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Analysing the Exposure of Low-volatility Equity Strategies to Interest Rates

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Analysing the Exposure of Low-volatility Equity Strategies to Interest Rates

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Abstract

At the dawn of a potential rise in rates triggered by Central Banks in both Europe and the United States, doubts are being raised about the ability of low-volatility portfolios to continue to deliver robust performance. We quantify this latent performance lag and provide empirical explanations, distinguishing parallel moves from non-parallel distortions in the yield curve. More specifically, we evaluate the implications from the low-volatility screening on the portfolio's industrial breakdown. The conclusion shows that the overweighting of defensive industries is the main source of underperformance in a risk-on environment. However, these bets happen to be the ones that allow the strategy to outperform over a full economic cycle. Therefore, we propose a method to control the low-volatility exposure to changes in interest rates, which should be of interest to benchmarked portfolio managers.

Keywords: Factor investing, low-volatility anomaly, interest rates, yield curve, monetary regimes.

JEL classification: G10, G11, G14.

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Key Points

- Low-volatility equity strategies have become very popular over recent years.
- In a low interest rate environment, low-volatility strategies have delivered significant outperformance compared to market cap indices.
- However, they are suspected to be highly sensitive to interest rate movements and doubts are being raised about the ability of those strategies to perform well if interest rates rise.
- The sensitivity of low-volatility equity strategies can be broken down into two main components:
  - Industry bias towards more defensive sectors;
  - Idiosyncratic exposure due to some stock characteristics (style, structure of their balance sheet, etc.).
- An analysis of the impact of parallel and non-parallel shifts shows that these strategies are sensitive to both dimensions.
- It is possible to adjust these low-volatility equity strategies to make them less sensitive but by doing so, one deliberately decides to move away from the original low- volatility portfolio.

About the authors

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Lauren Stagnol joined Amundi in 2014. She obtained a PhD in Economics and Finance from the University of Paris Ouest Nanterre La Défense in June 2017. She holds a BSc in Business Economics from Cardiff University (UK) and an MSc in Applied Economics and Econometrics from the University of Paris Nanterre, where she is research assistant giving lecture courses in econometrics. Her current research focuses on the design of smart beta indices for the fixed-income universe.

Bruno Taillardat

Bruno Taillardat joined Amundi in September 2016 as Global head of Smart Beta & Factor Investing. Bruno started his career at Paribas Asset Management in 1998 as a Quantitative Analyst on North-American equities management, where he was appointed Head of Quantitative Research. He joined Unigestion in March 2007 as Senior Portfolio Manager in the Equity team, where he participated to Equity portfolios management on the different markets covered (Europe, US, Japan, Global, Asia-Pacific and Emerging Markets) and to the development of the risk-based management process. At Unigestion, he was then appointed Head of Equity Investments and Responsible for quantitative and fundamental research. Bruno also strongly contributed to the Unigestion Equity management expertise promotion with international investors.

Bruno has a post-graduate degree in Mathematics from the University of Marseille and he completed executive education programs at the IMD Business School in Lausanne.

1 Introduction

Factor investing has been a very hot topic among finance professionals for a few years now. Even though some academics consider the increasing number of studies that identify new factors to be a "*factor zoo*" [Cochrane, 2011], it seems that research on the equity universe comes at maturity. There is a general agreement on the existence of value, momentum, low-volatility, size and quality risk factors. While some portfolios are built using all of these factors, some strategies rather tend to focus on a single one, thus avoiding orthogonality issues. As a matter of fact, low-volatility strategies gained in popularity after the sub-prime crisis, as investors became increasingly cautious and attempted to protect their strategies from massive drawdowns. These strategies have proven to work fairly well, in serving the ultimate goal of improving risk-adjusted returns. However, over the last couple of years and because of the unusual interest rate environment, concerns are increasing regarding the ability of low-volatility portfolios to deliver robust outperformance under a rising interest rate regime.

When alluding to the low-risk anomaly, some unresolved issues necessarily come along. First, there is a question of semantics: when an investor mentions "low-risk" does she distinguish idiosyncratic risk from market risk? And can low-volatility, low-beta and minimum-variance strategies be grouped under the same low-risk denominator? There is a need for clarity when addressing this topic. Second, there is a question of timing: why has the question of sensitivity to interest rates not been addressed earlier? Or put differently: why are today's market and monetary environment new compared to previous periods of rising interest rates and why are we particularly worried? On one hand, the context is different in the sense that the period of rising interest rates we are experiencing follows a rare zero-rate environment, and not a falling-rate regime as was the case for the last twenty years. On the other hand, the fact that interest rates have been on a downward trend since the 1980s, calling into question low-risk strategies' historical performance, places high expectations on backtest robustness.

In this paper, we acknowledge the existence of the so-called low-volatility anomaly and rather focus on appraising its robustness across the interest rate cycle. We define the term "low-risk" as a substitute for low-volatility, with the low-beta approach being only employed here as a weighting scheme. This study tries to answer the following questions: is the strategy effective in delivering outperformance across both rising and falling interest rates? If a gap was detected, what would be its determining factors? Does the weighting scheme adopted within the factor have an impact? Last but not least, can we mitigate the potential detrimental effect of interest rate risk on returns within the portfolio construction process?

The paper is then organised as follows. Section 2 goes through theoretical arguments put forward in the literature to explain the low-risk anomaly, while Section 3 disentangles the link between the sensitivity of economic sectors to interest rates and performance. In Section 4, we produce backtests on a low-volatility portfolio using different weighting schemes and assess the risk-adjusted returns metrics accordingly. Section 5 introduces a metric for interest rate sensitivity and Section 6 incorporates a method in the portfolio design that allows the sensitivity of the portfolio to be controlled. Finally, Section 7 offers some concluding remarks.

2 The low-volatility anomaly

The low-volatility anomaly has been identified for decades [Black, 1972, Haugen and Heins, 1975, Ang et al., 2006]. Coining it as an anomaly is not trivial. As a matter of fact, the low-volatility pattern in the equity world is often seen as a market anomaly rather than a real alternative risk premium [Roncalli, 2017]. Indeed, this factor's reward may depend on market conditions, discarding it as a pure alternative risk premium. Although academics have generally agreed on its existence, the reasons behind this puzzle remain a question. Some of them provide a behavioural explanation. For instance, Baker et al. [2011] touch on the irrational preference of over-confident market participants for highly volatile stocks. The idea is that investors may be attracted by "lottery-style" payoffs, that are positively skewed with excess kurtosis and thus echoes the human appeal for gambling [Barberis and Huang, 2008]. The generalisation of such behaviour on a large scale creates an above normal demand for very risky assets, which in turn drives their prices up, *ultimately* weakening expected returns.

Another body of literature provides an argument rather to do with regulatory constraints, with institutional investors usually prohibited from engaging in leverage. In order to enhance their portfolio performance, they may choose very risky securities, thereby ensuring high beta exposure to the equity risk premium [Frazzini and Pedersen, 2014]. Again, this drives up demand. This explanation is known as the "leverage aversion hypothesis" [Black, 1972]. Additionally, constraints on short-selling may lead to over-pricing of the riskiest stocks. It is likely that the riskiest stocks are also those for which the divergence in investors opinions is the most acute. Because of the winner curse (the fact that the most optimistic investors drive up prices) those stocks are likely to be overpriced. Finally, practitioners have also joined the debate, arguing that investors may consider low-risk stocks as substitutes to bonds in a low yield environment. This effect is magnified for high dividend (thus less volatile) stocks sometimes ignoring the mechanical effect of dividends on share prices and thus assimilating it to a coupon payment. This idea was put forward by Malkiel [2015] among others. By the same token, Chow et al. [2014] shed light on a so-called "duration premium" in the equity world. According to the authors, the latter is explained by the cash-flow steadiness of low-volatility stocks, thus making the parallel with fixed-income securities. This point echoes a more fundamental-oriented explanation, namely that low-volatility stocks are generally those with low price-to-book ratios [Chow et al., 2014]. As a matter of fact, Fama and French [2012] sum up this anomaly as the product of a value and a size effect.

