Safeguarding Downside Risk in Portfolio Insurance: Navigating Swiss Stock Market Regimes with Options, Trading Signals, and Financial Products

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Abstract: Our research uses options to safeguard equity portfolios from downside risk. Despite the cost challenges of passive put protection, we explore leveraging diverse market signals, backward and forward-looking ones, to enhance portfolio risk-return balance while maintaining acceptable safeguards. These signals aid in selecting underlying assets for option positions, aiming to achieve protection while minimizing put premium expenditure. Certain signals, like "trend" or "low volatility", either empirical or implied, demonstrate added value, although their effectiveness depends on market conditions (or regimes). We also evaluate whether a set of trading rules can enhance the efficiency of such strategies. Our study highlights the importance of financial product safety, akin to safety measures for industrial products. By doing so, we underline the importance of portfolio insurance in finance. Further developments will aim at implementing a trading system that offers greater adaptability to different market regimes, for example high volatility phases, and under real market conditions.

1 INTRODUCTION

Options strategies, when implemented and incorporated correctly into traditional equity portfolios, can be a powerful tool to modify the risk and return profiles of such portfolios, allowing investors to express more accurately their investment views, risk tolerance, and return objectives or mandates. Options expand the universe of opportunities available, that would be rather limited in equity-only portfolios. For instance, a simple covered call strategy can serve as a yield enhancement instrument that allows the investor to achieve a targeted return whereas capital remains at risk. Likewise, a plain vanilla protective put limits the downside risk of an investment and can serve as a tool to efficiently protect the portfolio. However, these strategies are not easily and efficiently implemented. It is widely known that a “passive” plain vanilla protective put strategy is too costly in terms of option premia, and the resulting drag in long-term performance likely does not compensate for the protection during drawdown periods, worsening the portfolio’s long-term risk-adjusted performance (Ilmanen et al., 2021). In this article, we test whether the introduction of an actively managed portfolio of long put options into an equity portfolio can improve the combined portfolio’s risk-adjusted performance. This active management is performed by exploiting a set of backward-looking trading signals coming from the equities space (momentum, trend, or empirical volatility) and forward-looking ones from the options themselves (implied volatility or skew) that help in selecting the right underlying for which to take option positions.

The backward-looking signals from the equities space have been widely tested and implemented as

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trading strategies on equity portfolios across different periods and geographies, both in long-only format (e.g., smart-beta funds) or long-short (alternative beta or alternative risk premia funds). Jegadeesh & Titman (1993) were the first to formally test the "momentum" factor, by showing that portfolios that buy past winners and sell past losers generate positive returns over the next 3 to 12 months, which was not explained by their systematic risk exposures. Assness, Moskowitz and Pedersen (2013) found this momentum factor to be relevant not only in equities but across asset classes and across geographies. A similar strategy is the popular "Trend Following" strategy, which is also exploited by practitioners in various asset classes. While the momentum signal is a relative one (ranking-based), trend (sometimes named time-series momentum) is an absolute signal. Incorporating trend strategies in equities portfolios is desirable not only because it is expected to generate abnormal returns over the long term, but also due to its convex return profile, which helps at mitigating the impact of equity market drawdowns. This phenomenon was studied by Moskowitz, Ooi and Pedersen (2012) and more recently by Dao et al. (2016), Hurst et al. (2017), Babu et al. (2020), AQR (2022) and Co (2023). The third backward-looking signal used in this study is low empirical volatility. Frazzini and Pedersen (2014) popularized the concept of the Low Beta strategy, which puzzles traditional finance theory by showing that lower beta stocks consistently outperform higher beta stocks. Blitz and Vidojevic (2017) confirmed the low-risk anomaly, but found the mispricing of low volatility stocks to be stronger than the one of low beta stocks.

Forward-looking signals that exploit information from the options markets, such as implied volatility and skew (or smile), have been less explored. The motivation to also examine these signals is that they represent investors' expectations on future risk or market movements. Baltussen (2012) found that information extracted from options market in US large-cap stocks could be used to build trading strategies that outperform the benchmark, after controlling for other known risk factors. Our use of forward-looking signals was inspired by this article.

The relevance of these backward-looking and forward-looking signals in the Swiss equity market, which is the one used in this article, has been studied by the authors. We aim to assess whether these signals, which appear to be valuable when constructing long-short equity portfolios, can also add value when selecting the underlying for a long-put position. In addition, we experiment with a set of trading rules that could intuitively help to improve the efficiency of the strategy, explained in more detail in the following sections.

These trading strategies are implemented here into two base equity portfolios: an equally weighted (EW) and a global minimum variance (GMV) portfolio.

Results are evaluated using two different approaches. First, we apply a series of out-of-sample historical backtests, that help not only at testing whether a strategy would have worked in the past or not but are especially useful in understanding the behavior of the strategies in different market regimes. Second, we test the strategies over 500 bootstrapped periods. This second method provides an estimate of the return distribution of such strategies.

