Low-risk anomaly everywhere:
Evidence from equity sectors

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Abstract:

We give strong empirical evidence of a risk anomaly in equity sectors in a number of regions and countries of developed and emerging markets, with the lowest risk stocks in each activity sector generating higher returns than would be expected given their levels of risk, and the converse outcome for the riskier stocks. We believe this evidence is a likely consequence of the fact that equity analyst and active fund managers tend to specialize in particular sectors and to mainly select stocks from those sectors. Additionally, constraints restricting the deviation of sector weights in active portfolios against their market capitalization benchmarks are often used by active fund managers, in particular by quantitative managers which tend to go as far as being sector neutral. As a consequence, we find that sector-neutral, low-risk approaches appear more efficient at generating alpha than non-sector neutral approaches, with the latter showing strong sector allocation towards financials, utilities and consumer staples than sector neutral, at least when applied to developed countries in a global universe. We also discuss some properties of low-risk investing such as tail risk, turnover and liquidity.

JEL classification: G11, G12, G14

Keywords: low risk, low volatility, equities, factor investing, market efficiency, CAPM

Low-risk investing in equities has been in the spotlight in recent years probably due in particular to the disappointing performance of equity markets since the start of the new millennium and until the 2008 crisis. The main focus of low-risk investing is to reduce portfolio risk, defending the portfolio in equity market downturns, while capturing the positive alpha from low-risk stocks to improve risk-adjusted returns. Indeed, the positive alpha found in low-risk stocks explains why the Sharpe ratio of strategies invested in these stocks has been larger than that for the market capitalization index. Low-risk investing also naturally excludes the riskier stocks which have been delivering the poorest risk-adjusted returns and have had significant negative alpha.

Low-risk investing dates back to the seminal paper of Haugen and Heins (1972) with empirical evidence that between 1926 and 1969 portfolios systematically investing in U.S. low-volatility stocks would have delivered much larger returns than expected from their low level of beta, while portfolios invested in high-volatility stocks would have delivered returns much below what should have been expected from their high level of beta. Brennan (1971) and Black (1972) showed that the violation of one of the assumptions behind the Capital Asset Pricing Model (CAPM) – that investors have no constraints, e.g. on leverage or borrowing – is sufficient to reduce the slope of the relationship between returns and beta. Blitz (2014) has recently reviewed the academic literature and summarized the different effects that have been proposed by academics to explain the low-risk anomaly.

The low-risk anomaly appears almost universally. Haugen and Baker (2012) demonstrated empirically that it can be found in the cross-section of stock returns of almost all developed and emerging market countries in the world. The comprehensive empirical analysis of De Carvalho, Dugnolle, Lu and Moulin (2014) strongly suggests that the low-risk anomaly goes beyond equity markets and can also be found in the cross-section of bond returns of all major segments of fixed-income markets and regions. Their results show that portfolios invested in low-risk bonds with the lowest beta generated the largest positive alpha, while portfolios invested in the riskier bonds with the highest beta generated the most negative alpha. This result was found for government bonds, quasi & foreign government bonds, securitized & collateralized bonds, corporate investment-grade bonds, corporate high-yield bonds, emerging market bonds and aggregations of some of these universes, and for bonds in USD, EUR, GBP and JPY. Frazzini and Pedersen (2014) suggest that the low-risk anomaly is also observed in commodities, currencies and at top-down level in fixed income and equities, i.e. in the cross-section of the returns of currency forwards, index futures, equity and Treasury country indices, portfolios aggregated by ratings, and in the cross-section of all these put together. Baker, Brendan and Taliaferro (2014) have recently looked at the decomposition of the low-risk anomaly into top-down country and industry contributions and bottom-up contributions. They found a risk anomaly in the cross-section of country returns and, to a lesser extent, in the cross-sectional of industry returns. Asness, Frazzini and Pedersen (2014) gave stronger evidence of a low-risk anomaly in the cross-section of industry returns by using more granular industry definitions.

The low-risk anomaly is not only found in the cross-section of asset classes but also in the time series of asset class premiums and in the time series of factor premiums. Perchet, De Carvalho, Heckel and Moulin (2014) showed that the time series of asset class returns shows volatility clustering, i.e. the volatility forms two distinct volatility regimes, one with low volatility and high average returns and on with high volatility and low average returns, or even negative, for most asset classes. In turn, Perchet, De Carvalho and Moulin (2014) showed that the time series of value and momentum factor returns in equity, government bonds and currency markets also shows volatility clustering, with two distinct volatility regimes: higher returns for the low volatility regime and lower returns for the high volatility regime.

In this paper we aim i) to investigate the universality of the risk volatility anomaly by focusing on the cross-section of stock returns in equity sectors in developed countries and emerging market countries, in aggregate and at individual country level; and ii) to compare sector-neutral low-risk investing with the traditional sector-biased low-risk approaches that are typically over-exposed to defensive sectors.

We also aim to shed additional light on the results of Baker, Brendan and Taliaferro (2014), who found that the risk anomaly is stronger at stock level by neutralizing industry exposure than in the cross-section of industry returns, contrary to what should have been expected from the suggestion by Samuelson (1998) that stocks are priced more efficiently than industries because industries have fewer substitutes than stocks, an argument they used to motivate their research. The results of Asness, Frazzini and Pedersen (2014) also point in the same direction, i.e. that the risk anomaly can be more efficiently captured by neutralizing industry exposures than by investing at top-down level in low risk industries and avoiding the riskier industries. Moreover, we did not find any explicit effect that could explain these results in the available literature.

In fact, we will argue that one possible explanation comes from the active management industry and the way active managers tend to pick stocks for their active portfolios. This explanation is thus closely related to what Blitz (2014) calls “relative utility” and “agents maximize option value”, but is likely to be a consequence of the practicalities of how fund managers tend to operate and manage portfolios with the objective of out-performing a benchmark index.

LOW VOLATILITY OR LOW BETA?

Neither the stock volatility nor the stock beta is constant over time. Hence, low-risk investing requires periodic rebalancing to take into account that some stocks which have been low risk in the past may no longer be low risk in the future. A strategy periodically rebalancing the stock allocation towards the minimum variance portfolio is an example of a low-risk strategy that can be shown to have delivered higher risk-adjusted returns than expected from its low level of beta. However, as shown by De Carvalho, Lu and Moulin (2012), the minimum variance portfolio can be replicated by simple portfolio strategies based on equally overweighting low beta stocks and underweighting high beta stocks. We thus prefer to use simpler strategies that involve selecting stocks from risk rankings to build low-risk portfolios, rather than using minimum variance strategies.

Research on the low-risk anomaly often relies on building portfolios invested in a selection of stocks with the lowest ex-ante beta, e.g. Baker, Brendan and Taliaferro (2014) and Asness, Frazzini and Pedersen (2014), and often in a selection of stocks with the lowest ex-ante volatility, e.g. Baker and Haugen (2012) and Li, Rodney, Sullivan and Garcia-Feijóo (2014). We chose to use ex-ante volatility instead of ex-ante beta for the reasons listed below.

We built two strategies and applied them to the MSCI World Index[1] stock universe. In the first strategy, stocks are first ranked every month by their level of ex-ante beta[2] calculated at that point in time from a two-year rolling regression of the stock total returns in excess of cash against the total returns of MSCI World Index in excess of cash, with returns in USD. Every month we built an equally-weighted portfolio invested in the stocks with the lowest ex-ante beta at the start of the month holding this portfolio until the next monthly re-balancing. We kept only 10% of the stocks in the universe. The historical simulation of this strategy runs from January 1995 through August 2013 and its results are compared with a similar strategy, which differs only in the fact that instead of ex-ante beta we used a two-year rolling standard deviation of returns[2].

