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Bigger Beta is not always Better:
A Study of Low-Beta Strategies

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Abstract

This paper tests to what extent it is possible by an individual investor to implement a low-beta strategy, using 78 MSCI indices of countries and industries with a naive diversification (equal-weighting). Five different strategies with three rebalancing windows are built, implementing a simple ranking method. The results suggest that it is possible to implement a low-beta strategy with a naive portfolio construction, thus offering positive total mean returns and Sharpe ratios with lower standard deviations than the benchmark index. The strategy has a negative relationship with the market index and can be used as a hedging strategy for investors. Our empirical evidence shows that the *Country* portfolios performs better, with a higher alpha, than the *Industry* portfolios. We test the attributions and find that the BAB factor positively explains performances, whereas the F-F Three-factor model results in mixed attributions. Behavioural explanations seem to be plausible to describe the excess demands of high-beta assets.

Keywords: BAB; Low-Beta Anomaly; Index Investing; Country vs. Industry; Naive Strategy

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

1

INTRODUCTION

In the 20^{th} century, exchanged traded funds (ETFs) have emerged as a cheap and convenient vehicle for investors to build up their portfolios through passive investing and asset allocation. ETF investors can now access global assets associated with a specific country, industry or alternative asset such as commodities, to enjoy better diversification. According to a FT report [1] sourced by ETFGI's data, the availability of ETFs is rising: there are 5,632 ETFs available which are worth over $3 trillion.

Following the 2008 financial crisis, new investment strategies exploiting low-beta or low-volatility anomalies are now worth exploring to improve a portfolio's risk-reward profile. There are many low-volatility indices in the market such as the MSCI All Country World Minimum Volatility index, and the S&P 500 Low Volatility index. Indeed, ETFs tracking a low-volatility index are numerously available for investors but it is also important to know if it is possible for an individual investor to use the strategy. If it is possible, it is interesting to know whether the returns are outperforming a selected benchmark or not, and to what extent country or industry ETFs outperform each other. Thus, we will explore to what extent it is possible to construct a low-beta anomaly portfolio in an equal-weighted approach with ETF proxies consisting of MSCI indices.

The concept of low-beta anomaly is not new and was illustrated by several academic studies (Jensen et al., 1972; Black, 1993; Frazzini and Pedersen, 2014), contradicting the traditional capital asset pricing model (CAPM). The low-beta anomaly is the mispricing of the CAPM estimation in which a low-beta asset is underpriced and

1 Read full article at Pluses and pitfalls in the ETF revolution by John Authers, Financial Times, March 24, 2015

a high-beta asset is overpriced. Furthermore, the relationship between *beta* and the security's expected return is not strongly positive but flat or even negative (Jensen et al., 1972; Black, 1993).

The low-beta anomaly exists almost everywhere in the world in many aspects such as geographical locations (developed and emerging markets), sector-level and different asset classes (Baker, Bradley and Wurgler, 2011; Baker and Haugen, 2012; Blitz, Pang et al., 2012; Frazzini and Pedersen, 2014; Baker, Bradley and Taliaferro, 2014; Asness et al., 2014). An abundant number of financial managers capture these low-risk effects in different types of portfolio constructions, thus confirming the existence of the low-beta anomaly (de Carvalho et al., 2012; Hsu and Li, 2013; Denoiseux, 2014).

We show that it is possible to implement the low-beta strategy with a naive portfolio construction (equal-weighting) reflecting a retail investor perspective. The simulated portfolios with one- to three-month rebalancing windows mostly offer higher total mean returns, and Sharpe ratios with lower standard deviations compared to the benchmark index, especially the *Country* portfolios perform best. We find poorer returns in the *Industry* space, and conclude that the anomaly in countries is greater than in industries. The returns are mostly from the short leg of overpriced indices rather than the long leg of underpriced indices. Only the *Country* has comparable long and short returns, we assume the wide dispersion of betas between two legs is the major reason. The portfolios display negative relationships with the benchmark market so that they can be used as a hedging strategy for investors. Furthermore, the Betting–Against–Beta (BAB) factor can positively explain performances in every one of the portfolios whereas we have mixed results in the Three-factor model. Yet, we find significant positive alpha in the country level but find none in the industry level at all.

There are several logical reasons worth mentioning to explain the low-beta anomaly in countries and industries. Behavioural explanations with the heuristics and limits to arbitrage seem plausible. Irrational investors tend to tilt or overweight high-beta assets because of an overconfident bias, accessing leverage exposures, benchmarking, market-capitalisation size or short-selling by institutional investors. These can result in crowded investments and yield lower expected returns for high risk stocks.

The remainder of our thesis is divided into six main parts. The literature review is presented in Section 2. Section 3 outlines the hypotheses. Our portfolio model is explained in Section 4. In addition, results and analytical discussions including limitations and further research are shown in Section 5. Lastly, our conclusion is presented in Section 6, and appendices in Section 7.

2

LITERATURE REVIEW

In this section, we present a brief summary of related literature. We especially focus on literature about the Beta Anomaly, Portfolio Diversification, and the Country vs. Industry discussion as our main ideas are based on these topics.

2.1 THE BETA ANOMALY

In the following section we will analyse different points in the beta anomaly literature. Firstly, we give a brief review of the CAPM, followed by a summary of important beta anomaly studies. Furthermore, we will discuss possible explanations, origins, investment strategies and limitations of beta anomaly strategies.

The CAPM provides an explanation for expected returns in financial markets. The model suggests that returns can be captured by either alpha, defined as the excess premium in return by pursuing an active management strategy, or by beta, defined as the return from systematic risk from the market. Sharpe (1964), Linter (1965) and Mossin (1966) concluded that a security with higher systematic risk requires a higher expected return than a security with lower systematic risk, described by the security market line. However, empirical evidences do not support the high risk high return idea. Jensen et al. (1972) and Black (1993) argued that the security market line in the US stock market was flatter than the standard CAPM suggested, and also showed a superior return from a *beta factor* portfolio, which was long in low-beta stocks and short in high-beta stocks.

Recently, many studies have concluded that the beta anomaly and low-volatility strategy are prevailing and profitable. Baker and Haugen (2012) and Blitz, Pang et al. (2012) described such evidences in both developed and emerging stock markets.

Furthermore, Frazzini and Pedersen (2014) illuminated us with their *Betting–Against–Beta* (*BAB*) factor in many asset classes. They found that low-beta portfolios have higher alpha and Sharpe ratios than high-beta portfolios. The security market lines were also flatter than the original CAPM; this was true for the US, international equity markets, treasury markets and futures markets. Messikh and Oderda (2010) also confirmed the outperformance of portfolios tilted towards low-beta assets rather than high-beta assets in log-returns over a long-time horizon by the Brownian motion process.

Beta anomalies occurred not only in individual stocks but also on the country and industry levels (Baker, Bradley and Taliaferro, 2014; Asness et al., 2014). Baker, Bradley and Taliaferro (2014) decomposed the low-beta anomaly into macro and micro effects. They defined the macro effect as selecting low-beta countries or industries while the micro effect was defined as selecting individual stocks themselves. Our paper focuses mainly on the industry and country effects, i.e. the macro effect. Their results exhibited positive alphas of 1.53% in the pure industry effect and 6.22% in the pure country effect. They concluded that the country bet produced higher alpha through significantly improving returns and modestly reducing risk. However, the industry bet featured modest performance, and the alpha was not significantly different from zero. Thus, the macro inefficiency was intact on a country level rather than an industry level, the results also suggested that behavioural demands tilt towards relatively riskier countries or industries.

Asness et al. (2014) conducted another study in non and pure industry bets to investigate their effects on the beta anomaly. Both concepts worked well and supported the low-risk investing argument in which the industry-neutral BAB loaded more than pure industry BAB in the US data, while weighted equally in the global sample. However, the industry-neutral portfolio had a superior performance than the regular BAB factor and the pure industry in terms of Sharpe ratio. Moreover, the pure industry BAB and industry-neutral BAB still provided significant abnormal returns after transaction costs.

Several studies suggested that investors can exploit beta anomalies by investing in specific low-volatility ETFs or constructing portfolios with ETFs with a minimum-variance optimisation to mimicking such strategy (de Carvalho et al., 2012; Hsu and Li, 2013; Denoiseux, 2014).

de Carvalho et al. (2012) tested five different risk-based strategies and concluded that an equal-weighted portfolio was exposed to small caps and the least defensive portfolio compared to the market-cap index. However, all strategies had negative beta relationships with MSCI World market-cap index. The equal-weighted portfolio also had a positive coefficient with a low-beta anomaly factor, whereas minimum variance and maximum diversification portfolios displayed the highest correlation with a low-beta anomaly factor. The researchers applied these approaches in the US, European and Japanese stock markets and found similar results. Interestingly, alpha intercepts were zero in all portfolios of studies of MSCI World Index, US, European and Japanese markets. Ultimately, the authors concluded that the strategies were quite defensive and useful for asset allocation in order to reduce risk, since all portfolios had negative betas.

Hsu and Li (2013) researched simulated portfolios with a factor-model consisting of a combination of the Carhart four-factors and the BAB factor. Abnormal returns could be captured by the value factor and the BAB factor. The authors also showed that the low-volatility portfolios tend to have higher returns, lower risks and thus higher Sharpe ratios compared to other large-cap indices among the US and developed markets (DM). The low-risk strategy was viewed as the risk-return profile improvement due to a diversification enhancement. Cazalet et al. (2013) produced similar findings and added the link between a small-cap factor and alpha.

Denoiseux (2014) investigated how to construct low-volatility portfolios of ETFs with a minimum-variance allocation as a pragmatic solution for investors. He tested the strategy in both developed and emerging market (EM) ETFs with a mix of country and industry indices to grasp the beta anomaly. The results showed that low-risk portfolios can be established from DM and EM ETFs to improve return and risk profiles, they outperformed the MSCI World and MSCI Emerging Markets indices. He also discussed the practical usefulness of ETF-based strategies due to costs and operational advantages.

Several papers suggested behavioural explanations for the low-beta or low-risk anomalies. Jensen et al. (1972), Black (1993), and Frazzini and Pedersen (2014) agreed on the condition of a leverage constraint, explained by the leverage aversion hypothesis. The leverage constraint resulted in bidding towards high-beta securities to take more risks in order to beat the market and thus led to a lower Sharpe ratio. Additionally, Baker, Bradley and Wurgler (2011) laid out several possible behavioural explanations for both individual and institutional investors. Firstly, irrational investors used high-volatility stocks as a lottery gamble to obtain higher volatility exposure. Moreover, representativeness and overconfident heuristics among investors were behaviours which made investors tilt their portfolios towards high volatile stocks (Cornell, 2009; Baker, Bradley and Wurgler, 2011).