This paper is organized as follows. Section 2 provides a brief literature review. Section 3 presents our dataset and the trading signals used select the underlyings in which put option positions are taken. Section 4 shows the bench test we have created to apply our different trading strategies, specifying the constraints and/or additional rules applied in each case. Sections 5 and 6 show the results of the backtests and bootstraps respectively, Section 7 concludes and provides direction for further research.

2 LITERATURE REVIEW

The landscape of portfolio risk management includes various strategies and approaches to protect downside risk and improve risk-adjusted performance. In this literature review, we briefly review the key studies that contribute to the understanding of portfolio insurance such as the traditional passive put protection and other alternative risk mitigating strategies. While passive put options have their merits, they also come with limitations. The cost associated with maintaining put options can erode portfolio returns over time. Moreover, the effectiveness of passive puts in various market conditions may be limited. Researchers have begun to explore alternative strategies to mitigate these limitations. Ilmanen et al. (2021) conducted a study comparing a passive long-put strategy with a long/short trend strategy. Their research highlights the trade-off between cost and efficiency in protecting an equity portfolio, shedding light on the efficacy of passive put options in risk management but concluding that trend is preferable, as the long-term cost of a passive long put is simply too high.

Moreover, Israelov and Nielsen (2016), in their work on portfolio protection in calm markets, shed light on practical applications of portfolio insurance strategies. Other studies, such as those by Boulier and

Kanniganti (2005), Annaert et al. (2009), and Figlewski et al. (1993), have evaluated the performance of protective put strategies, providing valuable insights into their effectiveness. Lhabitant (1998) highlighted the potential of enhancing portfolio performance using option strategies, emphasizing the feasibility of outperforming the market with the right approach.

Incorporating options market signals into portfolio management has also been explored by Kostakis, Panigirtzoglou, and Skiadopoulos (2011), who focused on market timing with option-implied distributions, and Harper and Sarkar (2019), who examined option market signals and the disposition effect around equity earnings announcements. Dew-Becker, Giglio, and Kelly (2017) and Mohanty (2018) explored investors' perceptions of risks and forward-looking indicators in portfolio allocation, offering further avenues for research and practical application.

Finally, other authors focused on the impact of different asset allocation techniques to portfolio performance and risk. DeMiguel et al. (2009) contributed to the discussion on portfolio allocation methods, highlighting the inefficiencies of optimized portfolios compared to the 1/N portfolio strategy. Maillard, Roncalli and Teiletche (2009) proposed the risk parity or Equal Risk Contribution allocation, with portfolio volatility as the standard risk measure. They showed analytically that resulting weights are between the ones from the EW and GMV solutions. Jurczenko and Teiletche (2015) extended the ERC version to a portfolio tail-risk measure: the expected shortfall (conditional VaR or CVaR). Rockafellar and Uryasev (2000) first presented the approach to optimize portfolios by minimizing their expected shortfall. Brodie et al. (2009) and more recently Kremer et al. (2020) emphasized the imposition of constraints or penalties on the classic mean-variance optimization problem in order to reduce the impact of estimation errors and achieve robust out-of-sample optimal portfolios.

In conclusion, the literature on portfolio and risk management encompasses a wide range of strategies and approaches, including allocation methods, option strategies, equity market signals, and forward-looking indicators from options markets. These studies provide valuable insights into the trade-offs, limitations, and potential enhancements associated with different portfolio protection and management techniques, informing our research's combined approach in employing these strategies.

3 DATA EXPERIMENTS AND TRADING SIGNALS REVIEW

The universe is composed of 24 large-cap stocks from the Swiss market that belong, or belonged at some point during the sample period, to the Swiss Market Index (SMI Index). The sample period spans from March 24, 2006, to January 7, 2022. For each of the 24 components, we have the time series of daily stock values and a complete daily dataset of the options available at each date, with different strikes and maturities (corresponding to millions of data points). Using an internal model from the commercial partner (Grammont), we can also extract, for every option, an implied volatility value and a skew (or smile) value. This dataset allows us to estimate accurately the price of any option at any point in time during the sample period, for any combination of moneyness and maturity. Using the options dataset, we apply interpolation methods to create a daily time series of implied volatility and skew values for 12-month maturity ATM options, which will be used to calculate the forward-looking signals. Smaller capitalization stocks are not considered due to the lack of availability in the options dataset. Options for most smaller cap underlyings are either inexistent or highly illiquid and thus it is not possible to construct reliable time series for these securities, neither to construct systematic trading strategies. A potential concern with our dataset is that the 24 components have data available until the end of the sample period. As a rule, if there was a large-cap stock that stopped trading during the sample period, it does not appear in the sample. However, and to the best of our knowledge, only Transocean (RIGN), which was delisted from the SIX in March 2016, is not included. Moreover, since the goal is to compare the relative performance among strategies and portfolios, we believe that the survivorship bias is mitigated, as it would affect, even though not to the same extent, all the strategies tested. The dataset includes the same options data for the SMI Index. For a proxy of the risk-free interest rate, we use the overnight SARON.