Low-volatility stocks have low beta because beta is simply the product of the stock volatility by the correlation of returns with the market returns divided by the market volatility. But not all low-beta stocks have low volatility. Some higher-volatility stocks can be low beta due to the low correlation with the market. If we look at the average overlap between the portfolios behind the two strategies we find that it is high, at 55%. This is in fact high knowing that there are about 1,700 stocks on average in the MSCI World index and that we retain only 10% of those stocks in each case. But despite being high, the universe of low-volatility stocks is not exactly the same as the universe of low-beta stocks. We also observe that the strategy based on low beta has a higher turnover at 19% (two-way) per month than the strategy based on low volatility at only 13%. That is a significant difference and shows that the persistence of beta is less strong than the persistence of volatility, which should have been expected since the beta will change in time not only because of changes in volatility but also because of changes in correlation with the index. We have thus included a third strategy whereby the selection is based on a Bayesian estimation of the beta, thus following the procedure proposed by Vasicek (1973), which aims at improving the estimation of beta.

The results of the simulations can be found in exhibit 1. We use US T-bill 3-month rates obtained via FactSet as the proxy for the risk-free rate and no transaction cost or market impact was considered. As we can see, the differences among the strategies are not large, in particular if we take into account the length of the back-test. Nevertheless, we find that when selecting the lowest beta stocks, the strategy delivers a slightly lower beta and alpha than when selecting the lowest volatility stocks. In turn, the volatility is slightly lower when selecting the lowest volatility stocks than when selecting the lowest beta stocks. Not surprisingly, we also find that the results based on a Bayesian estimation of the beta are closer to those based on volatility than those based on the standard beta estimation.

Exhibit 1: Annualized returns, volatility, Sharpe ratio, alpha and beta for monthly rebalanced low risk strategies based on ranking approaches using beta and volatility estimators. Selected low-risk stocks are equally weighted. World universe. Jan-95 – Aug-13.

	Low Beta		Low Volatility
	CAPM	Bayesian	
Annualized Excess return over Cash	7.6%	7.9%	8.1%
Volatility	11.4%	11.1%	10.9%
Sharpe Ratio	0.67	0.71	0.74
Annualized alpha	5.7%	6.0%	6.0%
Beta	0.52	0.51	0.55

Selecting low-volatility stocks generates much lower turnover, creates marginally more alpha and results in a beta that is almost as low as when selecting by low beta. For these reasons we shall use volatility instead of beta for the selection of stocks in the remainder of this paper.

An additional reason for using volatility instead of beta is the non-universality of beta. From a CAPM point of view the beta should be based on the market portfolio. But for a portfolio manager benchmarked against a segment of the market portfolio what really matters is the beta measured against the market capitalization-weighted portfolio for the stocks in that market segment. Thus, the relevant measure of beta is not the same for all market participants if we take into account their different objectives.

SECTOR-NEUTRAL LOW-RISK INVESTING

Motivation

The CAPM assumes that investors are risk-averse and maximize the expected utility of absolute wealth, caring only about the mean and the variance of returns. This is a large assumption which does not actually apply to all investors. Professional active portfolio managers are appraised on their performance relative to a benchmark index, typically a market-capitalization portfolio of a given segment of the equity market, usually a country or region. Consequently, these professional investors do not care about absolute wealth or risk, but only about the relative performance in excess of the benchmark and the tracking-error risk. They often have targets and constraints on the tracking-error risk they can take.

As argued by Falkenstein (2009), if CAPM was observed, active portfolio managers would then maximize their utility by investing in high-beta stocks instead of low-beta stocks. Under CAPM, given two stocks with the same level of tracking-error risk, one with high beta and one with low beta, the portfolio manager preference would necessarily be for the high-beta stock which, with a beta higher than one, would be expected to out-perform the market capitalization index in the medium to long term thanks to its higher exposure to the market risk premium. In turn, the low-beta stock, with beta below one, would be expected to under-perform the market capitalization index thanks to its low market exposure.

The higher demand for high-beta stocks created by these investors should push up the prices of such stocks and make cheaper the low beta stocks that are less in demand. As shown by Falkenstein (2009), the expected return for each stock is then the same in equilibrium. Even if these investors represent just part of the universal investor population and other investors maximize the expected utility of absolute wealth, a risk anomaly should still expected, even if less strong, as shown by Brennan (1993) and Brennan, Cheng and Li (2012).

A related explanation of the low-risk anomaly was proposed by Baker and Haugen (2012). They focus on the typical compensation structure of professional active portfolio managers and show that the incentive structures resemble a call option. The value of call options increases with volatility and thus, assuming that active portfolio managers seek to maximize the expected value of the call options upon which their compensation is based, they are incentivized to take risk and should prefer to invest in high-risk stocks than low-risk ones. Falkenstein (2009) goes further, arguing that since rewards are typically much larger for top quintile portfolio managers than for second quintile portfolio managers, the incentive to take risk and invest in risky stocks is heightened.

Baker and Haugen (2012) also argue that the investment teams responsible for selecting the stocks for actively-managed funds are usually incentivized to focus on high-risk stocks, mainly due to career pressure. It is those who select stocks with stellar performances that are more likely to be promoted, and stocks with stellar performances can be more likely found in the universe of riskier stocks, even if the average returns of the universe of all riskier stocks is shown to be poor. They are also under pressure to focus on stocks which are in the spotlight and receive above median coverage, the *hottest* stocks in the market, which are typically risky stocks. Discussions with lead portfolio managers and with clients are much easier when it comes to explaining the decision to invest in a given stock if they are also familiar with that particular stock. Finally, privately-owned asset management firms selling actively-managed funds have an incentive to generate more volatile fund performances, as discussed by Chevalier and Ellison (1997) and Sirri and Tufano (1998). This is because the funds with the top performance relative to peers, in particular following periods of good market performance, tend to receive the largest inflows. The relationship between fund flows and performance supports the idea that asset management firms should concentrate their efforts on high-beta funds to maximize their profits.

In conclusion, there is strong evidence that the way in which the active management industry operates creates strong demand for riskier stocks. But none of the authors above explores the practicalities of managing active funds. In particular, they do not take into account that, in most asset management firms managing active funds based on fundamental approaches, the stock selection is typically made by sector specialists who pick the stocks with the highest expected returns from their sector. There are reasons for this. Stocks from any given sector tend to be exposed to a number of common factors and are thus easier to compare. The decision behind stock selection is easier when apples are compared to apples. Analysts can also specialize and focus only on more manageable universes in terms of the number of stocks to cover.

Analysts involved in stock selection at asset management firms are nearly always organized by sector. And analysts involved in stock research in brokerage firms, providing company research to asset management firms, are also almost invariably organized by sector. We asked seven heads of research at large international brokerage firms[3] with bases in the U.S., Europe and Asia, how many of their clients operate on this basis and the answers suggested that the vast majority do. They also confirmed that the equity analysts at their brokerage firms are indeed also organized by sectors, much in line with their client base. When asked about the most commonly used sector definition used to delineate sector coverage we were told that even if the 10 sector GICS[4] definition is not always strictly used, for the most part, some relatively similar definition is employed with occasionally one or another sector broken into some of its constituent industries. Only one brokerage house highlighted that some clients tend to go down to the 24 industry GICS definition when managing portfolios benchmarked against broader indices.