Baker, Bradley and Wurgler (2011) deduced that fund managers tended to track a fixed benchmark and maximised the information ratio to beat it; consequently, this situation discouraged portfolio managers to capitalise the mispricings and instead encouraged them to invest more in riskier stocks (high β). The article also stated the lower tendency of institutional players to use leverage and short-selling due to fund policies and higher costs. They concluded that the beta was driving the anomaly in large stocks rather than the volatility, even though both were highly correlated because money managers focused disproportionately on large stocks. We also support the idea of disproportionate investment in large stocks because a fund policy might only allow managers to invest above a certain market-capitalisation.

These behavioural reasons lead to one direction: excess demand for high-beta stocks will increase prices and decrease expected returns (or future returns) and vice versa for low-beta securities. The common key explanations is the leverage constraint among investors stated in (Baker, Bradley and Wurgler, 2011; Frazzini and Pedersen, 2014), but we believe other fund mandates like investable market-capitalisation and short-selling are also possible explanation.

Another discussion is the source of return, more specifically whether the beta loading could be considered as an alpha. Berger et al. (2010) from AQR Capital Management presented such evidence in their research paper. It described the transformation of *alpha* to *beta* over time. Alpha firstly emerged as an active skill, then *equity beta* evolved from the CAPM theory, subsequently other betas, such as *style beta*, *exotic beta*, and *hedge fund beta*, were discovered. New financial models, theories and benchmarks have transformed the alpha to the betas along the way. Thus, it could be that the beta anomaly here has some sort of a relationship with alpha. Then, Baker, Bradley and Wurgler (2011) explicitly summarised that a low-beta asset has higher alpha return; thus displaying an inverse relationship between beta and alpha.

There are also limitations to the beta anomaly or low-volatility investing. Huang et al. (2014) pointed out that the cycle of arbitrage activity explains that it may take up to three years to realise profits in a thin trading environment; however, it takes only six months in a high trading environment. The authors also documented a firm-leverage effect in high-beta stocks. They concluded that the firm-level leverage in high-beta stocks widens the cross-sectional beta spread and thus one should hold the arbitrage position longer in order to result in a larger abnormal return.

Li et al. (2014) concluded that there are no abnormal returns at all in equal-weighted portfolios, while the alphas in value-weighted portfolios were largely eliminated when excluding penny stocks (Price <$5). Furthermore, the author concluded that the anomalous returns could be reduced further due to additional transaction costs. The strategy needed to be rebalanced frequently on small-cap stocks in order to capture profits. The literature also indicated that the arbitrage strategy is short-lived as it only lasts one month. Moreover, the results were somewhat weaker since 1990. The anomaly had little impact on the market, which could possibly indicate higher market efficiency (Li et al., 2014). However, the test was only implemented in the US stock markets.

Zaremba (2014) suggested that there is no low-beta anomaly on the country level, only on the stock level. He illustrated that the country level returns were more explained by idiosyncratic risks rather than systematic risk. Moreover, he discovered that a Value at Risk (VaR) sorting could improve the country level size and value performance; furthermore, volatility related measurements could also be useful for global investors to implement passive index investing like ETFs.

Hence previous research seems to be inconclusive on to what extent the beta anomaly exists in different situations and what its origins are. Furthermore, different portfolio constructions influence the conclusion.

2.2 PORTFOLIO DIVERSIFICATION

One concern prior to the portfolio construction was the *Portfolio Diversification*, which is important for both professional money managers and individual investors; however, the naive diversification does not seem to be a problem as explained in the following section.

A diversification process has a positive effect on a portfolio since it reduces *risk* to a lower bound until only *systematic risk* remains. The risk reduction is considered a benefit and an investor should diversify until the marginal cost is equal to the marginal benefit of diversification (Statman, 1987). We were initially concerned about the optimal diversification; however, later on satisfied with the power of naive diversification, discovered in academic literature. Benartzi and Thaler (2001); Huberman and Jiang (2006) concluded that retail investors are eager to use an equal-weighted approach (naive diversification), and thus is in line with the chosen portfolio construction.

A widely accepted minimum number of stocks for diversification is 10-15, as explained in many articles or textbooks (Statman, 1987; Tang, 2004); however, Statman (1987) demonstrated that a well-diversified equal-weighted portfolio, in terms of expected returns, consists of at least 30 stocks for a borrowing investor. The results were that increasing the number of stocks from 30 stocks to 500 stocks only resulted in a marginal diversification benefit of 0.517% respectively for a borrowing investor.

Tang (2004) also confirmed a that one needs more than 10-15 stocks to create a well-diversified portfolio. He investigated diversification in an equal-weighted portfolio and used the expected portfolio variance as a diversification measurement. The results did not depend on time horizon or markets thus making it easy for a naive investor to decide on a certain number of stocks to construct a sufficiently well-diversified portfolio. Tang (2004) suggested that only 20 stocks could eliminate 95% diversifiable risk, and that one needed up to 89 stocks to reduce the risk by 99%, when the population size was sufficient for random selection (# of stocks=20 when N=800).

Researchers also studied the differences between optimal and naive diversification (DeMiguel et al., 2009). They tested 14 in-sample mean-variance portfolios and concluded that none outperform the 1/N or Naive Diversification in terms of Sharpe ratios. Optimal portfolios, out of sample, needed up to 6,000 months with 50 assets to outperform the naive model. An estimation error was one major reason which undermined the optimal portfolios. The authors indicated that smaller margins of error estimation in the 1/N allocation (called allocation mistake) and lower idiosyncratic risks from investing in well-diversified portfolios rather than individual stocks led to the outperformance of the naive diversification model. However, their intention was not to exaggerate the 1/N rule as a proper asset allocation but only as a benchmark for the study.

2.3 COUNTRY VS. INDUSTRY

The country and industry effect have been investigated over a significant period of time. Heston and Rouwenhorst (1995) studied these two effects in international stock returns and found that the country level effect tended to have a larger impact than the industry level. A diversification effect was the major reason. A well-diversified industry portfolio had a variance of 38% whereas a well-diversified country portfolio only had a variance of 20%. Yet, the combination of both had the lowest variance of 18%. Moreover, at 3.00%, the mean returns of the country portfolios were twice the size of the mean returns of the industry portfolios. Cavaglia et al. (2000) conducted research in 12 developed markets and 36 industrial indices and in contrast found that the industry effect dominated the country effect in the late 1990s.

More recently Menchero and Morozov (2011) looked deeper into factor models comprising of country, industry and style factors equally, to explain cross-sectional volatility in global markets. The results showed that the country effect prevailed the industry effect from 1994 to around 2000, then the industry effect took the lead. However, they were comparable between 2003 to 2007, the country effect dominates since 2007. Hence, the country effect might seem to be larger than the industry effect, but we saw that there is also uncertainty in different time periods and investing themes.

As a global fund manager or an individual investor, one way to analyse initial investment opportunities is a top-down approach which is a macro economic driven strategy. The geographical analysis could overshadow the industry level located in each country and investors could diversify their portfolios from this approach to earn more risk-adjusted returns.

3

HYPOTHESES

Based on the preceding literature review we have established the following five hypotheses, and how our research is different to previous research.

We have seen evidence for beta anomalies in several previous studies. (Blitz and van Vliet, 2011; Baker and Haugen, 2012; de Carvalho et al., 2012; Hsu and Li, 2013; Frazzini and Pedersen, 2014; Asness et al., 2014; Denoiseux, 2014). Generally, there are low-beta anomalies in the global equity indices, not just in individual securities, and they outperform the benchmarks. Given that previous research found evidence of beta anomalies within equity indices our **Main Hypothesis** is that implementing a low-beta anomaly strategy with a naive construction using ETF-proxy portfolios should provide positive mean returns and Sharpe ratios that outperform the benchmark index. In contrast to previous research, which covered different restrictions and approaches such as market-neutral, double sorting and minimum variance techniques, we use a naive portfolio approach with simple ranking, representing an individual investors perspective. Thus, largely focusing on whether it is possible for an individual investor to capture the low-beta anomaly.

Furthermore, if the anomaly prevails, our findings should be in a similar direction with previous literature for return performances and attributions but certainly with various magnitudes. Therefore, **Sub-Hypothesis 1** is that the portfolios are expected to exhibit positive performances in mean return and Sharpe ratio. The portfolios' Sharpe ratios outperform the benchmark index reflecting the low-beta anomaly across country and/or industry.

Indeed, it is debatable to what extent the anomaly prevails on the country and industry level; Baker, Bradley and Taliaferro (2014) and Asness et al. (2014) concluded that the anomaly exists both on the country and the industry level, whereas Zaremba (2014) argued that the anomaly only occurs on the country level. Furthermore, three previous studies by Heston and Rouwenhorst (1995), Menchero and Morozov (2011) and Baker, Bradley and Taliaferro (2014) concluded that the country effect is greater than the industry effect. Thus **Sub-Hypothesis 2** is that the low-beta anomaly exists on both country level and industry level but that the country level contributes larger positive effects to the portfolio's returns than the industry level effect. Thus, the alpha of a country portfolio will be larger than the alpha of the industry portfolio. Hence, another contribution of our thesis is covering the source of beta anomaly returns, contributing more evidence to the debate.

Additionally it is expected that the short leg of the portfolios will on average outperform the long leg of the portfolios, due to limits to arbitrage. More specifically limitations such as fund mandates can reduce the legal possibility of exploiting short position returns as well as practical reasons such as implementation cost. Therefore, **Sub-Hypothesis 3** is that the short legs will outperform the long legs on average.

Hsu and Li (2013), show that BAB returns can partially be explained by HML factors due to their high correlations. Thus, extending the normal CAPM model to a Three-Factor Model should explain some of the positive alpha in the CAPM, given that we may find positive alphas. Hence, **Sub-Hypothesis 4** is that Three-factor loadings can be captured in the model in order to explain abnormal return findings. Positive HML (value effect) coefficients are particularly delivered for the performance attributions. It is expected that SMB factor loadings on the other hand will have negative coefficients. The SMB factor is based on the fact that small cap stocks on average outperform high cap stocks, thus a typical SMB strategy would involve buying small-cap stocks and selling high-cap stocks. However, our portfolios are constructed based on betas, which are a way to measure risk. Thus low-beta stocks, will be less volatile and therefore most likely be large-cap ETFs, whereas high-beta stocks, should be more volatile and therefore small-cap ETFs. Following a typical BAB strategy is expected to be to buy low-beta stocks, i.e. large-cap ETFs, and to sell high-beta stocks, i.e. low-cap ETFs. Therefore, the BAB strategy is the opposite of a SMB strategy and should result in negative coefficients with the SMB factor loading.

The next step is to extend the model by a BAB factor. **Sub-Hypothesis 5** is that the BAB factor will explain large portions of the abnormal return findings, and thus have a positive coefficient. This will be in-line with de Carvalho et al. (2012) and Hsu and Li (2013) who extended Carhart four-factor with the BAB factor.