3.1 Backward-Looking Signals

The first group of signals takes information from historical stocks' data and is thus "backward-looking". It includes trend, momentum and low empirical volatility.

Trend (TREND): A given underlying shows a positive signal if the return over the most recent 12-months, 6-months, and 3-months is positive. Likewise, it shows a negative signal if the return over the same 3 periods is negative. Note that the sign of the return must be the same for the three periods. If the sign is different for at least one of the periods, then the signal is neutral or, in other words, there is no trend signal. At any rebalancing date, all underlying can have positive, negative, or neutral signals.

Momentum (MOM): At each rebalancing date, the signal is positive for the best-performing 25% stocks and negative for the worst-performing 25% stocks. The performance measure to rank the stocks is the most recent 12-month return. As opposed to trend, momentum is a cross-sectional signal. Thus, even if a stock shows a negative return, it has a positive signal if it falls in the best quartile. In the same vein, stocks with positive returns can show a negative signal. This implies that at every rebalancing date in which the number of stocks is the same (e.g., 24 underlyings), there are always the same number of underlyings with positive and negative signals (e.g., 6 underlyings).

Historical Volatility (HVOL): Like momentum, at each rebalancing date this signal is positive for the 25% underlyings with the lowest empirical volatility and negative for the 25% underlyings with the highest empirical volatility. Volatility is calculated using the most recent 12-month period.

3.2 Forward-Looking Signals

The second group is made of signals that use data coming from the options prices, and thus are understood to be "forward-looking". These are implied volatility and skew, both cross-sectional and in time-series format. The signals are calculated using our daily time-series dataset of estimated implied volatility and skew for a 12-month ATM option. They are seen as forward-looking because they express investors' expectations on future risk and market variation (e.g., implied volatility can be interpreted as the investors' expected future market volatility).

Implied Volatility (IVOL): At each rebalancing date, the underlyings are ranked by their implied volatility value (using the implied volatility of the hypothetical ATM 12-month maturity option) and the signal is positive for the first quartile and negative for the fourth one. This signal is expected to yield similar results as the empirical volatility signal since underlyings with high (low) empirical volatility tend to exhibit high (low) implied volatility in their option prices.

Option's Skew (SKEW): At each rebalancing date, the underlyings are ranked by their skew value (using the skew of the hypothetical ATM 12-month maturity option) and the signal is positive for the first quartile and negative for the fourth one. A high skew happens when the implied volatility of OTM options is larger than the implied volatility of ATM options for the same expiries and underlyings. This means that investors demand more OTM options concerning ATM ones and are willing to pay more for the former ones, or that they expect large variations to be more frequent than expected by an options pricing model, such as Black-Scholes.

Implied Volatility Spike (IVOL-Spike): At each rebalancing date, the signal is negative for an underlying whose implied volatility on the previous day, extracted from our time-series data, is at least one standard deviation larger than its mean, taking the previous one-year daily implied volatility values. The signal is neutral (or no signal) otherwise.

Skew Spike (SKEW-Spike): At each rebalancing date, the signal is negative for an underlying whose skew on the previous day, extracted from our time-series data, is at least one standard deviation larger than its mean, taking the previous one-year daily skew values. The signal is neutral (or no signal) otherwise.

ALL: For comparison purposes, we will include a portfolio that takes option positions on all stocks available, regardless of signals.

4 PORTFOLIOS' CONSTRUCTION PROCESS

We test the relevance of these signals on active long-put strategies implemented into two base equity portfolios. an equally weighted (EW) and a global minimum variance (GMV) portfolio, rebalanced every 6 months. We also tested the Equal Risk Contribution (ERC) and CVaR minimization (CVaR-min) allocation methods. While ERC showed results in between EW and GMV, results from CVaR-min portfolios were almost the same as GMV. To comply with the article's format requirements and size limits, only EW and GMV results are presented in the paper. Also, we test for a set of trading rules that intuitively could improve the portfolios' performance, detailed below.

To determine the performance of the strategies and the relevance of the signals and trading rules, we perform historical backtests as well as tests on 500 one-year bootstrapped periods.

The portfolios are constructed as follows. We assume an investor with CHF 100 million to allocate at time t=0, which is April 4, 2007, for the historical backtests, and the first date (randomly selected) of each bootstrapped period. This capital can be used to purchase stocks or put options.