Active portfolio managers tend to invest in a limited number of selected stocks from the investment universe to which they are assigned. Sector active weights in portfolios are often constrained as a crude way of managing tracking-error risk. When asked about how many of their clients tend to keep tight-to-moderate sector constraints, the brokerage firms gave essentially the same answer. When it comes to portfolio construction, quantitative active managers, those who rely on quantitative systematic approaches for stock-picking and which have represented a large portion of the actively managed funds market in the past seem invariably to use tighter sector constraints than fundamental managers, who follow the process described above. When asked to put a number behind their answer we were given results with some level of dispersion. In terms of average, the brokerage firms put at about 40% the percentage of fundamental active managers who impose strong-to-moderate controls on active sector exposures, while for quantitative active managers this figure rises to about 70%. Moreover, quantitative managers often seem to add constraints on the beta of their portfolios, restricting it to be above one for benchmarked funds and above zero for long-short portfolios.

We believe this evidence is supportive of the results of Baker, Brendan and Taliaferro (2014) and Asness, Frazzini and Pedersen (2014) and probably explains why their results are not in line with what should have been expected from the reasoning advanced by Samuelson (1998), i.e. that stocks are priced more efficiently than sectors or industries. The fact that the stocks are almost invariably picked using sector-based approaches and that a large percentage of portfolio managers apply some level of sector control when building their portfolios is consistent with a stronger risk anomaly in the cross-section of stock returns within each sector rather than in the cross-section of sector returns. The evidence collected from heads of research at brokerage firms points towards a more widespread use of the 10 sector GICS definition than the more granular industry definition used by either Baker, Brendan and Taliaferro (2014) or the sub-industries definition used by Asness, Frazzini and Pedersen (2014). For this reason we concentrate our research on sectors rather than industries or sub-industries.

Universality of the low-risk anomaly in equity sectors

In this section we present results from historical simulations designed to compare the return and risk of systematic strategies invested in the lowest volatility stocks of each sector with those from a similar strategy invested in the riskier stocks of the same sector. We run the analysis through a number of developed and emerging markets. We used the following list of indices:

- Developed countries: MSCI World Index (MSCI Inc.). From 1995[1].
- U.S.: S&P 500 Index (U.S. stock exchanges). From 1990.
- Europe: Stoxx Europe 600 Index (18 countries of the European region which today are Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom). From 1991.
- Japan: Topix 500 Index (Tokyo stock exchange). From 1993.
- Canada: S&P/TSX Composite Index (Toronto stock exchange). From 2004.
- Emerging Markets: MSCI Emerging Markets Index (MSCI Inc.). From 2002[1].

- China: CSI 300 Index (Shanghai and Shenzhen stock exchanges). From 2005.
- Brazil: IBrX Index (São Paulo stock exchange). From 2001.
- Taiwan: TWSE Index (Taiwan stock exchange). From 1993.
- South Korea: Kospi Index (Stock Market Division of South Korea exchange). From 2001.

For each universe of stocks defined by these indices we used the longest history available. Since not all indexes have the same starting dates, the results cover different periods varying from nine to 24 years. All data was collected using FactSet and the original data providers are indicated adjacent to each index.

In the historical simulations for each index above we started by estimating the historical volatility of each stock in the index universe at the end of each month from the past two years[2] of total returns in local currencies. The stocks in each sector were then ranked by their historical volatility[2] into three portfolios with the same number of stocks. Stocks in each of these three portfolios were then equally-weighted. We used the 10 sector definition of GICS[4]; in cases where the GICS classification was missing for a given stock, the FactSet industry classification was used instead. A small number of stocks that had neither GICS nor FactSet classification were excluded. Only sectors with at least 15 stocks were considered at each point in time, i.e. a minimum of five stocks in each tercile portfolio was required. Over the period of the simulation the portfolios were rebalanced once every month at the start of each month to take into account changes in the historical volatility.

In exhibit 2 we show the results from these historical simulations for developed markets and for emerging markets, respectively. In these exhibits we include the beta of the portfolio strategy invested in the lowest volatility stocks of each sector *i*, $\beta^i_{Lowest\,Risk}$, and the beta of the portfolio strategy invested in the highest volatility stocks of each sector *i*, $\beta^i_{Highest\,Risk}$. These two metrics were calculated from a regression over the entire period of the monthly returns, in excess of cash, of each portfolio strategy against the monthly returns, in excess of cash, of the underlying benchmark index which includes all sectors. The alpha generated from the lowest risk portfolio strategy for a given sector *i* can be estimated from the same regression:

$$\alpha^i_{Lowest\,Risk} = \left(R^i_{Lowest\,Risk} - R_{Cash}\right) - \beta^i_{Lowest\,Risk}\left(R_{Benchmark\,Index} - R_{Cash}\right) \quad (1)$$

with $R^i_{Lowest\,Risk}$ the annualized performance of the lowest risk portfolio strategy, $R_{Benchmark\,Index}$ the annualized performance of the market capitalization-weighted benchmark index and R_{Cash} the annualized return of money market instruments in the currency used. A similar equation can be used to estimate the alpha from the highest-risk portfolio strategies, $\alpha^{i}_{Highest\ Risk}$. The alpha in each sector, α^{j}, shown in these exhibits is given by:

$$\alpha^{i} = \frac{1}{\lambda}\left(\frac{\alpha^{i}_{Lowest\ Risk}}{\beta^{i}_{Lowest\ Risk}} - \frac{\alpha^{i}_{Highest\ Risk}}{\beta^{i}_{Highest\ Risk}}\right) \tag{2}$$

Here λ is the constant that is required for the volatility of the returns to be exactly 5% annualized over the entire period of the simulations:

$$r^{i}_{t} = \frac{1}{\lambda}\left(\frac{r^{i}_{t,\ Lowest\ Risk} - r_{t,\ Cash}}{\beta^{i}_{Lowest\ Risk}} - \frac{r^{i}_{t,\ Highest\ Risk} - r_{t,\ Cash}}{\beta^{i}_{Highest\ Risk}}\right) \tag{3}$$

r^{i}_{t} is the time series of monthly returns to a long-short portfolio, long the portfolio strategy with the lowest risk stocks and monthly returns $r^{i}_{t,\ Lowest\ Risk}$, with a weight $1/\beta^{i}_{LowestRisk}$, and short portfolio strategy with the highest risk stocks and monthly returns $r^{i}_{t,\ Highest\ Risk}$, with weight $1/\beta^{i}_{HighestRisk}$. The weights are such that the final beta of the long-short portfolio is exactly zero and the strategy has zero exposure to the benchmark index in the period[5]. We call this long-short portfolio strategy Low Volatility minus High Volatility (LVMHV).

The results in exhibit 2 show that the lowest-volatility stocks of each sector in developed countries tend to have a beta below one with the exception of those in the information technology sector for which the beta is close to one or even higher, as is the case for the U.S. and Europe. The highest-volatility stocks tend to have a beta above one with the exception of those from the defensive sectors, i.e. consumer staples, health care and utilities. In Canada, defensive sectors did not have enough stock representation for the analysis to be carried out. Here, the lowest-risk stocks from the materials sectors have a beta above one.

The alpha from the LVMHV strategy is positive for all sectors in the MSCI World index, the index with the largest number of stocks. In the other universes, with smaller number of stocks, the alpha is positive with a few exceptions like financials in the U.S. and Japan, energy and information technology in Europe and materials in Canada. All these levels of alpha are for exactly 5% annualized volatility. They are significant more often than not.

Exhibit 2: Alpha from LVMHV for different sectors and countries or regions. The beta of the long portfolio, invested in the lowest-volatility stocks, and the short portfolio, with the highest-volatility stocks, are also shown. In A) developed countries and in B) emerging countries. T-stat is estimated at 5% significance level. Jan-95 – Dec-14.