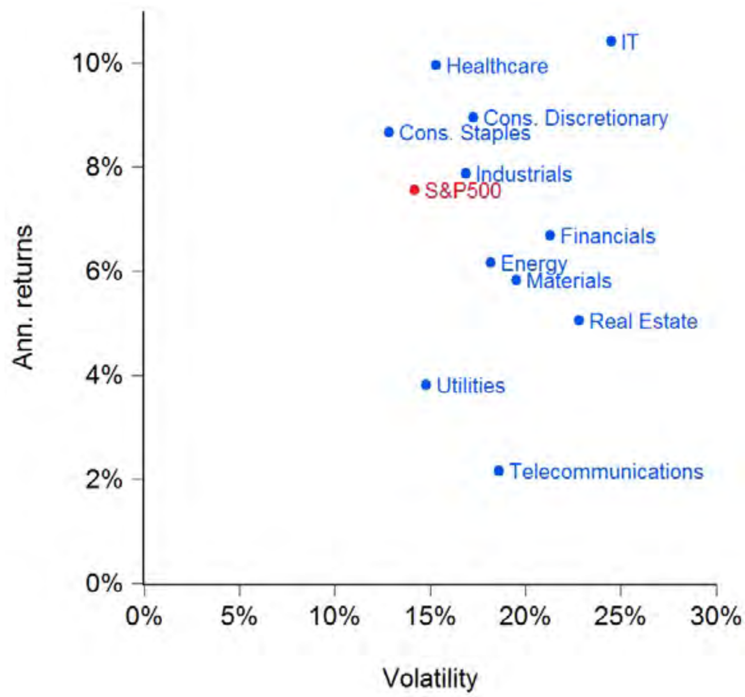
Although one may adhere to the existence of the low-volatility anomaly, the question of robustness across changing economic environments ought to be addressed. This study aims to investigate whether tilting a portfolio towards less risky stocks delivers robust performance across different interest rate regimes. That issue is not yet fully explored in the literature, but it seems as if most practitioners agree on the performance enhancements brought about by such a strategy when interest rates are falling. More troubling, is that they also tend to agree on the performance drag they may suffer when interest rates are rising. Indeed, under these circumstances, returns of fixed-income instruments have to increase at the same pace as interest rates, which may tarnish the appeal of this asset class, putting downward pressure on stock prices and creating an opportunity cost [Muijsson et al., 2014]. We refer to this mechanism as the "allocation effect".

Digging deeper into companies' fundamentals, some characteristics may increase a firm's responsiveness to rising interest rates. Some firms are intrinsically less sensitive to market movements. The reasons behind this may be threefold. First, some (typically non-cyclical) industries have less elastic demand, which in turn makes them less reactive to economic news. Second, it seems that the higher the leverage, the higher the sensitivity to interest rate risk [Staking and Babbel, 1995]. To give an illustration, leveraged firms that issue long-term bonds may face a higher debt burden, decreasing the profitability of their operations. Third, one should not neglect the impact of the regulatory framework that has the tendency to smooth earnings for some industries such as utilities. Furthermore, when mentioning interest rate fluctuations, it is key to distinguish between parallel (level) and non-parallel (slope) movements. Interest rates changing uniformly along the term structure are generally associated with inflationary pressures, while a rise in the slope factor (the yield curve steepening) signals a strong rise in economic activity [Diebold and Li, 2006, Diebold et al., 2008, Abbritti et al., 2013].

3 Industry classification

By construction, a low-risk equity strategy implies industry bets towards the less volatile economic sectors. Breaking down the risk-return profile of the S&P 500 sectors since 1990 provides us with a first glance at the so called low-risk industries. The most risk-return-efficient sectors appear to be the consumer staples and healthcare industries. Information technology and telecommunications companies appear the least efficient. A standard classification, notably used by large index providers categorises energy, consumer staples, healthcare, telecommunication services and utilities as "non-cyclical" and materials, industrials, consumer discretionary, financials, information technology and real estate as "cyclical". In Figure 1, these are indeed the ones that appear the riskiest. Therefore, we observe that cyclicality of earnings is a determining factor of volatility. However, other drivers may be at play. Chow et al. [2014] mention the importance of the business model, arguing that growth stocks have higher market exposure and are thus more likely to present volatile returns. These industries are obviously different in many points. In order to

Figure 1: Risk return profile by GICS



assess this more formally, a few key figures regarding their indebtedness (total debt to equity), profitability (return on equity), market sensitivity (correlation) and business model (price-to-book ratio) by GICS are presented in Table 1. More specifically, sub-indexes from the S&P 500 Index were retrieved and their respective average on the aforementioned metrics reported[1].

A first point can be made. The sectors considered as "cyclical" are the most sensitive to market movements, confirming the relevance of such distinction. Second, there are discrepancies in terms of leverage and profitability. Industries such as information technology or healthcare have low levels of indebtedness but high return on equity while companies from the financial or consumer discretionary sectors are among the most indebted with the lowest profitability. These diametrically opposed features also illustrate the duality between value and growth industries: information technology – a typical growth business model – having a price-to-book ratio more than twice larger than financials, which is a value business.

From a pure asset allocation point of view, stock returns should evolve in the opposite direction to interest rates. Indeed, fixed-income securities would appear more attractive, and may encourage investors to shift away from stocks. Additionally, a change in interest rates can be broken down between two components: parallel shift

[1]The price-to-book allows us to assess the differential between a firm's book value versus its market value and thus provide an indication of the industry's business model – growth or value.

Table 1: Industry typology

	Total Debt to Equity	Return on Equity	Market Correlation	Price to Book
Energy	43.24	13.60%	0.61***	2.34
Materials	82.02	11.01%	0.78***	2.56
Industrials	138.95	15.24%	0.91***	3.14
Consumer Discretionary	142.63	11.45%	0.89***	3.09
Consumer Staples	91.25	25.31%	0.64***	5.04
Healthcare	46.67	21.02%	0.67***	4.82
Financials	398.34	11.31%	0.84***	1.76
Information Technology	35.50	13.23%	0.81***	4.13
Telecommunication	80.34	9.92%	0.62***	2.74
Utilities	130.73	9.42%	0.41***	1.69
Real Estate	109.80	10.87%	0.70***	3.27

Total debt to equity, return on equity and price-to-book data has been averaged over the period for each S&P 500 GICS sub-index (S5ENRS, S5MATR, S5INDU, S5COND, S5CONS, S5HLTH, S5FINL, S5INFT, S5TELS, S5UTIL, S5RLST).
The real estate sub-index inception only goes back to September 2016.
P-values associated to market correlation are reported by *** for a 99% significance level.

(that is change in the level factor of the term structure) and non-parallel shift (and more specifically change in the slope factor). On one hand, a rise in the level is associated to inflationary pressure, which should have a negative impact on stock returns since companies may face higher input costs, lower demand etc. On the other hand, rising slope factor tends to signal higher economic activity, which should have a positive impact on returns. We believe that these effects (allocation, parallel shift and non-parallel shift) should affect all stocks, independently of their economic sectors. We expect the allocation effect and parallel shift in the yield curve to put downward pressure on returns, while the slope factor may be favourable.

We believe that some industrial characteristics may determine the sensitivity of returns to variations in the yield curve, namely cyclicality of demand, leverage and the business model (growth vs. value). While the cyclical component is kept unchanged for a given industry in our sample period, we allow industries to switch between high and low leverage, and between value and growth business models. To illustrate the construction of such classification, we compare the average level of leverage using sub-index data. Whether an industry is above or below the market leverage will determine whether leverage is high or low. In order to avoid hectic movements between categories, a switch from one category to another has to last for at least three years to be accounted for. The full classification is presented in Tables 6 and 7 on page 28.