4

PORTFOLIO MODEL

The following section introduces the models on which the thesis is based in order to simulate a strategy of low-beta investing. These theories act as an academic foundation to support the model construction and logic behind it.

4.1 DATASET & GENERAL SETTINGS

Two main datasets are used. The first is comprised of the returns of different MSCI indices. We do not use returns of actual ETFs as most have only been introduced recently. The second dataset contains the retrieved 3-month US Treasury Bills yields.

The initial MSCI dataset includes daily index returns for 79 indices, all of which are denoted in US dollars. The main index is the MSCI ACWI IMI which is currently composed of 46 different countries, 23 developed markets and 23 emerging markets. The MSCI ACWI IMI represents 99% of the investable equity in the world and thus seems to be an appropriate starting point. The 78 indices we will use as proxies for ETFs are four regional indices EM, Europe, EAFE, Pacific, 44 country and 30 different industry indices in ACWI (DM & EM), DM and EM. The data was reported on a daily basis starting on 30$^{\text{th}}$ of December 1994 until the 31$^{\text{st}}$ of December 2014. We calculated the natural log monthly returns from January 1995 until December 2014 for our model. Our simulated portfolios nonetheless only begin in January 2000 and end in December 2014, since we need 5-year beta estimations, as these betas will be less noisy and more stable.

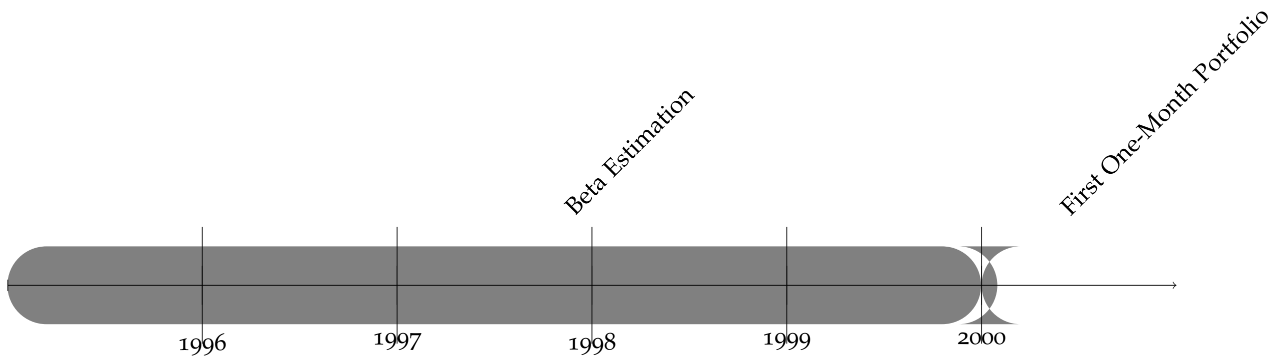
We would like to point out to the reader that the full list of all indices including countries and industries with their monthly mean returns and monthly average standard deviations can be found in Table 6 and Table 7. MSCI Qatar and MSCI United Arab Emirates are not available, thus we only included 44 countries out of 46. All MSCI indices are acquired from Datastream.

The 3-month T-Bills yield data is retrieved on a monthly basis from the Federal Reserves database, from January 1934 until February 2015 and used as the risk-free rate from January 2000 until December 2014 to calculate excess returns.

We define five different portfolios, specifically *Mixed*, *Mixed-Exc*, *Country*, *Industry* and *Industry-Exc*. The first will be a mix between region, country and industry indices, which is the full range of possible assets. The second portfolio is the *Mixed-Exclusion* portfolio, as it excludes MSCI ACWI industries, avoiding overlapping industries. The *Country* and *Industry* portfolios are based only on country level and industry level indices. The last portfolio, *Industry-Exc*, is similar to the *Mixed-Exc* except it does not include any regional indices.

The rebalancing approach is applied to portfolios with different time windows. The rolling windows are one-month, two-month and three-month; these were chosen to match the risk-free 3-month T-Bills and to increase robustness of our low-beta anomaly assessment.

On a time line the beta estimation and the first one-month portfolio would look as follows:



The time line for the second one-month portfolio would shift one month to the right. In the case of the two-month and three-month portfolios, only the length of the portfolio holding would differ. Furthermore, instead of shifting one month to the right, the time line shifts two and three months to the right for the two-month and three-month portfolios respectively.

Thus, we analyse 14 years of monthly excess log returns in 15 portfolios, five different asset mixes and three different rebalancing time frames, to test our hypotheses and the existence of low-beta anomaly.

Additionally, we obtain two more datasets for factor attributions for the regression models. Firstly, we need monthly data for the Fama-French global Three-factor model, data is available until January 2015. The global three-factor model represents the size and value effects in 23 developed markets which we believe is more relevant than than the traditional US Three-factor model. This time-series is available at Kenneth French's Data Library.[2] Secondly, we want to include a BAB-factor, thus requiring returns of different BAB strategies. The BAB factor resource is accessible at AQR Capital Manangement website.[3] The website provides several BAB factors for different geographical regions, we chose the global BAB factor due to the same reasons as we chose the global Three-factor model.

In the next section we will explain our portfolio construction and performance measurements with supporting theories.

4.2 CAPITAL ASSET PRICING MODEL, CAPM

Firstly, we would like to elaborate on the *Capital Asset Pricing Model* as it lays a foundation in the financial world in order to obtain theoretical security prices. Originally, the market model was introduced by Markowitz (1959) and extended by many researchers later on. The CAPM model is the model showing the relationship between expected return of an individual security and the systematic risk or *beta*. The relationship is plotted through the security market line.

2 Kenneth French's site: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data$_l$*ibrary.html*
3 Visit AQR Capital Management Library for available BAB factor data at https://www.aqr.com/library

Furthermore, CAPM estimates α, which represents the portion of return explained by active management skill or the return not attributed to *beta factors* (Jensen et al., 1972; Berger et al., 2010).

$$\hat{R}_{i,t} = \alpha_i + \beta_i(\hat{R}_{m,t}) + \varepsilon_{i,t} \tag{1}$$

where $\hat{R}_i, t$ is the expected excess return of an individual asset i at time t; $(\hat{R}_m, t)$ is the expected excess return of market m at time t; α_i is the alpha of asset i; β_i is the beta of asset i; and lastly $\varepsilon_{i,t}$ is an idiosyncratic risk of asset i assumed to be random.

Thus beta, as a measurement of systematic risk, is a positive coefficient to explain the expected excess return of an asset with the market. Hence, we should expect a *high risk, high return* situation where an investor requires more return from an asset with higher risk. Concluding from this equation, the market index in which an individual security is included, is the only risk factor.

As our thesis focuses on low-beta anomaly investing, we estimated our betas of each MSCI country and industry indices from a simple regression model with respect to the market of the MSCI ACWI IMI. Natural log returns have been used, and betas are based on 5-year estimation windows. Then, we ranked the assets in the descending order and selected them based on beta ranking criteria.

4.3 naive diversification

Several studies have presented evidences that an individual investor is prone to use simple diversification (Benartzi and Thaler, 2001; Huberman and Jiang, 2006). Hence, we also construct our portfolio using a naive equal-weighted approach to represent a retail investor perspective.

The general equation of the portfolio variance for N population is stated in (Tang, 2004) as following:

$$E(\sigma_P^2) = \frac{1}{n}{\sigma'_N}^2 + \frac{n-1}{n}{Cov'}_N \tag{2}$$

where $E(\sigma_P^2)$ is the expected variance of portfolio; n is the number of assets in a portfolio; N is the population size of assets. The first term on the right-hand side represents the *diversifiable risk* or *non-systematic risk* and the second term is the *systematic* *risk*. The diversifiable risk tends to move toward zero as n increases and Tang (2004) concluded that if we have a stock population of 800 or more, 20 stocks would eliminate 95% of diversifiable risk and it needs up to 89 stocks to reduce the risk by 99%.

Thus, we select 20 assets from the MSCI country and industry indices, after ranking them by the betas estimated by the regressions to build portfolios. In our case, 44 MSCI country level indices and 30 MSCI industry level indices represent more than 800 stocks. Thus, the equal-weighted selection of 20 MSCI indices is enough to reduce diversifiable risk, though we could have some covariance risks due to overlaps between them. Note that we do not focus on naive diversification, it is only a mechanism to create a portfolio which is frequently used by retail investors.

4.4 THE LOW-BETA STRATEGY

We adopt a low-beta trading strategy, as the main concept of the thesis, introduced by Frazzini and Pedersen (2014)— the so called *"Betting-Against-Beta"* strategy. The strategy is to long (overweight) low-beta assets, and short (underweight) high-beta assets in order to make a self-financing portfolio with a beta of 1. The equation from their study is the following:

$$\hat{R}^{BAB}_{t+1} = \frac{1}{\beta^L_t}(\hat{R}^L) - \frac{1}{\beta^H_t}(\hat{R}^H) \tag{3}$$

where $\hat{R}$ is the expected excess return of BAB factor; $\frac{1}{\beta_t}$ is the shrinkage beta weighing towards 1; the first term on the right-hand side represents the long leg of the low-beta assets while the second term represents the short leg of the high-beta assets. Note that we do not apply shrinkage beta to our portfolios.

After the beta ranking and deciding on the number of assets within the portfolio, we select and enter short positions for the 10 highest-beta assets and long position for the 10 lowest-beta assets, following the concept of the "Betting-Against-Beta" strategy. Consequently, each portfolio holds 20 assets, 10 short positions and 10 long positions. However as individual investors cannot sell short without collateral our strategy is not completely self-financing. Remark that we do not adjust betas toward 1 so it is not a *market-neutral* portfolio like in the study by Frazzini and Pedersen (2014).

4.5 SHARPE RATIO

The Sharpe ratio is a widely accepted risk-adjusted performance measurement in the financial industry. We here refer to the *ex post* Sharpe ratio formula from (Sharpe, 1994) as:

$$S_H = \sqrt{\frac{\bar{D}}{\sigma_D}} \tag{4}$$

where S_H is the Sharpe ratio; $\bar{D}$ is the average historical excess return from a benchmark as we used the risk-less asset; and σ_D is the standard deviation. Hence, this ratio tells us the performance of a fund or a portfolio per unit of risk. An investor should expect a positive Sharpe ratio, consequently the higher the ratio the better the investment. Blitz and van Vliet (2011) confirmed that the Sharpe ratio is an appropriate instrument to measure a low-risk trading strategy performance in order to draw a better picture.