A)

	Developed Markets MSCI World Index 1995-2014			U.S. S&P 500 Index 1990-2014			Europe Stoxx Europe 600 Index 1991-2014			Japan Topix 500 Index 1993-2014			Canada S&P/TSX Composite Index 2004-2014		
	α	$\beta_{\text{Lowest Risk}}$	$\beta_{\text{Highest Risk}}$	α	$\beta_{\text{Lowest Risk}}$	$\beta_{\text{Highest Risk}}$	α	$\beta_{\text{Lowest Risk}}$	$\beta_{\text{Highest Risk}}$	α	$\beta_{\text{Lowest Risk}}$	$\beta_{\text{Highest Risk}}$	α	$\beta_{\text{Lowest Risk}}$	$\beta_{\text{Highest Risk}}$
	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Consumer Discretionary	2.6%	0.83	1.34	1.1%	0.89	1.42	2.0%	0.87	1.38	1.4%	0.71	1.17	1.3%	0.50	1.20
	(2.22)	(30.7)	(28.5)	(1.00)	(24.7)	(21.0)	(1.75)	(28.1)	(25.2)	(1.27)	(24.7)	(27.6)	(0.91)	(8.35)	(10.3)
Consumer Staples	4.5%	0.47	0.79	1.9%	0.49	0.80	1.5%	0.50	0.87	3.0%	0.40	0.76	-	-	-
	(3.89)	(13.4)	(21.1)	(1.81)	(12.2)	(20.2)	(1.33)	(13.7)	(20.4)	(2.65)	(12.0)	(16.8)			
Energy	2.0%	0.79	1.40	1.9%	0.74	1.18	-0.6%	0.86	1.19	-	-	-	3.9%	0.83	1.74
	(1.72)	(14.0)	(13.5)	(1.77)	(11.8)	(11.8)	(-0.5)	(17.7)	(12.1)				(2.71)	(12.3)	(15.7)
Financials	1.8%	0.82	1.51	-0.1%	0.88	1.58	2.3%	0.80	1.59	-1.0%	0.57	1.54	2.9%	0.63	1.05
	(1.49)	(24.3)	(24.9)	(-0.0)	(19.4)	(22.7)	(2.04)	(28.4)	(26.5)	(-0.8)	(13.5)	(12.4)	(2.03)	(12.9)	(14.4)
Health Care	2.0%	0.55	1.02	1.7%	0.68	0.96	3.0%	0.52	0.94	1.5%	0.48	0.69	-	-	-
	(1.70)	(15.3)	(15.0)	(1.56)	(15.7)	(17.1)	(2.79)	(13.6)	(16.2)	(1.36)	(10.0)	(13.3)			
Industrials	3.2%	0.75	1.31	2.7%	0.86	1.37	2.0%	0.78	1.37	0.6%	0.64	1.24	4.9%	0.76	1.30
	(2.73)	(26.3)	(27.9)	(2.60)	(24.4)	(24.7)	(1.82)	(25.3)	(28.1)	(0.53)	(23.1)	(24.6)	(3.43)	(11.9)	(10.5)
Information Technology	1.0%	1.05	1.89	0.6%	1.24	1.94	-0.3%	1.23	1.76	2.8%	0.92	1.37	-	-	-
	(0.80)	(26.4)	(16.9)	(0.49)	(28.2)	(18.1)	(-0.2)	(21.0)	(17.8)	(2.54)	(25.8)	(24.0)			
Materials	1.7%	0.91	1.30	0.9%	0.89	1.31	0.7%	0.88	1.31	0.7%	0.85	1.19	-0.9%	1.16	1.68
	(1.42)	(23.8)	(18.0)	(0.78)	(21.5)	(16.3)	(0.51)	(24.5)	(19.0)	(0.60)	(22.7)	(22.0)	(-0.5)	(14.5)	(9.72)
Telecom. Services	2.4%	0.73	1.44	-	-	-	2.8%	0.73	1.46	-	-	-	-	-	-
	(2.06)	(19.0)	(15.8)				(2.09)	(11.9)	(12.1)						
Utilities	2.7%	0.26	0.87	2.3%	0.29	0.72	2.4%	0.41	0.86	-	-	-	-	-	-
	(2.34)	(5.89)	(14.5)	(2.22)	(5.59)	(8.92)	(2.19)	(10.3)	(16.2)						

B)

	Emerging Markets MSCI Emerging Market Index 2002-2014			China Csi 300 Index 2005-2014			Brazil IBrX Index 2001-2014			South Korea Kospi Index 1994-2014			Taiwan TWSE Index 2001-2014		
	α (t-stat)	$\beta_{\text{Lowest Risk}}$ (t-stat)	$\beta_{\text{Highest Risk}}$ (t-stat)	α (t-stat)	$\beta_{\text{Lowest Risk}}$ (t-stat)	$\beta_{\text{Highest Risk}}$ (t-stat)	α (t-stat)	$\beta_{\text{Lowest Risk}}$ (t-stat)	$\beta_{\text{Highest Risk}}$ (t-stat)	α (t-stat)	$\beta_{\text{Lowest Risk}}$ (t-stat)	$\beta_{\text{Highest Risk}}$ (t-stat)	α (t-stat)	$\beta_{\text{Lowest Risk}}$ (t-stat)	$\beta_{\text{Highest Risk}}$ (t-stat)
Consumer Discretionary	3.0%	0.77	1.27	-0.2%	0.94	1.13	-	-	-	0.9%	0.78	0.91	4.6%	0.76	1.28
	(2.01)	(22.5)	(23.7)	(-0.1)	(18.4)	(21.1)				(0.74)	(21.5)	(12.5)	(3.24)	(18.6)	(16.9)
Consumer Staples	3.7%	0.59	0.90	3.6%	0.74	0.80	-	-	-	0.2%	0.68	0.82	5.8%	0.69	1.21
	(2.49)	(17.8)	(24.8)	(2.08)	(11.9)	(13.3)				(0.14)	(15.7)	(8.70)	(4.01)	(12.8)	(12.6)
Energy	3.2%	0.93	1.21	-0.2%	0.95	1.39	-	-	-	-	-	-	-	-	-
	(2.16)	(23.8)	(23.5)	(-0.0)	(21.0)	(14.5)									
Financials	2.9%	0.79	1.30	1.2%	0.91	1.19	-	-	-	-0.3%	0.79	1.31	-0.6%	0.82	1.58
	(1.97)	(28.3)	(31.0)	(0.70)	(22.2)	(22.9)				(-0.1)	(15.7)	(13.2)	(-0.4)	(14.4)	(11.6)
Health Care	3.1%	0.57	0.74	-	-	-	-	-	-	2.4%	0.75	0.81	-	-	-
	(1.88)	(9.32)	(8.64)							(2.02)	(14.5)	(10.4)			
Industrials	1.3%	0.77	1.32	-2.3%	0.85	1.09	-	-	-	1.8%	0.81	0.96	5.4%	0.84	1.23
	(0.89)	(26.5)	(23.3)	(-1.3)	(22.6)	(24.2)				(1.50)	(20.2)	(12.0)	(3.72)	(17.0)	(16.1)
Information Technology	3.4%	0.85	1.10	-	-	-	-	-	-	1.8%	0.99	1.08	4.4%	0.99	1.37
	(2.30)	(18.1)	(15.8)							(1.51)	(23.5)	(11.4)	(3.02)	(19.1)	(16.3)
Materials	2.1%	0.87	1.40	-1.4%	1.07	1.30	-0.1%	0.76	1.15	1.2%	0.80	0.94	4.8%	0.83	1.37
	(1.43)	(30.2)	(28.8)	(-0.7)	(23.9)	(23.7)	(-0.0)	(11.4)	(12.7)	(0.96)	(21.4)	(12.4)	(3.28)	(14.5)	(12.1)
Telecom. Services	1.9%	0.52	1.01	-	-	-	-	-	-	-	-	-	-	-	-
	(1.31)	(16.5)	(16.4)												
Utilities	1.6%	0.53	1.06	1.1%	0.88	1.10	1.6%	0.60	0.73	-	-	-	-	-	-
	(1.07)	(16.1)	(16.8)	(0.47)	(15.4)	(12.9)	(0.94)	(9.94)	(6.82)						

The results for the MSCI Emerging Markets index in exhibit 2 B) are comparable to those for the MSCI World index in exhibit 2 A), with the alpha also positive for all sectors in emerging markets. However, we find that the riskier stocks in each sector are more likely to have a beta above one than in developed markets, since now only high-risk consumer staples have a beta below one. And similarly, low-risk stocks from all sectors seem more likely to have a beta below one.