Based on the distinction between parallel and non-parallel shifts and the characteristics presented above, we are able to build a set of testable hypotheses. First, the level (parallel shift) factor should have a negative impact on returns, because investors will sell stocks, and inflationary pressures will deteriorate companies' profitability. Second, the slope factor should have a positive impact on returns, as it signals an upward trend in economic activity. Third, cyclical sectors should be more impacted (in magnitude) by changes in interest rates (both parallel and non-parallel) than non-cyclical sectors. In a similar manner, highly leveraged sectors must be more affected by changes in interest rates (parallel) than low leveraged sectors. Finally, growth stocks should more responsive to changes in interest rates than value stocks, as these companies have lower cash flows today. Relying on panel data regression analysis using dummy variables for the distinctive features we have chosen, we are able to directly test those hypotheses. Results are presented in Table 2.

Table 2: Results of the OLS panel data analysis (January 1991 - June 2017)

Model			#1	#2	#3
Constant			0.87***	0.17***	0.16***
Growth			−0.13***		
Cyclical			−0.64***		
Leverage			−0.22***		
Level				−0.33*	−0.36*
Slope				0.01	0.05
Market				0.78***	0.79***
Growth	×	Level	−0.49***	0.01	0.12
Cyclical	×	Level	1.90***	2.31***	2.20***
Leverage	×	Level	−1.14***	−1.00***	−0.93***
Growth	×	Slope	−1.13***	−1.14***	−1.22***
Cyclical	×	Slope	1.33***	2.07***	2.16***
Leverage	×	Slope	−1.39***	−1.79***	−1.85***
Growth	×	Market	0.54***	0.07***	0.06***
Cyclical	×	Market	0.92***	0.47***	0.49***
Leverage	×	Market	0.14***	−0.17***	−0.17***
CS FE			No	No	Yes
R^2			18%	20%	21%

CS FE stands for cross-section fixed effects.
Market is the monthly return of the S&P 500 Index. The level factor is the average of the 2Y and 10Y T-bill yields, while the slope is the difference between the 10Y and 2Y T-bill yields (source: Bloomberg Generic Government Rates). Both factors are taken in first difference.
*** and * stands for 99% and 90% significance levels.

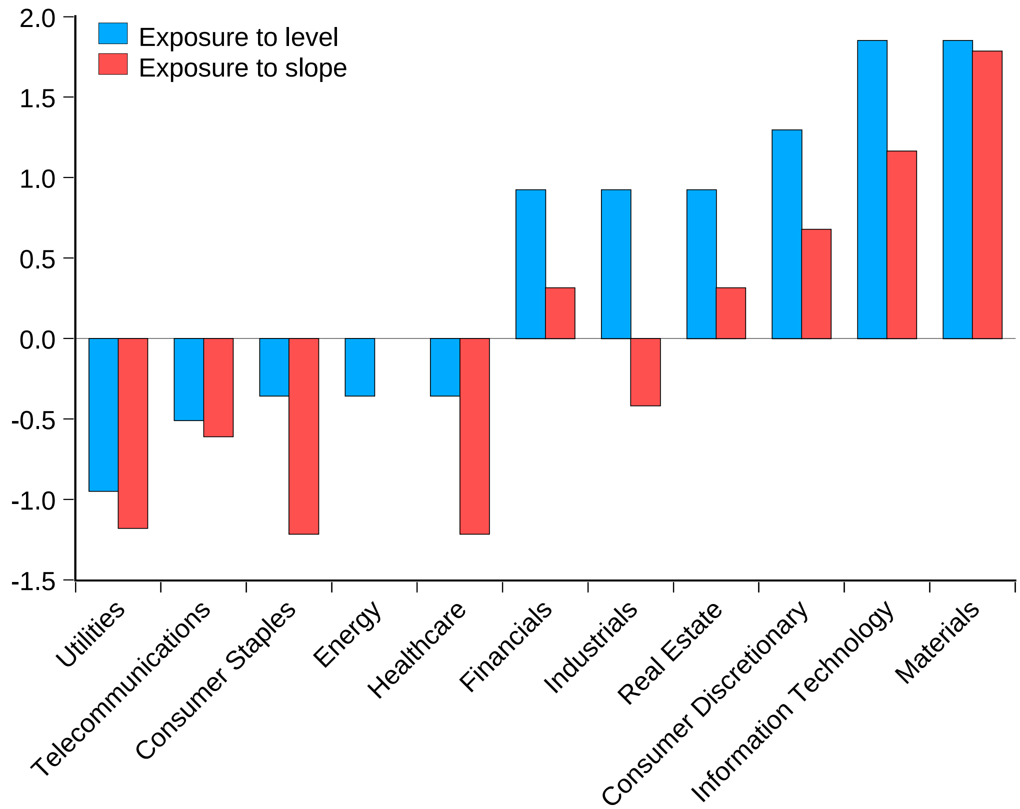
The first regression allows us to gauge the relevance of the characteristics mentioned above (model #1). Being highly leveraged, facing a cyclical demand or having a growth oriented business model is indeed a determining factor for return patterns.

Indeed, when looking at the coefficient associated with these dummies (all significant), it seems that structurally, cyclical economic sectors will display lower returns, which may be attributable to the cyclicality of their earnings. Growth oriented industries, and highly leveraged ones display a lower, but somewhat similar, performance drag. As far as returns' responsiveness to varying rates are concerned, it appears that cyclical industries are positively impacted, as coefficients for the level and slope interaction terms are statistically significant across all specifications. It contrasts with the same coefficients that apply to the whole sample where the level factor displays a negative sign while the slope factor does not appear significant (model #2). The improvements in business conditions prevail over the rising costs and the allocation effect for the cyclical industries. They are also more sensitive to market movements, a consistent result. As expected, highly leveraged firms are among those that suffer the most following a rise in rates, independently of the distortion shape (level or slope). Therefore, for those firms, the increase in debt servicing costs (level) dominates the potential benefits over strengthening economic activity (slope). Finally, industries following a growth-oriented business model are the least impacted by parallel shifts in the yield curve, as the coefficient associated with the interaction dummy is not significant and only the common coefficient close to -0.36 applies (model #3). As far as the specific exposure of growth industries to slope variations is concerned, the effect is negative. In fact, contrary to one of our hypotheses, an increase in the slope of the yield curve (and thus in economic activity) only seems to benefit cyclical industries, hindering returns for leveraged and growth-oriented industries. As a matter of fact, using the last regression (with cross-section fixed effects), we can compute the sensitivity of each sector to interest rates according to the typology defined in Tables 6 and 7 on page 28 and the classification of cyclical and non-cyclical sectors exhibited previously in Figure 1. Results are given in Figure 2.

A certain consistency appears. Industries that are positively (negatively) exposed to parallel shifts are also positively (negatively) impacted by non-parallel shifts. Among the industrial characteristics retained for this study, cyclical vs. defensive classification appears as the most discriminating factor. For instance, cyclical industries all show positive responses to interest rates, while returns from defensive industries are all undermined. The negative impact faced by defensive industries makes sense because in the case of a steepening yield curve (that is short rates moving more than long rates) these firms – with less elastic demand – will benefit from improving economic conditions with a lag, while in the meantime, returns are hampered, widening the gap with cyclical stocks.