In the portfolios where no option positions are taken, the portfolio will be fully invested in equities. To find the weights in GMV case, the parameters, namely the covariance matrix, are estimated using the underlyings' prior 12-month returns. Also, we set the constraint of maximum weight to an individual name to 20% and, for all stocks whose weight in the optimization is lower than 0.2%, we set their weights to be zero and redistribute them proportionally across the remaining components in the portfolio. The weights are re-calculated on every rebalancing date (i.e. every 6 months, for both the backtests and the bootstrap periods).

For the strategies that are long put options (with the exception of the "SMI" strategy, that is long puts on the SMI index and thus acting as a portfolio "macro hedge", explained in more detail below), a target budget of 2.5% of portfolio value to be spent on option premia on every rebalancing is set. However, for the "absolute value signals" (i.e. not relative ranking), such as trend, it is desirable to allow a varying budget that is a function of the number of underlyings with a signal, while keeping a limit. Therefore, the methodology applied is as follows: at t=0 and at each rebalancing date, a global budget is set equal to 10% of the portfolio value (e.g., CHF 10 mio. at t=0). Then, this global budget is divided equally among all the underlyings available (even those with no weight in the GMV portfolio), which represents the individual budget that will be spent to purchase put options of that underlying if it shows a negative signal. Note that, for relative (ranked) signals, in which a 25% of underlyings show a signal at each rebalancing date, a fixed 2.5% of portfolio value is spent on each rebalancing (in reality, this value ranges between 2.07% and 3.37%, due to rounding the 25% to the closest number of underlyings available, yet in most cases is between 2.3% and 2.8%). For "absolute signals", the range is between 0% if no underlying shows a signal and 10% if all underlyings show a signal. On the historical backtests, on average is spent 2.44% of portfolio value at each rebalancing period for the trend signal, 2.10% for the IVOL-TS signal and 2.90% for the SKEW-TS signal, close to the 2.50% target.

The strike is set at 90% of the spot price (OTM) and maturity is always 6 months, coinciding with the rebalancing period. The individual budget divided by each estimated option premium sets the number of put options that are purchased at each rebalancing date. Note that, by using this method, the combination of equities and put positions can be partially protective, fully protective or even speculative (negative delta), as the number of puts depends on the budget and the premium, and not on the number of stocks in the portfolio from each underlying.

The remaining capital available (portfolio value minus the amount spent in option premia) is used to purchase stocks.

The following trading strategies are simulated and compared:

BASE: Base portfolio. It is an equity-only portfolio, with no options. It serves as the benchmark.

OPT: At t=0 and each rebalancing date, it buys put options on individual names that show a negative signal.

LEV: It is constructed as the OPT strategy but with 20% leverage. Thus, the initial invested capital is CHF 120 million. It assumes a leverage cost of SARON + 40 bps, paid at each rebalancing period. The idea is that the risk reduction obtained from the options' protection can be used to leverage the equity portfolio and its long-term return.

TR1: It is built as the OPT strategy. Yet, during the investment period (i.e., between one rebalancing date and the next one), an additional trading rule is added (TR1): If an option's delta reaches a pre-defined trigger (-0.9 or less), the put that was initially bought is sold to close the position at a profit. The aim of this rule is that, in the case of a short-term upside reversal, the profit that is made in the options' positions is not lost with the reversal.

TR2: It is a variation of TR1: once an option's delta reaches the predefined trigger, if the negative signal is still present in the underlying, it won't close the positions. If the signal is positive or neutral, it will close the positions as in TR1. This trading rule is implemented in the backtests only.

TR3: It is built as the OPT strategy, in which put options are bought on stocks that show a negative signal, but with an additional rule: if the implied volatility of any option is below 10% (i.e., low implied volatility), it will purchase the put options, regardless of whether the underlying shows negative signal or not. Likewise, if the implied volatility is above 30% (i.e., high implied volatility), it won't purchase the put options even if they show a negative signal. This additional rule buys options when they are cheap and avoids them when they are expensive, regardless of the signal.

WEI.: This strategy does not take option positions. Instead, it sets the weights of the underlyings with a negative signal at zero and redistributes these weights proportionally across the remaining components in the portfolio.

SMI: This portfolio takes option positions on the SMI index, rather than on individual underlyings. To calculate the number of options, at t=0 and each rebalancing date it calculates the market beta of each equity portfolio (EW, GMV) and purchases the number of options proportional to each portfolio's beta. It also serves as a benchmark to compare whether taking positions on individuals is more effective than simply taking option positions on the index.

