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On the performance of volatility-managed equity factors — International and further evidence☆

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ABSTRACT

I study the performance of nine (downside) volatility-managed equity factors before and after considering transaction costs in 45 international equity markets. My results suggest that volatility management is most promising for market, value, profitability, and especially momentum portfolios. The performance of volatility-managed market and value portfolios can be further enhanced by applying downside volatility as a scaling factor. Nevertheless, only the managed market and momentum strategies are partially robust to transaction cost suggesting that the persistence of abnormal returns can largely be explained by the associated transaction costs. Cross-country analysis suggests that the slow trading hypothesis is partially able to explain cross-country performance differences of volatility-managed value and momentum portfolios. Finally, performance decomposition analysis reveals additional suggestive evidence in support of the slow trading hypothesis.

1. Introduction

A trading strategy that goes against the conventional wisdom to increase risk-taking or hold risk-taking constant when volatility increases has recently attracted a lot of attention from researchers and practitioners alike.[1] These so-called volatility-managed portfolio (VMP) strategies try to exploit the predictability in the second moments of equity returns, i.e., volatility persists from one month to the next (see, Engle and Bollerslev, 1986; Schwert, 1989), by increasing (decreasing) the exposure to a specific strategy when the most recent volatility of the strategy was low (high). Such a strategy can only be profitable if the mean–variance trade-off weakens in times of high volatility, i.e., volatility is only weakly or even negatively correlated with future returns. The performance of total volatility-managed equity factor strategies appears to be mainly driven by the volatility timing effect, whereas downside volatility-managed equity factor strategies also seem to profit from the return timing component, i.e., high downside volatility is associated with low future returns (see, Wang and Yan, 2021).

The most recent evidence on the performance of (downside) volatility-managed equity factor strategies is rather mixed and focused on the U.S. equity market.[2] Most studies (see, Moreira and Muir, 2017; Cederburg et al., 2020; Wang and Yan, 2021)

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[1] See, e.g., Fleming et al. (2001, 2003), Marquering and Verbeek (2004), Kirby and Ostdiek (2012), Barroso and Santa-Clara (2015), Moreira and Muir (2017, 2019), Eisdorfer and Misirli (2020), Cederburg et al. (2020), Bongaerts et al. (2020), Barroso and Detzel (2021), Wang and Yan (2021), Neuhierl et al. (2023) and Reschenhofer and Zechner (2024).

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find economically significant risk-adjusted returns for (downside) volatility-managed equity factor portfolios and a broader set of anomalies when a combination strategy is tested, i.e., the tested (downside) volatility-managed equity factor (anomaly) portfolio is a combination portfolio that invests both in the (downside) volatility-managed and the unmanaged factor portfolio. Downside VMPs perform significantly better than total volatility-managed strategies mainly due to the return timing component (see, Wang and Yan, 2021).

In addition to the combination strategy, a second set of tests examines direct investments in (downside) VMPs testing whether the Sharpe ratio of the (downside) volatility-managed equity factor is statistically different from the Sharpe ratio of the unmanaged factor. Most studies (see, Cederburg et al., 2020; Barroso and Detzel, 2021; Wang and Yan, 2021) find that direct investments in volatility-managed equity factors and a broader set of anomalies do not systematically outperform their unmanaged counterparts. The outperformance of downside VMPs is also evident in the direct Sharpe ratio comparisons.

An ongoing debate focuses on a third set of tests assessing whether the outperformance implied by the spanning regression approach is attainable by real-time investors. The discussion mainly centers around the argument that ex post optimal weights used in spanning tests are not known to investors in real-time. Cederburg et al. (2020) show that the estimation error in estimating optimal weights out-of-sample renders almost the entire performance insignificant. However, Wang and Yan (2021) show that a naïve 50/50 fixed-weight strategy significantly improves the bad out-of-sample performance of (downside) VMPs for real-time investors. Another straightforward approach to test whether real-time investors can profit from the performance of VMPs is to assess the performance net of transaction costs. Barroso and Detzel (2021) find that the transaction costs imposed by the time-varying leverage of volatility-managed strategies erode the performance of most equity factor strategies, as only the market portfolio and the momentum portfolio are partially robust to transaction costs. Wang and Yan (2021) find comparable results for downside volatility-managed strategies. DeMiguel et al. (2024) show that both difficulties can be overcome by implementing a conditional mean–variance multifactor portfolio whose weights on each factor vary with market volatility.

This paper contributes to the literature in at least three aspects. First, this paper provides a comprehensive study of the performance of downside and total volatility-managed equity factor strategies in a set of 45 international equity markets. Analyzing more than twice as many countries for volatility-managed market portfolios as in Moreira and Muir (2017), expanding the sample to include the major equity factors of leading asset pricing models, and looking at downside volatility adds to previous international findings which mainly focus on market and momentum strategies (see, Barroso and Santa-Clara, 2015; Moreira and Muir, 2017; Bongaerts et al., 2020; Hanauer and Windmüller, 2023). International stock markets are economically and scientifically important. During my sample period from January 1982 to December 2021, non-U.S. countries on average account for 74% of the global gross domestic product and 59% of the world market capitalization.[3] As the majority of the existing literature is focused on the U.S. equity market I try to attenuate the large U.S. (home) bias in academic finance research (see, Karolyi, 2016) by conducting a comprehensive out-of-sample performance test of the existing findings. Furthermore, existing finance research has shown that it is not obvious ex ante to generalize U.S. evidence to international markets.[4] The ongoing debate about the degree of integration of individual country stock markets/economies into the world stock market/economy as well as the documented differences in various market frictions across different country stock markets substantiate the necessity of more global analyses.[5] In particular, these broader tests are essential as the existing findings question the basic risk-return trade-off and thus a central part of modern financial theory.

Second, the paper contributes to the literature that investigates the after-cost performance of equity factor returns. Transaction costs are often neglected in asset pricing studies. In international studies, in particular, this is due to the lack of comprehensive data. This paper tries to overcome this burden by suggesting an approach inspired by Chen and Velikov (2022) to estimate stock-level effective spreads (transaction costs) for every stock used in the construction of international equity factors. Using stock-level effective spreads allows for capturing both heterogeneity and time variation in trading costs which is especially important when assessing a dynamic trading strategy.[6] This approach makes it possible to test whether the international performance persistence of (downside) volatility-managed equity factor portfolios can be explained by the most obvious limit to arbitrage, namely transaction costs.

Third, the paper contributes to the literature that investigates the drivers of cross-country differences in the returns of equity factors/anomalies (see, e.g., Titman et al., 2013; Watanabe et al., 2013; Hanauer and Windmüller, 2023). I add to this literature by investigating whether cultural differences (see, e.g., Chui et al., 2010; Dou et al., 2016; Docherty and Hurst, 2018) can explain the varying outperformance of (downside) volatility-managed equity factors across countries. Specifically, I review the slow trading hypothesis proposed by Moreira and Muir (2017) by linking a potentially slower trading reaction in response to shocks in volatility to differences in cultural traits such as uncertainty avoidance and long-term orientation.

My main findings can be summarized as follows. First, using a set of 45 international equity markets from 1982 to 2021, I show that volatility-managed equity factor strategies seem most promising for market, value, profitability, and especially momentum

[2] Volatility timing strategies have mainly been tested for international market and momentum portfolios; see, for market portfolios in a set of 20 OECD countries (Moreira and Muir, 2017) and for momentum portfolios in international stock markets (Barroso and Santa-Clara, 2015; Docherty and Hurst, 2018) and for enhanced momentum strategies in a set of more than 40 countries (Hanauer and Windmüller, 2023). Only Bongaerts et al. (2020) have tested a total volatility-managed factor set (size, value, profitability and investment) for broader regions (Global ex U.S., Europe, Japan, Pacific ex Japan).

[3] See, World Bank data for global gross domestic product and global market capitalization.

[4] See, e.g., Auer and Rottmann (2019) find weaker time effects in return predictors in international markets than in the U.S. market; Jacobs and Müller (2020) show that post-publication effects in anomaly returns are weaker in international markets than in the U.S. market.

[5] See, e.g., Akbari and Ng (2020) for a survey on international market integration; Griffin et al. (2010), Brockman et al. (2009) and Bris et al. (2007) for global differences in transaction costs, liquidity and short-selling, respectively.

[6] Many asset pricing studies assume flat transaction costs or calculate break-even transaction costs to judge the after-cost implementability of a trading strategy.

portfolios. Most of the spanning regression alpha estimates are positive, suggesting a possible outperformance of the combination strategy. This performance can be significantly enhanced predominantly for market and value portfolios by applying downside volatility instead of total volatility as a scaling factor. Judging the international performance based on direct Sharpe ratio comparisons of the managed and the unmanaged factors significantly weakens the performance picture as only momentum portfolios seem to survive the direct comparison tests.

Second, in my baseline approach, I find that the international performance of volatility-managed and the partially enhanced performance of downside volatility-managed equity factors is not robust to transaction costs. Volatility-managed equity factor strategies are rebalanced monthly due to the inherent time-varying leverage induced by the volatility-timing. This leads to a significant increase in turnover compared to the original equity factor construction, which significantly deteriorates the after-cost performance. Applying a set of cost-mitigation techniques shows that equity factors scaled by six-month (downside) volatility are robust to transaction costs only for managed momentum portfolios. Another exception has to be made for (downside) volatility-managed market portfolios if they can be successfully implemented through the use of Exchange-Traded Funds (ETFs). This implementation seems more difficult in an international setting due to the lack of ETFs that mirror the performance of the market portfolios in my data set. Volatility-managed market and momentum portfolios appear to be most promising as they deliver both the absolute greatest benefits from volatility-timing and at the same time allow these benefits to be realized at the relatively lowest transaction cost increases compared to their unmanaged counterparts. Overall, my results substantiate the U.S. findings of Barroso and Detzel (2021) showing that transaction costs also explain the international performance persistence of (downside) volatility-managed equity factor strategies.

Third, I find that a significant portion of the cross-country differences in the outperformance of (downside) volatility management in the best-performing factors (value and momentum) may be attributable to a slower trading response. I document that the outperformance of (downside) volatility-managed value and momentum portfolios is stronger in countries associated with lower levels of uncertainty avoidance and higher levels of long-term orientation. I argue that these cultural dimensions can be used as a proxy for a potentially slower trading reaction in response to changes in volatility. Furthermore, a performance decomposition of the VPMs into times following high and low volatility largely confirms that the performance of most factors clusters predominantly in times following low and moderate volatility, which is also in line with the prediction of the slow trading hypothesis. Therefore, I suggest that the slower trading reaction contributes in part to the creation of mispricing that strengthens the outperformance of (downside) volatility-managed equity factor strategies. However, the slower trading reaction is unlikely to be the sole driver behind the emergence of the outperformance.

