the security market line. Following the theory, in the presence of no margin requirement, implicit or explicit, the security market line becomes its standard CAPM form. The modified CAPM can be written as follows:

$$E_t(r_s - r_f) = \psi m + \beta_{s,t}[E_t(r_M - r_f) - \psi m] \tag{1}$$

in which m presents the margin constraint and ψ its shadow price.

From the standard decomposition of beta one can derive an alternative definition as correlation with the market return times a volatility term [e.g. Frazzini and Pedersen (2014)]. These two components jointly determine a security's beta. If the risk-return relation is assumed strictly positive, elevation in either of the determinants has a positive non-zero impact on a security's expected return. Following the logic it should be therefore possible to construct weaker but economically sound security market line mockups in which the expected return would be positively related to either one of these two components. Alternative beta definition can then be written as:

$$\hat{\beta_t^{ts}} = \hat{\rho}\frac{\hat{\sigma_s}}{\hat{\sigma_m}} \tag{2}$$

in which $\hat{\rho}$ is the correlation between the stock and the market and $\hat{\sigma_s}$ and $\hat{\sigma_m}$ are the respective volatilities

The alternative decomposition also allows one to address the different ways to arrive at a similar beta. The seemingly same risk measure can be achieved through higher or lower correlation given a different level in security volatility in relation to the market and vice versa. This is also important in dissolving the beta anomaly; i.e. if the weak return to high beta assets is truly driven by increased allocation to systematic risk to cope with leverage constraints. On the other hand this allows one to examine whether investors truly increase their allocation to beta in its traditional sense as a measure of systematic risk or if additional returns are sought through primarily by increasing allocation to level of volatility in relation to the market.

If overallocation to systematic risk as proposed by Asness et al. (2016) is proxied by the correlation component in my beta decomposition and driven by leverage constraints, it should hold that increase in market correlation has a negative impact on risk-adjusted returns. High correlation portfolios should therefore exhibit lower alphas on standard factor models compared to low correlation portfolios. As argued by Asness et al. (2016), correlation should be the term of interest for institutional investors in this alternative beta decomposition as it represents a “pure bet on systematic risk”. Consequently in the presence of binding margin constraints sophisticated and somewhat diversified investors should over allocate their funds in stocks with high correlation with the market. Explicit market-wide increase in margin constraints therefore reduces the slope and increases the intercept in a model in which returns are driven by correlation with the market.

As beta is jointly determined by both the correlation and volatility terms, it may be difficult to determine the impact of margin constraints on each of these terms. Following the logic of the Betting Against Correlation factor introduced by Asness et al. (2016), when normalized for volatility, increase in leverage constraints should lead to a weaker return to market correlation. The impact should materialize from implicitly increasing beta without making the stocks more attractive to volatility related or behavioral explanations such as lottery preferences, idiosyncratic volatility or short-sale impediments. Similarly, when controlling for correlation with the market, the margin impact on high volatility stocks should not be significant if one is to assume that the volatility term is largely related to behavioral explanations. If this were the case contrary to the factor model view of asset pricing, it would seem that investors also resort to high volatility stocks as a way to cope with binding leverage constraints, painting a picture of far less sophisticated investors than proposed by the CAPM.

One important implication of the chosen time period for this study is the significantly lower institutional stock ownership than is experienced today. As also noted by Jylhä (2018), households held an average of 84.7 % of all US corporate equities compared to 37.3 % in 2018 and institutional investors only averaged 12.8 % compared to 46.7 % in 2015. In addition to making the regulatory margin requirement a relevant leverage constraint in the Jylhä (2018) paper, the low institutional ownership of stocks is likely to have an impact on the relevant measure of risk.

Levy (1978) proposes an amended version of the CAPM to take into account the varying maximum number of stocks held by individual investors. Based on the empirically low numbers of individual stocks held by investors the model implies that a true measure for systematic risk can be derived from the average constrained investor’s systematic risk rather than the CAPM beta for each security. Levy (1978) argues that at least part of the investors can only hold a suboptimal portfolio with the number of stocks lower than the mean variance efficient portfolio, but optimize their portfolio with respect to the number of stocks they can include. This leads to lower observed beta coefficients than implied by the CAPM and the individual stock variance playing a much more prevalent role in determining expected returns. Merton (1987) backs this sentiment when defining an equilibrium model in when the investors possess incomplete information in the market; informed investors form mean variance efficient portfolios only within the stocks of which they have information yet again resulting in suboptimal portfolios from the CAPM perspective.

Against this backdrop, one can intuitively expect two things in noting the selected time period. Firstly, as the number of household investors in the sample is clearly higher than at the time of this study, the average number of securities that investors have information on and therefore have invested in is likely to be significantly lower than today driven by both the number of resourceful investors and the cost of acquiring sufficient information. Secondly, given the lower number of stocks held in individual portfolios, the role of residual risk over the CAPM implied systematic portion should be higher than today. The weight of systematic risk as a primary driver for expected return is less and less important as the number of stocks held decreases strengthening the role of residual stock-specific variance. Going back to the impact of leverage constraints one would therefore expect that when faced with leverage constraints, the investors with the least shares would be more inclined to pursue higher returns from the volatility component of beta instead of pure systematic risk.

2.3 Hypothesis Formulation

In coping with leverage constraints, leverage constrained investors are forced to take on implicit leverage in the form of increasing beta [e.g. Christoffersen and Simutin (2017), Boguth and Simutin (2018)]. My first and second propositions have to do with this implicit leverage in relation to the my beta decomposition. Similarly to Asness et al. (2016) I treat my correlation measure as a proxy for a pure measure of systematic risk as it should be fairly unrelated to behavioral factors when conditioned on the volatility term. On the other hand, the volatility term should be separate from the systematic risk aspect, when conditioned on the correlation with the market.

Proposition 1: A security's correlation with the market mirrors the implicit leverage that the security offers to a diversified investor and is therefore priced higher than implied by the CAPM.

Most households and typical mutual funds are constrained for leverage. Treating disproportionate funds allocation to higher beta assets as binding leverage constraints and a way to substitute for taking leverage is consistent with the existing research involving leverage constrained fund managers [e.g. Baker et al. (2011), Christoffersen and Simutin (2017) and Karceski (2002)]. Further, as a security's correlation with the market reflects a stock's exposure to systematic risk volatility held constant, it should hold that compensation for tight leverage constraints would be sought from assets with higher correlation with the market. Assuming investors still seek to construct mean-variance efficient portfolios conditioned on their limitations to take on leverage, pure volatility should not play much of a role. The volatility and correlation components should by definition be relatively uncorrelated. By substituting beta decomposition in the constrained model one can divide the expected return into parts related to systematic and behavioral explanations. The correlation component acts similarly to applied leverage when comparing two assets with similar volatility based risk profiles.

Constrained SML following Jylhä (2018) with the alternative beta decomposition can be formulated as follows:

$$E_t(r_s - r_f) = \psi m + \hat{\rho}_t \frac{\hat{\sigma_{s,t}}}{\hat{\sigma_{m,t}}}[E_t(r_M - r_f) - \psi m] \tag{3}$$

in which $\hat{\rho}_t$ is the correlation between the stock and the market, $\hat{\sigma_{s,t}}$ is the volatility of stock s and $\hat{\sigma_{m,t}}$ is the volatility of the market.

Holding volatility constant the slope of the correlation – return relation should be lowered by higher margin constraints. This is intuitive since in my beta definition the correlation component merely describes the exposure of stock level volatility to market movements. This being the case, correlation with the market should be almost equally available for all levels of volatility and therefore allow investors to pick stocks with similar volatility but higher risk measured by beta – much like applying explicit leverage. In a world of changing explicit leverage constraints, the possibility of investing in such stocks should be more valuable during times of high margin requirement and therefore reflected in the shadow price for margin constraints.