5 HISTORICAL BACKTESTED RESULTS

As mentioned previously, the historical backtests begin on April 4, 2007, and are rebalanced every 6 months, coinciding with the options' expiry dates. Summary results are presented in Table 1 for the EW allocation and Table 2 for GMV. These results represent the average annualized return, the worst 6-month period, and the ratio of average return over the worst 6-month return. First, it is noticeable that all GMV portfolios outperform EW ones, with or without options. They show both higher average return and a smaller loss in the worst 6-month period. Focusing on the signals, trend appears to be the one that provides the best results, largely outperforming the Base portfolio regardless of the allocation method or trading rule, except for the TR3 case. This is due to the large profit of the put options during the 2008 GFC period and 2011 (EU sovereign debt crisis). Another signal that outperforms the Base in both EW and GMV, both at the simple portfolio with options (OPT) and in the case of TR1, TR2, and LEV is the IVOL-spike signal. IVOL, SKEW, and SKEW-Spike signals outperform in the GMV case, but their results are more mixed on EW portfolios.

Finally, momentum (MOM) and historical volatility (HVOL) do not add value, except for the WEI. strategy which does not take any option positions. Overall, the added value of the trading rules TR1, TR2, and TR3 is negative in most cases, and, when positive, its effect is very minor. Interestingly, the passive put strategy that takes options' positions on all underlyings (OPT portfolio with Signal 1 or ALL) drops the average return from 3.39% (Base) to -3.51% in the EW case and from 5.30% to -2.63% in GMV, comparable values found by Ilmanen et al. (2021).

Table 1: Historical backtested results: EW allocation.

Port.	**SIGNAL**							
	1	***2***	***3***	***4***	***5***	***6***	***7***	***8***
	3.39							
BASE	-29.5							
	0.12							
	0.00							
SMI	-16.9							
	0.00							
	-3.51	3.77	2.55	3.01	3.14	2.26	3.85	2.95
OPT	-10.6	-13.3	-25.6	-25.3	-25.3	-17.6	-20.2	-21.3
	-0.33	0.28	0.10	0.12	0.12	0.13	0.19	0.14
	-4.53	4.27	2.89	3.41	3.55	2.56	4.36	3.35
LEV	-13.2	-16.0	-31.3	-31.4	-31.5	-22.0	-24.2	-25.2
	-0.34	0.27	0.09	0.11	0.11	0.12	0.18	0.13
	-0.97	3.58	3.44	3.53	3.54	2.39	3.29	2.35
TR1	-18.3	-20.8	-27.9	-28.1	-28.1	-25.5	-20.2	-22.1
	-0.05	0.17	0.12	0.13	0.13	0.09	0.16	0.11
		3.95	2.92	3.16	3.39	2.56	3.29	3.20
TR2		-13.0	-26.5	-25.3	-25.3	-20.2	-20.2	-21.3
		0.30	0.11	0.12	0.13	0.13	0.16	0.15
	-0.67	2.80	-0.67	-0.67	3.48	2.29	2.71	2.51
TR3	-29.5	-29.5	-29.5	-29.5	-29.5	-29.5	-29.5	-29.5
	-0.02	0.09	-0.02	-0.02	0.12	0.08	0.09	0.09
		4.01	4.14	4.38	4.06	5.08	3.94	4.34
WEI.		-29.2	-30.5	-29.9	-29.9	-24.0	-39.0	-22.5
		0.14	0.14	0.15	0.14	0.21	0.10	0.19

Signals: 1=ALL, 2=TREND, 3=MOM, 4=HVOL, 5=IVOL, 6=SKEW, 7=IVOL-SPIKE, 8=SKEW-SPIKE In each cell, results show the average annualized return (%) above, worst 6-month period return (%) in the middle, and the ratio of avg. return to worst 6M return below.

Table 2: Historical backtested results: GMV allocation.

Port.	**SIGNAL**							
	1	***2***	***3***	***4***	***5***	***6***	***7***	***8***
	5.30							
BASE	-18.8							
	0.28							
	2.84							
SMI	-10.9							
	0.26							
	-2.63	5.15	4.09	4.55	4.68	3.81	5.33	4.34
OPT	-13.3	-8.2	-15.2	-14.9	-14.9	-08.6	-11.2	-12.7
	-0.20	0.63	0.27	0.31	0.31	0.44	0.48	0.34
	-3.34	5.80	4.63	5.14	5.28	4.32	5.99	4.92
LEV	-16.1	-9.8	-18.3	-18.2	-18.3	-10.3	-13.1	-14.4
	-0.21	0.59	0.25	0.28	0.29	0.42	0.46	0.34
	0.02	5.03	5.01	5.12	5.13	4.04	4.86	3.87
TR1	-13.0	-10.8	-17.5	-17.7	-17.7	-15.1	-11.2	-12.4
	0.00	0.46	0.29	0.29	0.29	0.27	0.43	0.31
		5.32	4.46	4.71	4.93	4.13	4.86	4.61
TR2		-8.2	-16.1	-14.9	-14.9	-09.8	-11.2	-12.4
		0.65	0.28	0.32	0.33	0.42	0.43	0.37
	1.07	4.66	1.07	1.07	5.36	4.14	4.60	4.35
TR3	-18.8	-18.8	-18.8	-18.8	-18.8	-18.8	-18.8	-18.8
	0.06	0.25	0.06	0.06	0.28	0.22	0.24	0.23
		4.78	5.19	5.23	5.31	5.93	5.60	7.30
WEI.		-19.2	-18.8	-18.8	-18.8	-18.8	-14.0	-16.0
		0.25	0.28	0.28	0.28	0.32	0.40	0.46