2. Data

2.1. Stock market data

The international equity factors are constructed from stock market data collected from Refinitiv Datastream. The accounting data is collected from Worldscope. To ensure data quality, I apply a set of static and dynamic screens mainly following Landis and Skouras (2021). The generic and country-specific static screens are applied to ensure that only common equity stocks are part of the final data set. In addition, I apply dynamic screens for stock return and price data. Similarly to Hou et al. (2011), I require the availability of basic accounting data to assure that data (i.e., common equity) needed in the equity factor construction is available for every stock. In particular, I require stocks to have a valid return, market capitalization, and market-to-book ratio. The specific static and dynamic screens as well as the general data collection process are described in Appendix A.1. The country selection follows the MSCI developed and emerging market indices. The final data set in this paper contains 45 of the original 52 countries, as I discharged all countries with insufficient data, i.e., too few stocks in a country month, to construct reliable equity factors. This procedure leads to a final data set of 65,300 stocks (about 9.8 million stock months observations) from 45 equity markets from January 1982 to December 2021. The sample periods vary substantially by country and factor, as I follow the bias-free sample start date approach suggested by Landis and Skouras (2021). The country-specific start dates are provided in Table A.6 of Appendix A.1. All daily and monthly returns are measured in U.S. dollars.

2.2. Equity factors

The market factor (MKT) is the value-weighted return on all valid stocks measured in excess of the risk-free rate. I use the one-month U.S. T-bill obtained from Kenneth French's data library as all returns are measured in U.S. dollars. I follow the standard procedure of Fama and French (2012, 2017) for international equity factors in constructing all my value-weighted non-market equity factors based on an independent 2×3 sort on size (market capitalization) and the respective factor criteria. Following Schmidt et al. (2019), I use the 80th percentile of the country market capitalization as size breakpoints for the U.S. equity market.[7] For all non-U.S. equity markets, I follow Fama and French (2012, 2017) by using the top 90% of the aggregate market capitalization of a country as country-specific size breakpoints. I follow the common approach to use the 30th and 70th percentiles of the big stocks per country

[7] Schmidt et al. (2019) approximate size breakpoints based on the whole sample (no NYSE screen applied), which closely mirror the Fama and French (1993) breakpoints based on NYSE stocks. This approach mitigates potential problems with calculating NYSE breakpoints based on the Datastream exchange classification (only latest value) and should be preferred to simply using NYSE breakpoints from CRSP.

to calculate the factor breakpoints for the high and low portfolios. I use country-specific breakpoints following Hanauer (2020) as opposed to regional-specific breakpoints as in Fama and French (2012, 2017) to rule out differences due to country-specific accounting practices.

Portfolios are either updated monthly at the end of month $t-1$ to construct a portfolio that is held until the end of month t or yearly at the end of June in year $y-1$ to construct a portfolio that is held from July in year $y-1$ until June of year y. The accounting data used for portfolio construction is always from the fiscal year ending in calendar year $y-2$ to ensure that the information would have been available when constructing portfolios in real-time ($y-1$). The market capitalization used in the factor construction is either from December of year $y-2$ or from month $t-1$ to avoid a look-ahead bias.

A monthly factor return, i.e., a zero-investment long-short portfolio return, is determined by calculating the difference between the average value-weighted return of the two long and the two short portfolios for the respective criteria. The only exception is the size factor (SMB, small minus big) which is the average return of the three small stock and the three big stock portfolios at the intersection of size and book-to-market equity (value factor).

The adoption of a common set of construction rules for all equity factors ensures comparability and a coverage of equity factors of comparable quality between countries. To ensure the quality of the equity factors, I require a minimum of 30 stocks to construct the six portfolios in each country month. The commonly used 2 × 3 × 3 sort following Hou et al. (2015) requires 18 diversified portfolios, effectively making it impossible to construct reliable (diversified) factors for smaller equity markets. The approach used in this paper seems reasonable, as Fama and French (2015) show that the difference between doing double- or quadruple-sorts is neglectable.

The equity factor set in this paper is restricted to all factors that are part of the most commonly used factor models. Specifically, I calculate the following factor models: (i) the Fama and French (1993) three-factor model (FF3: MKT + size [SMB] + value [HML]), (ii) the Fama and French (2015) five-factor model (FF5: FF3 + investment [CMA] + profitability [RMW]), (iii) the Fama and French (2018) six-factor model (FF6: FF5 + Momentum [WML]), (iv) the Fama and French (2018) six-factor model ($\mathrm{FF6_{CP}}$), which substitutes the profitability factor with a cash-based profitability [RMW_c] factor, (v) the Hou et al. (2015) four-factor model[8] (HXZ4: $MKT + SMB + CMA +$ [ROE] based profitability), and (vi) the Barillas et al. (2020) six-factor model ($\mathrm{FF6_{CP,m}}$), which substitutes the value factor in the Fama and French (2018) six-factor model with the monthly updated value factor [HML_m] from Asness et al. (2013). Detailed factor definitions and factor performances for each equity factor country combination are provided in Appendix A.2 and Table A.7, respectively.

2.3. Transaction costs (effective spreads)

In order to calculate the after-cost performance of the volatility-managed equity factor portfolios for a marginal trader (i.e., price impact costs are neglected), one-way spread (transaction cost) estimations have to be made for all stocks in the respective country samples. I follow the approach of Chen and Velikov (2022) to calculate a one-way spread estimate (aggregate spread: hence, AS) by averaging multiple commonly used low-frequency data spread estimates. Specifically, I calculate the Corwin and Schultz (2012) high-low spread (HL) and the Abdi and Ranaldo (2017) close-high-low spread (CHL), both built on the classic microstructure model of Roll (1984). As a third spread estimate, I calculate the Fong et al. (2017) volatility-over-volume (VoV) effective spread which builds on the microstructure invariance hypothesis of Kyle and Obizhaeva (2016). Subsequently, I calculate an average spread estimate (AS) for every stock in a country-month if at least one individual estimate is not missing. Due to the individual requirements for the spread estimates and the rather poor data coverage on high and low prices for some countries, even the average spread estimate still has a significant number of missings. To have a valid and reliable spread estimate for all stocks, I apply the data filling procedure of Novy-Marx and Velikov (2016) filling missings using an euclidean distance matching on idiosyncratic volatility and size (market equity) in each country month. This approach is motivated by high observed cross-sectional correlations between transaction costs and size, as well as transaction costs and idiosyncratic volatility. The remaining missings due to missings of idiosyncratic volatility are filled using the same approach on size only. For most countries, the average spreads clearly confirm that the data filling procedure results in a moderate increase in value-weighted spreads and a much larger increase in equal-weighted spreads. This suggests that the procedure mostly fills in the missing spreads for smaller stocks with correspondingly higher matched spread estimates. Fig. 1 shows the monthly time series of the value-weighted portfolio average of the final aggregated effective spread estimates (AS) equally averaged across all countries in a given region for four size portfolios.

Fig. 1 confirms that the spreads (transaction costs) are relatively high for the smallest stocks and decrease by size quartile in all regions throughout the sample period. The high transaction cost estimates for small cap stocks will have a significant impact on the after-cost performance of the VMPs as small stocks receive a substantial weight in the constructed equity factors. The figure also demonstrates that transaction costs seem to increase across all size quartiles in times of economic uncertainty. The three peaks in the time series in the aftermath of the dot-com bubble (2000), during the global financial crisis (2008), and during the covid pandemic (2020) are clearly visible. It is also interesting to note that transaction costs for smaller stocks seem to decrease in the U.S. after 2000, in line with the introduction of electronic trading and the decimalization of the U.S. stock market. Finally, it can be noted that transaction costs are higher for bigger stocks in the emerging markets as compared to the developed markets (ex U.S.) and that transaction costs seem to be higher across all size quartiles outside the U.S. stock market. Detailed calculations of the individual spread estimators and by country summary statistics for the monthly cross-sectional equally-weighted and value-weighted average spread estimates before and after the data filling procedure are provided in Appendix A.4 and Table A.10, respectively.

[8] Due to the adoption of the common factor construction rules, the size and investment factors of the q-factor model are equivalent to the size and investment factors of the Fama and French (2015) five-factor model, as I do not apply the 2 × 3 × 3 sort from Hou et al. (2015). Furthermore, the investment factor and the ROE based profitability factor are based on annual as opposed to quarterly data as in Hou et al. (2015).