4.6 PERFORMANCE ATTRIBUTIONS

We do not only calculate mean returns and Sharpe ratios for performance measurements but also take into account the factor attributions to explore their factor explanations. We run all our portfolio regressions with respect to the MSCI ACWI IMI index (Market). Furthermore, we extend the CAPM to the Three-factor model including SML (size) and HML (value) factors from Fama and French (Fama and French, 1993) and lastly extend the full model with the BAB factor from Frazzini and Pedersen (2014). de Carvalho et al. (2012); Hsu and Li (2013) also concluded that the low-beta anomaly strategy can be explained by these factor attributions. This thesis does not include the momentum factor (UMD) in the model. The full regression model equation is as follows:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}(R_{m,t}) + s(SML_t) + h(HML_t) + v(BAB_t) + \varepsilon_{i,t} \tag{5}$$

where $R_{i,t}$ is monthly log excess return of a portfolio i; $R_{m,t}$ is the MSCI ACWI IMI index; SML is the size factor; HML is the value factor; BAB is Betting-Against-Beta factor; s,h,v are coefficients to each factor respectively; and $\varepsilon_{i,t}$ is the idiosyncratic risk.

In this process, we include one factor at a time when running the regression model starting with the market, then Three-factor and lastly the BAB factor as shown in equation (5).

The two studies by de Carvalho et al. (2012) and Hsu and Li (2013) give interesting guidance. de Carvalho et al. (2012) illustrated that, in their 5 risk-based strategies, there are no alphas and only negative betas, but positive coefficients of low-beta anomaly factors in the World, US, EU and Japan universes. The portfolios mostly have positive coefficients to SML and HML factors. Additionally, Hsu and Li (2013) concluded that their low-risk portfolios have explanatory powers of HML and BAB with a direct relationship. Both studies provided very high R^2 in their models.

The next chapter presents our Results and Discussion including annualised mean returns and standard deviations of benchmarks and simulated portfolios. Sharpe ratios of portfolios are also shown while benchmarks' Sharpe ratios are in the appendix. We will discuss and analyse their performances and attribution with results found in regression models.

5

RESULTS AND DISCUSSION

5.1 RETURNS & STANDARD DEVIATIONS

In this section, we elaborate on our results obtained from the model to test our hypotheses. The results below are annualised for suitable comparisons.

Firstly, the following Table 1 presents the benchmarks summary of mean excess returns, standard deviations and number of observations. The market benchmark is the MSCI ACWI IMI index and it shows slight positive returns among different rolling windows at the maximum of 0.61%. The standard deviation is around 0.18 and aligned to the equity asset norm. However, the size (SML), the value (HML) and BAB obviously outperform the market with higher positive returns and much lower standard deviation. The Three-factor model by Fama and French (1993); Fama and French (2012) reported similar results as well as Frazzini and Pedersen (2014) for the BAB factor. All of them except the SML perform much better in terms of risk premia than the market; the HML (value) strategy offers over 7% while the BAB offers an astonishingly high return of up to 13.69%. The SML (size) instead returns just around 2%. Additionally, they tend to offer sharply lower risk with approximately 0.10 or slightly over on average, whereas only SML has the lowest standard deviation below 0.08. The SML and HML returns might differ compared to other studies as we chose to use global factors, which are more relevant, instead of the US market factors, which are more balanced with regards to returns.

Next in Table 2, we present a summary of our simulated portfolios including mean returns and standard deviation in the long leg, short leg and total portfolio. Note that we have various numbers of observations (#N) for different rebalancing windows. The average total return of 14 portfolios is positive, the exception is the *Industry-Exc* portfolio, and tends to outperform the MSCI ACWI IMI benchmark indices. The one-month *Country* portfolio has the highest annualised return of 4.62%. Our *Mixed* and *Mixed-Exc* portfolios tie for second place, after the *Country* portfolios, in terms of performance. Where the *Mixed* portfolio performs better in the one-month window, with 3.11% return, the *Mixed-Exc* portfolio performs better in the three-month window with 3.24%.

Table 1: Annualised Benchmark Returns & Standard Deviations

		Return	StDev	#N
	One Month	0.44%	0.17	180
Market	Two Month	0.61%	0.18	90
	Three Month	0.43%	0.18	60
	One Month	1.87%	0.07	180
SML	Two Month	1.93%	0.08	90
	Three Month	1.80%	0.06	60
	One Month	7.40%	0.09	180
HML	Two Month	7.52%	0.10	90
	Three Month	7.59%	0.11	60
	One Month	13.57%	0.11	180
BAB	Two Month	13.59%	0.12	90
	Three Month	13.69%	0.13	60

This table presents the annualised mean returns, standard deviation of each benchmark in different rolling windows. Market is the MSCI ACWI IMI. SML and HML are the global size and value effects retrieved from French's Library. BAB is the Betting-Against-Beta factor obtained from the AQR Capital Management's library. All data is using monthly log excess returns. The time horizon is January 2000 to December 2014.

According to the total standard deviation results, only the *Mixed* portfolios have risks comparable to the *Market* benchmark at 0.18; the other portfolios perform better compared to the market, yet poorly if we compare to other benchmarks of SML, HML and BAB, as seen in Table 1. The *Industry-Exc* strategy is the least risky, having standard deviations of 0.12 and 0.13 but only slight positive returns.

Here, we can see that the *Country* is the best portfolio considering both returns and standard deviations since it offers the highest mean returns and second-best standard deviation at 0.13. Thus, we can obviously observe and grasp the low-beta anomaly around the globe, especially in the country level which has the strongest effect compared to others in our in-sample period.

We then consider returns and standard deviations in each leg. In the long leg, the *Country* portfolio still takes the lead starting with 2.04% in one-month and dropping slightly to 1.99% on thee-month basis. The risk premia on the country level is very appealing. The rest perform poorly in the long leg with small positive returns around zero, where only the *Mixed-Exc* three-month portfolio returns over 1%. In this sense, it seems that industry level portfolios are not as heavily mispriced as the regions with two possible reasons. Firstly, the anomaly among industries is not strong enough to capture. We observe that the portfolios tend to long utility, health care, and consumer staples sectors in developed markets as well as in the combination (ACWI). Although, they usually have relatively low betas, investors are prone to ignore these stable equity indices, thus the anomaly does not seem to work here as they do not offer much value. The poor industry level performances also hit the *Mixed* and *Mixed-Exc* portfolios, as they provide only up to 1% in the long leg.

The reported long leg risks in Table 2 are mixed. The country bet is the most risky over time, with a standard deviation ranging from 0.17 to 0.19 while the industry bet is dramatically lower at 0.12. The *Industry-Exc* is more risky than the *Industry* portfolio with a standard deviation of 0.14. The reduction of possible overlapped assets does not decrease the risk but actually increases it. In the exclusion circumstance, we have less industries available to be selected (#20 out of #30) so that we possibly have less diversification effect. This counters an anticipated preliminary intuition when we removed plausible covariance from MSCI ACWI Industry; considering this the risk increase seems reasonable. As a result, the *Mix-Exc* portfolios also have a slightly higher standard deviation than the *Mixed* portfolios.

In the short leg, the portfolios generally yield higher returns than in the long leg. The *Mixed* portfolio is the best overall performer with 3.06% in return and 0.26 in standard deviation in the one-month window. In addition, the *Country* portfolios are the second runner with 2.53% return and 0.26 risk in the one-month portfolio. So the difference between the two is about 50 bps with similar standard deviation of 0.26. The *Mixed-Exc* strategy performs similarly to the country level, only slightly lower in returns. Nevertheless the *Industry* portfolios yield only 0.41% to 0.69%. The *Industry-Exc* portfolio has roughly 20 to 70 bps lower returns than the *Industry* portfolios and similar risk at 0.22 to 0.23. Thus, we have more volatility and fluctuations (high standard deviations) in the short legs while we also obtain higher returns than the long legs.

All in all, comparing Table 2 to all benchmarks, in returns perspective, all portfolios, apart of the *Industry-Exc* portfolio, outperform the MSCI ACWI IMI index, and particularly the *Country* portfolios obviously beats the market by almost 4.00% on average, which is fairly large. It also beats the market in terms of risk by 0.04 to 0.05. The long leg country portfolio is tilted towards developed markets and some emerging markets like Chile, Colombia, Czech Republic, and Philippines; on the other hand, the short leg country positions are holding more emerging markets and some developed markets such as Belgium, Germany, Norway, and Sweden. The *Mixed* and *Mixed-Exc* portfolios do perform well above the market by almost 2.00% to 2.50%; however, the *Industry* and *Industry-Exc* are worse than the other types and only the *Industry* portfolios beat the market. Indeed, our trading strategy is outstanding and successful in some senses but not all.

The SML benchmark does offer lower performances than our portfolios, exceptions are the *Industry* and *Industry-Exc* portfolios. Furthermore, HML and BAB benchmarks sharply outperform all simulated portfolios with lower risk. We have to admit that we certainly fail to beat those benchmarks. Different constructions, approaches and restrictions may cause such big gaps of captured returns. Hence, this tells us that the industry level ETFs may not be good at exploiting possible low-beta anomalies, in contrast to the country level ETFs which is the best one.

These evidences partially support **Sub-Hypotheses 1 & 2**, namely that our hypothetical portfolios exhibit positive performance in mean returns across country and industry, and that the country effect is larger than the industry effect in the anomaly. Sharpe ratios and alpha measurement from regression model will be discussed further to fully answer **Sub-Hypotheses 1 & 2**.