Some sectors present distinctive features. On one hand, the energy sector seems to be the most disconnected from variations in the yield curve, especially to non-parallel shifts. However, energy stocks are peculiar in the sense that their returns are closely tied to energy prices, curtailing the potential explanatory power of interest rate variations. On the other hand, both healthcare and consumer staples stocks seem more impacted by the slope of the yield curve than by its level. The reasons

Figure 2: Industry exposure to interest rates risk

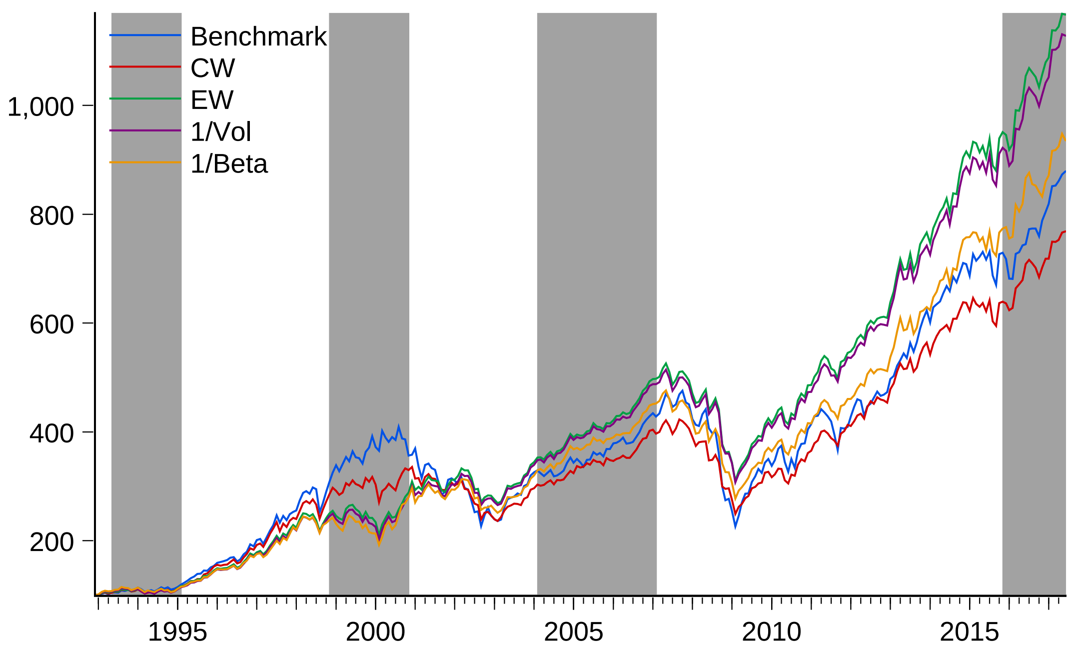


are twofold. First, these sectors are not highly leveraged, and the performance drag caused by inflationary pressures through the level factor is therefore minor. Second, because of their cash-flow structure as growth oriented industries, booming economic sentiment will rather tend to benefit value stocks. Undertaking a parallel analysis with Figure 1 reveals that applying a low-volatility screening when constructing a portfolio will lead to an overweighting of industries such as consumer staples, utilities and healthcare. However according to our regression results, these economic sectors are the ones that suffer the most from an interest rate hike. Thus, disregarding volatile sectors such as consumer discretionary and information technology is likely to lead to a certain performance drag. Conversely, employing a low-risk filter under a falling rate regime would enable higher returns to be secured. In all, those first results at the industry level hint that applying a low-risk screening means taking positions on the worst performing economic sectors under a rising rate regime.

4 Backtesting low-volatility portfolios

We present different heuristic strategies for weighting low-volatility portfolios, namely capitalisation weighting, equal weighting, $1/\sigma$ and $1/\beta$, that are standard in a risk budgeting framework [Roncalli, 2013]. The measure used to screen the S&P 500 universe is trailing 36-month volatility, a standard metric used in the literature. We build a factor on the lowest quintile, testing different weighting schemes: capitalisation weighting, equally weighted and risk weighting (inversely proportional to the risk measure employed) using both volatility and beta. We work on the S&P 500 Index, starting in December 1989. We compute volatility of each stock over 36 months, meaning that our analysis starts in January 1992. Each month, we select the first quintile of stocks with the lowest volatility. This constitutes our low-risk screening, as is done for all indexes presented here. After the screen, we only modify the weighting scheme. By testing these different approaches, we are able to assess the robustness of low-risk strategies' performance[2]. Results of cumulative performance are presented in Figure 3.

Figure 3: Returns of low-volatility portfolios

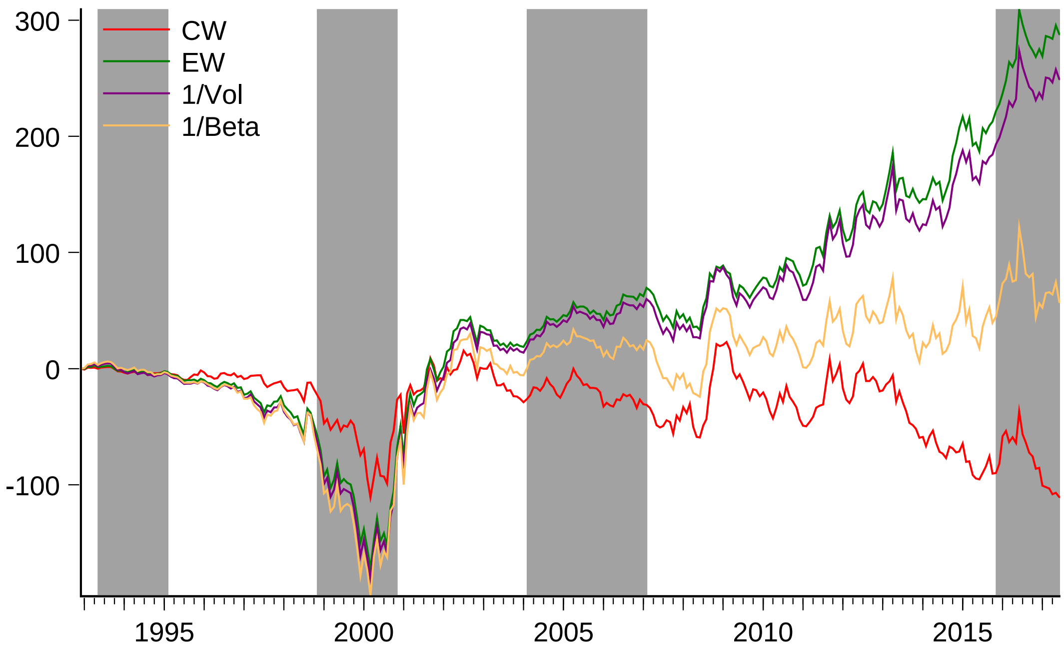


It can be seen that all strategies outperformed the S&P 500 Index over our sample period, except for the cap-weighted low-volatility portfolio. It also appears obvious that low-volatility strategies underperformed during the dot-com bubble[3].

[2]For inverse risk weighting schemes ($1/\sigma$ and $1/\beta$), both volatility and beta statistics are also computed over 36 months. One of the drawbacks of this approach is that mechanically, as risk tends towards zero, the weight allocated to an asset will increase drastically. Consequently, and in order to avoid excessive concentration in one single stock, we set minimal values for volatility and beta, so that a stock cannot represent more than 5 percent within the factor.

[3]We use the 3-month T-bill secondary market from the Federal Reserve Bank of St Louis database to differentiate between the different regimes. A rising T-Bill rate regime occurred during the periods from May 1993 to February 1995, November 1998 to November 2000, February 2004 to February 2007 and since November 2015. A falling T-bill rate regime occurred during the periods from January 1992 to April 1993, March 1995 to October 1998, December 2000 to January 2004 and

Figure 4: Excess returns of low-volatility portfolios



However, we cannot argue the same for other periods of rising rates (represented by grey areas). Therefore, we complement this analysis with performance in excess of the reference benchmark in Figure 4. We can observe the disrupting effect of Quantitative Easing at the end of the sample, making it hard to argue that periods of rising rates all look alike. As far as the weighting schemes are concerned, an asymmetry is observed between cap-weighting versus other approaches. While it held up fairly well until the end of the 1990s, it seems that cap-weighted weighting has generated significant underperformance since. As a matter of fact, this approach overweights stocks from large, blue-chip companies and neglects the smaller caps that may have outperformed for the rest of the period. In a similar manner, despite delivering consistent outperformance since the dot-com bubble burst, the $1/\beta$ weighting scheme seems to lag the equally-weighted and $1/\sigma$, with the latter two being very close.