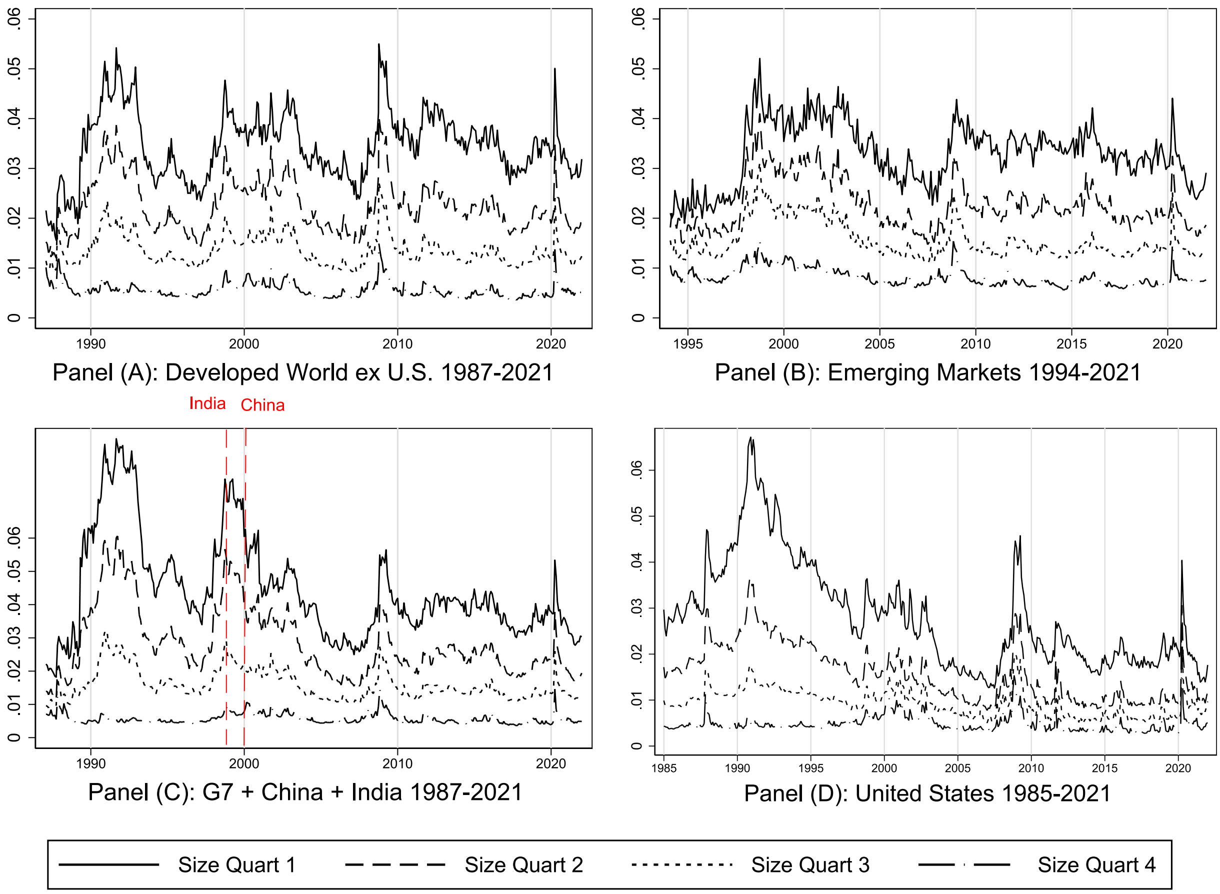

Fig. 1. Transaction costs by size quartile. The figure shows the monthly time series of the value-weighted portfolio average of an estimated stock-level effective spread equally averaged across all countries in a given region for four size portfolios of common stocks. Panels A, B, C, and D, respectively, present the estimated transaction cost by size quartile over the respective sample period for each region. For each region, reporting begins as soon as a sufficient number of countries are available for averaging the spreads. The red dashed lines indicate when India and China became part of the sample. Size in each month is defined as the market capitalization at the end of the last month in a given country. The portfolios are formed with quartile breakpoints in a given country.

3. Methodology

3.1. Volatility-managed factor strategies

I follow the existing literature (see, Barroso and Santa-Clara, 2015; Moreira and Muir, 2017) by constructing the volatility-managed equity factor portfolios (f^{σ}) as a scaled version of the original equity factor:

$$f_t^{\sigma} = \frac{c^*}{RV_{t-1}^2} f_t, \tag{1}$$

where f_t is the monthly excess return of the original equity factor portfolio, RV_{t-1}^2 is the realized monthly variance (downside volatility, dRV_{t-1}) of the original portfolio in month $t-1$, and c^* is a constant chosen to ensure that f_t and f_t^{σ} have the same full-sample variance.[9] Eq. (1) demonstrates that the portfolio choice (weight in f_t) in $t-1$ of a mean–variance investor is only driven by the expected risk-return trade-off ($E_t(f_t)/\sigma_t^2(f_t)$), which can be approximated by c^*/RV_{t-1}^2, if expected returns are unpredictable at a monthly frequency while volatility persists.

The original equity factor is scaled by a dynamic investment position (c^*/RV_{t-1}^2), which is proportional to the inverse of lagged realized variance (downside volatility) and is a measure of leverage as the original factor return is a zero-cost portfolio. In order to

[9] As pointed out by many studies (see, e.g., Moreira and Muir, 2017; Cederburg et al., 2020) c^* is not known by real-time investors and thus imposes a potential problem for implementing the exact same performance due to a look-ahead bias. Noteworthy, the Sharpe ratio tests are invariant to the choice of c^*.

calculate the leverage weights that are used to scale the returns in the volatility-managed strategies, I calculate the realized monthly sample variance (RV^2) following Cederburg et al. (2020) as:

$$RV_{i,t-1}^2 = 21 \cdot \frac{\sum_{j=1}^{N_{t-1}} r_{i,j}^2}{N_{t-1}}, \tag{2}$$

where $r_{i,j}$ is the daily return of factor i on day j in month $t-1$, and N_{t-1} is the number of daily returns in month $t-1$. The scaling of the average daily variance (volatility) by 21 trading sessions ensures that the monthly realized variance (volatility) is not mechanically diluted by missing daily returns. A minimum of 15 valid daily returns is required for the variance calculation. In order to calculate the leverage weights that are used to scale the returns in the downside volatility-managed strategies, I calculate the realized monthly sample downside volatility (dRV) following Wang and Yan (2021) as:

$$dRV_{i,t-1} = \sqrt{\sum_{j=1}^{N_{t-1}} r_{i,j}^2 \mathbb{1}_{\{r_{i,j}<0\}}}, \tag{3}$$

where $r_{i,j}$ is the daily return of factor i on day j in month $t-1$ using only negative returns, and N_{t-1} is the number of daily negative returns in month $t-1$. A minimum of three valid negative daily returns is required for the volatility calculation.

As common in the after-cost performance literature, I also apply a set of alternative leverage weights, i.e., maximum leverage of 150% of the baseline strategy, volatility instead of variance, six-month (downside) volatility, expected (downside) variance, and excluding small stocks from the factor construction. These are supposed to mitigate costs by slowing down trading or avoiding expensive to trade stocks, while still sufficiently capturing the volatility timing effect. Detailed calculations of the alternative leverage weights are provided in Appendix A.10.

3.2. Spanning regressions

The risk-adjusted before-cost performance of the volatility-managed equity factors is evaluated by performing spanning regressions (see, Huberman and Kandel, 1987) from the managed factors on those of their unmanaged counterparts:

$$f_t^\sigma = \alpha + \beta f_t + \epsilon_t, \tag{4}$$

where $f_t^\sigma = \frac{c^*}{RV_{t-1}^2} * f_t$ is the managed return of the respective factor, i.e., the unmanaged return f_t scaled by the realized sample variance (downside volatility) of the daily returns over the previous month. To ease interpretation, the constant c^* is chosen so that the standard deviation of the managed factor equals the unconditional standard deviation of the unmanaged factor.

By regressing the returns of the test asset (i.e., the volatility-managed equity factor) on the returns of the benchmark asset (i.e., the unmanaged equity factor), I test the null hypothesis that the test asset is spanned (i.e., the intercept is equal to zero). A statistically significant intercept (α) indicates that the volatility-managed equity factor is not spanned by the respective unmanaged factor. The alpha quantifies the magnitude of abnormal return and indicates that the mean–variance-efficient frontier can be extended through the addition of the test asset. The alpha can be earned by investing in the extended efficient frontier consisting of the unmanaged and managed equity factor. In other words, the Sharpe ratio of an optimal portfolio consisting of the unmanaged and managed factor, $SR(f, f^\sigma)$, is higher than the Sharpe ratio of the unmanaged factor, $SR(f)$. In Tables B.2 and B.3 of the Online Appendix, I additionally report the gains in certainty-equivalent returns experienced by a mean–variance investor with a risk aversion coefficient of three who achieves the increased Sharpe ratio from the unmanaged equity factor $SR(f)$ to $SR(f, f^\sigma)$. This measure expresses the economic significance of the alphas.

3.3. Differences in sharpe ratios

I calculate the z-statistic of the Jobson and Korkie (1981) test with the correction of Memmel (2003). The Sharpe ratio difference test is performed to address the criticism of Cederburg et al. (2020) that the alpha of a spanning regression is not attainable for investors in real-time due to the estimation error of the optimal out-of-sample weights calculation. A positive significant z-statistic ($z > 1.96$ for the 5% significance level) suggests that the Sharpe ratio of the volatility-managed equity factor is greater than the Sharpe ratio of the unmanaged counterpart. This performance difference can be earned by directly investing in the volatility-managed equity factor instead of the unmanaged counterpart.

3.4. After-cost performance

In order to calculate the after-cost performance of (downside) volatility-managed equity factors for a marginal trader (i.e., a small trader with no price impact) turnover (TO) and transaction costs (TC) have to be determined for the portfolios involved in the factor construction. In the standard factor construction approach of Fama and French (2012, 2017) (with the exception of the SMB factor) four of the six base portfolios are used to construct a long and a short portfolio (leg). The turnover of a managed asset-pricing factor is the sum of the turnover of the long and short portfolio.

Following Barroso and Santa-Clara (2015) and Barroso and Detzel (2021), the turnover ($TO_{Long^{\sigma}}$) and transaction costs ($TC_{Long^{\sigma}}$) of a managed portfolio (f^{σ}) are calculated as follows:

$$TO_{Long^{\sigma},t} = \frac{1}{2}\sum_{i=1}^{N_t} |L_t(f)w_{i,t} - L_{t-1}(f)\tilde{w}_{i,t-1}|, \text{ and} \tag{5}$$

$$TC_{Long^{\sigma},t} = \sum_{i=1}^{N_t} |L_t(f)w_{i,t} - L_{t-1}(f)\tilde{w}_{i,t-1}| \cdot c_{i,t}, \tag{6}$$

where $w_{i,t}$ is the weight of stock i in the long leg at time t just after updating the unmanaged portfolio, $\tilde{w}_{i,t-1}$ is the weight of stock i in the long leg at time t just before updating the unmanaged portfolio, $L_t(f)$ $[L_{t-1}(f)]$ is the leverage of the managed long leg at the end [beginning] of period t and $c_{i,t}$ is the one-way cost of stock i at time t (i.e., the monthly aggregated half spread estimate $= \frac{AS_{i,t}}{2}$ derived in Section 2.3) for stock i at time t. The turnover and the transaction costs of the managed short portfolios are computed accordingly.

Thus, the net-of-costs return on a managed equity factor is:

$$f^{\sigma}_{net,t} = f^{\sigma}_t - TC_{Long^{\sigma},t} - TC_{Short^{\sigma},t}, \tag{7}$$

where f^{σ}_t is the gross return of the volatility-managed factor at time t.

In order to measure the performance of the volatility-managed equity factors after considering transaction costs, spanning regressions using the generalized α_{net} from Novy-Marx and Velikov (2016) are applied:

$$\frac{MVE_{net_{(f,f^{\sigma})}}}{w_{f^{\sigma},MVE_{net_{(f,f^{\sigma})}}}} = \alpha_{net} + \beta f_{net,t} + \epsilon_t, \tag{8}$$

where $MVE_{net_{(f,f^{\sigma})}}$ is the after-cost excess return on the ex post mean–variance efficient (MVE) portfolio consisting of f and f^{σ}, $w_{f^{\sigma},MVE_{net_{(f,f^{\sigma})}}}$ is the ex post optimal weight of f^{σ} in $MVE_{net_{(f,f^{\sigma})}}$ and f_{net} is the net of cost return of the unmanaged equity factor. The intercept of the regression (α_{net}) is set to zero if the weight of the managed factor ($w_{f^{\sigma},MVE_{net_{(f,f^{\sigma})}}} = 0$) in the MVE portfolio is zero.