Signals: 1=ALL, 2=TREND, 3=MOM, 4=HVOL, 5=IVOL, 6=SKEW, 7=IVOL-SPIKE, 8=SKEW-SPIKE In each cell, results show the average annualized return (%) above, worst 6-month period return (%) in the middle, and the ratio of avg. return to worst 6M return below.

6 BOOTSTRAPPED RESULTS

Bootstrap results, displayed in Table 3 and Table 4 for EW and GMV allocation methods respectively, somehow differ from those of the backtests. In this case, only empirical and implied volatility (HVOL and IVOL) signals outperform the Base when no additional trading rules are implemented. Both signals are indeed closely related, as stocks whose returns have been volatile the past year tend to show a high implied volatility value. TR1 seems to add value to all signals, making trend and momentum signals outperform both EW and GMV allocations.

The disparity of results between backtest and bootstrap suggests that the results are indeed sample-dependent: either the backtested results are too reliant on the one-time 2008 GFC gain, or the bootstraps are overrepresented in a sample period that has been calm in general for equities, for which they have experienced a long rally with exceptionally low volatility. We performed the same tests but using a restricted sample period ending on February 14, 2014. Using this restricted sample results closely align with the backtests: historical and implied volatility signals still show outperformance, as in the original bootstrapped results, but it is the trend signal that improves the portfolio's performance the most. These results suggest that classic signals such as trend or low volatility (empirical or implied) can help improve the risk-adjusted performance of equity portfolios using put options: the signals help reduce the long-term cost of the option strategies but still offer partial protection on large equity market drawdown periods. Yet, no signal works at every period and market regime. A more dynamic strategy that identifies, for instance, when trend or low volatility signals are useful and when they are not, could certainly improve the performance of the strategies.

Table 3: Bootstrapped results: EW allocation.

Port.	SIGNAL							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
	6.44							
BASE	-24.2							
	0.27							
	2.25							
SMI	-23.6							
	0.10							
	-8.62	4.59	3.15	4.69	4.83	2.12	2.83	1.53
OPT	-28.7	-18.5	-17.8	-13.6	-14.9	-20.6	-25.0	-20.6
	-0.30	0.25	0.18	0.34	0.32	0.10	0.11	0.07
	-10.39	5.47	3.74	5.59	5.76	2.50	3.36	1.80
LEV	-34.4	-22.6	-21.2	-16.6	-17.8	-24.6	-30.1	-24.6
	-0.30	0.24	0.18	0.34	0.32	0.10	0.11	0.07
	-4.10	5.53	4.96	5.55	5.74	3.33	3.94	3.77
TR1	-26.0	-16.5	-15.4	-15.1	-15.2	-20.1	-23.9	-20.1
	-0.16	0.34	0.32	0.37	0.38	0.17	0.16	0.19
	-2.70	5.49	4.78	6.72	7.22	3.69	4.51	2.97
TR3	-31.2	-24.9	-24.9	-22.2	-23.7	-22.4	-23.7	-22.4
	-0.09	0.22	0.19	0.30	0.30	0.16	0.19	0.13
		5.45	3.50	4.98	5.21	2.46	3.52	2.17
WEI.		-18.5	-16.6	-13.5	-14.9	-20.2	-24.7	-20.2
		0.29	0.21	0.37	0.35	0.12	0.14	0.11

Signals: 1=ALL, 2=TREND, 3=MOM, 4=HVOL, 5=IVOL, 6=SKEW, 7=IVOL-SPIKE, 8=SKEW-SPIKE In each cell, results show the average annualized return (%) among the 500 bootstraps above, the annualized return (%) of the worst 5% case in the middle, and the ratio of avg. return to worst 5% return below.

Table 4: Bootstrapped results: GMV allocation.