Carrying out the analysis in each individual emerging market country was not as easy as for developed countries because of the smaller number of stocks in each sector, in particular in Brazil, and because of shorter history of returns, in particular in China. The evidence of a low-risk anomaly seems stronger for South Korea and Taiwan than for China or Brazil. In the latter, only two sectors had enough stocks to perform the analysis and only in utilities is there evidence of positive alpha, despite the fact that the beta of high-risk utilities is below one. In China, stronger evidence of a positive alpha is found only in consumer staples, along with some weak evidence in financials and utilities. But the history of returns is relatively short. In Taiwan, the evidence is stronger and only financials do not have a strong positive alpha. Evidence is less strong for South Korea than for Taiwan, with two sectors in seven no showing significant alpha.

Diversification in sector-neutral low-volatility investing

In exhibit 3 we show the pair-wise correlation of the time series of return for the LVMHV strategies defined in (3) for any two pairs of sectors, for the MSCI World index and for the MSCI Emerging Markets index.

The correlation of LVMHV returns for any two sectors is always positive with the exception of the correlation between the LVMHV returns for the energy sector and the LVMHV returns for the health care sector in emerging markets. Nevertheless, the average correlation of LVMHV returns from sectors in the MSCI World index is low, at 34%, and from the MSCI Emerging Markets index is only 20%. These results show a potential diversification gain from investing in low-volatility stocks from different sectors. We shall discuss this point later.

Exhibit 3: Correlation of LVMHV returns for any two sectors from A) the MSCI World index and B) the MSCI Emerging Markets index. Jan-95 – Dec-14.

A)

	Developed countries								
	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom. Services	Utilities
Consumer Discretionary	45%	31%	42%	41%	58%	43%	31%	37%	39%
Consumer Staples		28%	45%	39%	51%	20%	20%	35%	41%
Energy			31%	33%	23%	33%	11%	45%	26%
Financials				20%	38%	22%	15%	31%	47%
Health Care					45%	52%	8%	51%	26%
Industrials						34%	48%	42%	46%
Information Technology							13%	40%	25%
Materials								21%	17%
Telecom. Services									33%

B)

	Emerging countries								
	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom. Services	Utilities
Consumer Discretionary	41%	20%	50%	8%	51%	17%	34%	14%	19%
Consumer Staples		9%	38%	16%	17%	-3%	22%	10%	16%
Energy			12%	-10%	23%	1%	18%	7%	10%
Financials				17%	52%	13%	52%	22%	39%
Health Care					4%	4%	12%	4%	21%
Industrials						20%	52%	11%	24%
Information Technology							11%	12%	11%
Materials								15%	21%
Telecom. Services									24%

In exhibit 4 we show the correlation of the returns to LVMHV strategies applied to the different sectors of the MSCI World index and MSCI the Emerging Markets index with the returns to equivalent strategies positively exposed to small capitalization, value and momentum. What we call SMB (Small-minus-Big) is a long-short strategy that invests in the one-third of stocks in the universe with the smallest capitalization in the MSCI indices and sells short the one-third of stocks with the largest capitalization. The stocks are equally weighted in the long and short legs of the portfolio. The beta is neutralized as before by allocating a weight $1/\beta^{i}_{Smallest\ Market\ Cap}$ to the long leg and $1/\beta^{i}_{Largest\ Market\ Cap}$ to the short leg fully neutralizing the beta, with $\beta^{i}_{Smallest\ Market\ Cap}$ and $\beta^{i}_{Largest\ Market\ Cap}$ the ex-post beta for each leg over the entire period. The final leverage is adjusted so that the ex-post volatility is exactly 5% over the period. A similar strategy is built, this time ranking stocks every month by price-to-book and investing in the stocks with the lowest price-to-book while selling short the stocks with the largest price-to-book. We call this strategy HML (High-minus-Low) in analogy to the HML strategy as defined by Fama and French (1992), although we follow a somewhat different approach. Finally, we construct another similar strategy but with stocks now ranked by momentum defined as the past 11-month return of each stock measured one month before portfolio formation. We call this portfolio Mom in analogy to what was defined by Carhart (1997), although again our strategy is not exactly the same.

Exhibit 4: Correlations between the returns to LVMHV strategies applied to the sectors in A) MSCI World index and B) MSCI Emerging Markets index with the returns to SMB, HML, and Mom returns applied to the same universes, respectively. In A) the period is Jan-95 to Aug-14 and in B) Jan-02 to Aug-14) markets. Monthly USD total returns.

A)

	Developed countries											
			LVMHV									
	HML	Mom	Consumer Disc.	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom. Services	Utilities
SMB	50%	-45%	-4%	-13%	-13%	-12%	-7%	-3%	-7%	-2%	-7%	2%
HML		-69%	11%	12%	20%	-7%	43%	21%	28%	1%	21%	19%
Mom			16%	3%	10%	18%	-6%	0%	1%	3%	11%	5%

B)

	Emerging countries											
			LVMHV									
	HML	Mom	Consumer Disc.	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom. Services	Utilities
SMB	51%	-57%	-26%	-9%	-20%	-6%	-6%	1%	-5%	8%	-1%	11%
HML		-57%	-19%	-18%	-22%	-15%	1%	-18%	3%	-7%	-11%	-2%
Mom			22%	1%	16%	12%	15%	4%	7%	-13%	13%	-5%

The average correlation of the returns to LVMHV strategies with the returns to SMB, HML and Mom is only 5% when formed using stocks from the MSCI World index and -3% when formed with stocks from the MSCI Emerging Markets index. This shows clearly that the returns to LVMHV strategies are uncorrelated from the returns of these other strategies, SMB, HML and Mom.

Tail risk in sector-neutral low-volatility investing

We shall now show that low-risk investing has only a small or no exposure to stocks with future poor performances. In a simple exercise, each month we ranked stocks in each sector of the MSCI World index[1] by historical volatility[2] and formed decile portfolios in each sector. We then put together the corresponding decile portfolios from each sector to form 10 portfolios, from 1, the lowest volatility in each sector, to 10, the highest volatility in each sector. We then checked the future returns of the stocks in each of these portfolios and asked the question of how many had monthly returns below -50%, or inferior to -70%, in subsequent months. The results can be found in exhibit 5, where we show the probability that a stock with a monthly return inferior to -50% in A) or inferior to -70% in B) was in found in a given decile portfolio up to three months before that month and up to three months after that month.