As shown in Barroso and Detzel (2021), the α_{net} still measures how access to the left-hand-side excess return expands the ex post investment opportunity set beyond the set of the right-hand-side factors if the dependent variable is the MVE portfolio (instead of f^{σ}_{net}). In order to make the α_{net} comparable to the standard regression alpha in Eq. (4) the left-hand-side excess return $MVE_{net_{(f,f^{\sigma})}}$ has to be scaled by $w_{f^{\sigma},MVE_{net_{(f,f^{\sigma})}}}$ to hold \$1 in f^{σ}.

4. Empirical results

4.1. Performance of volatility-managed equity factors

In this section, I evaluate the performance of (downside) volatility-managed equity factor portfolios in international equity markets. Table 1 reports gross performance statistics of the volatility-managed equity factor portfolios for all 45 equity markets.

Overall, the performance of the volatility-managed equity factors is mixed. Five volatility-managed equity factors (MKT^{σ}, HML^{σ}, RMW^{σ}, ROE^{σ}, WML^{σ}) seem to perform quite well, as all have at least 30 positive country alpha estimates in the applied spanning regressions. The most promising factor is the volatility-managed momentum factor (WML^{σ}) with 44 positive alpha point estimates of which 39 are statistically significant at the five-percent level. The volatility-managed market portfolio (MKT^{σ}) and the volatility-managed value factor (HML^{σ}) produce 36 and 30 positive alpha point estimates with 6 and 10 of them being statistically significant. The performance of the volatility-managed profitability factors (RMW^{σ} and ROE^{σ}) is similar with 31 and 34 positive alpha point estimates of which 7 and 6 are statistically significant. The other four volatility-managed equity factors (SMB^{σ}, HML^{σ}_m, CMA^{σ}, RMW^{σ}_c) show no clear picture as positive and negative alpha point estimates offset each other with only a few statistically significant alpha point estimates on both sides. The direct Sharpe ratio comparisons support the strong performance of the volatility-managed momentum factor showing 44 positive Sharpe ratio improvements, 25 of which are statistically significant at the five-percent level. For all other volatility-managed equity factors, the direct Sharpe ratio comparison suggests that it is rather difficult to systematically profit from the performance through direct investments in the volatility-managed equity factors. The positive and negative z-statistics show no clear direction as they balance each other out and with the exception of the profitability factor (RMW^{σ}), with 4 positive significant Sharpe ratio improvements, all other factors show hardly any significant Sharpe ratio improvements.

Overall, the results suggest that the stylized facts, i.e., volatility is persistent while the risk-return relation is flat (or negative), which make total volatility management strategies successful in previous studies are not strong enough to produce gains across all factors and around the world.

Next, I examine whether the performance of volatility-managed equity factors changes when using downside volatility instead of total volatility as a scaling factor. Table 2 reports gross performance statistics of the downside volatility-managed equity factor portfolios for all 45 equity markets.

Table 1
Performance of volatility-managed factors before transaction costs.

		MKT	SMB	HML	HML_m	CMA	RMW	RMW_c	ROE	WML
Australia	α	0.84	−1.73*	−0.04	−1.58	0.50	1.14	−0.61	1.54	8.53***
	$z(SR(f^\sigma))$	−0.56	−1.40	−1.12	−0.95	−0.80	0.16	−1.22	1.20	2.49
Austria	α	2.10	−0.15	2.70*	0.87	2.84*	−2.59*	−0.99	−2.04*	8.94***
	$z(SR(f^\sigma))$	0.06	−0.18	0.68	−0.82	0.71	−2.32	−0.59	−2.20	2.30
Belgium	α	4.73*	0.69	4.55***	2.84	−0.82	−1.38	−0.56	1.58	8.94***
	$z(SR(f^\sigma))$	0.92	0.74	2.65	1.08	−0.51	−1.15	0.11	0.68	1.88
Canada	α	−0.86	−0.65	3.79**	−1.98	0.54	2.81*	2.32	0.78	10.01***
	$z(SR(f^\sigma))$	−1.33	−0.55	1.15	−1.30	−0.03	0.59	0.90	−0.05	2.47
Denmark	α	6.74***	0.54	3.76*	−0.62	−0.77	0.05	−2.03	−3.04*	6.70***
	$z(SR(f^\sigma))$	1.70	0.72	1.44	0.40	−1.34	−0.30	−1.17	−2.20	1.16
Finland	α	4.61	0.76	−3.14	−2.03	−4.61*	1.54	1.43	2.26	9.20***
	$z(SR(f^\sigma))$	0.49	0.72	−1.69	−1.12	−1.48	−0.10	0.17	0.65	1.70
France	α	1.73	1.09	−0.18	−2.56	1.94	1.86*	0.80	2.21**	13.38***
	$z(SR(f^\sigma))$	−0.21	1.39	−1.35	−1.84	0.82	0.87	0.54	1.79	4.18
Germany	α	1.73	0.85	2.16	−1.31	−3.44**	−0.27	−0.81	−0.34	13.27***
	$z(SR(f^\sigma))$	−0.04	0.91	−0.05	−1.06	−2.87	−1.37	−1.32	−0.51	2.74
Hong Kong	α	7.78***	−3.60	5.08**	−0.88	−1.24	0.96	0.12	0.48	11.39***
	$z(SR(f^\sigma))$	1.24	−0.89	1.39	−1.27	−1.21	0.37	−0.18	0.13	4.13
Israel	α	−1.75	−2.08	4.67**	2.86	1.97	−1.18	−1.67	0.30	10.36***
	$z(SR(f^\sigma))$	−1.33	−1.40	1.52	1.09	0.74	−1.24	−1.13	−0.36	2.48
Italy	α	3.10	2.16*	3.18**	0.84	−0.27	−0.38	0.55	0.72	12.28***
	$z(SR(f^\sigma))$	0.64	1.90	1.76	0.31	0.05	−1.93	−0.14	−0.64	2.90
Japan	α	−2.45	−0.71	3.38***	4.99***	0.45	−0.65	−0.31	−0.55	1.67
	$z(SR(f^\sigma))$	−1.37	−0.46	1.16	0.72	0.08	−0.81	−0.30	−0.74	0.62
Netherlands	α	4.66*	0.41	3.12*	−0.13	0.31	−1.94	−0.43	0.56	8.80***
	$z(SR(f^\sigma))$	0.85	0.35	1.37	0.03	0.11	−1.62	−0.53	−0.03	1.92
New Zealand	α	4.63*	−0.91	−0.97	−0.77	−1.67	0.91	0.70	1.14	4.07**
	$z(SR(f^\sigma))$	0.76	−0.88	−0.05	−0.35	−1.32	0.39	0.55	1.00	0.53
Norway	α	4.58	1.61	−1.24	−2.18	1.75	−0.18	−0.68	−1.80	6.88***
	$z(SR(f^\sigma))$	0.69	0.96	−0.92	−1.03	0.12	−0.66	−0.77	−1.92	1.60
Portugal	α	6.00**	−2.54	8.05**	−0.19	0.69	−2.54	−1.49	−1.11	7.37***
	$z(SR(f^\sigma))$	1.33	−0.50	1.62	−0.22	0.16	−1.41	−0.74	−1.07	1.13
Singapore	α	0.67	−2.87*	3.38*	1.27	2.28	3.44**	−0.75	3.59**	15.74***
	$z(SR(f^\sigma))$	−0.54	−1.15	0.02	−0.32	0.82	1.55	−0.61	1.52	3.95
Spain	α	2.02	−1.37	1.34	0.26	−2.20	3.28***	1.56	1.85	6.28**
	$z(SR(f^\sigma))$	0.03	−0.99	0.30	−0.13	−1.28	2.07	0.66	0.85	1.06
Sweden	α	3.36	0.89	1.27	−0.24	−0.08	−1.00	−0.94	0.51	11.86***
	$z(SR(f^\sigma))$	0.09	0.68	−0.04	−0.70	−1.01	−0.90	−0.51	−0.28	2.90
Switzerland	α	2.72	−0.21	0.10	−1.42	1.33	3.48***	1.40	2.66**	8.09***
	$z(SR(f^\sigma))$	0.28	0.18	−0.25	−1.06	0.19	1.84	0.45	1.46	1.73
U.K.	α	2.21	1.99	1.07	−1.50	2.70	0.39	−1.02	0.84	13.45***
	$z(SR(f^\sigma))$	0.20	1.29	−0.32	−1.30	0.36	−0.28	−1.06	0.00	2.91
U.S.	α	3.90*	−1.03	−0.91	−0.61	0.31	1.98*	1.24	0.48	9.25***
	$z(SR(f^\sigma))$	0.27	−0.89	−0.75	−0.49	−0.78	0.20	0.18	−0.17	2.90
Brazil	α	7.85	4.75*	1.31	2.44	3.58	0.64	−0.27	−1.62	9.68***
	$z(SR(f^\sigma))$	−0.16	2.21	−0.41	−0.35	0.68	−0.21	0.00	−0.43	2.49
Chile	α	−2.54	1.39	−0.14	−2.40	2.94**	1.39	2.22*	1.02	4.38***
	$z(SR(f^\sigma))$	−1.35	0.80	−1.01	−2.32	1.42	0.86	1.57	0.46	0.98
China	α	−0.37	−7.78***	4.76**	5.69**	−1.21	3.97**	0.53	2.16	6.50***
	$z(SR(f^\sigma))$	−0.55	−3.22	1.84	0.95	−1.03	2.26	0.58	1.37	2.99
Egypt	α	−2.21	0.68	6.48*	11.06**	−0.55	−0.60	−2.16	1.55	8.83**
	$z(SR(f^\sigma))$	−0.58	−0.33	1.73	1.79	−0.19	−0.90	−1.59	−0.31	2.21
Greece	α	7.33	−7.14**	−0.62	−4.01	−1.73	4.84**	0.88	4.75**	17.33***
	$z(SR(f^\sigma))$	1.15	−1.93	−1.38	−1.81	−0.38	0.65	−0.85	0.95	3.53
India	α	5.72	1.79	1.12	−2.92	1.42	0.52	−0.58	−2.04	19.57***
	$z(SR(f^\sigma))$	0.31	0.33	−0.56	−1.09	0.52	0.19	−0.08	−0.74	2.91
Indonesia	α	9.86*	1.60	4.87*	−4.16	8.16***	3.25	−0.12	2.26	18.36***
	$z(SR(f^\sigma))$	0.83	0.48	0.43	−1.44	1.85	−0.46	−0.55	0.16	2.82
Korea	α	1.08	−2.96	8.57***	7.14**	4.98**	−3.40*	−4.13**	−5.30**	9.95***
	$z(SR(f^\sigma))$	−0.19	−0.91	1.66	0.84	1.62	−1.97	−1.81	−2.26	2.49
Malaysia	α	3.42	−4.94*	0.73	−4.06	−1.62	4.27***	0.98	2.42	26.20***
	$z(SR(f^\sigma))$	0.19	−1.52	−0.53	−1.75	−1.37	1.54	0.54	0.23	4.54
Mexico	α	0.04	−0.60	−2.51	1.01	0.72	4.12*	0.91	0.82	7.51***
	$z(SR(f^\sigma))$	−0.51	1.64	−2.90	−0.10	−0.22	1.85	0.38	−0.26	1.92
Pakistan	α	−6.54	2.81	3.58	−2.40	3.30	0.99	−3.54	−4.14	8.95***
	$z(SR(f^\sigma))$	−1.55	−0.13	−1.01	−1.12	0.24	0.05	−0.63	−0.77	2.40

(*continued on next page*)

Table 1 (*continued*).