Proposition 2.1: Exogeneous margin constraints flatten the return compensation for taking on higher correlation with the market.

Proposition 2.2: Exogeneous margin constraints flatten the return compensation for taking on higher correlation with the market, given a set level of volatility

My second proposition is two-fold: following my first hypothesis as investors seek assets with higher expected return from systematic risk in reacting to tightening leverage constraints the impact should materialize through correlation with the market, i.e. bets on the systematic risk. Simultaneously I recognize the potential implications of the major shift in stock ownership from almost fully household-owned to majority being managed by institutional investors and foreign participants. Given a fixed return benchmark, the CAPM and the contribution by e.g. Asness et al. (2016) imply that solely systematic risk should be sought after in optimally balancing out the leverage constraints. This however does not seem to hold water in a world with mean variance portfolios being constructed from a very small subset of assets. Boehme, Danielsen, Kumar, and Sorescu (2009) further support the theories of under-diversification in finding that higher contemporaneous idiosyncratic volatility indeed generates statistically significant positive alphas indicating the more important role of residual variance proposed by e.g. Merton (1987).

Proposition 3.1: Leverage constraints drive BAB factor returns primarily through the BAC factor, i.e. due to investors seeking systematic risk from market correlation.

Proposition 3.2: Market-wide changes in margin requirements do not increase demand for behavioral, volatility related explanations to the beta anomaly.

My third proposition is a derivation of the two first ones, leaning on the central hypothesis by Asness et al. (2016): volatility held constant, correlation with the market represents a bet on systematic risk without the behavioral explanations linked to volatility. This formulation also continues on the intuition presented by e.g. Frazzini and Pedersen (2014) and Jylhä (2018) as it states that investors' leverage constraints increase the price pressure on high beta assets, but primarily the ones for which higher beta comes from higher correlation with the market rather than the level of stock specific volatility in relation to the market, a factor that can largely be mitigated in a well diversified portfolio. From this trail of thought it then follows that if investors in fact cope with the changing margin requirements by seeking more systematic risk through correlation with the market, the returns to the BAC factor should reflect such behavior just as Asness et al. (2016) argue. On the other hand, the BAV factor should have little to do with this systematic, portfolio risk driven behavior. In the presence of market wide leverage constraints, my first two propositions state that the shape of the volatility-return relation should not be dependent on changing margin requirements. Therefore, to confirm the lack of this link, I also hypothesize that returns to the BAV factor as a pure volatility driven construct, should not be dependent on the prevalent leverage constraints.

3 Data and Summary Statistics

As I focus on the impacts of FED's explicit margin changes between 1934 and 1974, the scope of my test dataset is limited to the same interval. I use the dataset on margin changes as provided by Jylhä (2018), including 22 explicit changes in the level of minimum margin requirement for positions in listed US equities between October 1, 1934 and January 3, 1974. The level of initial margin requirement ranges from 40 % in November 1937 to 100% January 1946 with significant variation within the period.

I obtain daily and monthly stock returns between January 1, 1931 and December 31, 1974 from CRSP to compute running stock volatilities and correlations between the each security and the market. Following Jylhä (2018), I only use stocks with share codes 10 and 11, listed in NYSE. AMEX and NASDAQ are established during the data period and may therefore cause distortion in the results. I exclude all stocks with daily or monthly returns of more than 100 % or less than -100 %. My clean dataset includes 489 thousand monthly and 11.2 million daily observations. For market excess return, I use CRSP value-weighted market index less a risk-free rate from Kenneth French's website.

Table 1 reports the main characteristics of my monthly data set. The total monthly stock data set for which one can compute relevant correlation and volatility measures covers 297 thousand total observations. Notably, the average beta in the data is around 1.15 with a standard deviation of 0.53. Taking a closer look at the determinants in correlation and volatility, it is evident that volatility exhibits far greater maximum deviations from the mean, but is still on par in terms of standard deviation.

Table 1: Monthly Descriptive Statistics

This table reports summary statistics on the monthly return data along with the correlation term with the market ($\hat{\rho}$) and the volatility term used in beta construction ($\frac{\hat{\sigma_s}}{\hat{\sigma_m}}$). Returns are in monthly percentages. Market capitalization is reported in $ Billion. For comparability with Jylhä (2018) Beta is computed by regressing monthly excess returns on the market return less the risk free rate from month $t-36$ to month $t-1$.

Statistic	N	Mean	Pctl(25)	Pctl(75)	St. Dev.	Min	Max
Return	296,808	0.012	−0.038	0.056	0.086	−0.565	0.970
Market Cap	296,808	0.340	0.027	0.241	1.404	0.001	50.592
Beta	296,808	1.152	0.785	1.467	0.526	−1.488	4.821
Market Correlation	296,808	0.264	0.189	0.342	0.107	−0.252	0.609
Volatility Term	296,808	3.051	2.105	3.687	1.351	0.265	15.751

4 Empirical Methodology

In this section I discuss the empirical approach and the key methods I use to test my hypotheses. First I briefly gloss over the key estimates I use to further study the impact of margin constraints including estimating correlation, volatility and beta. Second I run through my methodology for testing the overall impact margin constraints have on the security market line and analogously constructed security line mockups based on volatility and correlation. Thirdly, I elaborate on my methodology in isolating the effect of the initial margin requirement within portfolios constructed by sorting on correlation and volatility. Finally, I present the construction of BAB, BAC, and BAV factors in my setting and their connection to the preceding tests.

4.1 Correlation, Volatility and Beta

I use daily return data to estimate the volatility and correlation terms. For volatilities I apply a a one-year rolling window and use a longer three-year window for correlations. Similarly, I use overlapping three day returns to estimate correlation and one day log returns for volatilities. I run the volatility estimation through rolling periods of 250 trading days and use 750 trading days for correlation to account for slower movement. In constructing the correlation and volatility terms I only include companies for which the data covers at least one rolling period at a daily frequency. To build my first beta estimate I utilize the correlation and volatility terms as discussed earlier and following Vasicek (1973) I also apply time series shrinkage towards the cross-sectional mean $\beta_t^{\hat{X}S}$.

$$\hat{\beta}_t = w_i \beta_t^{\hat{T}S} + (1 - w_i)\beta_t^{\hat{X}S} \tag{4}$$

In which, following Frazzini and Pedersen (2014), I apply constant values of $w_i = 0.6$ and $\beta_t^{\hat{X}S} = 1$, across all stocks to maintain comparability

To distinguish between the effects of the correlation and volatility terms, each month t, I sort all stocks independently into five quantiles on my correlation and volatility measures based on the values in the end of month $t - 1$. The summary statistics for the sorted portfolios are presented in table 2. Within the highest and lowest correlation portfolios the mean correlation with market return varies between 0.17 and 0.37 with the with the minimum and maximum being -0.12 and 0.52 respectively. For volatility the relative variation is far greater with mean values ranging from 1.76 to 4.25 when scaled for market volatility. As is expected, the independently estimated beta increases monotonically in going up the portfolios constructed by both correlation and volatility. Notably, the higher the correlation portfolio, the lower the mean volatility term resulting a 11 % volatility difference between the high and low correlation portfolios. This is also evident in the negative Pearson correlation between the correlation and volatility terms of -0.07 in monthly data. However this relationship is not quite as evident when looking at the portfolios constructed by sorting on volatility as the mean market correlation remains rather close in all quantiles.

The standard deviation in betas, between quantiles, seems to be quite strongly driven by variation in the volatility term. In table 2 Panel A, the standard deviation of the monthly beta estimates is driven by the increasing volatility term as correlation decreases. The same effect is visible in panel B, in which standard deviation in betas doubles going from the lowest volatility portfolio to the highest.