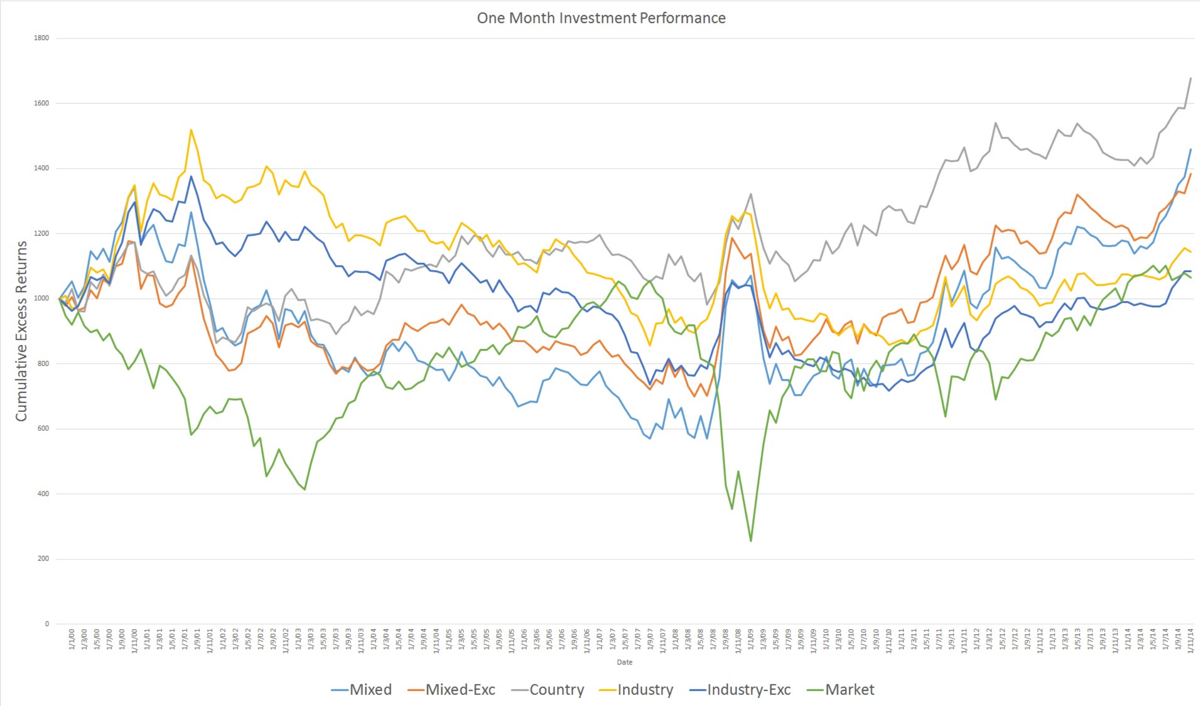
Table 2: Annualised Portfolio Returns & Standard Deviations-Full Sample

		Long Leg		Short Leg		Total		
		Return	StDev	Return	StDev	Return	StDev	#N
Mixed	One Month	0.04%	0.12	3.06%	0.26	3.11%	0.18	180
	Two Month	-0.15%	0.13	3.03%	0.26	2.87%	0.18	90
	Three Month	0.47%	0.13	2.36%	0.27	2.84%	0.19	60
Mixed-Exc	One Month	0.88%	0.13	1.70%	0.25	2.59%	0.15	180
	Two Month	0.92%	0.14	1.92%	0.25	2.85%	0.15	90
	Three Month	1.19%	0.15	2.04%	0.25	3.24%	0.16	60
Country	One Month	2.04%	0.17	2.53%	0.26	4.62%	0.13	180
	Two Month	2.14%	0.18	1.84%	0.26	4.02%	0.13	90
	Three Month	1.99%	0.19	2.25%	0.26	4.27%	0.13	60
Industry	One Month	0.28%	0.12	0.69%	0.22	0.96%	0.14	180
	Two Month	0.36%	0.12	0.41%	0.22	0.78%	0.14	90
	Three Month	0.34%	0.12	0.57%	0.23	0.92%	0.15	60
Industry-Exc	One Month	0.07%	0.14	0.50%	0.22	0.57%	0.12	180
	Two Month	0.13%	0.14	0.30%	0.22	0.43%	0.12	90
	Three Month	-0.09%	0.14	-0.08%	0.23	-0.17%	0.13	60

This table presents the annualised total mean returns, standard deviations of each portfolio in different rolling windows, and in long & short position. The definition of each portfolio is defined in Dataset & General Setting section. All data is using monthly log excess returns. The time horizon is January 2000 to December 2014.

In addition to mean returns and standard deviations, we have also looked at cumulative returns for all strategies. Figure 1 shows the cumulative returns of all portfolios and the benchmark cumulative excess returns since 2000 until 2014.

Figure 1: All Portfolios Cumulative Investment Performances on One-month Basis



This figure shows all cumulative performances of five portfolios in one-month rebalancing window vs. the benchmark index MSCI ACWI IMI. The initial investment starts at $1000. The time horizon is January 2000 to December 2014. All returns are monthly log excess returns.

Starting with an initial capital investment of $1000, the MSCI ACWI IMI generally underperformed all of our simulated portfolios until the end of 2003. The benchmark gradually rose and beat our portfolios, except the *Country* portfolio, starting in the third quarter of 2004 until 2007. Then, the market plummeted at the end of 2008. The *Industry* and *Industry-Exc* portfolio performed well in early 2000, followed by the *Country*, *Mixed* and *Mixed-Exc* portfolios respectively. The *Country* portfolio started to gradually outperform others in 2003 until now. The cumulative *Country* portfolio returns ended up at almost $1700, a 70-percent increase over 14 years. We can certainly observe that after the 2008-crisis, our strategies performed very well particularly the country level, the *Mixed* and *Mixed-Exc* portfolios also obtained benefits from the country level inclusion whereas the industry level grew at a much slower pace.

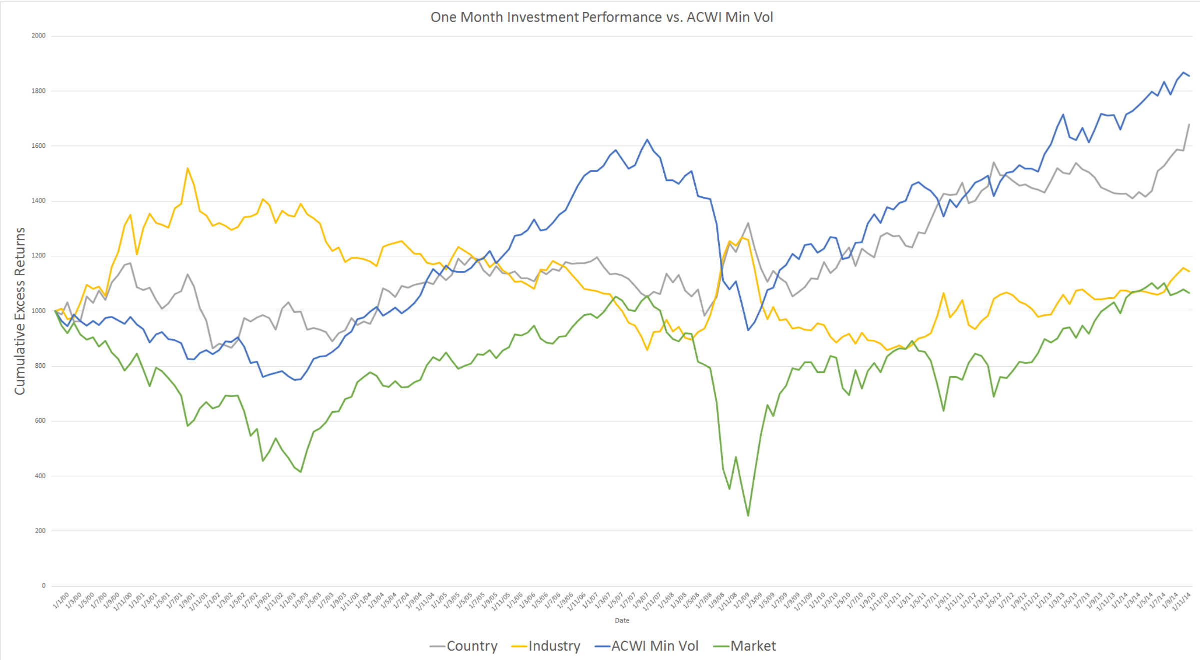
As we implemented the low-beta anomaly, which is claimed to be a low-risk based strategy, it is not surprising that we can confirm the low-risk characteristics in the two crises of 2002 and the Financial Crisis in 2008. All portfolios revealed their hedging powers against the MSCI ACWI IMI as we clearly see positive return spikes over time in both 2002 and 2008. By the strategy construction, we entered short positions in high-beta assets and long positions in low-beta assets, so we obviously outperformed during the downtrend. After the benchmark hit the bottom, the performances of low-beta portfolios would drop for a while before picking up to outperform again. We believe that the rebalancing with new asset selection is the reason which took up one to two quarters.

5.2 COMPARISON WITH LOW-VOLATILITY PRODUCTS

Furthermore, we also compared the country and industry one-month cumulative excess returns with a real low-volatility index, the MSCI ACWI Minimum Volatility to obtain a clearer picture of both effects in Figure 2. However, in Figure 3, we do the same but with iShares MSCI ACWV, a low-volatility ETF product. Note that the ETF data is available only from 2011 onwards on DataStream.

According to Figure 2, the MSCI ACWI Minimum Volatility index (ACWV) was performing very well unlike the normal the MSCI ACWI IMI. It dramatically outperformed every portfolio in 2004 until the crisis hit in 2008, and increased by 80% by the end of 2014, higher than the *Country* portfolio. Yet, there was a glamour period for our simulated strategies, from 2000 to 2004, we performed better with both the *Industry* and *Country* portfolios. Ultimately, our strategies beat the market-cap ACWI IMI, but we could not outperform the ACWV index in recent times.

Figure 2: Cumulative Investment Performances on One-month Basis vs. MSCI ACWI Minimum Volatility Index

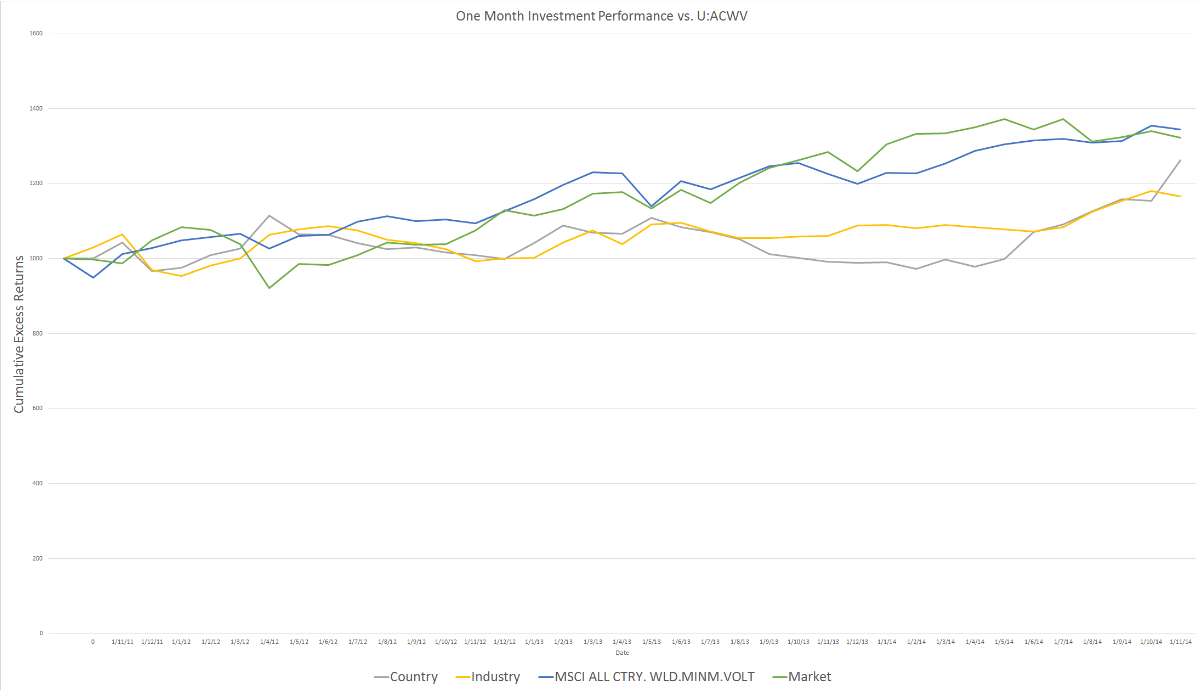


This figure shows cumulative performances of Country & Industry portfolios in one-month rebalancing window vs. the benchmark index MSCI ACWI IMI & MSCI ACWI Minimum Volatility. The initial investment starts at $1000. The time horizon is January 2000 to December 2014. All returns are monthly log excess returns.