Peru	α	0.79	4.61	−3.04	−8.08	−6.90**	−0.51	4.62	10.58**	−6.07
	$z(SR(f^{\sigma}))$	−0.36	0.45	−0.28	−1.50	−1.26	−0.73	0.33	1.64	−0.52
Philippines	α	−1.28	−0.85	3.38	−1.64	1.69	0.27	1.70	0.32	13.54***
	$z(SR(f^{\sigma}))$	−0.80	−0.03	0.03	−1.69	0.62	−0.50	0.03	−0.44	2.54
Poland	α	−5.95	−5.17**	−0.87	−1.49	0.70	0.97	1.93	2.40	11.38***
	$z(SR(f^{\sigma}))$	−1.75	−2.14	−1.32	−0.57	0.30	−0.01	1.21	1.52	2.58
Russia	α	7.84	−0.51	−4.72*	−5.89**	0.31	4.12*	4.27*	3.64	11.35***
	$z(SR(f^{\sigma}))$	0.56	−0.42	−1.85	−2.72	−0.03	0.64	1.66	1.26	2.00
Saudi Arabia	α	11.03**	−4.90	3.37	−2.62	−0.52	1.46	−1.37	3.06	7.28***
	$z(SR(f^{\sigma}))$	2.02	−1.15	0.36	−2.26	−0.32	0.66	−0.41	1.35	2.59
South Africa	α	0.45	3.40**	−4.01**	−4.37**	0.05	2.72*	1.21	3.60*	8.71***
	$z(SR(f^{\sigma}))$	−0.55	2.39	−2.93	−3.28	−0.09	2.21	1.45	2.15	1.87
Taiwan	α	8.88**	0.04	2.94	−1.34	4.02*	1.51	0.39	0.65	10.55***
	$z(SR(f^{\sigma}))$	1.21	−0.57	0.44	−0.55	1.64	0.36	−0.05	−0.16	2.25
Thailand	α	13.51***	−10.86***	2.69	−6.10*	−0.40	2.36	1.42	0.93	11.69**
	$z(SR(f^{\sigma}))$	2.02	−2.36	−1.25	−2.54	−0.28	0.36	1.05	0.43	2.03
Turkey	α	0.44	−5.39*	6.52**	11.57**	0.26	6.19**	3.00	2.36	4.67
	$z(SR(f^{\sigma}))$	−0.69	−2.09	1.84	1.30	−0.16	1.53	0.96	0.91	1.27
U.A.E.	α	4.69	−5.58**	2.72	0.25	−2.00	−2.63	−2.26	−6.44*	3.38
	$z(SR(f^{\sigma}))$	0.39	−1.88	0.07	0.06	−0.23	−0.91	−0.17	−2.14	0.02
Morocco	α	4.75*	0.06	−2.00	−0.27	−0.27	2.42	−1.57	2.58	4.13*
	$z(SR(f^{\sigma}))$	1.13	−0.18	−0.76	−0.24	−0.16	0.42	−1.43	0.45	0.30
Jordan	α	2.41	−2.30	−2.84	−3.85	−4.22*	3.80*	6.11**	5.00**	2.68
	$z(SR(f^{\sigma}))$	0.40	0.33	−1.67	−1.48	−1.74	0.91	2.05	1.68	0.22
Total $\alpha > 0$ [Signif.]		36 [6]	20 [1]	30 [10]	14 [5]	26 [3]	31 [7]	23 [1]	34 [6]	44 [39]
	DM	19 [3]	10 [0]	16 [7]	7 [1]	13 [0]	12 [3]	9 [0]	16 [3]	22 [21]
	EM	17 [3]	10 [1]	14 [3]	7 [4]	13 [3]	19 [4]	14 [1]	18 [3]	22 [18]
Total $\alpha < 0$ [Signif.]		9 [0]	25 [5]	15 [1]	31 [2]	19 [2]	14 [0]	22 [1]	11 [1]	1 [0]
	DM	3 [0]	12 [0]	6 [0]	15 [0]	9 [1]	10 [0]	13 [0]	6 [0]	0 [0]
	EM	6 [0]	13 [5]	9 [1]	16 [2]	10 [1]	4 [0]	9 [1]	5 [1]	1 [0]
Total $z(SR(f^{\sigma})) > 0$ [Signif.]		26 [2]	19 [2]	21 [1]	11 [0]	20 [0]	24 [4]	21 [1]	23 [2]	44 [25]
	DM	15 [0]	11 [0]	12 [1]	6 [0]	11 [0]	9 [2]	8 [0]	9 [1]	22 [10]
	EM	11 [2]	8 [2]	9 [0]	5 [0]	9 [0]	15 [2]	13 [1]	14 [1]	22 [15]
Total $z(SR(f^{\sigma})) < 0$ [Signif.]		19 [0]	26 [0]	24 [0]	34 [0]	25 [2]	21 [2]	24 [0]	22 [4]	1 [0]
	DM	7 [0]	11 [0]	10 [0]	16 [0]	11 [1]	13 [1]	14 [0]	13 [2]	0 [0]
	EM	12 [0]	15 [0]	14 [0]	18 [0]	14 [1]	8 [1]	10 [0]	9 [2]	1 [0]

The table reports gross performance statistics for each volatility-managed equity factor country combination over the 1982 to 2021 sample period. Table B.2 of the Online Appendix reports the specific sample periods and further performance statistics (Sharpe ratios and improvements in certainty equivalent returns). I run regressions of each volatility-managed factor on the unmanaged factor: $f_t^{\sigma} = \alpha + \beta f_t + \epsilon_t$. The managed factor scales by the unmanaged factor's inverse realized variance in the preceding month: $f_t^{\sigma} = (c^*/RV_{t-1}^2) f_t$. $z(SR(f^{\sigma}))$ denotes the z-statistic from the Jobson and Korkie (1981) test of the null hypothesis that $SR(f^{\sigma}) - SR(f) = 0$. All alphas (%) are annualized. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Using downside volatility instead of total volatility increases the overall performance of all volatility-managed equity factors except for the volatility-managed momentum factor. Now, seven volatility-managed factors ($MKT^{d\sigma}$, $HML^{d\sigma}$, $HML_m^{d\sigma}$, $CMA^{d\sigma}$, $RMW^{d\sigma}$, $ROE^{d\sigma}$, $WML^{d\sigma}$) show at least 31 positive country alpha point estimates. For six of which either the number of positive alpha point estimates or the number of statistically significant alpha estimates or both have increased compared to the performance of the total volatility-managed factors. The downside volatility-managed momentum factor ($WML^{d\sigma}$) has only positive alpha estimates, but a decreased number of statistically significant ones [39 → 34] in comparison to the total volatility approach. Notably, the monthly value factor ($HML_m^{d\sigma}$) and the investment factor ($CMA^{d\sigma}$) improve through the downside volatility scaling, as now 6 and 7 alpha estimates of the 31 and 32 positive estimates are statistically significant, respectively. The other two downside volatility-managed equity factors ($SMB^{d\sigma}$ and $RMW_c^{d\sigma}$) again show no clear picture with only very few statistically significant alpha point estimates on both sides. The direct Sharpe ratio comparisons also support the strong performance of the downside volatility-managed momentum factor with 44 positive Sharpe ratio improvements of which 25 are statistically significant. Using downside volatility improves the z-statistics mainly for the market ($MKT^{d\sigma}$), the return on equity based profitability factor ($ROE^{d\sigma}$), and especially the value factor ($HML^{d\sigma}$) with now 4, 5 and 10 significant Sharpe ratio improvements, respectively. While the profitability factor ($RMW^{d\sigma}$) remains at 4 significant Sharpe ratio improvements, all other factors still show hardly any significant Sharpe ratio improvements.

To judge the performance improvements of downside volatility-managed portfolios relative to total volatility-managed portfolios, I run spanning regressions following Wang and Yan (2021). By regressing the downside volatility-managed on the total volatility-managed equity factors, I test whether a combination strategy of the downside volatility-managed and the total volatility-managed factors outperforms the total volatility-managed equity factors. Table 3 reports gross performance statistics of the combination strategies for all 45 equity markets.

The direct comparison tests support the general assessment of Table 2, i.e., downside volatility-managed portfolios potentially further increase the performance of volatility management. All equity factor strategies have 29 to 42 positive country alpha estimates

Table 2
Performance of downside volatility-managed factors before transaction costs.