The period of the analysis is Jan-95 to Mar-14. This corresponds to 231 months with a total of 390,380 monthly stock returns observed, i.e. 1,689 stocks on average per month. Of these we find 53 monthly returns observed to be inferior to -70% from 46 unique stocks and 356 observations inferior to -50% with 275 unique stocks. In exhibit 5 we show the results of our analysis. We found no stock with a monthly return inferior to -70% in a given month ranking in the lowest volatility decile in the preceding month, or in the preceding two or three months. These stocks are found with increasing frequency in the most volatility deciles. Only 10% of these observations come from stocks ranking in the half of the universe with the lowest-volatility stocks in the preceding month, 16% two months before and 17% three months before. If we put the threshold at -50%, then there is a largest percentage found in the lowest volatility universe but most stocks with the poorest performances still come from the risker half of the universe. Only 18%, 21% and 23% of these observations were from stocks ranking in the lowest volatility half of the universe one, two and three months before the event, respectively.

Exhibit 5: Percentage of the stocks with an absolute monthly return inferior to -50% A) or inferior to -70% B) found in each decile portfolio before and after that event. USD returns. Stocks from the MSCI World index universe[1]. Jan-95 to Mar-14.

A)

Probability that a stock with monthly return < -50% is observed in one given decile											
		Lowest volatility									Highest volatility
Volatility decile		1	2	3	4	5	6	7	8	9	10
Months before	3	2%	2%	6%	5%	8%	6%	6%	17%	17%	31%
	2	2%	1%	6%	5%	7%	4%	8%	15%	16%	36%
	1	1%	2%	4%	5%	6%	5%	6%	16%	19%	36%
Month of observation		1%	1%	5%	4%	5%	5%	7%	16%	17%	39%
Months after	1	1%	0%	3%	5%	5%	5%	5%	13%	22%	41%
	2	0%	0%	1%	3%	3%	4%	2%	11%	23%	53%
	3	0%	0%	1%	3%	2%	3%	2%	10%	19%	61%

B)

Probability that a stock with monthly return < -70% is observed in one given decile											
		Low volatility									High volatility
Volatility decile		1	2	3	4	5	6	7	8	9	10
Months before	3	0%	2%	5%	5%	5%	2%	2%	14%	14%	51%
	2	0%	0%	7%	2%	7%	0%	5%	9%	16%	55%
	1	0%	2%	2%	4%	2%	7%	2%	9%	17%	54%
Month of observation		0%	0%	4%	2%	2%	4%	0%	11%	20%	57%
Months after	1	0%	0%	2%	0%	2%	2%	2%	5%	21%	65%
	2	0%	0%	0%	0%	0%	0%	0%	0%	9%	91%
	3	0%	0%	0%	0%	0%	0%	0%	0%	4%	96%

SECTOR-NEUTRAL VERSUS NON-SECTOR NEUTRAL LOW-RISK INVESTING

In this section we compare traditional low-risk investing based on investing in the lowest-risk stocks and strongly biased towards defensive sectors with sector-neutral low-risk investing. We focus only on the MSCI World index universe for developed countries with the larger number of stocks and sufficiently long history, from January 1995 through May 2013[1].

Performance and sector exposures

In exhibit 6 we compare the alpha of two beta-neutral strategies, both with exactly 5% annualized volatility. The first strategy, which we call sector neutral, is an aggregation of LVMHV sector long-short portfolios, one for each sector, as defined before but using deciles instead of terciles. Each sector LVMHV is allocated an equal weight over the entire period, and the leverage of aggregation of these 10 sector LVMHV is such that the ex-post volatility is exactly 5%.

The second strategy, which we call non-sector neutral, is based on a LVHMV long-short portfolio which does not take into account sectors. The stocks are ranked by historical volatility once a month and the portfolio is rebalanced once at the start of each month. Stocks are equally weighted just as before. But this portfolio invests in the decile of stocks with the lowest historical volatility and short sells the decile of stocks with the highest historical volatility, irrespective of their sectors. As before, the weight of the long and short legs are equal to the inverse of each observed beta, $1/\beta_{LowestRisk}$ and $1/\beta_{Highest\,Risk}$ respectively, and the allocation is re-scaled by λ as in (2) so that the ex-post volatility is 5%. In exhibit 6 we also consider the same strategies but now implemented with a six month lag, i.e. the portfolio is implemented six month after formation.

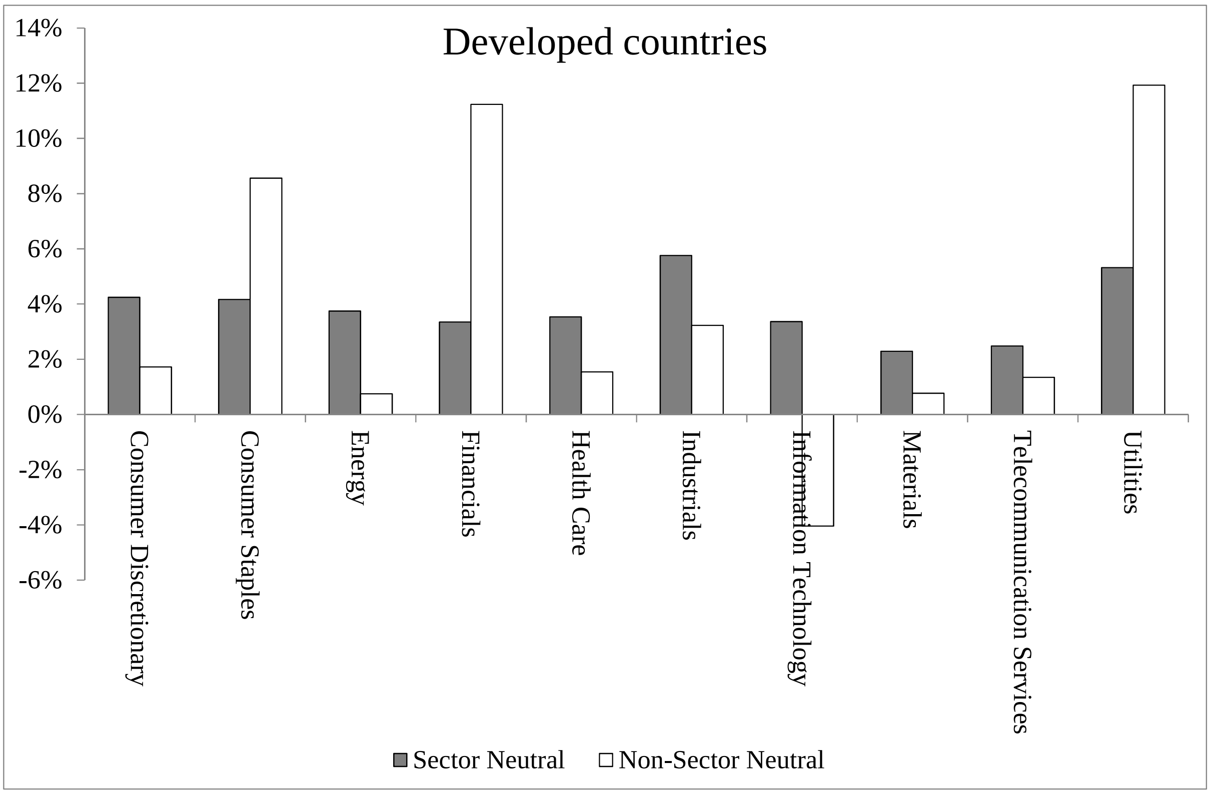
Exhibit 6: Alpha and information ratio for two LVMHV strategies, one based on equally weighting individual LVMHV sector strategies, which we call sector-neutral, and one applying the LVMHV across the entire stock universe ignoring sectors, which we call non-sector neutral. The beta of both strategies is zero and the volatility is 5% by construction. We also consider the same strategies implemented with six months lag.