Although, the *Country* and *Industry* portfolios offered higher returns in the crisis for a brief period, the MSCI ACWV seized a great bull run later while the country level portfolio was trying to catch up, however especially the industry level portfolio laid low.

Looking into a smaller time horizon from an ETF perspective, Figure 3 shows a comparison to an actual low vol ETF. However, as many ETFs have only become available recently, we only present a comparison from 2011 onwards. Both portfolios under-perform the MSCI ACWI IMI as well as the iShares MSCI ACWV. Both *Country* and *Industry* delivered roughly 0% just until 2014 when they started to rise again, but not as high as the benchmarks.

Figure 3: Cumulative Investment Performances on One-month Basis vs. iShares MSCI ACWV



This figure illustrates cumulative performances of Country & Industry portfolios in one-month rebalancing window vs. the benchmark index MSCI ACWI IMI & iShares MSCI ACWV. The initial investment starts at $1000. The time horizon is November 2011 to December 2014. All returns are monthly log excess returns.

The iShares ACWV ETF is based on the MSCI ACWI Minimum Volatility index and both are constructed from the global security-level covariance matrix with an optimiser to achieve the lowest absolute idiosyncratic risk. It is interesting to see that the *Country* portfolios, constructed with a very different approach, could deliver a similar direction though a lower magnitude in returns, which is less likely in the *Industry* portfolios. Findings in Figure 2 & 3 also support that the country effect surpasses the industry effect in the low-beta anomaly even though they fail to beat MSCI All Country World Minimum Volatility and the iShares ETF.

5.3 SHARPE RATIO

According to Blitz and van Vliet (2011), Sharpe ratio is an appropriate measure of risk-adjusted returns for this strategy. In Table 3, we notice that all portfolios deliver positive total Sharpe ratios, except the *Industry-Exc* portfolio; furthermore, we also divide the ratios into long and short leg to observe the source of risk-adjusted return.

This section is devoted to answer **Sub-Hypothesis 1 & 3** on whether the Sharpe Ratio of our portfolios' outperform the Sharpe ratios of the benchmark as well as covering the return origin. Furthermore, the high-beta assets Sharpe Ratios should be greater than the low-beta assets Sharpe ratios, reflecting better risk-adjusted returns due to the anomaly. Our Sharpe Ratio numbers are derived on an annualised basis, using annualised mean returns and annualised standard deviations.

From a Sharpe Ratio perspective, the *Country* low-risk portfolios have annualised Sharpe ratios of 0.34, 0.31 and 0.33 on different rolling basis respectively. The geographical bet is the best performer in risk-adjusted performance measurement compared with other portfolios and the market benchmark, MSCI ACWI IMI, which yields only 0.03 in general. The summary of the benchmarks Sharpe ratios is presented in Table 5 in Appendix 1. The *Mixed-Exc* is the second runner with Sharpe ratios of 0.17 to 0.20 whereas the *Mixed* portfolio is slightly lower. The industry level portfolios are worse than the others, both provide Sharpe ratios lower than 0.03, but still beat the benchmark in every rolling windows except the *Industry-Exc* three-month window which has a small negative Sharpe ratio of -0.01. If we compare them with SML, HML and BAB factors for risk-adjusted return measurement, we are far from victory. Only the *Country* portfolio can outperform the SMB Sharpe ratios in all rebalancing times since they are lower than 0.30 and range from 0.24 to 0.28. HML offers Sharpe ratios of 0.69 to 0.85 and BAB has the highest Sharpe ratios from 1.09 to 1.21; both present a decreasing pattern in Sharpe ratios where one-month performance is the greatest. We observe this pattern in the *Mixed*, *Country*, *Industry*, and *Industry-Exc* portfolios.

Table 3: Annualised Sharpe Ratio-Full Sample

		Sharpe Ratio		
		Long Leg	Short Leg	Total
Mixed	One Month	0.00	0.12	0.17
	Two Month	-0.01	0.12	0.16
	Three Month	0.04	0.09	0.15
Mixed-Exc	One Month	0.07	0.07	0.17
	Two Month	0.06	0.08	0.19
	Three Month	0.08	0.08	0.20
Country	One Month	0.12	0.10	0.34
	Two Month	0.12	0.07	0.31
	Three Month	0.10	0.09	0.33
Industry	One Month	0.02	0.03	0.07
	Two Month	0.03	0.02	0.06
	Three Month	0.03	0.02	0.06
Industry-Exc	One Month	0.01	0.02	0.05
	Two Month	0.01	0.01	0.04
	Three Month	-0.01	0.00	-0.01

The table exhibits long leg, short leg and annualised total Sharpe ratios of five portfolios with three different rolling windows. The time horizon is January 2000 to December 2014. The Sharpe ratio is calculated from an annualised average return divided by an annualised standard deviation.

We notice mixed findings for our expectation that the long positions of low-beta assets will have a lower Sharpe ratio than short positions. However, most portfolios do not follow this anticipation. Only the *Mixed* portfolios follows the trends containing higher Sharpe ratios in the short leg which contains high-beta assets; this portfolio earns more from the short side than the long side. The rest perform almost equally between the two legs of Sharpe ratios.

In conclusion, the results are positive where the *Country* has the highest Sharpe ratio ranging from 0.31 to 0.34 while the industry level portfolios are the worst performers. All can obviously beat the market-cap benchmark, except the three-month

Industry-Exc bet. Risk-adjusted performances in each leg are uncertain;only the long leg in *Country* is greater than the short leg. Thus, these mentioned findings can partially fulfil **Sub-Hypothesis 1** because we generally found positive Sharpe ratio measurement among simulated portfolios. Thus following a similar trend as in Section 5.1, and hence supporting **Sub-Hypothesis 3**.

Ultimately, we would like to summarise the behavioural explanations for mean returns and Sharpe ratio performances. As we learnt from articles written by Baker, Bradley and Wurgler (2011), Frazzini and Pedersen (2014) and Baker, Bradley and Taliaferro (2014) there are several behavioural actions that could lead both retail and institutional investor to overweight high-beta assets and obtain lower expected returns. The findings support **Sub-Hypothesis 3** that the short leg position generally dominates the long leg position owning to the limit to arbitrage by institutional investors. Portfolio managers tend to bid up high-beta assets and encounter crowded investments as well as low future returns but discourage to exploit the mispricing because they have to invest according to several fund requirement mandates such as no leverage, no short position, and no investment in small size. Another behavioural explanation rather than the limits to arbitrage is an overconfident heuristic. Optimistic and overconfident investors towards growth forecasts and high expected returns are prone to overweight in emerging markets which have high β and underweight developed markets which have low β. This leads to the overpriced emerging markets and underpriced developed markets. The *Country* portfolio benefits from this inefficiency because we long and short positions oppositely from the market participants' expectations and limits to arbitrage conditions.

The limits to arbitrage and overconfident bias theories also apply to the industry universe similarly as to the country universe, as we have seen higher returns in the short leg than in the long leg. So we exploit the crowded trades, yet the performances are not really strong in both legs. We believe that is due to the narrow dispersion of betas in the *Industry* portfolios projecting the perceived risk among market participants on the industry level. Interestingly, the range of industry beta is two with a maximum of 2.2 and a minimum of 0.2. The industries beta mean is only one. The more extreme case is in the country assets where the beta has a range of four with a maximum of 4.1 and a minimum of 0.1. The countries beta mean is 1.2, slightly higher than the industries beta mean. It means that the industry beta is less mispriced than the country beta. These evidences also explain the *Mixed* portfolios where the long leg holds more industries and the short leg holds more countries. Consequently the *Mixed* universe portfolios present higher returns in the short side than the long side because we exploit the larger inefficient country effect rather than the smaller inefficient industry effect.

All in all, our portfolios will have higher returns in short positions since we are going against other market participants to obtain high future returns from overpriced assets, especially country indices. We also earn from the undervalued countries in the long leg because the scale of mispricing in the country universe is larger while the scale of mispricing in the industry universe is smaller yielding returns around zero.

5.4 REGRESSION MODELS

The following section contains an analysis of the 45 regressions we ran to establish if the portfolios return alphas and if they did, to dissect what the origin of these alphas was and if they were persistent over time. The full results of the regressions can be found in section 7.2. We will examine one strategy by another, analyse each one over time and will start with the CAPM followed by the Three-Factor model and last by a full model combining the Three-Factor model with the BAB factor. Please note that the alphas in the Appendix are not annualised, where as for comparison reasons we annualise the alphas. Notice that our regressions illustrate mixed findings of coefficients especially for SMB and HML in different windows.

The *Mixed* portfolio generates alphas of 3.41%, 2.43% and 0.00% using a one-month window respectively, in the three different regression models. The two- and three-month windows provide slightly lower alphas in the CAPM model; however, the alphas increase to 3.41% and 3.98% respectively, when using the F-F Three-factor model. The alphas of the one-month, two-month and three-month windows drop by

2.43%, 1.47% and 2.49% when including the BAB factor. Additionally one can observe negative market betas ranging from -0.58 to -0.76, they seem to decrease with longer time frames, all market betas are significant. The *SMB* betas range from -0.21 to -1.07, all of the one-month and three-month betas are significant at 10%. The *HML* betas are on average slightly positive and in the range of -0.04 to 0.19, none is significant. Lastly the *BAB* betas are between 0.16 and 0.30 and the one-month beta is significant.

The *Mixed-Exc* portfolios perform slightly worse compared to the *Mixed* portfolios, when comparing alphas. The one-month alphas are 2.92%, 1.57% and -0.36%. Unlike the *Mixed* portfolio alphas, the *Mixed-Exc* alphas increase over the different time horizons when using the CAPM rather than decrease. The Three-factor regression alphas are all worse compared to the *Mixed* portfolio counterparts, but increase with longer investment windows just like in the *Mixed* portfolio. And the alphas of the *BAB* regression are all worse. Again the market beta is negative for all nine regressions in range of -0.44 to -0.63, all of which are highly significant. The *SMB* betas are very similar to the betas in the *Mixed* portfolio and are between -0.09 and -0.72, the three-month *SMB* betas are significant at 5%. The HML betas also follow a similar pattern as in the Mixed portfolio and range from 0.03 to 0.22, where the one-month Three-Factor beta is significant. The *BAB* are between 0.14 and 0.27, of which the first month beta is significant.