Table 2: Summary Statistics on Portfolios Sorted on Correlation and Volatility

This table presents the summary statistics on portfolios sorted independently on correlation with the market and volatility in relation to market volatility between 1934 and 1974. Correlation is computed over a 750 trading day rolling window using overlapping three-day log returns. Volatility is estimated from a rolling window of 250 daily log returns for both each stock and the market. I compute the portfolio beta independently be regressing each stock's monthly excess returns from $t-36$ to $t-1$ over the corresponding market excess returns proxied by the CRSP value weighted index less the risk free rate.

Panel A: Sort on Correlation

Cor PF	Mean Cor	Max Cor	Min Cor	Mean Vola	Mean Beta	SD Beta
1	0.17	0.31	-0.12	2.94	0.80	0.53
2	0.24	0.37	0.13	2.87	1.02	0.50
3	0.28	0.40	0.17	2.86	1.16	0.49
4	0.31	0.44	0.20	2.81	1.25	0.46
5	0.37	0.52	0.23	2.62	1.31	0.42

Panel B: Sort on Volatility

Vola PF	Mean Vola	Max Vola	Min Vola	Mean Cor	Mean Beta	SD Beta
1	1.76	4.24	0.26	0.28	0.75	0.32
2	2.26	4.88	0.97	0.28	0.93	0.36
3	2.66	6.10	1.20	0.27	1.07	0.40
4	3.17	7.40	1.38	0.27	1.25	0.45
5	4.25	30.88	1.55	0.27	1.56	0.59

4.2 Margin Level Impact on Returns to Correlation and Volatility

In order to estimate the potential effects of changing margin regulation on the return compensation I follow the approach by Jylhä (2018) and adapt the methodology to my more granular setting. In addition to estimating the security market lines for each month, I construct two distinct security market line mockups based on the two beta components: correlation with the market and volatility. I then study the impact of changing margin requirements on the return compensation of each of the terms individually.

The methodology for betas, correlation and volatility consists of three stages. First, each month I sort the stocks into portfolios based on betas, correlation and volatility (depending on which I treat as the return driver in each model) to create maximum measure spread in the test assets. In the second stage I regress the cross-sectional returns on the portfolio betas, correlations and volatilities, again depending on the sorting variable. This results in a time series of security market line intercepts and slopes for beta, and "security market line mockups". Finally, I regress the security market line (or mockup) intercept and slope on the prevailing margin requirement to study the final effect of the exogeneous margin requirements.

To distinguish between different levels in the variable in question, each month I sort the stocks into 20 equally sized portfolios based on the variable level (beta, correlation or volatility). For each of the portfolios I estimate the monthly variable values: I regress monthly portfolio returns in excess of the risk free rate on the market excess return from month t-36 to month t-1 to following Jylhä (2018) to obtain portfolio level betas. I estimate correlation with the market similarly to individual stock level returns, i.e. using a 750 day rolling window and three-day log returns. Similarly, the volatility estimate comes from a 250 day rolling window of daily returns. I then obtain the security market line (or mockup) estimates each month by regressing the portfolio excess returns on the ex-ante betas (or mockup drivers) from the second stage. These regressions yield estimates for the SML intercept and slope for each month. The SML (mockups) from the second stage takes the form:

$$r^e_{pf,t} = intercept_t + slope_t \hat{\gamma_{pf,t-1}} + e_t \tag{5}$$

in which $\hat{\gamma_{pf,t-1}}$ stands for the each of the one-month lagged variables of interest in each of the models, i.e. beta, market correlation and volatility.

Lastly, having obtained the estimates for intercept and slope from the second stage, I study the impact the initial margin requirements have on the shape of my SML and SML mockups. I follow the methodology by Jylhä (2018) in regressing the intercept and slope coefficients from the second stage on the lagged initial margin requirement as well as additional controls including e.g. contemporaneous market return. Similarly to Jylhä's setting, the coefficient $b1$ should be positive and coefficient $b2$ should be negative if margin constraints drive up the cross-sectional price for additional risk. The third stage regressions yield the margin level impact on the previously estimated intercept and slope. $margin_{t-1}$ stands for the one-month lagged initial margin requirement and X_t presents a vector of the additional control variables in the setting.

$$intercept_t = a_1 + b_1 margin_{t-1} + c_1 X_t + u_{1,t} \tag{6}$$

$$slope_t = a_2 + b_2 margin_{t-1} + c_2 X_t + u_{2,t} \tag{7}$$

4.3 Initial Margin Requirement and Portfolios Sorted on Volatility and Correlation

In order to further analyze how the impact of margin constraints materializes with respect to correlation with the market and volatility I run similar analogous security market line mockups for both correlation and volatility but aim to eliminate the effects of the other contemporaneous determinant of beta. To achieve this distinction, in the beginning of each month I sort the stocks in five equal size portfolios on one-month lagged correlation and volatility. Table 2 reports the summary statistics on the independently sorted portfolios. Then, within each portfolio, I perform the three-stage process similarly to the methodology applied to the full sample. This is to minimize the undesired spread in the other determining variable, i.e. to limit the impact of volatility on beta when studying the effects of correlation with the market. Additionally, this is also to maintain some comparability to the BAC and BAV factors introduced by Asness et al. (2016), albeit without dimension arising from rank-weighing within the different quantiles.

4.4 BAB, BAC and BAV

I decompose the BAB-factor following Asness et al. (2016) by creating two portfolios, BAC and BAV. BAC goes long (short) in stocks with low (high) correlation with the market return, while matching the volatility of its constituents. BAV goes long (short) in stocks with low (high) estimated volatility and similarly tries to match the correlations between the long- and short legs. These factors then represent the two determinants of the BAB factor, while excluding the effect of each other.

More specifically, I construct the BAC factor by first sorting the stocks into five quantiles based on their volatility estimate in the previous month. In each of the volatility quantiles I rank the stocks based on their correlation with the market, and place them in two portfolios: high- and low market correlation. The stocks are then assigned weights based on their rank – stocks with highest correlation stocks receiving the most weight in the high correlation portfolio and low correlation stocks receiving the most weight in the low portfolio. Further, the portfolios are re-balanced by in the beginning of each month and levered to have a beta of one during formation. The BAC factor is then the equal-weighted average of the five portfolios. I apply the same methodology form the BAV factor, but reverse the roles (first sort stocks by correlation, then rank by estimate of volatility). Portfolio weights are then given by:

$$w_H^Q = k^q(z^q - z^{-\overline{q}})^+ \tag{8}$$

$$w_L^Q = k^q(z^q - z^{-\overline{q}})^- \tag{9}$$

in which z^q is an $n(q) * 1$ vector of correlation ranks within each volatility quantile.

The two factors aim to explain the returns to a BAB factor from two distinctive directions, systematic risk and volatility. Figure 1 reports the cumulative returns to each of the factors during the period. Notably, until the end of 1950's, the BAB factor performance is very much hand-in-hand with the BAV factor return with little to no cumulative gains. From this moment onwards the balance between the determinants changes visibly as the BAB factor catches up with BAC during the 1960's and early 1970's. Figure 1 also illustrates the relation between these three factors: changes in BAB return are determined by both the correlation and variance parts with changing weight across time. I also verify this relation by regressing the BAB factor return on both of its analogous determinants, BAV and BAC and present the results in table 3. The BAB factor generates a statistically insignificant intercept of 4 bps and loads heavily on both the BAC and BAV factors as is expected with an adjusted R^2 of 0.78. Also, as we just observed from figure 1, the BAV factor seems to be the more dominant determinant of the BAB returns in the period.

Motivated by this decomposition it seems then relevant to study the potential impacts of margin constraints on both of these factors.