Table 3 corroborates the outperformance of the least volatile quintile independently of the weighting scheme chosen, with the exception of the CW portfolio. Using results given in Table 4, we are able to more formally assess the drag of these strategies under rising rate regimes. Indeed, when turning to Sharpe ratios, we note that most of the enhancements occur during periods of falling and zero rates, with improvements being marginal under rising rates. An analogical observation can be made concerning the maximum drawdown. This first set of backtests sheds light on a potential performance drag faced by low-volatility strategies when interest rates are rising, independently of the weighting schemes employed when constructing the fac-

March 2007 to December 2008. Between January 2009 and October 2015 we consider that we are in the zero T-bill rate regime.

tor. In the current climate it appears rational for investors to quantify this potential lag.

Table 3: Backtesting results of low-volatility strategies

Statistics	Benchmark	EW	CW	$1/\sigma$	$1/\beta$
Annualized return (in %)	9.28	10.55	8.68	10.40	9.56
Volatility (in %)	14.42	11.24	11.40	11.10	11.57
Sharpe ratio	0.47	0.72	0.54	0.71	0.69
TE (in %)		9.03	8.00	9.53	10.99
Beta	1.00	0.61	0.66	0.58	0.53
Maximum drawdown	−52%	−41%	−41%	−40%	−42%

Table 4: Statistics across interest rate cycles

	Statistics	Benchmark	EW	CW	$1/\sigma$	$1/\beta$
Rising Regime	Annualized return (in %)	10.12	10.55	9.59	10.00	9.97
	Volatility (in %)	10.31	9.77	9.24	9.86	10.87
	Sharpe ratio	0.74	0.82	0.77	0.76	0.69
	TE (in %)		9.76	7.77	10.22	12.19
	Beta	1.00	0.50	0.62	0.47	0.36
	Maximum drawdown	−22%	−21%	−15%	−21%	−22%
Falling Regime	Annualized return (in %)	5.74	7.94	6.29	8.31	7.20
	Volatility (in %)	17.15	12.78	13.40	12.50	12.82
	Sharpe ratio	0.19	0.43	0.28	0.46	0.37
	TE (in %)		9.26	8.62	9.61	11.28
	Beta	1.00	0.63	0.68	0.61	0.56
	Maximum drawdown	−45%	−31%	−30%	−30%	−32%
Zero Regime	Annualized return (in %)	15.31	14.56	11.85	14.21	13.15
	Volatility (in %)	14.80	10.71	10.95	10.54	10.57
	Sharpe ratio	0.87	1.13	0.85	1.11	1.01
	TE (in %)		7.64	7.37	8.42	8.74
	Beta	1.00	0.63	0.65	0.59	0.58
	Maximum drawdown	−52%	−41%	−41%	−40%	−42%

5 Appraising stock sensitivity to interest rate changes

The question of how to measure sensitivity to interest rate movements differs across asset classes. For instance, when working on fixed-income securities, the straightforward answer is to use duration. However, on equities there is less consensus on that point. Consequently, this section is devoted to the choice of such a metric. We believe it has to satisfy a few criteria. First, it must be at the stock level, considering the volatility screening process. Even though the industry has to be accounted for, we argue that focusing on a sector-level metric is oversimplifying. Second, it has to be fairly dynamic and available at sufficiently high frequency. For instance, relying on balance-sheet data, that are generally available on a quarterly basis may not be timely enough to compare with changes in interest rates.

Based on the results in the previous section, we argue that the industry in which a firm operates is a prime determining factor of interest rate sensitivity. Accounting for leverage, cyclicality of earnings as well as the business model is therefore key. As mentioned previously, we distinguish between two features of interest rate variations: parallel shift (that is the change in the level of the yield curve) as well as the slope changes. First, we turn towards the part of the sensitivity to interest rates that is explained by the fact that a company belongs to a certain industry. Using the resulting coefficients from the last regression of our panel data analysis in Table 2, we are able to compute the structural sensitivity of each industry[4]. This will constitute the industry component of each stock's sensitivity to variations in the yield curve. The latter can be broken down as:

$$\delta_{\text{stock}} = \delta_{\text{industry}} + \delta_{\text{idiosyncratic}}$$

Using the sensitivity δ_{industry} computed through the OLS panel data analysis, we make the implicit assumption that the sensitivity of an economic sector to interest rates is structural. However, we want to augment the latter with an idiosyncratic component. The logic is as follows. Belonging to a given industry predetermines a certain responsiveness to changes in interest rates, notably because of the amount of leverage, cyclicality of earnings and the business model[5]. Still each stock has its peculiarities, and may diverge from its peer-group standard. Therefore, we model each stock sensitivity to interest rates, accounting for its industry, meaning that we compute returns in excess of the industry to which it belongs. More formally, we estimate the following equation for each stock i:

$$\text{Excess Return}_{i,t} = c + \Delta_t^{\text{Level}} + \Delta_t^{\text{Slope}} + \epsilon_{i,t}$$

where:

$$\text{Excess Return}_{i,t} = \text{Return}_{i,t} - \frac{1}{n}\sum_{i=1}^{n} \text{Return}_{i,t} \qquad \forall\, i \in \text{Industry}$$

Differentiating each stock from its industry in fact implies estimating a "within model", allowing us to focus on the assessment of stocks whose behavior differ from its peer-group. We thus highlight stocks that are highly sensitive to variations in

[4] It is given in Figure 2.

[5] It is also convenient for stocks that have just entered the industry or for which we do not have a sufficient number of observations to estimate robust regressions: their sensitivity is not set to 0 arbitrarily.

level and slope of the yield curve, even when we have controlled for the industry effect upstream. For parsimony matters, regression results for each stock are not presented here, instead we present box plots for level and slope idiosyncratic sensitivities in Figures 5 and 6 respectively.

In Figure 5, we note that on average, the idiosyncratic stock sensitivities are in line with the industry to which they belong (see Figure 2). Although, when looking at a 95% confidence interval, it seems that at the stock level, a parallel shift in the yield curve may be detrimental, in line with the "allocation" and "inflation" hypotheses. For healthcare firms, it is also interesting to turn towards the dispersion in those idiosyncratic effects within a single industry. For instance, when turning to consumer discretionary stocks, we observe that the firms in the lower part of the box plot are mostly homebuilding companies (such as KB Home) while the upper, positive sensitivity to rising interest rates are observed for specialty stores such as Tiffany & Co. Similarly, for information technology, the least volatile part of the sector (such as semi-conductor producers like Advanced Micro Devices) seem to perform well under rising rates, compared to Oracle and Microsoft whose performance is hindered in case of an upward parallel shift in rates. These "blue chips" have an above average media and public coverage and operate in riskier business lines than computing components which may make them more responsive to economic news.

As far as idiosyncratic sensitivity to the slope factor is concerned, healthcare stocks once again appear very robust when faced with rising rates. Industrials and telecommunication services are the most negatively impacted by a rise in the slope factor, although discrepancies exist within a single industry. For instance, construction materials companies constitute the lowest part of the box plot, while containers and packaging generally display positive sensitivity. Augmenting the aforementioned industry effects with idiosyncratic components, we conclude that parallel shifts in the yield curve generally place downward pressures on stock returns. However, if the latter is accompanied by a rise in the slope factor, it may have a positive effect, depending on the economic sector. Indeed, low leveraged and cyclical industries may hold up well.

Focusing on a comparison between the benchmark and the equally-weighted low-volatility strategy (thus discarding weighting schemes considerations), we compute historical exposures to interest rates in Figures 7 and 8, aggregating the "industry" and the "stock-specific" components[6]. These metrics can be interpreted as exposures to rates, implying that below zero, returns of the underlying portfolio will evolve in opposite direction to interest rates. So, they change according to the constituents (that is the least volatile stocks), industry classification (leverage and business model) and weighting scheme. As shown earlier in Figure 2, it seems that structurally, the low-volatility filter will overweight segments of the market that are

[6] We have also tested the alternative weighting schemes. In all, it seems the weighting scheme chosen does not impact results in a significant way, although the inverse weighting approaches ($1/\beta$ and $1/\sigma$) results in metrics that are often deeper in negative territory and more volatile.