The *Country* alphas outperform all alphas of both the *Mixed* and the *Mixed-Exc* portfolios. The one-month alphas are 4.78%, 4.66% and 2.67% for the different models respectively. Both the CAPM and the Three-factor model alphas are significant at 10%. The two-month alphas are 4.27%, 4.71% and 2.49%, thus similar to the one-month alphas. Again the Three-Factor alpha is significant at 10%. The CAPM alpha for the three-month window is slightly higher than the two-month alpha; however, the Three-factor model alpha is a lot higher at 5.76%, the Three-factor model alpha is significant at 10%. The betas mostly seem to follow the same pattern as in the two previous portfolios. The market betas are always negative and significant, the *SMB* betas are around zero in the one- and two-month windows but highly negative and significant in the three-month investment window, the *BAB* betas are always positive and always significant. However the *HML* betas are quite different, in the way that they are always negative in the two- and three-month windows, and even significant at 10% in the the three-month full model. In that way the *Country* portfolio seems to be quite similar to a *Momentum* strategy, which also seems to be a good hedge against the Three-Factor model (Dahlquist, 2015).

The *Industry* portfolio alphas are all worse than of the previous portfolios. All the CAPM alphas are between 1.08% and 1.21%. The Three-factor model alphas are between -0.18% and -0.96%, the full model alphas are between -1.08% and -3.19%. Otherwise all market betas are negative and significant. All *SMB* betas are negative and significant. All of the *HML* betas are positive and at a 10% level significance, except the two-month full model beta which is not significant. All *BAB* betas are positive and are significant in the one- and two-month windows.

The *Industry-Exc* portfolios underperform almost all other alphas, where the one-month alphas are 0.72%, -0.96% and -2.26% respectively; none is significant. It does not even outperform the normal *Industry* portfolio. Besides this underperformance, we see similar trends as in the the other portfolios. Firstly, all the market betas are negative and significant. Secondly, all *SMB* betas are negative and significant like in the previous regressions. All *HML* betas are positive, and both the one-month and the three-month betas are significant. Lastly all *BAB* betas are positive, and the one-month and two-month results are significant.

Thus, we see several similar patterns in the different strategies. Starting with alpha, we can see that the three-factor model explains some of the alpha in 11 out of 15 cases, i.e. some of the mispricing. However especially in the *Mixed* and in the *Country* portfolios it does not explain alpha over longer time horizon, i.e. alphas increase in the two- and three-month windows when adding *SMB* and *HML* factors. In most cases one can see a highly negative *SMB* beta and a relatively low *HML* beta, apart of in the *Country* portfolio where both are either negative (three-month window) or the *HML* factor is negative and the *SMB* is around 0. Thus, especially the *Country* portfolio seems to be a good hedge against both *SMB* and *HML* over a three-month period, which increases the alpha, thus the excess return is not explained by risk factors. In the cases where the Three-Factor model does explain some of the alpha, it is at most 2.16% in the one-month *Industry* portfolio.

The *BAB* factor is a very different story, it explains at least 0.72% of the alpha and at most 3.05%. Even though we include the *BAB* factor, many alphas stay positive, namely the alphas of the *Mixed, Mixed-Exc and Country* portfolios in all windows. However, the positive alphas in the *Mixed* and Mixed-Exc portfolios are probably due to the contribution of the country indices.

There seem to be no big differences in the CAPM alpha over time, only in the three-month *Industry-Exc* portfolio can one observe a big drop from 0.66% to 0.04% when moving from two- to three-month windows. However, when analysing the Three-Factor model alphas, there is an increase in alpha when moving from the one-month windows to the two- and three-month windows. The increases in the *Country* portfolio are 0.49% and 0.82% respectively. Similar trends can be seen in the *Mixed* and *Mixed-Exc* portfolios. Thus, it might be a good idea to investigate longer investment windows in future research.

We can clearly see that the strategy generates alphas to a certain extent, and that especially the *Country* alphas are quite high as well as significant. However, the industry strategies do not seem to provide any alphas different from zero. Thus, the results further strengthen the hypothesis that the *Country* alphas outperform both Industry strategies. Therefore they partially support the **Main Hypothesis** and **Sub-Hypothesis 2**.

Looking closer at the betas of the different factors, we also find several similarities across the different portfolios. Firstly all market betas are negative as well as significant, as would be expected by the portfolio construction.

Secondly, the *SMB* beta is mostly negative, only the one- and two-month *Country* windows do become slightly positive (up to 0.06). Thus this would in partially support **Sub-Hypothesis 4**. Additionally note that the *SMB* betas seem relatively low in most of the one- and two-month windows when compared to the three-month windows. That could simply mean that it takes longer time for information to materialise, i.e. that the market underreacts and that the longer one waits the more opposite our strategy is of a *SMB* strategy.

Thirdly, **Sub-Hypothesis 4** also states that Three-factor loadings can be captured in the model, and that HML betas should be positive. Both only seem supported in the *Industry* portfolios but not in the *Country* portfolios. Thus **Sub-Hypothesis 4** is only partially supported. The negative *HML* betas and increases in alpha in the *Country* strategy could again be explained by the composition of the *Country* portfolio. A negative beta would indicate that the strategy is opposite to a *HML* strategy. *HML* strategies invest in high Book-to-market (B/M) firms and short low B/M firms. Thus our short and long positions have opposite characteristics. For example, many of the countries in our long portfolio are either developed countries where services traditionally contribute a large amount to GDP such as the UK, Denmark and Switzerland or emerging countries such as Indonesia, the Philippines and Colombia, thus going long in countries which we would expect to have lower B/M. The indices which are shorted are either countries which traditionally have a higher contribution from industrial activity such as Germany and China or countries which are perceived to be risky such as Greece, Brazil or Russia; thus going short in countries with high B/M. Furthermore the *HML* betas drop when adding the *BAB* factor, thus signalling that the *BAB* factor is correlated with the *HML* factor, as shown by previous research (Hsu and Li, 2013).

Lastly, **Sub-Hypothesis 5** states that the *BAB* factor will explain large portions of the abnormal return, this seems to be supported by all five different strategies; however, the positive alphas of the *Country* portfolios seem to indicate that some of the alpha are beyond the regular *BAB* factor. Interestingly the *BAB* betas are mostly significant at shorter time horizons, this could for example be due to the fact that the *BAB* factor was originally designed for one-month periods (Frazzini and Pedersen, 2014).

5.5 LIMITATIONS AND FUTURE RESEARCH

There are obviously many ways to extend our study and thus extend it in future research. Firstly, the procedure of beta estimation such as scaling or shrinking beta and different sorting techniques could lead to different results.

Secondly, different time horizon of data may also cause some varying findings not in line with previous literature, especially as it appears that the strategy works better with longer horizons in the *Country* portfolios, which is contradicting the research by Frazzini and Pedersen (2014).

Thirdly, we use ETF proxies from MSCI equity indices which are common for ETF tracking, but still not the real ETF data. We do not consider any tracking errors, liquidity risk and operational costs of our portfolio performances; furthermore, tax legislation, bid-ask spread and trading turnover are other important issues which may hinder positive performances. Therefore, one should either consider these or try to use actual ETF data. Moreover, the industry portfolios are limited, especially when considering the *Industry-Exc* portfolio, thus extending the industry horizon might alter the results.

Lastly, means to make it less of a paper portfolio but more applied could be to replace the F-F Three-Factor model with actual traded returns such as the SP 500 minus risk free, Russel 2000 minus SP 500 and the Russel 3000 minus Russel 3000 growth (Cremers et al., 2012). Furthermore, as described before, it is difficult to truly benefit from the short leg due to limitations to arbitrage. Thus, one might want to extend the research by instead over and under weighing the long and short positions.

Additionally to applying these changes to the strategy to make it more realistic and applicable, one can also research more on the academic side. Firstly, there is room for further studies on the effect of a particular continent, a country or an industry on the low-beta anomaly. Moreover, one especially interesting point could be to further investigate the origins of beta anomalies by; for example, investigating the country and industry effect on a *BAB* strategy on an individual stock level. This could also be extended into regression analysis of the long and short leg, thereby for example clarifying why the *Country* long leg performs as good as the short leg.

One could also combine these changes with a different portfolio construction itself. Minimum variance tends to be most commonly used while we have also seen a Brownian motion approach from Messikh and Oderda (2010).

Furthermore, restricting constraints such as leverage, self-financing or market-neutral could be relaxed for dissimilar perspective. Yet what limits the anomaly exploitation are worth mentioning as seen in (Li et al., 2014). They can also look deeper into other asset classes, similarly as Frazzini and Pedersen (2014) to confirm robustness.

Even though a Momentum strategy seems to have similar betas as our *Country* portfolios, there seems to be no correlation between these two strategies (de Carvalho et al., 2012) as would be expected from the different ways to construct the portfolio; however, it might still be interesting to investigate if a combination would deliver good results.

Lastly, one should take a more careful look at the riskiness of the strategy, it would for example be interesting to see to what extend the betas are stable or time varying, as much of our research was during crises. This could also be combined with research on the currently popular low-vol products and how these products perform in crises. Additions could also include Value-at-Risk, maximum drawdown, drawdown duration and expected shortfall to be able to estimate the downside of the strategies.

6

CONCLUSION

We have presented five different compositions of low-beta strategy portfolios and analysed their performances among country and industry indices. The paper starts with asking questions about the possible implementation and the outperformance of the low-beta strategy when individual investors invest in ETFs of countries and industries around the world. Then, the hypotheses are extensively developed to test the strategy's outperformances and relationships with its benchmarks, additionally we test the performance attributions with the F-F Three-factor model and the BAB factor.

We show that it is possible to implement a low-beta strategy with a naive portfolio construction (equal-weighting) reflecting a retail investor perspective. The simulated portfolios with one- to three-month rebalancing windows mostly offer higher total mean returns, and Sharpe ratios with lower standard deviations compared to the benchmark index, especially the *Country* portfolios which are the best performers. We find poorer returns in the *Industry* space, and conclude that the anomaly in countries is greater than in industries. The returns are mostly from the short leg of overpriced indices rather than the long leg of underpriced indices. Only the *Country* has comparable long and short leg returns, we assume the wide dispersion of betas between the two legs is the major reason. The portfolios display negative relationships with the benchmark market so that it can be used as a hedging strategy for investors. Furthermore, the Betting–Against–Beta (BAB) factor can positively explain performances in every portfolio, whereas we have mixed results in the Three-factor model. Yet, we find significant positive alphas on the country level, but find none on the industry level.