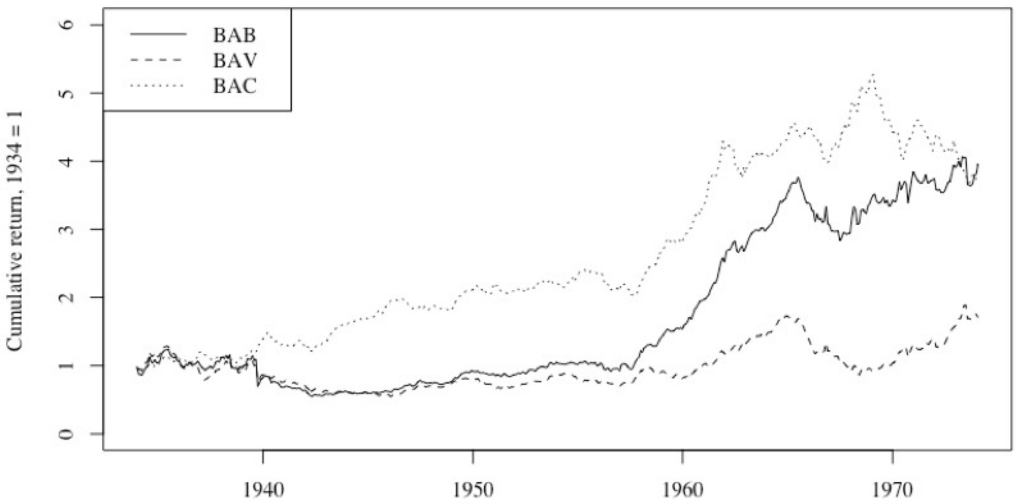


Figure 1: Cumulative Returns in the Period from BAB, BAC and BAV

Table 3: BAB Factor Regressed on BAC and BAV

This table reports the BAB factor as a linear combination of a Betting Against Variance (BAV) and Betting Against Correlation (BAC) factors. I construct BAC and BAV following the logic presented by Asness et al. (2016). The factors are rank-weighed with e.g. in the case of BAC, the factor going long in low and short in high correlation assets, the highest beta receive sthe highest rank in the short leg and vice versa for lowest correlation in the long portfolio. Monthly alphas are in relation to total price (percentage / 100). T-statistics for each of the coefficients are in parentheses

	Dependent variable:
	BAB Factor Return
Constant	0.0004
	(0.546)
BAV	0.829
	(37.898)***
BAC	0.562
	(15.219)***
Observations	456
R^2	0.777
Adjusted R^2	0.776
Note:	*p<0.1; **p<0.05; ***p<0.01

5 Findings

This section presents the empirical findings from the tests introduced in the previous section. In addition to the quantitative outcomes I discuss the theoretical and practical implications of my findings as well as how they tie into my initial hypotheses. Additionally I include the potential limitations for my approach. First, I address the overall performance of the beta coefficient, correlation and volatility as return drivers in the cross-section as well as their relevance and scalability given the time period. Secondly, I discuss the overall impact of the margin requirement on beta, correlation and volatility. Thirdly, I expand the analysis by eliminating the effects of volatility and correlation on each other by performing the same tests within sub-samples sorted on each of the variables. Finally, I examine the performance of the BAB, BAC and BAV factors in the context of how the margin constraints impact seems to materialize.

5.1 Return Compensation by Beta Component

Table 4 reports the Fama and French (1993) three-factor alphas on portfolios sorted on correlation with the market and volatility. The results for both sorts back the overall sentiment presented in much of the literature surrounding the low risk anomaly. Low returns being much more prevalent in the high risk end of the portfolios is reflected in both sorts, in line with beta level empirical findings of e.g. Frazzini and Pedersen (2014) and Liu et al. (2018) as well as sorts on correlation and volatility between 1926 and 2015 by Asness et al. (2016).

Correlation in particular seems to have an asymmetric, primarily negative effect on (Fama & French, 1993) three-factor alphas. High correlation deciles 8-10 all produce statistically significant negative alphas on a 5% level, albeit averaging only around 10 bps per month. The respective t-statistics range between -2.4 and -2.0. At the same time, as correlation with the market increases, the stocks' loading on the SMB factor increases monotonically, having a positive effect on the returns in all deciles.

Volatility plays a similar role in return compensation, but with an even more robust implications on the produced alphas. In addition to the negative effect witnessed when sorting on correlation, volatility portfolios exhibit both statistically significant positive alphas in the low end and negative alphas in the high end of the volatility spectrum. Deciles 1-3 with the lowest ex-ante volatility estimates produce positive alphas between 10 and 20 bps with respective t-statistics between 3.2 and 2.6. At the same time, the effect is inverse when it comes to high volatility stocks, as also found by e.g. Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009) with regards to high idiosyncratic volatility as well as Bali et al. (2017) in arguing for lottery demand as the primary driver for the phenomenon. Volatility deciles also exhibit different behavior in terms of loadings on SMB – deciles 1-3 all have a substantial negative relation to the SMB factor entailing that the low volatility deciles consist primarily of larger firms.

The return patterns in the full sample are in line with my first hypothesis of correlation having a negative impact on returns as it reflects the implicit leverage an investor can take on. What is more, despite carrying lower variance, shorter tails and smaller beta spread, the negative return impact of correlation is noticeable in the full sample without normalizing the somewhat inverse effects of the negatively correlated volatility. Moreover, the negative trend in both beta determinants echoes similar findings when sorting with beta, but more importantly confirms the key roles of both variables in seemingly contributing to the low risk anomaly in the full sample.

Table 5 reports the monthly Fama and French (1993) three-factor alphas when sorting independently on both correlation and volatility. The results are much more messy when both variables are included with no clear, uniform trends in the sample. What is notable however, is that in the intersection of the highest correlation portfolio and the two highest volatility portfolios, the alphas are particularly negative at around -60 and -70 bps, while in the three lowest volatility portfolios the alphas are significantly closer to zero. This relation however, does not manifest itself in the full sample for either of the beta determinants. Contrary to the what the longer data period used by Asness et al. (2016) exhibits, independent sorts with both of the beta determinants reveal little of the relative importance between the two in being the underlying cause of the low risk anomaly.

Table 4: Three-Factor Regressions by Correlation and Volatility Decile

This table reports results from Fama and French (1993) three-factor model regressions by correlation (Panel A) and volatility (Panel B) portfolios, with 1 being the lowest and 10 being the highest. I compute correlation over a 750 trading day rolling window using overlapping three-day log returns. Similarly I estimate volatility from a rolling window of 250 daily log returns for both each stock and the market . I place the stocks into 10 deciles in the beginning of each month based on their ex-ante estimates at the end of the previous month. This table includes all observations between January 1934 and December 1974 for which relevant beta estimates can be computed. T-statistics are reported in parentheses.

Panel A: Correlation	Correlation Decile									
	1	2	3	4	5	6	7	8	9	10
Alpha	0.001	0.001	0.0001	−0.0003	−0.0005	−0.001	−0.0004	−0.001	−0.001	−0.001
	(1.753)*	(1.244)	(0.218)	(−0.750)	(−1.208)	(−1.328)	(−1.025)	(−2.017)**	(−2.411)**	(−2.400)**
Market Return	0.781	0.945	1.032	1.071	1.116	1.149	1.169	1.229	1.262	1.316
	(58.479)***	(89.787)***	(102.365)***	(120.001)***	(113.587)***	(104.299)***	(109.001)***	(90.215)***	(90.530)***	(85.776)***
SMB	0.007	0.076	0.121	0.134	0.166	0.201	0.220	0.265	0.297	0.338
	(0.344)	(4.461)***	(7.429)***	(9.248)***	(10.450)***	(11.284)***	(12.646)***	(12.020)***	(13.168)***	(13.606)***
HML	0.013	0.048	0.088	0.085	0.105	0.122	0.119	0.163	0.154	0.118
	(0.626)	(2.949)***	(5.658)***	(6.204)***	(6.946)***	(7.199)***	(7.222)***	(7.785)***	(7.188)***	(5.003)***
Observations	456	456	456	456	456	456	456	456	456	456
R^2	0.910	0.962	0.971	0.979	0.977	0.973	0.976	0.966	0.966	0.963
Adjusted R^2	0.909	0.961	0.971	0.979	0.977	0.973	0.976	0.966	0.966	0.963