Figure 5: Idiosyncratic sensitivity to interest rates (level component)

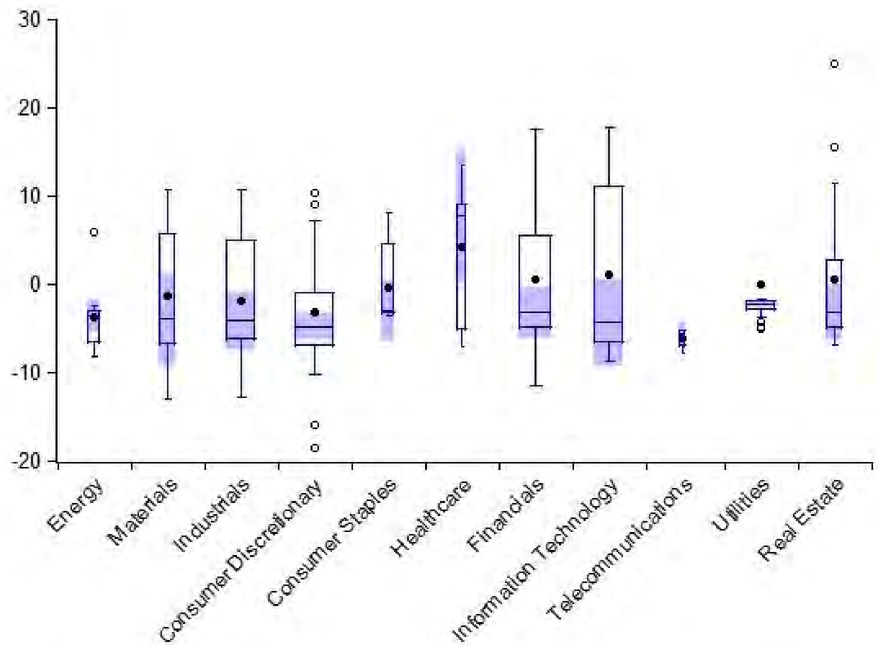
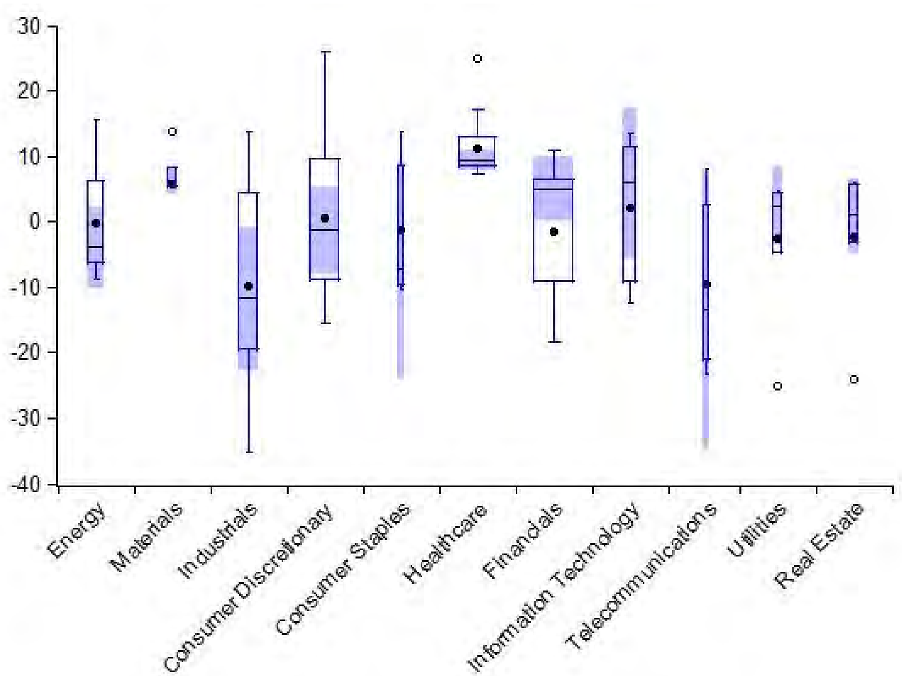


Figure 6: Idiosyncratic sensitivity to interest rates (slope component)



• = mean, ◦ = outliers and shaded area represents the 95% confidence interval.
The width of the box plot is proportional to the number of observations whose sensitivity is significantly different from its industrial peer-group.

Figure 7: Sensitivity to interest rate level

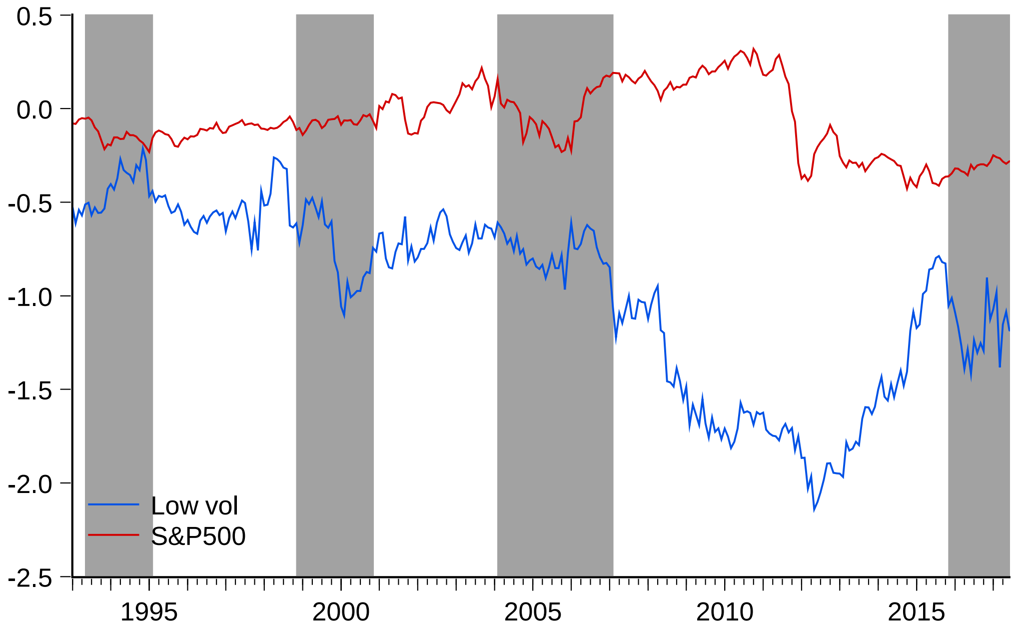
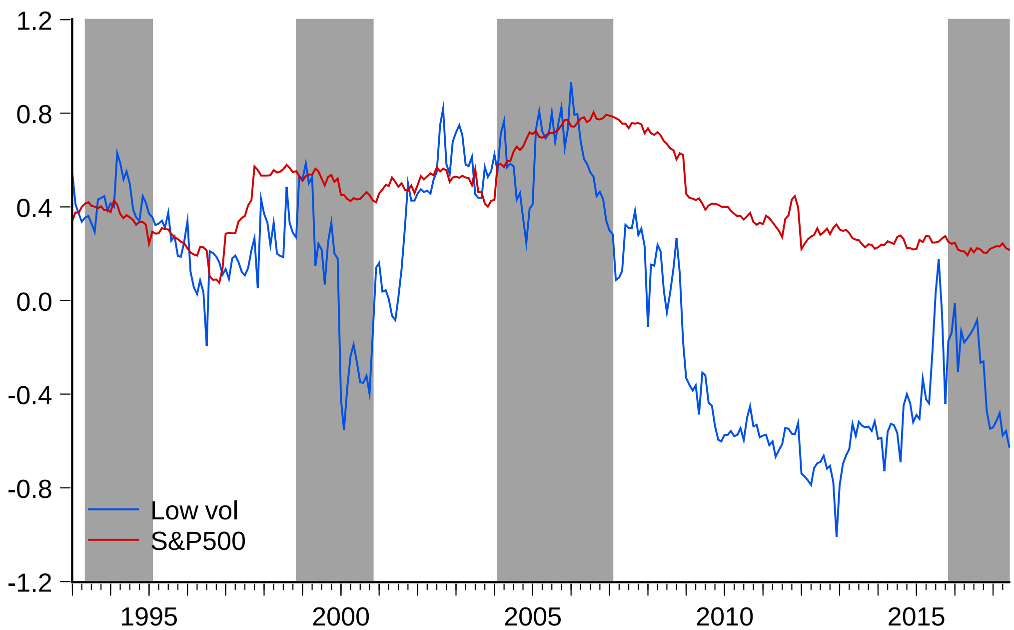


Figure 8: Sensitivity to yield curve slope



negatively correlated to interest rates, or put differently, that perform well when interest rates are falling, but struggle when they rise. Indeed, on average over the period, the S&P 500 Index has a sensitivity to parallel shifts in the term structure close to zero while the equality-weighted low-volatility strategy is consistently negative. Results are more contrasted for the exposure to non-parallel shifts. In fact, the exposure of the low-volatility strategy is less persistent compared to the benchmark although performed favourably during the last increase in rates between 2004 and 2007.