		MKT	SMB	HML	HML_m	CMA	RMW	RMW_c	ROE	WML
Australia	α	2.18	−0.24	1.27	1.11	1.50**	2.26***	1.05*	2.32***	5.22***
	$z(SR(f^{d\sigma}))$	0.39	−0.35	0.65	1.06	1.49	1.61	1.26	2.92	2.05
Austria	α	4.63*	0.45	2.04**	1.26	2.35**	0.06	−0.12	−0.31	6.78**
	$z(SR(f^{d\sigma}))$	1.39	0.48	1.23	0.03	1.35	−0.44	0.09	−0.77	2.14
Belgium	α	3.84*	−0.23	2.98***	1.76	0.83	−0.66	−0.43	2.09*	7.26***
	$z(SR(f^{d\sigma}))$	1.08	−0.01	2.67	0.99	1.18	−0.72	−0.18	1.11	1.98
Canada	α	2.42	1.08	4.44***	−0.73	1.07	3.76***	3.26**	2.20*	7.60***
	$z(SR(f^{d\sigma}))$	0.54	1.12	2.45	−0.78	0.85	1.81	2.11	1.28	2.46
Denmark	α	3.97**	1.63	4.01**	0.59	0.21	−1.40	−1.09	−1.80	5.57***
	$z(SR(f^{d\sigma}))$	1.14	1.82	2.38	0.91	−0.15	−1.53	−1.10	−1.82	2.31
Finland	α	6.47***	0.95	−1.21	−0.12	−2.26	2.22	1.80	3.96**	4.98**
	$z(SR(f^{d\sigma}))$	1.92	0.99	−1.04	−0.40	−1.14	0.85	0.85	2.10	1.18
France	α	1.64	1.02	1.62	0.55	2.33**	1.24*	0.28	2.11**	9.30***
	$z(SR(f^{d\sigma}))$	0.09	1.76	0.46	−0.04	1.94	1.21	0.31	2.26	4.67
Germany	α	1.31	0.78	2.82**	−0.55	−1.60	0.34	−0.78	−0.42	8.71***
	$z(SR(f^{d\sigma}))$	−0.02	1.03	1.34	−0.69	−1.97	−0.30	−1.39	−0.69	2.97
Hong Kong	α	5.44**	−0.06	6.88***	1.48	0.19	2.84***	0.69	1.82*	11.15***
	$z(SR(f^{d\sigma}))$	1.51	0.48	2.88	0.53	0.00	2.62	0.50	1.49	4.64
Israel	α	1.08	−0.13	2.98**	3.67**	0.32	−0.13	0.91	−0.61	8.40***
	$z(SR(f^{d\sigma}))$	0.00	−0.55	1.48	2.59	0.15	−0.63	0.03	−1.02	2.93
Italy	α	2.33	2.26**	3.04***	2.27	0.14	0.99	0.27	0.50	8.28***
	$z(SR(f^{d\sigma}))$	0.76	2.19	2.38	1.46	0.41	0.01	−0.04	−0.32	2.99
Japan	α	0.97	0.39	3.67***	4.36***	0.74	−0.32	−0.65	−0.10	2.93*
	$z(SR(f^{d\sigma}))$	0.32	0.53	2.33	1.71	0.72	−0.50	−0.96	−0.24	1.71
Netherlands	α	1.24	0.87	2.04*	−1.27	0.64	−1.40	−0.34	−0.07	7.81***
	$z(SR(f^{d\sigma}))$	−0.12	0.97	1.52	−0.75	0.45	−1.63	−0.49	−0.39	3.44
New Zealand	α	3.34*	−0.72	−0.72	0.32	0.07	−0.65	0.81	0.20	3.43***
	$z(SR(f^{d\sigma}))$	0.95	−0.90	−0.05	0.24	−0.16	−0.73	0.88	0.30	1.42
Norway	α	3.67	1.48	2.20*	1.24	0.85	−0.20	0.12	−0.86	4.68***
	$z(SR(f^{d\sigma}))$	0.65	1.34	1.59	1.19	0.05	−0.62	−0.29	−1.38	1.56
Portugal	α	7.49***	−0.77	7.03**	2.87	2.94**	−0.95	−0.77	−0.91	6.48***
	$z(SR(f^{d\sigma}))$	2.69	−0.08	2.07	1.06	1.84	−0.86	−0.67	−0.97	2.06
Singapore	α	0.67	0.13	2.23*	1.04	1.07	3.08***	0.40	4.10***	12.95***
	$z(SR(f^{d\sigma}))$	−0.28	0.46	0.75	0.04	0.81	2.48	0.55	3.31	4.51
Spain	α	2.64	−0.02	1.32	1.10	−0.72	2.56***	1.45	0.99	4.74*
	$z(SR(f^{d\sigma}))$	0.38	−0.06	0.84	0.71	−0.77	1.89	0.74	0.66	1.32
Sweden	α	2.44	0.30	2.56**	1.87	−0.21	−1.27	−0.31	0.43	6.97***
	$z(SR(f^{d\sigma}))$	0.06	0.31	1.41	0.87	−0.83	−1.34	−0.18	−0.14	2.61
Switzerland	α	2.74*	−0.57	0.72	0.45	1.02	1.91**	0.38	1.80*	8.15***
	$z(SR(f^{d\sigma}))$	0.90	−0.29	0.65	0.47	0.48	1.62	0.11	1.59	2.91
U.K.	α	1.11	2.14**	4.14**	2.51*	1.63	0.66	−0.41	1.15	10.94***
	$z(SR(f^{d\sigma}))$	0.02	1.83	1.49	1.35	0.84	0.33	−0.72	0.78	3.04
U.S.	α	3.17*	−0.73	2.57**	1.90	1.28*	2.32***	1.22*	1.28*	5.53***
	$z(SR(f^{d\sigma}))$	0.74	−1.03	1.79	0.96	0.92	1.61	0.82	1.24	2.40
Brazil	α	6.07	2.40	1.94	4.61**	2.60	0.90	−1.42	−0.20	8.84***
	$z(SR(f^{d\sigma}))$	0.70	1.67	0.17	1.18	0.83	0.35	−0.80	0.19	3.35
Chile	α	4.00	1.06	−1.01	−1.96*	1.01	1.93*	1.45	−1.55	2.71**
	$z(SR(f^{d\sigma}))$	0.93	0.83	−1.79	−2.69	0.69	1.36	1.25	−1.36	0.83
China	α	4.49*	−1.64	4.87***	4.15**	−1.04	3.11**	0.97	2.68	4.87**
	$z(SR(f^{d\sigma}))$	1.28	−1.44	2.51	1.24	−0.87	2.32	1.16	1.45	1.96
Egypt	α	3.53	1.98	5.68**	14.60***	0.18	−1.92	−1.45	1.61	4.46
	$z(SR(f^{d\sigma}))$	0.60	0.25	2.18	3.01	0.00	−2.04	−1.94	−0.25	1.75
Greece	α	10.34***	−1.81	−1.63	−2.57	−0.09	4.08**	0.84	3.80**	9.16***
	$z(SR(f^{d\sigma}))$	2.42	−0.77	−2.06	−1.92	0.27	1.27	−0.43	1.44	2.74
India	α	7.58**	0.11	1.92	0.24	2.52**	2.56**	1.03	2.48	13.38***
	$z(SR(f^{d\sigma}))$	1.41	−0.29	0.36	−0.09	1.55	1.85	1.11	1.19	2.05
Indonesia	α	6.84	1.79	5.45**	−0.82	7.44***	3.83*	0.27	4.30**	12.94***
	$z(SR(f^{d\sigma}))$	0.74	0.98	1.37	−0.71	2.83	0.71	−0.04	1.95	2.52
Korea	α	2.96	0.80	6.24***	5.33**	3.94**	−1.87	−2.35*	−2.41	5.74**
	$z(SR(f^{d\sigma}))$	0.44	0.43	2.08	1.49	2.19	−1.55	−1.47	−1.48	2.17
Malaysia	α	8.27**	−2.46	1.54	−0.85	−0.66	2.16	0.79	1.05	21.98***
	$z(SR(f^{d\sigma}))$	1.54	−1.13	0.60	−0.79	−1.02	0.90	0.71	−0.01	4.41
Mexico	α	4.94	−1.50	−0.50	2.08	1.26	2.68*	1.81	1.91	3.54
	$z(SR(f^{d\sigma}))$	0.90	0.56	−1.88	0.90	0.40	1.57	0.94	0.81	0.87
Pakistan	α	0.71	4.08*	0.45	−1.19	2.89	2.87	−4.66	−4.46	4.92*
	$z(SR(f^{d\sigma}))$	−0.34	0.99	−0.55	−0.52	0.52	0.41	−1.22	−0.93	1.52

(*continued on next page*)

Table 2 (*continued*).

Peru	α	6.84**	3.38	−1.96	0.91	−4.93**	−0.14	0.99	4.73*	2.77
	$z(SR(f^{d\sigma}))$	1.71	0.78	−0.19	−0.48	−2.07	−0.86	−0.20	0.85	0.67
Philippines	α	5.50**	−0.32	1.11	0.61	0.35	0.41	1.58	0.79	6.12**
	$z(SR(f^{d\sigma}))$	1.69	−0.01	−0.23	−0.62	0.09	−0.13	0.43	0.16	1.67
Poland	α	−2.41	−0.16	0.17	0.83	1.84	−0.84	1.37	1.58	7.52***
	$z(SR(f^{d\sigma}))$	−0.96	0.04	−0.73	0.38	1.15	−0.84	1.39	1.50	2.21
Russia	α	10.40**	1.44	−1.68	−4.08**	−0.49	3.29*	4.38***	3.49*	7.73**
	$z(SR(f^{d\sigma}))$	1.08	0.63	−1.10	−2.77	−0.63	1.03	2.58	1.94	1.52
Saudi Arabia	α	6.94	−0.26	2.78	−0.53	−1.63	2.16	−0.27	2.27	4.62**
	$z(SR(f^{d\sigma}))$	1.39	0.07	0.62	−1.03	−1.04	1.05	−0.18	1.32	2.11
South Africa	α	−0.69	2.06*	−0.87	−0.72	0.74	2.18**	1.54	2.38**	6.49***
	$z(SR(f^{d\sigma}))$	−0.87	2.00	−1.14	−1.31	1.03	2.35	1.88	2.02	2.51
Taiwan	α	7.46***	3.73**	3.65	−0.33	1.97	1.96	1.04	0.06	6.59***
	$z(SR(f^{d\sigma}))$	2.08	2.43	1.14	−0.18	1.12	1.25	0.51	−0.23	2.10
Thailand	α	11.69***	−5.05**	4.08*	1.98	1.99	3.83*	2.02	2.87	7.91*
	$z(SR(f^{d\sigma}))$	2.22	−1.98	0.35	−0.01	1.35	1.63	1.79	1.60	1.87
Turkey	α	6.08	−0.74	0.78	4.94	0.91	2.78	2.02	2.34	2.77
	$z(SR(f^{d\sigma}))$	0.96	−0.65	0.38	0.44	0.43	0.84	0.74	1.06	1.18
U.A.E.	α	6.98**	−3.24**	2.14	2.02	−0.82	−0.23	−1.60	−3.91*	6.20*
	$z(SR(f^{d\sigma}))$	1.13	−1.41	0.31	0.77	−0.20	−0.12	−0.27	−1.87	1.19
Morocco	α	4.76**	−0.26	−3.11**	1.10	−0.47	0.81	−0.66	1.86	1.50
	$z(SR(f^{d\sigma}))$	1.69	−0.39	−1.83	0.97	−0.45	0.03	−1.00	0.95	−0.12
Jordan	α	4.68*	−0.27	−2.69	−1.04	−3.18**	4.03**	3.26	4.91***	1.31
	$z(SR(f^{d\sigma}))$	1.65	0.60	−1.93	−0.70	−2.10	1.50	1.21	2.25	0.24
Total $\alpha > 0$ [Signif.]		43 [14]	24 [4]	35 [17]	31 [6]	32 [7]	31 [12]	29 [2]	32 [8]	45 [34]
	DM	22 [4]	13 [2]	20 [13]	18 [2]	18 [4]	13 [7]	13 [1]	14 [4]	22 [20]
	EM	21 [10]	11 [2]	15 [4]	13 [4]	14 [3]	18 [5]	16 [1]	18 [4]	23 [14]
Total $\alpha < 0$ [Signif.]		2 [0]	21 [2]	10 [1]	14 [1]	13 [2]	14 [0]	16 [0]	13 [0]	0 [0]
	DM	0 [0]	9 [0]	2 [0]	4 [0]	4 [0]	9 [0]	9 [0]	8 [0]	0 [0]
	EM	2 [0]	12 [2]	8 [1]	10 [1]	9 [2]	5 [0]	7 [0]	5 [0]	0 [0]
Total $z(SR(f^{d\sigma})) > 0$ [Signif.]		39 [4]	28 [3]	32 [10]	26 [2]	30 [2]	28 [4]	25 [2]	28 [5]	44 [25]
	DM	19 [1]	14 [1]	20 [7]	17 [1]	15 [0]	11 [2]	12 [1]	12 [3]	22 [15]
	EM	20 [3]	14 [2]	12 [3]	9 [1]	15 [2]	17 [2]	13 [1]	16 [2]	22 [10]
Total $z(SR(f^{d\sigma})) < 0$ [Signif.]		6 [0]	17 [0]	13 [0]	19 [0]	15 [2]	17 [0]	20 [0]	17 [0]	1 [0]
	DM	3 [0]	8 [0]	2 [0]	5 [0]	7 [1]	11 [0]	10 [0]	10 [0]	0 [0]
	EM	3 [0]	9 [0]	11 [0]	14 [0]	8 [1]	6 [0]	10 [0]	7 [0]	1 [0]