Panel B: Volatility	Volatility Decile									
	1	2	3	4	5	6	7	8	9	10
Alpha	0.002	0.001	0.001	0.0001	−0.0002	−0.001	−0.001	−0.001	−0.002	−0.002
	(3.233)***	(3.198)***	(2.569)**	(0.443)	(−0.630)	(−1.307)	(−1.632)	(−1.821)*	(−2.357)**	(−2.467)**
Market Return	0.736	0.875	0.962	1.035	1.086	1.149	1.202	1.253	1.309	1.360
	(61.250)***	(116.295)***	(158.370)***	(143.845)***	(123.653)***	(98.764)***	(83.181)***	(77.353)***	(67.037)***	(65.278)***
SMB	−0.083	−0.062	−0.028	0.038	0.095	0.176	0.261	0.322	0.437	0.524
	(−4.244)***	(−5.102)***	(−2.860)***	(3.286)***	(6.704)***	(9.365)***	(11.131)***	(12.258)***	(13.805)***	(15.511)***
HML	−0.046	0.012	0.030	0.067	0.090	0.129	0.177	0.182	0.216	0.223
	(−2.503)**	(1.053)	(3.229)***	(6.027)***	(6.675)***	(7.211)***	(7.986)***	(7.313)***	(7.186)***	(6.954)***
Observations	456	456	456	456	456	456	456	456	456	456
R^2	0.910	0.974	0.986	0.984	0.980	0.970	0.960	0.956	0.945	0.944
Adjusted R^2	0.909	0.974	0.986	0.984	0.980	0.970	0.960	0.955	0.944	0.943

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Three-Factor Alphas on Portfolios Sorted Independently on Correlation and Volatility

This table presents the monthly Fama and French (1993) three factor alphas on portfolios sorted independently on ex-ante correlation with the market and volatility between 1934 and 1974. Correlation is computed over a 750 trading day rolling window using overlapping three-day log returns. Volatility is estimated from a rolling window of 250 daily log returns for both each stock and the market. Alphas are in monthly percentage and respective t-stats are presented in parentheses. Value-weighted Portfolios are constructed in the beginning of each month based on the correlation and volatility estimates at the end of the previous month and rebalanced on a monthly basis.

	Correlation Portfolio:									
Volatility	Low	P2	P3	P4	P5	P6	P7	P8	P9	High
Low	0.002	0.003	0.000	0.002	0.002	0.002	0.001	0.001	0.001	0.001
	(1.749)*	(2.913)**	(-0.066)	(2.035)**	(1.824)*	(1.787)*	(1.091)	(0.737)	(1.339)	(2.005)**
P2	0.002	0.003	0.002	0.001	0.000	0.000	0.000	0.000	0.001	-0.001
	(1.194)	(2.171)**	(1.127)	(0.727)	(0.238)	(-0.063)	(-0.410)	(0.178)	(0.639)	(-0.477)
P3	0.000	0.002	0.000	0.001	-0.001	0.000	0.000	-0.001	-0.001	-0.001
	(-0.133)	(1.012)	(-0.006)	(0.400)	(-0.605)	(-0.102)	(0.327)	(-0.852)	(-1.077)	(-0.971)
P4	0.005	-0.002	-0.001	0.000	-0.002	-0.001	-0.002	-0.002	-0.002	-0.006
	(1.999)**	(-0.975)	(-0.776)	(0.126)	(-1.464)	(-0.911)	(-1.278)	(-1.350)	(-1.055)	(-3.465)***
High	0.003	0.002	-0.001	-0.005	-0.003	0.000	-0.002	-0.003	-0.001	-0.007
	(1.063)	(1.072)	(-0.454)	(-2.592)**	(-1.296)	(0.148)	(-1.045)	(-1.567)	(-0.659)	(-3.479)***

Note: *p<0.1; **p<0.05; ***p<0.01

5.2 Margin Impact on Beta Constituents and SML Mockups

Results in table 6 strongly resemble the findings by (Jylhä, 2018) in a similar setting. Aligning with expectations, the results show a flattening effect on the security market line as binding margin constraints tighten. Margin level has a statistically significant positive effect on the security market line intercept and an even stronger negative effect on the slope.

For the main contributions of this study I set my sights on the initial margin regulation's impact on the returns on the beta determinants, correlation and volatility. In the full sample correlation with the market exhibits somewhat puzzling results. The initial margin requirement in month $t-1$ has a significant *negative* impact on the intercept with a t-statistic of -3.5 in the model (1) and -2.4 in model (2). The effect is contrarian to the impact on beta compensation and close to on par in robustness.[1]Additionally, on the contrary to the impact on beta, the contemporaneous market return holds statistically significant explanatory power on the intercept whereas the security market line intercept should not by definition be dependent on the market return. In table **??** model (2) the market return coefficient holds a t-statistic of 10.0 and has a positive effect on correlation's return compensation. Constructing security market line mockups based on correlation and volatility however changes the dynamics of the line ever so slightly. In the case of the traditional security market line, the beta coefficient should capture the variation driven by the market return, rendering the intercept term to capture other hypothetical return drivers. This is not the case with either of my additional SML mockups as the other beta component is not captured by the variable of interest.

With slope for correlation the story is also different from the full security market line. Initial margin regulation in $t-1$ has a statistically significant positive impact on the slope in table 7 panel A model (4). While the effect of margin requirements does not materialize in model (3), the model in itself explains little of the variation in slope with an adjusted R^2 of 0.3% compared to 5.4% in model (4). Therefore, in violation of my second hypothesis in the full sample, not only do the higher margin requirements decrease the intercept of the SML mockup, but in fact also steepen the slope. The change in the shape of the line is not consistent with investors allocating more funds to higher correlation assets to cope with leverage constraints as it is when examining beta.

Same analysis for volatility in table 7 panel B shows the for the most part non-significant dependence on margin constraints. Models (1) and (2) for the intercept show no statistical significance for initial margin. In model (3), without the inclusion of contemporaneous market return, the initial margin requirement seems to have a negative effect on the slope

[1]Higher statistical significance in model (1) with t-statistics of -3.5 vs. 2.9. Lower in model (2) with -2.4 and 2.9 respectively.

of the SML mockup. However, this is also rendered insignificant when including market return in model (4).

Neither of the two determinants alone show conclusive evidence of being the bearer of the SML flattening force of leverage constraints. Further, neither is this empirical evidence in favor of what Asness et al. (2016) argue to be the driver of Betting Against Correlation profits.[2]Still, there are potential hindrances to the results I present in this section. As also shown in table 2, the variation in betas between the high and low correlation quantiles is lower than when sorting for volatility. A direct practical implication of the beta spread is that the risk measured by beta is exacerbated more by changes in volatility than by correlation with the market. Therefore, as correlation goes down, volatility goes up in disproportionate amount, translating to potentially weaker returns to lower correlation assets and higher returns to high correlation assets driven by volatility rather than the properties of the correlation term.

[2]Section 5.4 takes a closer look on BAB, BAC and BAV performance during times of different margin requirements.

Table 6: Margin Regulation Impact on SML

This table presents the results of regressing the monthly security market line's slope and intercept on the lagged regulatory margin requirement. I estimate the portfolio betas following Jylhä (2018) and regress the monthly excess returns on the monthly market return less the risk free rate from the month $t-36$ to month $t-1$. Security Market Line intercepts and slopes for each month are estimated by regressing monthly portfolio returns on portfolio betas. Monthly t-statistics are reported in parentheses and 5% confidence level is highlighted in bold. The sample period ranges from 1934 to 1974.