In Figure 10 on page 27, we break down the "industry" exposure from the "stock-specific" exposure to rise in interest rates. By doing so, it is possible to answer the following question: Can the industry bets be held responsible for the relatively smaller outperformance of the low-volatility strategy when rates are rising or is it the stock picking process? According to our measures, the industry bias introduced by the filter may be mostly responsible for most of the differentials in these strategies' exposures to interest rates. For instance, we note a sharp drop in both the parallel and non-parallel exposures to rates during the dot com bubble burst, where the low-volatility screening process implies a large overweight of the telecom industry. As far as stock picking is concerned, it is clearly detrimental in case of a parallel interest rate hike, while somehow it is close to the benchmark in case of a twist. To conclude, both stock picking and industry bias can be held responsible for the difference in performance between the low-volatility strategy and the S&P 500 Index. These bets pay off under a falling rate regime, but appear detrimental (because of the negative correlation of the low-volatility exposure) under a rising rate regime.

6 Constraints on interest rate risk exposure

Even though the low-volatility filter implies selecting the most impacted industries (the ones that are negatively correlated with interest rates), there is still room for altering the weighting scheme so that the exposure to interest rates matches that of the benchmark. More precisely, we propose a methodology to track the benchmark's sensitivity to rates. As a first step, stock weights are inversely proportional to their volatility, the most popular weighting scheme deployed by index providers. We face a trade-off, since we want to match the interest rate risk sensitivity of the benchmark, but also preserve the essence of low-volatility investing. Therefore, the idea is to modify the weights minimally using the following optimisation programme:

$$\begin{aligned} x^{\star}_{\text{constrained}} &= \arg\min \left\| x - x^{\star}_{\text{unconstrained}} \right\|^2 \\ &\text{u.c.} \quad \left\{ \begin{array}{l} \sum_{i=1}^{n} x_i = 1 \\ \sum_{i=1}^{n} x_i \delta_i^{\text{Level}} = \sum_{i=1}^{n} x_i^{\text{S\&P 500}} \delta_i^{\text{Level}} \\ \sum_{i=1}^{n} x_i \delta_i^{\text{Slope}} = \sum_{i=1}^{n} x_i^{\text{S\&P 500}} \delta_i^{\text{Slope}} \end{array} \right. \end{aligned}$$

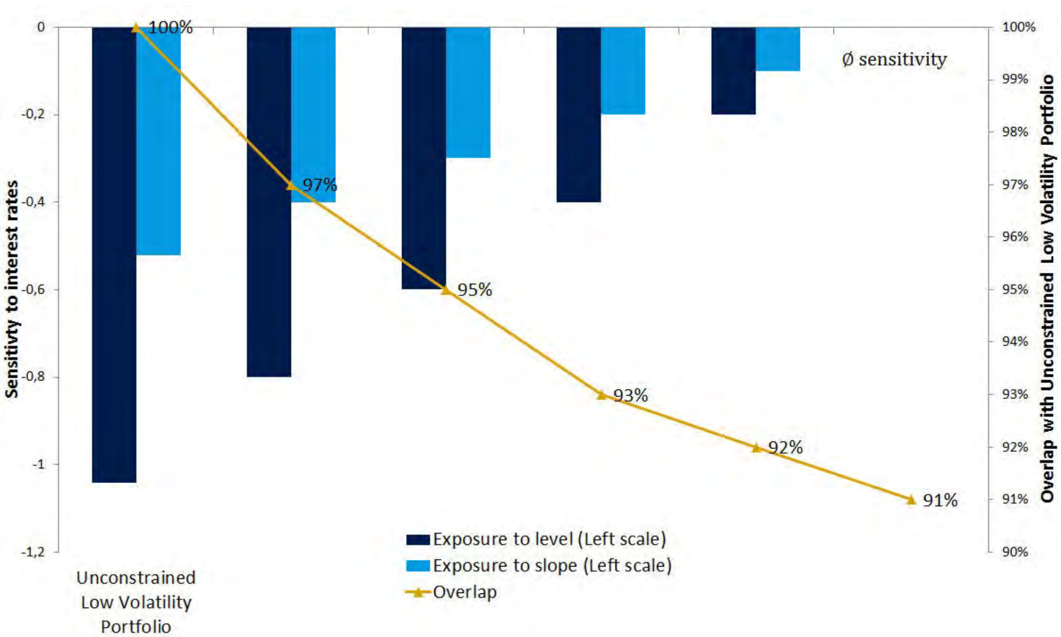
where x_i is the weight of asset i. We solve this optimisation problem every month. Backtesting results are presented in Table 5, and performance is plotted in Figure 11 on page 27. The first noteworthy result is that the tracking error between the two portfolios is low and around 2%. The approach we propose in order to stick to the benchmark exposure to interest rates does not seem to disrupt the characteristics of the low-volatility strategy in a significant way.

Table 5: Backtesting results of the constrained low-volatility strategy

Statistics	Unconstrained Portfolio	Constrained Portfolio
Annualized return (in %)	10.40	10.49
Volatility (in %)	11.10	11.47
Sharpe ratio	0.71	0.70
TE wrt S&P 500 Index (in %)	9.53	13.81
TE wrt unconstrained strategy (in %)		2.06
Beta	0.58	0.63
Maximum drawdown	−40%	−44%

However, as illustrated in Figure 9, it is important to bear in mind that the more stringent the condition on a portfolio's exposure to interest rate variations, the lower will be the overlap with the original portfolio. We conclude that the basic adjustment we propose is a convenient way to settle the trade-off between the low-risk philosophy and benchmarked portfolio management.

Figure 9: Interest rate exposure of constrained low-volatility strategies



7 Conclusion

Academics have identified the low-volatility anomaly since the 1970s, which contradicts a core principle in finance that higher risk must be rewarded by higher returns. With the rise of factor investing, investors have been increasingly inclined to tilt their portfolio towards the least volatile stocks. Low-volatility equity strategies have appeared as a winning formula over past decades. However, with the upcoming change in monetary policy triggered by Central Banks, doubts are being raised about the ability of such a strategy to deliver consistent performance under a rising rate regime. In this paper, we investigate the determining factors behind this potential drag. As a matter of fact, accounting for industry's peculiarities in terms of leverage, business model and defensiveness can partly explain the low-volatility anomaly. More specifically, we show that screening for the lowest volatile quintile of the S&P 500 Index implies an industry bias towards defensive industries and a significant exposure to companies with leveraged balance sheets. According to our analysis, the latter are the worst performers in terms of returns when rates step up. Concerns about the ability of low-volatility strategies to deliver consistent outperformance going forward are thus legitimate. However, since the approach we propose allows us to quantify the gap between the index's and the low-volatility portfolio's exposure to interest rates, it is thus possible to slightly modify the weighting scheme designed in order to reduce this exposure. Nevertheless, by doing so, one deliberately decides to move away the original low-volatility portfolio.