Port.	SIGNAL							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
	6.67							
BASE	-14.6							
	0.46							
	3.72							
SMI	-15.6							
	0.24							
	-8.96	4.57	3.22	4.75	4.91	2.15	2.84	1.50
OPT	-29.1	-11.7	-10.2	-09.1	-09.2	-12.4	-15.0	-12.4
	-0.31	0.39	0.31	0.52	0.54	0.17	0.19	0.12
	-10.80	5.45	3.82	5.67	5.85	2.54	3.37	1.76
LEV	-34.8	-14.0	-12.3	-10.9	-11.1	-15.1	-18.5	-15.1
	-0.31	0.39	0.31	0.52	0.53	0.17	0.18	0.12
	-4.42	5.57	5.02	5.66	5.86	3.36	3.97	3.74
TR1	-27.7	-11.4	-08.7	-08.4	-08.8	-11.6	-14.6	-11.6
	-0.16	0.49	0.58	0.67	0.66	0.29	0.27	0.32
	-3.25	5.60	4.86	6.78	7.27	3.65	4.66	3.04
TR3	-26.4	-14.2	-14.0	-12.4	-12.6	-13.6	-15.0	-13.6
	-0.12	0.39	0.35	0.55	0.58	0.27	0.31	0.22
		5.41	3.55	5.02	5.26	2.46	3.53	2.14
WEI.		-11.7	-10.2	-08.9	-09.2	-12.6	-15.0	-12.6
		0.46	0.35	0.56	0.57	0.19	0.24	0.17

Signals: 1=ALL, 2=TREND, 3=MOM, 4=HVOL, 5=IVOL, 6=SKEW, 7=IVOL-SPIKE, 8=SKEW-SPIKE In each cell, results show the average annualized return (%) among the 500 bootstraps above, the annualized return (%) of the worst 5% case in the middle, and the ratio of avg. return to worst 5% return below.

7 CONCLUSIONS

Protecting the downside risk of equity portfolios is a paramount aspiration for any risk-averse investor or portfolio manager, and options can be very effective instruments to achieve this objective, thanks to their flexibility in their payoff profiles. However, the high cost of passive put protection and its large negative impact on a portfolio's long-term performance makes this type of strategy implausible in practice. In this article, we test for a set of market signals that could help take option positions more efficiently, reducing the cost spent in options' premia but still benefiting from an acceptable degree of portfolio protection, even though this one is partially offset. We test for a set of backward-looking market signals widely used in the equities space, such as trend, momentum, and historical volatility, and forward-looking signals coming from the options markets, which are less explored by the industry. The latter are implied volatility and skew, both cross-sectionally (relative rank) and in time-series format (implied volatility or skew rise). The benefit of these signals is that they show investors' expectations about future market movements, as opposed to past information. We perform backtest and bootstrap tests to determine whether the signals add value to a portfolio of Swiss large-cap equities. Also, we test for different strategies that implement a set of trading rules that intuitively could improve the portfolios' performance. Two equity allocations are simulated: an equally weighted and a minimum variance portfolio. The results suggest that it is possible to use market signals to select the underlyings to which purchase put options, similarly to the use of signals to construct long-short portfolios, and improve the risk-return relationship of a portfolio made of equities and put options. However, the signals' efficacy depend largely on the market regime. For instance, trend appears to add substantial value during large and long-dated equity market drawdowns, but less clearly during calm markets, when historical volatility or implied volatility seems to work better. More sophisticated trading signals do not improve the results consistently. Finally, it is worthwhile noticing that GMV portfolios systematically outperform their EW counterparts in all strategies (with or without options, with or without trading rules, with or without leverage), both in backtests and bootstrapped results, even though GMV portfolios tend to be heavily concentrated in a few individual stocks.

The empirical results of this study should be considered in the light of some limitations. First, the limited dataset composed only by Swiss large-cap underlyings results into rather concentrated portfolios. Practically, equity portfolios would likely be more diversified, by holding a larger number of different names and including smaller-capitalization stocks. Also, according to the authors' own backtests, the signals appear to be more relevant in a larger universe that includes smaller-capitalization stocks. Moreover, the strategies' relevance in markets other than Switzerland, or even international portfolios, remains to be tested. Another shortcoming is the uniqueness and simplicity of the strategy implemented to purchase put options that is presented in this article. Certainly, alternative methods exist and their efficiency is worthwhile being tested. The authors have tested the incorporation of other option strategies with different risk-return objectives into the same Swiss equity portfolios. For instance, the classic protective put (fully protecting the underlying equity position below some strike) on negative-signal underlyings, selling OTM covered call options (e.g. at 110% of strike) on those same underlyings for yield enhancement, or by going long OTM calls on underlyings with a positive signal, thus exploiting the potential of the positive side of the signals. However, due to space limitations, only this simple long-put strategy that exploits the negative side of the signals is presented. In the same way, the strategies' sensitivities to parameter modifications remain to be tested. For instance, strikes can be set at different levels (e.g. 80% or 95% instead of the 90% used), signals could be defined using other lookback windows (e.g. 6 months instead of 12 months). Finally, the results of this current study show that the effectiveness of the different signals on the put option strategies are dependent on different market regimes. Thus, further research is necessary to test the effectiveness of the signals conditional to market regimes and whether these regimes can be consistently and timely identified.