The table reports gross performance statistics for each downside volatility-managed equity factor country combination over the 1982 to 2021 sample period. Table B.3 of the Online Appendix reports the specific sample periods and further performance statistics (Sharpe ratios and improvements in certainty equivalent returns). I run regressions of each downside volatility-managed factor on the unmanaged factor: $f_t^{d\sigma} = \alpha + \beta f_t + \epsilon_t$. The managed factor scales by the unmanaged factor's inverse realized downside volatility in the preceding month: $f_t^{d\sigma} = (c^*/dRV_{t-1}) f_t$. $z(SR(f^{d\sigma}))$ denotes the z-statistic from the Jobson and Korkie (1981) test of the null hypothesis that $SR(f^{d\sigma}) - SR(f) = 0$. All alphas (%) are annualized. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

in the applied spanning regressions. The most promising factors are the market ($MKT^{d\sigma}$) and the two value factors ($HML^{d\sigma}$ + $HML_m^{d\sigma}$) with 42, 32, and 39 positive alpha point estimates, of which 13, 15, and 17 are statistically significant at the five-percent level, respectively. The direct Sharpe ratio comparisons also support this assessment with 10, 8, and 13 significant Sharpe ratio improvements for the market and the two value factors, respectively. Notably, the combination strategy does not appear to improve much for the most promising total volatility-managed factor, WML^{σ}.

In international equity markets, volatility-managed equity factor portfolios seem most promising for market, value, profitability, and especially momentum portfolios. The majority of the spanning regression alpha estimates are positive suggesting a possible outperformance of the combination strategy over the original equity factor. The performance can be enhanced by applying downside volatility instead of total volatility as a scaling factor predominantly for market and value portfolios. Judging the international performance based on direct Sharpe ratio comparisons of the managed and the unmanaged factors significantly weakens the performance picture as only momentum portfolios seem to survive the direct comparison tests in both scaling approaches.

4.2. After-cost performance of volatility-managed equity factors

Even though the good performance of the original equity factors could partially be further improved through volatility management, it has to be noted that the improvement comes at the cost of an increased turnover due to the time-varying leverage of the volatility-managed factors. The strategy creates monthly turnover even when none would otherwise exist, i.e., the entire factor portfolio is bought or sold based on the realized variance (downside volatility) of the previous month, even though the original factor might only be rebalanced once a year. Fig. 2 shows the equal-weighted monthly average turnover of the unmanaged and the (downside) volatility-managed equity factors across four regions and confirms that volatility management leads to significantly increased turnover in all countries compared to the original equity factor construction.

Table 3
Performance improvement of downside volatility-managed factors.

		MKT	SMB	HML	HML_m	CMA	RMW	RMW_c	ROE	WML
Australia	α	2.85*	1.39**	2.69**	2.21**	2.38**	1.93**	2.17**	1.28**	1.05
	$z(SR(f^{d\sigma}))$	1.52	1.75	2.09	2.40	2.63	1.68	3.05	1.33	−1.27
Austria	α	3.92**	0.60	1.12	2.24**	0.93	3.03**	0.95	2.14**	0.90
	$z(SR(f^{d\sigma}))$	1.81	0.79	0.21	1.45	0.36	3.32	1.14	2.50	−0.86
Belgium	α	0.85	−0.80	−0.73	−0.24	1.42**	0.69	−0.53	1.25	1.52
	$z(SR(f^{d\sigma}))$	−0.17	−1.27	−1.47	−0.61	2.08	1.04	−0.35	0.47	−0.33
Canada	α	4.68**	1.64**	2.15*	1.49	1.10	2.35**	1.63	2.12**	2.98*
	$z(SR(f^{d\sigma}))$	3.07	2.23	1.16	1.37	1.00	1.29	1.09	1.53	−0.54
Denmark	α	−0.38	0.89	0.96	−0.11	2.04**	−1.08	0.72	1.68	3.06**
	$z(SR(f^{d\sigma}))$	−1.37	1.14	0.12	0.27	1.91	−1.09	0.79	1.48	0.73
Finland	α	4.41**	−0.27	3.19*	2.76*	1.49	2.33	1.33	2.23	−0.14
	$z(SR(f^{d\sigma}))$	1.43	−0.12	1.85	1.59	1.30	1.09	0.72	1.00	−1.23
France	α	1.65	−0.32	3.40**	3.77**	1.10	0.27	−0.23	0.30	0.33
	$z(SR(f^{d\sigma}))$	0.42	−0.41	2.77	3.18	0.82	−0.19	−0.57	−0.01	−1.60
Germany	α	0.90	−0.28	2.42**	1.32	2.52**	1.66**	0.39	0.05	1.80
	$z(SR(f^{d\sigma}))$	0.03	−0.37	1.88	1.16	2.48	1.50	0.47	−0.02	−1.02
Hong Kong	α	0.81	2.40	3.03**	3.23**	2.09**	2.31**	0.81	1.72*	2.59**
	$z(SR(f^{d\sigma}))$	−0.34	2.10	1.61	3.06	1.96	2.14	0.87	1.43	0.07
Israel	α	3.74*	1.91*	−0.15	1.93	−1.92	2.92*	3.95**	−0.10	0.73
	$z(SR(f^{d\sigma}))$	2.02	1.77	−0.48	1.20	−0.94	1.25	2.02	−0.51	−0.26
Italy	α	0.31	0.01	0.63	1.65	0.12	3.32**	0.41	1.26	0.62
	$z(SR(f^{d\sigma}))$	−0.13	−0.10	0.08	1.24	0.37	3.10	0.20	0.56	−1.19
Japan	α	3.65**	1.11	2.19**	2.90**	0.59	0.27	−0.38	0.53	1.63
	$z(SR(f^{d\sigma}))$	2.87	1.30	0.92	0.80	0.78	0.78	−0.49	0.98	0.89
Netherlands	α	−1.68	0.46	−0.20	−1.29	0.40	0.87	0.37	−0.09	3.07**
	$z(SR(f^{d\sigma}))$	−1.87	0.58	−0.64	−0.93	0.30	0.90	0.31	−0.34	0.48
New Zealand	α	0.87	0.26	−0.18	0.77	1.51*	−1.23	0.13	−1.31	2.36**
	$z(SR(f^{d\sigma}))$	−0.10	0.31	0.02	0.81	1.84	−1.22	0.11	−1.17	0.76
Norway	α	1.15	0.10	4.08**	3.85**	1.04	0.69	0.89	1.90*	0.72
	$z(SR(f^{d\sigma}))$	−0.22	−0.07	2.84	2.78	−0.10	0.25	0.86	1.59	−0.63
Portugal	α	3.25*	0.67	0.53	2.92	2.73*	1.82	0.59	1.58	2.88*
	$z(SR(f^{d\sigma}))$	1.19	0.80	−0.29	1.52	1.57	1.41	0.55	0.67	0.59
Singapore	α	1.62	1.93	2.00*	1.27	−0.02	0.74	1.32	1.39	1.04
	$z(SR(f^{d\sigma}))$	0.63	2.00	0.72	0.61	−0.55	0.19	1.57	0.71	−0.88
Spain	α	1.73	1.25	0.86	1.31	0.89	0.27	0.44	0.05	1.44
	$z(SR(f^{d\sigma}))$	0.51	1.60	0.41	0.90	1.30	−0.53	0.02	−0.52	0.00
Sweden	α	0.65	−0.46	2.30**	2.80**	1.30	0.17	0.48	0.64	−0.19
	$z(SR(f^{d\sigma}))$	−0.08	−0.73	1.85	2.59	0.87	0.07	0.59	0.33	−1.89
Switzerland	α	1.49	−0.62	0.91	1.43**	0.55	−0.49	−0.08	−0.04	3.26**
	$z(SR(f^{d\sigma}))$	0.75	−0.75	1.25	2.33	0.28	−1.21	−0.6	−0.55	0.93
U.K.	α	0.23	0.49	4.31**	4.59**	1.13	0.98	0.87	1.19	4.17**
	$z(SR(f^{d\sigma}))$	−0.32	0.18	2.31	4.10	0.27	0.72	0.92	0.73	−0.47
U.S.	α	1.60	0.28	3.65**	2.76**	1.84**	1.73**	0.75	1.29**	−0.70
	$z(SR(f^{d\sigma}))$	0.57	0.38	3.17	2.14	2.66	1.77	0.81	2.01	−1.88
Brazil	α	8.57*	−2.91**	2.27	4.89**	0.85	1.37	−1.18	0.93	1.50
	$z(SR(f^{d\sigma}))$	0.80	−1.98	0.81	1.90	−0.10	0.79	−0.86	0.88	0.02
Chile	α	6.79**	0.07	0.63	1.67	−1.05	0.88	−0.61	−2.18*	0.48
	$z(SR(f^{d\sigma}))$	2.71	−0.22	−0.25	1.13	−1.59	0.48	−0.97	−1.98	−0.58
China	α	6.79**	5.98**	0.92	1.45	0.26	−0.20	0.37	0.60	0.39
	$z(SR(f^{d\sigma}))$	2.32	2.87	−0.06	−0.11	0.70	−0.94	0.43	−0.40	−0.89
Egypt	α	6.20*	3.42	0.97	4.90	0.49	−0.06	2.22	1.10	−3.45
	$z(SR(f^{d\sigma}))$	1.66	0.61	−0.12	0.96	0.35	−0.15	0.69	0.23	−1.55
Greece	α	4.92	4.28**	0.19	2.47	1.12	2.07	2.23	1.38	−4.19*
	$z(SR(f^{d\sigma}))$	0.92	2.28	−0.11	1.16	0.86	0.39	0.94	0.08	−2.64
India	α	5.60**	−0.61	3.83*	3.82	1.36	2.17*	1.12	4.36**	3.23
	$z(SR(f^{d\sigma}))$	1.15	−0.75	1.07	1.37	0.71	1.65	1.28	2.53	−1.27
Indonesia	α	3.51	0.71	3.54**	4.79*	2.31	4.96**	1.14	4.13**	−0.42
	$z(SR(f^{d\sigma}))$	−0.39	0.27	0.93	1.72	0.21	1.47	0.93	2.13	−1.35
Korea	α	3.40	2.87**	1.51	2.79	0.49	1.71	0.77	2.27**	−2.32
	$z(SR(f^{d\sigma}))$	0.98	2.24	−0.25	0.28	−0.26	1.58	1.25	2.21	−1.81
Malaysia	α	6.48**	1.21	2.33**	5.10**	0.95	−0.69	0.12	0.20	2.04
	$z(SR(f^{d\sigma}))$	1.91	1.22	1.51	2.15	1.27	−1.55	−0.04	−0.43	−1.23
Mexico	α	5.52**	−4.18**	7.94**	3.32**	1.83	−1.41	0.27	2.39	−1.26
	$z(SR(f^{d\sigma}))$	2.01	−2.11	2.16	1.38	0.58	−1.16	0.34	1.21	−1.88
Pakistan	α	8.97**	4.52*	6.38*	3.04	1.10	2.46	−1.73	−0.45	−1.72
	$z(SR(f^{d\sigma}))$	3.04	1.20	0.94	1.05	0.38	0.45	−0.77	−0.50	−1.68