There are several logical reasons worth mentioning to explain the low-beta anomaly in countries and industries. Behavioural explanations with the heuristics and limits to arbitrage seem plausible. Irrational investors tend to tilt or overweight high-beta assets because of an overconfident bias, accessing leverage exposures, benchmarking, market-capitalisation size or short-selling by institutional investors can result in crowded investments and yield low expected returns for high risk stocks.

Thus, we can implement the low-beta strategy to exploit the market inefficiency especially on the country level ETFs as we have stronger magnitudes of the low-beta anomaly and positive performances than in the industry level ETFs. This paper would contribute the profound evidence to investors, portfolio managers, and financial advisers as an investment idea guidance, and definitely to academics as an empirical support in the finance research field.

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7

APPENDICES

7.1 APPENDIX 1 - SHARPE RATIO, MONTHLY MEAN RETURNS & STANDARD DEVIATION

Table 4: Sharpe Ratio-Benchmarks

		Sharpe Ratio
Market	One Month	0.03
	Two Month	0.03
	Three Month	0.02
SML	One Month	0.25
	Two Month	0.24
	Three Month	0.28
HML	One Month	0.85
	Two Month	0.75
	Three Month	0.69
BAB	One Month	1.21
	Two Month	1.18
	Three Month	1.09

The table exhibits annualised Sharpe ratios of various benchmark indices with three different rolling windows. The time horizon is January 2000 to December 2014. The Sharpe ratio is calculated from an annualised average return divided by an annualised standard deviation.

Table 5: Full Data List of Regional and Country Indices: Monthly Mean Returns & Standard Deviations

Index	Return	StDev
ACWI IMI	0.19%	0.05
Europe	-0.14%	0.056
EAEF	-0.13%	0.051
Pacific	-0.12%	0.048
EM	0.14%	0.067
Australia	0.35%	0.068
Austria	-0.15%	0.082
Belgium	-0.16%	0.072
Canada	0.28%	0.061
Denmark	0.43%	0.061
Finland	-0.64%	0.095
France	-0.16%	0.063
Germany	-0.09%	0.071
Hong Kong	0.11%	0.062
Ireland	-0.57%	0.072
Israel	-0.05%	0.067
Italy	-0.35%	0.070
Japan	-0.24%	0.048
Netherlands	-0.16%	0.064
New Zealand	0.23%	0.065
Norway	0.12%	0.082
Portugal	0.55%	0.068
Singapore	0.17%	0.069
Spain	0.00%	0.074
Sweden	-0.10%	0.078
Switzerland	0.21%	0.049
UK	-0.22%	0.049
US	0.05%	0.045
Brazil	0.12%	0.099
Chile	0.36%	0.065
China	0.25%	0.081
Colombia	1.36%	0.086
Czech Rep	0.47%	0.080
Egypt	0.32%	0.095
Greece	-1.53%	0.104
Hungary	-0.13%	0.105
India	0.34%	0.089
Indonesia	0.68%	0.098
Korea	0.24%	0.088
Malaysia	0.48%	0.052
Mexico	0.16%	0.071
Peru	0.89%	0.087
Philippines	0.34%	0.083
Poland	-0.16%	0.095
Russia	0.08%	0.106
Qatar	n/a	n/a
South Africa	0.31%	0.075
Taiwan	-0.07%	0.075
Thailand	0.36%	0.089
Turkey	-0.18%	0.140
UAE	n/a	n/a

Table 6: Full Data List of Industry Indices: Monthly Mean Returns & Standard Deviations

Index	Return	StDev
ACWI Energy	0.22%	0.059
ACWI Consm. Discretionary	0.08%	0.052
ACWI Consm. Staples	0.33%	0.035
ACWI Financials	-0.09%	0.062
ACWI Health Care	0.33%	0.037
ACWI Insdutrials	0.15%	0.053
ACWI Materials	0.16%	0.066
ACWI Utilities	0.13%	0.040
ACWI IT	-0.35%	0.073
ACWI Telecom Services	0.34%	0.073
World Energy	0.24%	0.057
World Consm. Discretionary	0.08%	0.051
World Consm. Staples	0.33%	0.034
World Financials	-0.10%	0.062
World Health Care	0.32%	0.037
World Insdutrials	0.17%	0.052
World Materials	0.19%	0.065
World Utilities	0.14%	0.040
World IT	-0.37%	0.073
World Telecom Services	-0.60%	0.053
EM Energy	0.21%	0.084
EM Consm. Discretionary	0.34%	0.073
EM Consm. Staples	0.46%	0.053
EM Financials	0.21%	0.073
EM Health Care	0.68%	0.049
EM Insdutrials	0.05%	0.074
EM Materials	0.09%	0.079
EM Utilities	0.27%	0.060
EM IT	0.02%	0.081
EM Telecom Services	-0.08%	0.060

Table 5 & 6 exhibit monthly mean returns and average standard deviation among regions, developed and emerging countries, as well as ACWI, developed and emerging industries. The time horizon is January 2000 to December 2014. These present return-risk profiles of all time-series that have been used in the simulated portfolios.

7.2 APPENDIX 2 - REGRESSIONS

Table 7: One-month Regressions

Dependent Variable		Mixed		Mixed-Exc.		Country		Ind.		Ind-Exc.	
						Coef. (P)					
CAPM	Cons	0.28%	(0.29)	0.24%	(0.30)	0.39%	(0.08)	0.10%	(0.64)	0.06%	(0.74)
	Market	-0.75	(0.00)	-0.62	(0.00)	-0.49	(0.00)	-0.57	(0.00)	-0.43	(0.00)
Three Factor	Cons	0.20%	(0.47)	0.13%	(0.64)	0.38%	(0.09)	-0.08%	(0.68)	-0.08%	(0.67)
	Market	-0.76	(0.00)	-0.63	(0.00)	-0.49	(0.00)	-0.58	(0.00)	-0.44	(0.00)
	SMB	-0.23	(0.08)	-0.13	(0.28)	0.04	(0.71)	-0.37	(0.00)	-0.35	(0.00)
	HML	0.19	(0.12)	0.22	(0.04)	0.01	(0.89)	0.41	(0.00)	0.33	(0.00)
Full Model	Cons	0.00%	(1.00)	-0.03%	(0.92)	0.22%	(0.36)	0.10%	(0.64)	-0.19%	(0.34)
	Market	-0.71	(0.00)	-0.59	(0.00)	-0.46	(0.00)	-0.53	(0.00)	-0.41	(0.00)
	SMB	-0.34	(0.03)	-0.21	(0.09)	-0.04	(0.75)	-0.46	(0.00)	-0.41	(0.00)
	HML	0.01	(0.93)	0.08	(0.48)	-0.13	(0.21)	0.24	(0.01)	0.23	(0.00)
	BAB	0.30	(0.01)	0.23	(0.04)	0.24	(0.00)	0.28	(0.00)	0.17	(0.02)

Table 8: Two-month Regressions

Dependent Variable		Mixed		Mixed-Exc.		Country		Ind.		Ind-Exc.	
						Coef. (P)					
CAPM	Cons	0.54%	(0.34)	0.52%	(0.28)	0.70%	(0.12)	0.18%	(0.68)	0.11%	(0.79)
	Market	-0.67	(0.00)	-0.53	(0.00)	-0.44	(0.00)	-0.53	(0.00)	-0.38	(0.00)
Three Factor	Cons	0.56%	(0.35)	0.41%	(0.44)	0.77%	(0.10)	-0.03%	(0.94)	-0.07%	(0.86)
	Market	-0.67	(0.00)	-0.54	(0.00)	-0.43	(0.00)	-0.54	(0.00)	-0.39	(0.00)
	SMB	-0.21	(0.37)	-0.09	(0.61)	0.06	(0.72)	-0.36	(0.00)	-0.35	(0.00)
	HML	0.04	(0.87)	0.12	(0.43)	-0.07	(0.55)	0.27	(0.06)	0.24	(0.08)
Full Model	Cons	0.32%	(0.63)	0.19%	(0.76)	0.41%	(0.41)	-0.33%	(0.49)	-0.33%	(0.45)
	Market	-0.66	(0.00)	-0.53	(0.00)	-0.42	(0.00)	-0.53	(0.00)	-0.38	(0.00)
	SMB	-0.26	(0.29)	-0.14	(0.45)	-0.02	(0.90)	-0.43	(0.00)	-0.41	(0.00)
	HML	-0.03	(0.90)	0.06	(0.71)	-0.17	(0.17)	0.19	(0.17)	0.17	(0.21)
	BAB	0.16	(0.28)	0.14	(0.32)	0.23	(0.02)	0.20	(0.05)	0.17	(0.04)

Table 9: Three-month Regressions

Dependent Variable		Mixed		Mixed-Exc.		Country		Ind.		Ind-Exc.	
		Coef.	(P)	Coef.	(P)	Coef.	(P)	Coef.	(P)	Coef.	(P)
CAPM	Cons	0.78%	(0.42)	0.86%	(0.32)	1.09%	(0.14)	0.30%	(0.65)	0.01%	(0.99)
	Market	-0.68	(0.00)	-0.51	(0.00)	-0.38	(0.00)	-0.63	(0.00)	-0.46	(0.00)
Three Factor	Cons	0.98%	(0.36)	0.80%	(0.40)	1.41%	(0.08)	-0.09%	(0.89)	-0.35%	(0.61)
	Market	-0.58	(0.00)	-0.45	(0.00)	-0.34	(0.00)	-0.56	(0.00)	-0.40	(0.00)
	SMB	-0.94	(0.00)	-0.60	(0.05)	-0.51	(0.07)	-0.66	(0.00)	-0.56	(0.00)
	HML	0.11	(0.60)	0.17	(0.40)	-0.05	(0.71)	0.37	(0.06)	0.33	(0.01)
Full Model	Cons	0.37%	(0.77)	0.23%	(0.85)	0.67%	(0.45)	-0.27%	(0.72)	-0.56%	(0.48)
	Market	-0.58	(0.00)	-0.44	(0.00)	-0.33	(0.00)	-0.56	(0.00)	-0.40	(0.00)
	SMB	-1.07	(0.00)	-0.72	(0.02)	-0.67	(0.01)	-0.70	(0.00)	-0.61	(0.01)
	HML	-0.04	(0.87)	0.03	(0.85)	-0.23	(0.07)	0.32	(0.01)	0.28	(0.02)
	BAB	0.29	(0.18)	0.27	(0.25)	0.35	(0.02)	0.08	(0.49)	0.10	(0.44)

Table 7-9 depict regression results of each portfolio tested with the CAPM, the F-F Three-factor model and the BAB factor. The numbers are coefficients, and their p-value are presented in parentheses next to the coefficient values. When p-value is below 0.05, it shows the statistical significance at 5% level.