	Dependent variable:			
	Intercept		Slope	
	(1)	(2)	(3)	(4)
Constant	−0.012	−0.012	0.039	0.013
	(−2.127)**	(−2.074)**	(3.781)***	(2.183)**
Margin	0.026	0.026	−0.055	−0.027
	(2.917)***	(2.876)***	(−3.543)***	(−2.940)***
Market Return		−0.006		1.024
		(−0.183)		(28.685)***
R^2	0.020	0.020	0.029	0.672
Adjusted R^2	0.017	0.015	0.027	0.670
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 7: Margin Regulation Impact on Returns to Correlation and Volatility

This table presents the results of regressing the monthly security market line mockups' slope and intercept on the lagged regulatory margin requirement. I use daily return data to estimate the volatility and correlation terms. For volatilities I apply a a one-year rolling window and use a longer three-year window for correlations. Similarly, I use overlapping three day returns to estimate correlation and one day log returns for volatilities. I run the volatility estimation through rolling periods of 250 trading days and use 750 trading days for correlation to account for slower movement. The SML mockups are built analogously to Jylhä (2018), but by treating correlation and volatility as the return drivers. Panel A reports the results from treating correlation as the primary return drive and Panel B from applying the same logic to volatility. Monthly t-statistics are reported in parentheses and 5% confidence level is highlighted in bold. The sample period ranges from 1934 to 1974

Panel A: SML mockup based on correlation

	Dependent variable:			
	Intercept		Slope	
	(1)	(2)	(3)	(4)
Constant	0.065	0.039	−0.053	−0.079
	(4.402)***	(2.908)***	(−1.842)*	(−2.768)***
Margin	−0.079	−0.049	0.063	0.093
	(−3.516)***	(−2.389)**	(1.444)	(2.176)**
Market Return		0.825		0.831
		(9.960)***		(4.752)***
R^2	0.030	0.223	0.005	0.058
Adjusted R^2	0.027	0.219	0.003	0.054
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B: SML mockup based on volatility

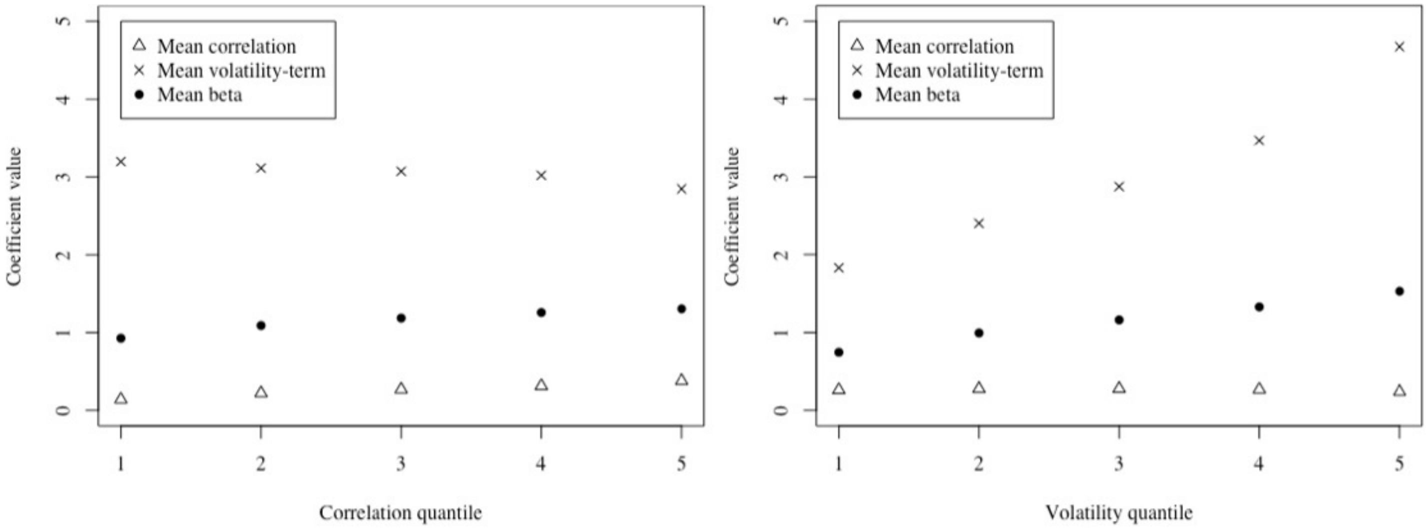
	Dependent variable:			
	Intercept		Slope	
	(1)	(2)	(3)	(4)
Constant	0.007	−0.007	0.015	0.003
	(0.948)	(−1.170)	(2.882)***	(0.743)
Margin	−0.005	0.012	−0.018	−0.005
	(−0.441)	(1.246)	(−2.337)**	(−0.712)
Market Return		0.457		0.366
		(11.707)***		(14.153)***
Observations	403	403	403	403
R^2	0.0005	0.256	0.013	0.343
Adjusted R^2	-0.002	0.252	0.011	0.339
Note:				*p<0.1; **p<0.05; ***p<0.01

5.3 Margin Impact on Sorted Portfolios

The results of my precedent analysis merely exhibit either weak or contradictory findings to much of my second hypothesis. However, the analysis does not fully take into account the jointly determined nature of beta; different combinations of volatility and correlation can and do produce betas of similar levels. As shown in section 5.1, residual variance seems to play a disproportionate role in comparison to what is implied by the mean variance framework. Therefore, treating correlation and volatility as independent return drivers may entail substantial issues with noise caused by the other determinant. To mitigate this concern, I repeat the precedent analysis while also controlling for volatility (correlation) in estimating the effect of margin requirements correlation (volatility). The methodology allows one to isolate the outcome of increasing beta through either one of the components keeping the other one close to constant. Additionally, the approach allows for a more analogous setting to the Betting Against Correlation factor construction in attempting to standardize the effects of volatility, albeit still value weighting the stocks as opposed to the rank weights used in Asness et al. (2016). The consequent results from regressing the intercept and slope on the margin requirement across portfolios are presented in table 8.

As stated in my hypothesis 2.2, conditioning on volatility produces a flatter SML mockup for correlation even if this may not manifest itself in the full sample due to noise or any similar weakening of the pure measure by changes in volatility. Further analysis on portfolio level provides more encouraging results in favor of this proposition: the negative return relation of volatility seems to trump the more delicate return driver in correlation. Initial margin requirement has a monotonically decreasing effect on the slope of my security market line mockup as volatility decreases. The increasing initial margin requirement has a statistically significant negative effect on my correlation security market line mockup in three out of the five volatility portfolios with t-statistics between -2.4 and -3.1. What is more, in the lowest volatility portfolio the initial margin requirement has a statistically positive impact on the intercept on a 5% level with a t-statistic of 2.3. Contrary to the full sample the second hypothesis still holds partially in flattening the SML mockup when correlation is treated separately from volatility. The flattening impact however does not span the full sample.

The high volatility portfolio however behaves very differently with the margin level having a negative impact on the intercept. While unintuitive in some respects, this may be due to the smaller correlation spread in the high volatility portfolio. Alternatively, this may exhibit a lottery-demand based explanation. Positively skewed stocks tend to be correlated with high ex-ante volatility and in demand for such stocks' correlation with the market plays an inverse role in that increased correlation with the market should



(a) By Correlation Quantile **(b)** By Volatility Quantile

Figure 2: Beta Composition Across Volatility and Correlation Quantiles

not have anything to do with lottery-like payoffs but still increases the total risk of the stocks.

Conditioned on correlation the impact of initial margin requirement on returns to volatility is rendered insignificant across all quantiles. This result is also in favor of my second hypothesis in that (residual) volatility does not seem to play much of a role in compensating for tighter leverage constraints. While the effect is not completely unequivocal when sorting on volatility, the opposite is true for sorting with correlation: the impact of $t-1$ initial margin requirement on the security market line mockup for volatility is blatantly ambiguous or non-existent.