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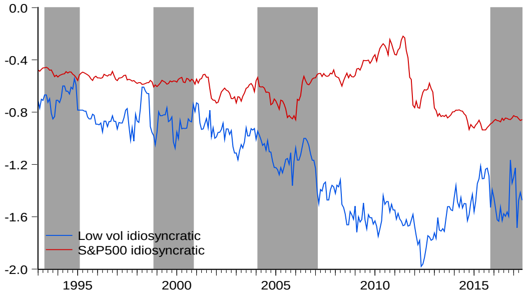
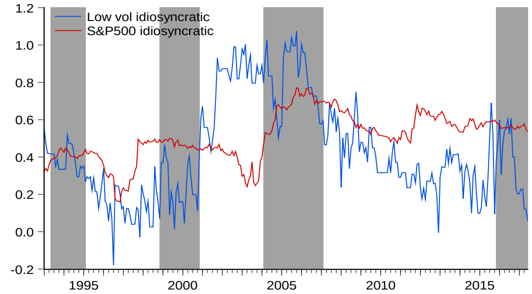
Appendix

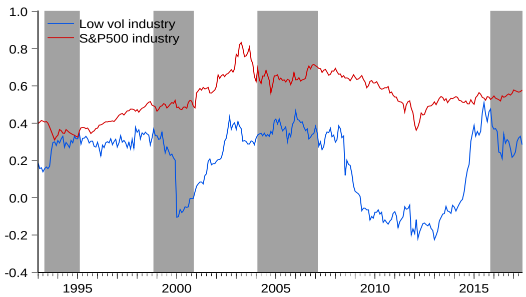
Figure 10: Breakdown of the interest rate risk exposure



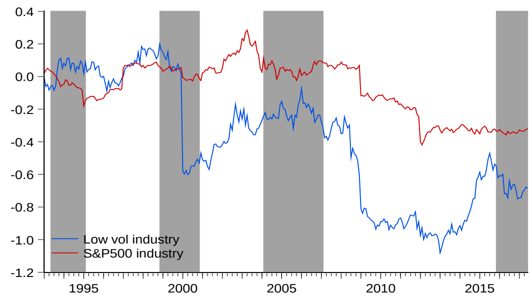
(a) Level / Idiosyncratic



(b) Slope / Idiosyncratic



(c) Level / Industry



(d) Slope / Industry

Figure 11: Performance of unconstrained and constrained low volatility strategies

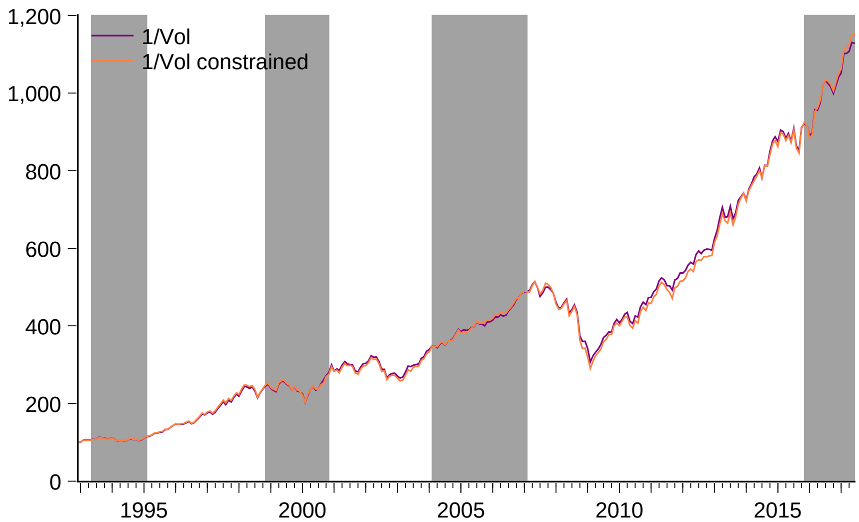


Table 6: Value and growth classification

Year	Healthcare	IT	Energy	Financials	Consumer Discretionary	Consumer Staples	Utilities	Industrials	Materials	Telecommunications	Real Estate
1990	Growth	Value	Value	Value	Value	Growth	Value	Value	Value	Growth	Value
1991	Growth	Value	Value	Value	Value	Growth	Value	Value	Value	Growth	Value
1992	Growth	Value	Value	Value	Value	Growth	Value	Value	Value	Growth	Value
1993	Growth	Value	Value	Value	Value	Growth	Value	Value	Value	Growth	Value
1994	Growth	Value	Value	Value	Value	Growth	Value	Value	Value	Growth	Value
1995	Growth	Growth	Value	Value	Value	Growth	Value	Value	Value	Growth	Value
1996	Growth	Growth	Value	Value	Value	Growth	Value	Value	Value	Growth	Value
1997	Growth	Growth	Value	Value	Value	Growth	Value	Value	Value	Value	Value
1998	Growth	Growth	Value	Value	Value	Growth	Value	Value	Value	Value	Value
1999	Growth	Growth	Value	Value	Value	Growth	Value	Value	Value	Value	Value
2000	Growth	Growth	Value	Value	Value	Growth	Value	Value	Value	Value	Value
2001	Growth	Growth	Value	Value	Value	Growth	Value	Growth	Value	Value	Value
2002	Growth	Growth	Value	Value	Value	Growth	Value	Growth	Value	Value	Value
2003	Growth	Growth	Value	Value	Value	Growth	Value	Growth	Value	Value	Value
2004	Growth	Growth	Value	Value	Value	Growth	Value	Growth	Value	Value	Value
2005	Growth	Growth	Value	Value	Value	Growth	Value	Growth	Value	Value	Value
2006	Growth	Growth	Value	Value	Value	Growth	Value	Growth	Value	Value	Value
2007	Growth	Growth	Value	Value	Value	Growth	Value	Growth	Value	Value	Value
2008	Growth	Growth	Value	Value	Value	Growth	Value	Growth	Value	Value	Value
2009	Growth	Growth	Value	Value	Growth	Growth	Value	Growth	Growth	Value	Value
2010	Growth	Growth	Value	Value	Growth	Growth	Value	Growth	Growth	Value	Value
2011	Growth	Growth	Value	Value	Growth	Growth	Value	Growth	Growth	Value	Value
2012	Growth	Growth	Value	Value	Growth	Growth	Value	Growth	Growth	Value	Value
2013	Growth	Growth	Value	Value	Growth	Growth	Value	Growth	Growth	Value	Value
2014	Growth	Growth	Value	Value	Growth	Growth	Value	Growth	Growth	Value	Value
2015	Growth	Growth	Value	Value	Growth	Growth	Value	Growth	Growth	Value	Value
2016	Growth	Growth	Value	Value	Growth	Growth	Value	Growth	Growth	Value	Value
2017	Growth	Growth	Value	Value	Growth	Growth	Value	Growth	Growth	Value	Value

Table 7: Leverage classification

Year	Healthcare	IT	Energy	Financials	Consumer Discretionary	Consumer Staples	Utilities	Industrials	Materials	Telecommunications	Real Estate
1990	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
1991	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
1992	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
1993	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
1994	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
1995	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
1996	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
1997	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
1998	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
1999	Low	Low	Low	High	High	Low	Low	High	Low	Low	High
2000	Low	Low	Low	High	High	Low	High	High	Low	Low	High
2001	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2002	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2003	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2004	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2005	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2006	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2007	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2008	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2009	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2010	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2011	Low	Low	Low	High	Low	Low	High	High	Low	Low	High
2012	Low	Low	Low	High	High	Low	High	High	Low	Low	High
2013	Low	Low	Low	High	High	Low	High	High	Low	High	High
2014	Low	Low	Low	High	High	Low	High	High	Low	High	High
2015	Low	Low	Low	High	High	Low	High	High	Low	High	High
2016	Low	Low	Low	High	High	Low	High	High	Low	High	High
2017	Low	Low	Low	High	High	Low	High	High	Low	High	High

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