	MSCI World Index Jan-1995 - May-2013			
	Sector neutral		Non-sector neutral	
	1 month	6 months	1 month	6 months
Alpha	3.7%	3.8%	3.2%	3.2%
Information ratio	0.73	0.77	0.65	0.64

The results in exhibit 6 show an improvement of 14% in the information ratio of the sector-neutral strategy when compared to that of the non-sector neutral. It is also interesting to see that the strategies with lower turnover reach the same levels of alpha as those rebalanced more frequently. This seems to indicate that the rotation of stocks in the portfolios is low, something we shall investigate in the next section.

In exhibit 7 we show the average net sector weights in each of these two strategies. The net sector weight is the sum of the weights allocated to each stock in a given sector. The sector-neutral strategy has a positive weight in all sectors. This is because, in order to neutralize the market exposure and reach a beta equal to zero, the strategy allocates a larger weight to the low-volatility stocks it buys than to the high-volatility stocks it sells short. The size of the net sector weights is a function of the dispersion of beta, i.e. the larger the difference between the beta of low-volatility stocks and high volatility stocks, the larger the net sector weight. The main difference between the sector-neutral strategy and the non-sector neutral is the much larger weight allocated to consumer staples, financials and utilities and the much smaller weight allocated to information technology, consumer discretionary and energy found in the non-sector neutral strategy. The non-sector neutral strategy has always been strongly biased towards financials except for a few months in the aftermath of the 2008 crisis.

Exhibit 7: Average net sector weights for sector-neutral and non-sector neutral LVMHV strategies for stocks from the MSCI World index[1]. Jan-95 to May-14.



Persistence of volatility

We now focus on the reasons why, in exhibit 6, the turnover could be reduced significantly without a reduction in the alpha of the LVHMV strategies. This is in fact due to the persistence of volatility. Perchet, De Carvalho, Heckel and Moulin (2014) have recently investigated the persistence of volatility at aggregate market level, for different asset classes, and Perchet, De Carvalho and Moulin (2014) have done the same for value and momentum factor premium. They found that the persistency of volatility is strong at the aggregate level, which explains why volatility can to some extent be predicted at an aggregate level.

In exhibit 8 we show transition probability matrices for stocks in the MSCI World index and MSCI Emerging Markets index, respectively. With the sector-neutral portfolio, stocks in each sector are ranked by historical volatility[2] every month and then, in each sector, the universe of stocks is ranked by historical volatility and divided into terciles. For the non-sector neutral portfolio, this is done across the universe defined by the index rather than on a sector-by-sector basis.

This exercise is repeated each month. We then calculated the average number of stocks which ranked as being of low volatility in a given month and also in the immediately following month. We repeated the exercise for stocks that ranked as mid-volatility and high-volatility. The probabilities are the average percentage of stocks staying in the same tercile of volatility from one month to another. Similarly, we also estimated the probability that a stock remains in the same tercile of volatility six months after being ranked. And we also included the probability that a stock leaves the index in the following month or within the following six months. These are indicated as *out*.

Exhibit 8: Probabilities that a stock ranking in a given tercile of volatility in a given month is still found in the same tercile of volatility in the following month. Also shows the probability of that stock being found in the same tercile of volatility in the following six months. Results for sector-neutral and non-sector neutral portfolios are included. In A) the universe is defined from the MSCI World index[1] and the period is Jan-95 to May-14. In B) the universe if defined from the MSCI Emerging Markets index[1] and the period is Jan-02 to May-14.

A)

		MSCI World Index Jan-1995 - May-2014							
		Sector Neutral				Non-Sector neutral			
		1-month transition probability matrix							
		Volatility tercile next month				Volatility tercile next month			
		Low	Mid	High	Out	Low	Mid	High	Out
Volatility	Low	95%	5%	0%	0%	96%	4%	0%	0%
tercile	Mid	5%	90%	4%	1%	4%	92%	4%	1%
today	High	0%	4%	94%	1%	0%	4%	95%	1%
		6-month transition probability matrix							
		Volatility tercile next month				Volatility tercile next month			
		Low	Mid	High	Out	Low	Mid	High	Out
Volatility	Low	83%	14%	1%	2%	85%	12%	1%	2%
tercile	Mid	14%	69%	14%	3%	12%	72%	13%	3%
today	High	0%	13%	80%	6%	0%	12%	82%	6%

B)

MSCI Emerging Markets Index Jan-2002 - May-2014									
		Sector Neutral				Non-Sector neutral			
1-month transition probability matrix									
		Volatility tercile next month				Volatility tercile next month			
		Low	Mid	High	Out	Low	Mid	High	Out
Volatility	Low	94%	5%	0%	2%	95%	4%	0%	2%
tercile	Mid	5%	89%	5%	1%	4%	91%	4%	1%
today	High	0%	5%	93%	2%	0%	4%	94%	2%
6-month transition probability matrix									
		Volatility tercile next month				Volatility tercile next month			
		Low	Mid	High	Out	Low	Mid	High	Out
Volatility	Low	80%	13%	1%	6%	81%	12%	0%	6%
tercile	Mid	14%	67%	13%	6%	13%	69%	13%	6%
today	High	1%	15%	77%	8%	0%	15%	78%	8%

The results in exhibit 8 show a strong persistency in the volatility of stocks. For the sector-neutral strategy, 95% of the stocks ranked lowest volatility in the MSCI World index in a given month then remained ranked lowest volatility in the following month and the other 5% ranked mid-volatility. The results are comparable for the non-sector neutral strategy, with 96% and 4%, respectively. The results are also comparable for the stocks in the MSCI Emerging Markets index, with 94% of stocks ranked lowest volatility still remaining lowest volatility one month later for the sector-neutral approach and 95% for the non-sector neutral approach. Six months after being ranked, 83% of lowest volatility stocks in the MSCI World index still rank lowest volatility for the sector neutral approach and 85% for the non-sector neutral approach. For the MSCI Emerging markets index this is just slightly lower at 80% and 81%, respectively. It is also interesting to note that the probability of stocks leaving the index is higher for the highest-volatility stocks than for the lowest-volatility stocks.

Liquidity of low-volatility strategies

Low-volatility investing is an active strategy that invests away from the market capitalization portfolio and requires re-balancing. Liquidity is thus an important issue. Here we give some crude idea of the liquidity of simple low-volatility strategies and compare this liquidity to other simple style strategies for small capitalization, value and momentum. We consider both sector-neutral and non-sector neutral low-volatility strategies.

In exhibit 9 we show the average number of days needed to liquidate a USD 100 million portfolio invested in the decile of stocks with lowest volatility, sector-neutral and non-sector neutral, and compare this to the average number of days to liquidate a portfolio of a similar size invested in the decile of stocks with the smallest market capitalization, the stocks with the lowest price-to-book ratio and momentum stocks with the highest 11-month return measured one month before portfolio construction. The averages are based on the allocation at the start of each month. The number of days required to liquidate the portfolio assumes that a maximum of 30% of the monthly volume of each stock can be traded every day. We ran the analysis between 2008 and 2013. Stock volume data is provided from MSCI. The results are for stocks in the MSCI World index.

Not surprisingly, the market capitalization index has the greatest liquidity and can be liquidated with the least difficulty. There is not a large difference between the sector-neutral and the non-sector neutral low-volatility portfolios, with perhaps no significant advantage for the non-sector neutral portfolio seen at the level of full liquidation only. Liquidity of the low-volatility portfolios is large at this level and comparable to that of momentum portfolios. Not surprisingly, the small capitalization portfolio has the poorest liquidity. Value also shows poor liquidity because we did not remove the small capitalization bias that a selection based on the lowest price-to-book ratios tends to create.

At 50% and 70% levels of liquidation of the portfolio, low volatility fares better than the other strategies and even in 2008 the portfolio could still be liquidated with less difficulty than both the sector-neutral and the non-sector neutral low-volatility portfolios.