Figure 2 demonstrates the beta decomposition across the correlation and volatility quantiles. Sorting on volatility produces a wider beta spread in spite of the declining level of correlation as volatility increases. This together with table 2 demonstrates the somewhat divided nature of beta in this decomposition. The negative correlation between the two determinants is clearly visible in both graphs but seems to have a stronger impact on the total beta when sorting on correlation. The level of correlation with the market is particularly low in the highest volatility portfolio: as volatility increases the level of correlation with the market becomes less and less important in determining a stock's beta risk and therefore these slight changes in systematic risk warrant lesser attention from investors seeking to increase their market risk exposure.

Table 8: Margin Impact on Portfolios Sorted on Volatility and Correlation

This table presents the results of regressing the monthly security market line mockups' slope and intercept on the lagged regulatory margin requirement. Intercept and slope are constructed within each correlation and volatility quantile. Correlation with the market is treated as the positive return driver when sorting for volatility and vice versa. The correlation and volatility quantiles are rebalanced in the beginning of each calendar month based on the estimates at the end of month $t-1$. Panel A presents the regression results for volatility sorted portfolios when treating market correlation as the return driver. Panel B presents the results when sorting for correlation and treating volatility as the return driver. Monthly t-statistics are reported in parentheses. The sample period ranges from 1934 to 1974.

Panel A: Sort on Volatility

	Intercept		Slope	
	Constant	Margin	Constant	Margin
Low	−0.030	0.046	0.122	−0.166
	(−2.251)**	(2.301)**	(3.468)***	(−3.120)***
2	−0.013	0.026	0.110	−0.156
	(−0.853)	(1.126)	(2.792)**	(−2.619)**
3	−0.008	0.017	0.127	−0.173
	(−0.466)	(0.641)	(2.610)**	(−2.359)**
4	0.024	−0.020	0.072	−0.114
	(1.366)	(−0.737)	(1.397)	(−1.480)
High	0.083	−0.097	−0.049	0.049
	(4.142)***	(−3.206)***	(−0.858)	(0.574)

Panel B: Sort on Correlation

	Intercept		Slope	
	Constant	Margin	Constant	Margin
Low	0.001	0.003	0.017	−0.021
	(0.107)	(0.204)	(2.243)**	(−1.802)*
2	0.000	0.007	0.017	−0.024
	(0.011)	(0.375)	(1.602)	(−1.449)
3	0.023	−0.028	0.007	−0.007
	(1.491)	(1.199)	(0.740)	(−0.482)
4	0.037	−0.049	−0.002	0.007
	(2.055)**	(−1.810)*	(−0.254)	(0.529)
High	0.033	−0.040	−0.002	0.005
	(1.756)*	(−1.417)	(−0.235)	(0.348)

Note: *p<0.1; **p<0.05; ***p<0.01

5.4 BAB, BAC and BAV Performance and Leverage Constraints

Table 9 reports the results on regressing the BAB factor return on Fama and French (1993) common risk factors and the change in initial margin requirement. Negative change in margin requirement characterizes the observed SML movement towards its CAPM prediction when market-wide margin constraints are relaxed. This measure is particularly interesting as it indicates the magnitude of change towards a known reference model as opposed to varying levels of flatter security market line estimates. During the period I classify changes in margin level into three categories: most negative, neutral and most positive with one third of all the changes in each.

The lagged changes in initial margin requirement reflect the perceived changes investors have to deal with in allocating their funds, in that large changes, either positive or negative should warrant for more dramatic moves in the following period. Relaxing the margin requirement substantially in this context should therefore restate the security market line more towards its CAPM prediction and release the price pressure on high beta assets. The declining demand in the following period should materialize in the market in two ways: lower returns to high beta assets and higher returns to low beta assets as the disproportionately low demand somewhat neutralizes. I use and indicator for changing margin levels in the simple regressions in lieu of margin level due to the disproportionately small variation in a monthly setting. Change in the strictness of the constraints is also a relevant in assessing the impact of a portfolio readjustment process attributed to changing leverage constraints.

The Betting Against Beta factor performance is in line with previous research (by e.g. Frazzini and Pedersen (2014) and Liu et al. (2018) given pure BAB performance) and the flattening of the security market line in response to tighter leverage constraints. The BAB factor delivers a 0.5% monthly alpha in both the pure CAPM and an FF3 model specifications with respective t-statistics of 3.7 and 4.2. Large relaxing changes in the margin requirement increase the returns to the BAB factor in both models (3) and (4). The margin change indicator generates positive t-statistics of 2.9 and 2.3 in the two models rendering simple CAPM alpha insignificant on a 5-% level. The Fama and French (1993) three-factor alpha however still persists, indicating that there may be more variables at play in producing the robust BAB risk-adjusted returns to the BAB factor as documented in models (1) and (2).

The BAC factor exhibits similar behavior as documented by Asness et al. (2016) in producing positive monthly alphas of around 20 bps in models (1) and (2) with respective t-statistics of 2.7 and 2.9. As expected, the first two models capture the strong performance of BAC across the full period against standard CAPM and Fama and French (1993) models. My third proposition states that the impact of exogenous margin constraints on

BAB materializes primarily through the correlation component, as investors adjust their portfolios mainly through changing portfolio allocations to systematic risk. In testing the behavior, similarly to my previous regressions on the BAB factor, I include the negative margin change variable in measuring the impact of easing up margin regulation. Models (3) and (4) in table 10 show varying degrees of margin impact. In model (3), regressing the BAC return only on the contemporaneous market return, relaxing the market-wide margin requirement does not exhibit statistically significant explanatory power over the BAC return. However, including the full Fama and French (1993) factors shows an impact with on par significance when comparing to regressing the full BAB factor on the same explanatory variables. In model (4) the BAC factor only loads on SMB and negative margin change on statistically significant levels. The result is in line with proposition 3 and at the same time driven by one of the basic properties of BAC, firm size. Larger firms tend to be more correlated with the market, as they also represent a more sizable chunk of the market index as a whole. An intuitive direct implication of model (4) is that BAC represents a bet against large firms that attract funds in the presence of margin constraints.

As far as profitability goes, the BAV factor outperforms BAC by delivering monthly alphas of around 40 bps as opposed to 20 bps with BAC. Models (1) and (2) without the change in margin constraints show robust negative loading on the market return as well as SMB and HML factors. Peculiarly, in models (3) and (4) the behavior with regards to change in leverage conditions is opposite to BAC. In model (3), including only the market excess return, relaxing the prevalent margin requirement has a positive effect of similar magnitude as with BAB. Including the Fama and French (1993) risk factors in turn renders the effect statistically insignificant. The results with BAV in model (3) are consequently somewhat puzzling in the light of my findings in section 5.3, as the level of margin requirements does not seem to play a role in determining returns to volatility.

This behavior in the results seems to come down to model selection. The impact of changes in initial margin requirement is of nearly the same statistical robustness both in model (3) between BAB and BAV as well as in model (4) between BAB and BAC. Applying the methodology to BAB produces similar results for both of the models, implying that the negative margin change variable has indeed a statistically significant effect on the BAB return, even reducing the model (3) alpha's t-statistic down from 3.7 to 1.8. However, taking a closer look with BAC and BAV, a linear combination of which approximates BAB to a high degree, we can see that the effects are highly dependent on the applied model. This dependency on the model seems like a minor pain point – the variation shifts notably between the CAPM and Fama and French (1993) three factor model when including the additional SMB and HML factors. Bear in mind that the correlation term used in BAC is positively correlated with market return. It is then evident in model (3) that market return should not by definition have a positive impact on the BAC factor return. Including other common risk factors changes this picture drastically, reducing the t-statistic on market return down to -0.2. With BAV the change is not as dramatic, but still rather noticeable. The negative impact of market return is clearly reduced and attributed more to SMB and HML factors. Including the two also renders the effect of margin requirement changes insignificant. The closer look at expected factor loadings then provides some encouraging support in favor of the effects realizing through BAC rather than BAV. To an extent, these results then echo the hypothesis by Asness et al. (2016) in higher correlation being a proxy for stocks attractive for adjusting for contraints to leverage and BAC being a relevant vehicle for profiting from these properties.