In conclusion, this paper, primarily focused on the field of financial engineering, aims to demonstrate that the complex concepts of portfolio insurance, options, and trading signals, which have been widely discussed in the financial risk management literature, should be subject to a comprehensive, global benchmark test. The intention behind this undertaking is to emphasize that these complex notions should not simply remain in the realm of financial theory but should also serve as valuable tools for effective portfolio management. Our project, supported by Innosuisse and conducted in collaboration with an options trading house, highlighted a key point. We confirmed that the optimal portfolio protection strategy, despite its potential cost, should be adaptable to different market regimes.

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REFERENCES

AQR (2022). Trend-Following: Why Now? A Macro Perspective. *White paper.*

Annaert, J., Van Osselaer, S., Verstraete, B. (2009). Performance evaluation of portfolio insurance strategies using stochastic dominance criteria. *Journal of Banking & Finance*, 33(2), 272-280.

Asness, C. S., Moskowitz, T. J., Pedersen, L. H. (2013). Value and momentum everywhere. *The journal of Finance*, 68(3), 929-985.

Babu, A., Hoffman, B., Levine, A., Ooi, Y. H., Schroeder, S., Stamelos, E. (2020). You can't always trend when you want. *The Journal of Portfolio Management*, 46(4), 52-68.

Baltussen, G., van der Grient, B., de Groot, W., Hennink, E., Zhou, W. (2012). Exploiting option information in the equity market. *Financial Analysts Journal*, 68(4), 56-72.

Blitz, D., Vidojevic, M. (2017). The profitability of low-volatility. *Journal of Empirical Finance*, 43, 33-42.

Boulier, J. F., Kanniganti, A. (2005). Expected performance and risk of various portfolio insurance strategies. *Proceedings of the 5th AFIR International Colloquium* (pp. 1093-1124).

Brodie, J., Daubechies, I., De Mol, C., Giannone, D., Loris, I. (2009). Sparse and stable Markowitz portfolios. *Proceedings of the National Academy of Sciences*, 106(30), 12267-12272.

Co, D. (2023). A new approach to trend-following. *Unpublished manuscript.*

Dao, T. L., Nguyen, T. T., Deremble, C., Lemperiere, Y., Bouchaud, J. P., Potters, M. (2016). Tail protection for long investors: Trend convexity at work. *arXiv preprint arXiv:1607.02410.*

DeMiguel, V., Garlappi, L., Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *The Review of Financial Studies*, 22(5), 1915-1953.

Dew-Becker, I., Giglio, S., Kelly, B. (2017). How do investors perceive the risks from macroeconomic and financial uncertainty? Evidence from 19 option markets. *Working paper*.

Figlewski, S., Chidambaran, N. K., Kaplan, S. (1993). Evaluating the performance of the protective put strategy. *Financial Analysts Journal*, 49(4), 46-56.

Frazzini A., Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 111(1), 1-25.

Harper, A. C., Sarkar, S. K. (2019). Option Market Signals and the Disposition Effect Around Equity Earnings Announcements. *Journal of Behavioral Finance*, 20(4), 471-489.

Hurst, B., Ooi, Y. H., Pedersen, L. H. (2017). A century of evidence on trend-following investing. *The Journal of Portfolio Management*, 44(1), 15-29.

Ilmanen, A., Thapar, A., Tummala, H., Villalon, D. (2021). Tail risk hedging: Contrasting put and trend strategies. *Journal of Systematic Investing*, 1(1), 111-124.

Israelov, R., Nielsen, L. N. (2015). Still not cheap: Portfolio protection in calm markets. *The Journal of Portfolio Management*, 41(4), 108-120.

Jegadeesh, N., Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65-91.

Jurczenko, E., Teiletche, J. (2015). Risk-Based Investing but What Risk (s)? *Risk-Based and Factor Investing*, pp. 147-171. Elsevier.

Kostakis, A., Panigirtzoglou, N., Skiadopoulos, G. (2011). Market timing with option-implied distributions: A forward-looking approach. *Management Science*, 57(7), 1231-1249.

Kremer, P. J., Lee, S., Bogdan, M., Paterlini, S. (2020). Sparse portfolio selection via the sorted ℓ1-Norm. *Journal of Banking & Finance*, 110, 105687.

Lhabitant, F. S. (1998). Enhancing portfolio performance using option strategies: why beating the market is easy (No. rp1). *International Center for Financial Asset Management and Engineering*.

Maillard, S., Roncalli, T., Teïletche, J. (2010). The properties of equally weighted risk contribution portfolios. *The Journal of Portfolio Management*, 36(4), 60-70.

Mohanty, S. S. (2018). Enhancing Portfolio Performance in Global Equity Allocation with a Forward-Looking Indicator. *The Journal of Investing*, 27(4), 81-97.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial economics*, 104(2), 228-250.

Rockafellar, R. T., Uryasev, S. (2000). Optimization of conditional value-at-risk. *Journal of risk*, 2, 21-42.