Exhibit 9: Average number of days in each year needed to liquidate 50%, 70% and 100% of a USD 100 million sector-neutral and non-sector neutral low-volatility portfolios compared to equally weighted, non-sector neutral portfolios invested in the 10% top ranked stocks by lowest market capitalization, value as measured by the lowest price-to-earnings ratio and momentum as measured by the highest 11-month returns measured one month before portfolio formation. Stocks are from the MSCI World index.

	50%						70%						100%					
	2008	2009	2010	2011	2012	2013	2008	2009	2010	2011	2012	2013	2008	2009	2010	2011	2012	2013
Low volatility non-sector neutral	3	4	6	4	4	4	6	14	14	10	10	9	52	94	70	49	74	92
Low volatility sector neutral	3	4	5	8	10	4	7	12	14	63	109	8	165	139	97	9	10	67
Small capitalization	32	44	37	33	37	40	49	71	59	52	60	64	4890	779	1070	791	280	239
Value	10	13	15	13	12	14	21	26	30	26	25	31	1222	451	118	645	280	99
Momentum	5	9	7	6	7	7	12	16	15	15	13	15	55	104	61	65	67	134
Market Capitalization	0	0	0	0	0	0	0	1	1	1	1	1	41	111	15	15	11	4

CONCLUSIONS

In this paper we give empirical evidence of risk anomalies in the sector of activity at a global level, in developed and emerging markets. Positive returns to beta sector-neutral long-short portfolios invested in the lowest-volatility stocks of a given sector and short the highest-volatility stocks of the same sector cannot be explained by market exposure. Portfolios invested in the lowest-volatility stocks of a given sector have been returning more than expected from their level of risk, whereas portfolios invested in the highest-volatility stocks of the same sector have been returning less than expected from their level of risk. This risk anomaly had been reported in the cross-section of stock returns of almost all countries and regions in the world by Baker and Haugen (2012) and also in the cross-section of country returns by Baker, Brendan and Taliaferro (2104). But evidence of such a risk anomaly is much weaker in the cross-section of industry returns as shown by Baker, Brendan and Taliaferro (2104) and Asness, Frazzini and Pedersen (2014), with the latter suggesting that it is in fact more efficient to capture low-risk alpha using industry-neutral approaches. Indeed, they give evidence of the risk anomaly in the cross-section of stock returns in industries but without advancing any explanation or analyzing each industry in detail.

To our knowledge this paper is the first to provide evidence of the risk anomaly in the cross-section of stock returns in each sector of activity using the 10 sector GICS definitions and to put forward an explanation for why there are good reasons to expect the anomaly to be stronger in the cross-section of stock returns in sectors than in the cross-section of sector returns. Indeed, we believe that active managers benchmarked against market capitalization indices are most likely behind the anomaly in the cross-section of stock returns in sectors. Evidence that active managers have a preference for risky stocks was given by Falkenstein (2009), Brennan (1993), Brennan, Cheng and Li (2012), Baker and Haugen (2012), Chevalier and Ellison (1997) and Sirri and Tufano (1998). But we argue that because equity analysts and fund managers select stocks almost invariably from within sectors and because a number of these fund managers, in particular quantitative active managers, tend to impose constraints on the level of sector deviation of their portfolios against the market capitalization index, it is then reasonable to expect the risk anomaly to be stronger in sectors and to show in all sectors. Our empirical results for stocks for developed countries at global level do suggest that the risk anomaly is stronger when some level of sector neutrality is imposed, thus corroborating the results from Asness, Frazzini and Pedersen (2014), who reached a similar conclusion when imposing industry neutrality. For the period considered we found 14% more risk-adjusted alpha in the sector-neutral strategy than in the non-sector neutral strategy. Imposing sector neutrality in the portfolios tilted in favor of low volatility stocks leads to much smaller exposures in particular to the financials, utilities and consumer staples sectors and to a much larger exposure to the information technology, consumer discretionary and energy sectors than when sector neutrality is not imposed.

The higher risk-adjusted alpha found in the sector-neutral strategy is explained by the diversification gain arising from the low correlation of the returns generated from beta-neutral long-short portfolios invested in the lowest-volatility stocks in a given sector and selling short the highest-volatility stocks from the same sector. We also found a low correlation of the returns to these portfolios with the returns to beta-neutral long-short portfolios invested in value stocks and selling short expensive stocks, to beta-neutral long-short portfolios invested in the smaller capitalization stocks and selling short the largest-capitalization stocks and to beta-neutral long-short portfolios invested in the stocks with the strongest momentum and selling short the stocks with the poorest momentum.

Finally, we have shown that low-volatility investing offers a level of liquidity higher than that found in other styles such as momentum, value and in particular small capitalization. We have also shown that the level of turnover required for low volatility investing can be reduced without a significant impact on the risk-adjusted alpha thanks to the persistency of the volatility of individual stocks. As demonstrated, stocks which ranked among the lowest volatility show a very low probability of becoming higher volatility in the near future. A consequence of this low probability is the fact that in the history used in our analysis we also find that low-risk investing naturally filters out the stocks more likely to deliver extremely poor performances in the near future.

END NOTES

1. Due to licensing constrains, for data prior to August 2006, we use the global universe of stocks of developed countries in the Exshare database for which the market-cap allocation minimizes the tracking risk against the total returns of the MSCI World Index in U.S. dollars. Therefore, the universe for the period prior to August 2006 may not be the exact same universe that underlies the MSCI World Index. We believe that our universe is likely to contain more stocks than those in the MSCI Index in the period January 1995 – August 2006. In our view, however, the impact of not using exactly the MSCI World index universe on the results of this paper should be minor.
2. Only stocks with at least 450 days of pricing data in the two years used in the estimation of ex-ante volatility and beta are retained. Otherwise they are excluded from the selection process. The results are not very sensitive to the length of the window used in the estimation of the ex-ante volatility and beta. But for shorter windows the error estimation increases which generates more turnover in the strategy while for longer windows more stocks will be excluded for not having sufficient pricing data. A two-year rolling window offers a good compromise between these two effects.
3. The persons contacted kindly provided the information on their behalf and based on their own experience. The views provided are not based on a rigorous statistical analysis. The views expressed do not, by any means, reflect an official view of the firms employing the persons contacted and they were never intended to represent official firm views.
4. The Global Industry Classification Standard (GICS®) is an industry taxonomy developed by MSCI and Standard & Poor's (S&P). The GICS structure consists of 10 sectors, 24 industry groups, 68 industries and 154 sub-industries into which S&P has categorized all major public companies. The system is similar to ICB (Industry Classification Benchmark), a classification

structure maintained by Dow Jones Indexes and FTSE Group. GICS® is a registered trademark of McGraw-Hill and MSCI Inc. Due to licensing constraints we have replicated as much as possible the GICS classification prior to August 2006 using the publicly available information on the methodology. We believe that differences between the actual GICS classification and our classification should be minor and have no relevant impact on the results of this paper.

5. Asness, Frazzini and Pedersen (2014) use a relatively similar approach, which they call BAB (betting-against-beta). The key difference is that these authors apply the beta neutralization and risk adjustment every month using ex-ante beta and ex-ante volatility. The returns to this strategy are not exactly beta neutral as discussed by De Carvalho, R.L., X. Lu, and P. Moulin (2012) since the ex-post beta for the lowest-risk portfolio strategy tends to be higher than the ex-ante beta and the ex-post beta for the highest-risk portfolio strategy tends to be lower than the ex-ante beta. The returns to the BAB strategy are thus positively exposed to the benchmark index and cannot be associated with pure alpha.

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