Table 9: BAB Factor Performance with Margin Constraints

This table reports the performance of the BAB factor when regressed on FF3 risk-factors and negative initial margin change. I construct BAB, BAC and BAV following the logic presented by Frazzini and Pedersen (2014) and Asness et al. (2016). All factors are rank-weighed with, in the case of BAB, the factor going long in low and short in high beta assets, the highest beta receives the highest rank in the short leg and vice versa for lowest beta in the long portfolio. Monthly alphas are in relation to total price (percentage / 100). T-stats for each of the coefficients are in parentheses.

	Dependent variable:			
	BAB Factor Return			
	(1)	(2)	(3)	(4)
Alpha	0.005	0.005	0.003	0.004
	(3.716)***	(4.167)***	(1.798)*	(2.483)**
Market Return	−0.310	−0.189	−0.316	−0.197
	(−10.768)***	(−6.111)***	(−11.018)***	(−6.354)***
SMB		−0.340		−0.324
		(−6.772)***		(−6.433)***
HML		−0.144		−0.151
		(−3.033)***		(−3.180)***
Neg. Margin chg			0.009	0.007
			(2.929)***	(2.385)**
R^2	0.203	0.302	0.218	0.311
Adjusted R^2	0.202	0.298	0.215	0.305
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 10: BAC and BAV Factors Performance with Margin Constraints

This table reports the performance of BAC (Panel A) and BAV (Panel B) factors when regressed on FF3 risk-factors and negative initial margin change. I construct BAC and BAV following the logic presented by Asness et al. (2016). The factors are rank-weighed with e.g. in the case of BAC, the factor going long in low and short in high correlation assets, the highest beta receives the highest rank in the short leg and vice versa for lowest correlation in the long portfolio. Monthly alphas are in relation to total price (percentage / 100). T-statistics for each of the coefficients are in parentheses.

	Dependent variable:			
	Factor Return			
	(1)	(2)	(3)	(4)
Panel A: BAC				
Alpha	0.002	0.002	0.002	0.001
	(2.706)***	(2.918)***	(1.730)*	(1.423)
Market Return	0.081	0.001	0.080	−0.004
	(4.172)***	(0.037)	(4.089)***	(−0.200)
SMB		0.264		0.274
		(7.781)***		(8.055)***
HML		0.029		0.025
		(0.903)		(0.774)
Neg. Margin chg			0.003	0.004
			(1.249)	(2.314)**
Panel B: BAV				
Alpha	0.004	0.004	0.002	0.003
	(2.657)***	(3.483)***	(1.222)	(2.512)**
Market Return	−0.345	−0.138	−0.349	−0.141
	(−11.816)***	(−5.117)***	(−11.980)***	(−5.200)***
SMB		−0.628		−0.622
		(−14.398)***		(−14.133)***
HML		−0.168		−0.171
		(−4.062)***		(−4.117)***
Neg. Margin chg			0.007	0.003
			(2.204)**	(1.070)
Note:				*p<0.1; **p<0.05; ***p<0.01

6 Conclusion

Leverage constraints provide an economically intuitive explanation for the low risk anomaly – investors that cannot use leverage to sufficiently adjust their risk to suit their appetite have to resort to riskier securities. Yet, despite recent efforts in the existing literature by e.g. Jylhä (2018), it seems that there may still be other explanations at play. With data from the US stock market ranging between 1934 and 1974, I take a more granular look on the low risk anomaly and the changing shape of the security market line in dividing beta into its systematic (correlation with the market) and behavioral (volatility) parts.

I find that conditioned on volatility, the return compensation to market correlation is negatively affected by tighter margin requirements, as predicted by previous findings by e.g. Jylhä (2018), Frazzini and Pedersen (2014) and Asness et al. (2016). In line with previous research I propose that this negative relationship represents the 'implicit, non-financial leverage' that investors are forced to take when constrained for financial leverage. I also show empirically that this relation only holds when considering the part of beta that represents systematic risk, i.e. correlation with the market, as opposed to seeking to increase portfolio risk from higher volatility in relation to the market. While volatility and behavioral factors may still manifest themselves in producing at least parts of the anomaly, as proposed by e.g. Stambaugh and Yuan (2017) and Bali et al. (2017), there seems to be little overlap with my findings on the effect of tighter leverage constraints.

Further, I tie my results to the papers by Frazzini and Pedersen (2014) and Asness et al. (2016) in applying the logic in the context of Betting Against Beta, Betting Against Correlation and Betting Against Variance. My findings provide additional support for the BAC factor profit being largely related to the lagged changes in system-wide margin requirements. However, I cannot fully rule out leverage constraints having an impact also on the variance portion of BAB.

The alternative decomposition of beta into correlation and volatility provides intriguing possibilities for further research. One of the clear avenues has to do with expanding the data set – I use the same data on the FED mandated margin requirements in the U.S. as Jylhä (2018). Even though this choice of data provides a market-wide take on the pure exogenous changes in margin requirements, it would be valuable to repeat the analysis during a longer time period to capture the vast changes in stock ownership and information availability in the stock market. Secondly, using alternative indicators, such as the margin debt held by NYSE broker dealers applied by Asness et al. (2016), would help shed light on return variability with more continuous changes and within shorter time frames. Finally, decomposing beta and the security market line into systematic and behavioral risk may help address to relative importance of the systematic and behavioral factors at play bridging the gap between the two schools of thought.

7 Appendix

Table 11: Fama French Three-Factor Regressions by Beta Decile

This table reports results from Fama and French (1993) three-factor model regressions by beta portfolio. I estimate betas following Jylhä (2018) for comparability and regress the monthly excess returns on the market index less the risk free rate from the month $t-36$ to month $t-1$. I place the stocks into 10 deciles in the beginning of each month based on their ex-ante beta estimate in the end of the previous month. This table includes all observations between January 1934 and December 1974 for which relevant beta estimates can be computed. T-statistics are reported in parentheses. Portfolios are constructed in the beginning of each month based on the correlation and volatility estimates at the end of the previous month and re-balanced on a monthly basis.

	Beta Decile									
	1	2	3	4	5	6	7	8	9	10
Alpha	0.002	0.002	0.001	−0.001	0.001	−0.001	−0.001	−0.001	−0.003	−0.003
	(2.048)**	(2.311)**	(0.932)	(−1.002)	(1.262)	(−1.052)	(−0.922)	(−1.384)	(−2.374)**	(−2.393)**
Market Return	0.571	0.732	0.878	1.021	1.076	1.164	1.245	1.347	1.442	1.579
	(28.371)***	(41.675)***	(54.903)***	(64.619)***	(59.274)***	(57.747)***	(58.098)***	(56.540)***	(53.566)***	(47.398)***
SMB	−0.073	−0.033	−0.052	−0.047	0.037	0.110	0.282	0.338	0.578	0.841
	(−2.228)**	(−1.170)	(−2.027)**	(−1.821)*	(1.244)	(3.354)***	(8.116)***	(8.745)***	(13.260)***	(15.569)***
HML	−0.062	0.012	0.028	0.086	0.070	0.145	0.162	0.122	0.194	0.276
	(−1.993)**	(0.426)	(1.134)	(3.526)***	(2.528)**	(4.696)***	(4.911)***	(3.344)***	(4.701)***	(5.400)***
R^2	0.679	0.832	0.895	0.924	0.914	0.915	0.922	0.918	0.919	0.907
Adjusted R^2	0.677	0.831	0.895	0.924	0.914	0.914	0.921	0.918	0.918	0.907

Note: *p<0.1; **p<0.05; ***p<0.01

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