(*continued on next page*)

Table 3 (*continued*).

Peru	α	8.44**	−1.61	3.15	7.48	−1.62	1.13	−1.94	−0.89	2.50
	$z(SR(f^{d\sigma}))$	2.09	0.21	0.23	1.11	0.01	0.38	−0.63	−1.63	1.72
Philippines	α	8.73**	−0.33	0.64	4.48**	−1.26	1.39	1.11	1.81	−4.43
	$z(SR(f^{d\sigma}))$	2.56	0.03	−0.31	2.08	−0.97	0.58	0.47	0.89	−2.36
Poland	α	4.07*	4.48**	2.42**	2.43	0.95	−1.00	−0.30	−0.73	−0.16
	$z(SR(f^{d\sigma}))$	1.67	3.69	1.63	1.41	0.69	−1.11	−0.50	−0.97	−1.39
Russia	α	4.76*	2.16	2.97*	2.36	−0.96	1.42	1.37	0.67	−0.61
	$z(SR(f^{d\sigma}))$	0.76	1.44	1.92	1.57	−0.69	0.19	0.52	0.16	−1.07
Saudi Arabia	α	−1.58	3.61*	0.19	3.04**	−0.72	0.09	0.47	−0.89	−1.41
	$z(SR(f^{d\sigma}))$	−1.10	2.09	0.26	2.13	−1.01	0.06	0.50	−0.74	−1.68
South Africa	α	0.25	−1.50*	5.10**	4.06**	0.90	−1.28	−0.39	−1.65	2.07*
	$z(SR(f^{d\sigma}))$	−0.20	−1.76	3.37	2.86	1.04	−1.32	−0.34	−1.57	−0.10
Taiwan	α	0.85	1.92	1.57	1.53	−1.63	0.99	0.92	−0.24	−1.63
	$z(SR(f^{d\sigma}))$	0.58	3.72	0.64	0.84	−1.53	0.63	0.62	0.01	−1.40
Thailand	α	1.21	1.76	7.42**	8.45**	2.98*	2.86*	0.26	1.94	−1.26
	$z(SR(f^{d\sigma}))$	−0.29	1.93	2.24	3.59	1.66	1.35	0.28	1.15	−1.16
Turkey	α	9.17**	4.53**	−4.29*	−3.21	0.94	−0.99	−0.94	−0.20	−1.12
	$z(SR(f^{d\sigma}))$	2.36	2.75	−2.47	−1.51	0.81	−1.88	−0.92	−0.37	−0.66
U.A.E.	α	4.76*	1.51	1.58	2.63	−0.46	2.22	−0.61	3.04	4.30
	$z(SR(f^{d\sigma}))$	0.82	1.30	0.22	0.79	0.15	1.07	−0.05	1.60	1.41
Morocco	α	1.63	0.07	−1.49	1.44	−0.23	−0.18	1.34	1.17	0.44
	$z(SR(f^{d\sigma}))$	0.36	−0.10	−0.83	1.30	−0.23	−0.61	1.11	0.16	−0.59
Jordan	α	3.41*	−1.07	1.58	2.57	0.40	1.19	−2.04	1.18	0.74
	$z(SR(f^{d\sigma}))$	1.23	0.11	0.61	1.61	0.61	0.53	−1.71	0.12	−0.10
Total $\alpha > 0$ [Signif.]		42[13]	32[7]	39[15]	41[17]	35[6]	34[8]	32[2]	33[7]	29[6]
	DM	20[4]	16[2]	18[9]	19[10]	20[6]	19[7]	18[2]	18[4]	19[6]
	EM	22[9]	16[5]	21[6]	22[7]	15[0]	15[1]	14[0]	15[3]	10[0]
Total $\alpha < 0$ [Signif.]		3[0]	13[2]	6[0]	4[0]	10[0]	11[0]	13[0]	12[0]	16[0]
	DM	2[0]	6[0]	4[0]	3[0]	2[0]	3[0]	4[0]	4[0]	3[0]
	EM	1[0]	7[2]	2[0]	1[0]	8[0]	8[0]	9[0]	8[0]	13[0]
Total $z(SR(f^{d\sigma})) > 0$ [Signif.]		32[10]	31[9]	33[8]	41[13]	34[4]	32[3]	31[2]	29[5]	10[0]
	DM	13[3]	14[2]	18[5]	20[8]	19[4]	17[3]	18[2]	15[2]	7[0]
	EM	19[7]	17[7]	15[3]	21[5]	15[0]	15[0]	13[0]	14[3]	3[0]
Total $z(SR(f^{d\sigma})) < 0$ [Signif.]		13[0]	14[1]	12[1]	4[0]	11[0]	13[0]	14[0]	16[0]	35[2]
	DM	9[0]	8[0]	4[0]	2[0]	3[0]	5[0]	4[0]	7[0]	15[0]
	EM	4[0]	6[1]	8[1]	2[0]	8[0]	8[0]	10[0]	9[0]	20[2]

The table reports gross relative performance statistics for each downside volatility-managed equity factor country combination over the 1982 to 2021 sample period. I run regressions of each downside volatility-managed factor on the volatility-managed factor: $f_t^{d\sigma} = \alpha + \beta f_t^{\sigma} + \epsilon_t$. The downside volatility-managed factor scales by the unmanaged factor's inverse realized downside volatility in the preceding month: $f_t^{d\sigma} = (c^*/dRV_{t-1})f_t$ and the volatility-managed factor scales by the unmanaged factor's inverse realized variance in the preceding month: $f_t^{\sigma} = (c^*/RV_{t-1}^2)f_t$. $z(SR(f^{d\sigma}))$ denotes the z-statistic from the Jobson and Korkie (1981) test of the null hypothesis that $SR(f^{d\sigma}) - SR(f^{\sigma}) = 0$. All alphas (%) are annualized. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

Total volatility management increases the average monthly turnover of the annually (monthly) rebalanced factors by a factor ranging from 4.8 to 9.1 (1.9 to 3.1) for the developed markets ex U.S. and from 4.8 to 7.7 (1.9 to 2.8) for the emerging markets, respectively. The results are slightly higher for the G7+ region with an increased average monthly turnover of the annually (monthly) rebalanced factors by a factor ranging from 5.8 to 10.2 (2.1 to 3.8). The U.S. has the highest increase with an increased average monthly turnover of the annually (monthly) rebalanced factors by a factor ranging from 6.7 to 12 (2.6 to 4.8).[10] The turnover increases are slightly lower for the downside volatility strategies as these apply volatility instead of variance based scaling factors which in general lead to less extreme investment positions and thus lower turnover.[11] Nevertheless, the implications are the same for volatility and downside volatility-managed equity factors, namely that volatility management increases turnover significantly.

This increase in turnover paired with the effective spread estimates from Section 2.3 (Fig. 1) lead to the transaction costs depicted in Fig. 3.

The annual absolute transaction costs of the total volatility-managed equity factors that yield significant positive alphas in Table 1 are the highest for the emerging markets ranging from 7.7% (ROE^{σ}) to 13.1% (WML^{σ}). The annual absolute transaction costs are almost identical for the developed world ex U.S. and the G7+ region as they range from 5.6% (RMW^{σ}) to 9.6% (WML^{σ}) and 5%

[10] Interestingly, the factor ranges for the annually (monthly) rebalanced factors always begin with the increase in CMA (WML) turnover and end with the increase in SMB (HML_m) turnover, hence the turnover increase range for the promising annually rebalanced factors is always smaller than the upper bound and bigger than the lower bound.

[11] Assessing the turnover increases of downside and total volatility-managed strategies based on comparable scaling factors, i.e., both approaches scale with e.g., variance and downside variance, reveals a higher relative turnover increase for downside volatility-managed strategies.

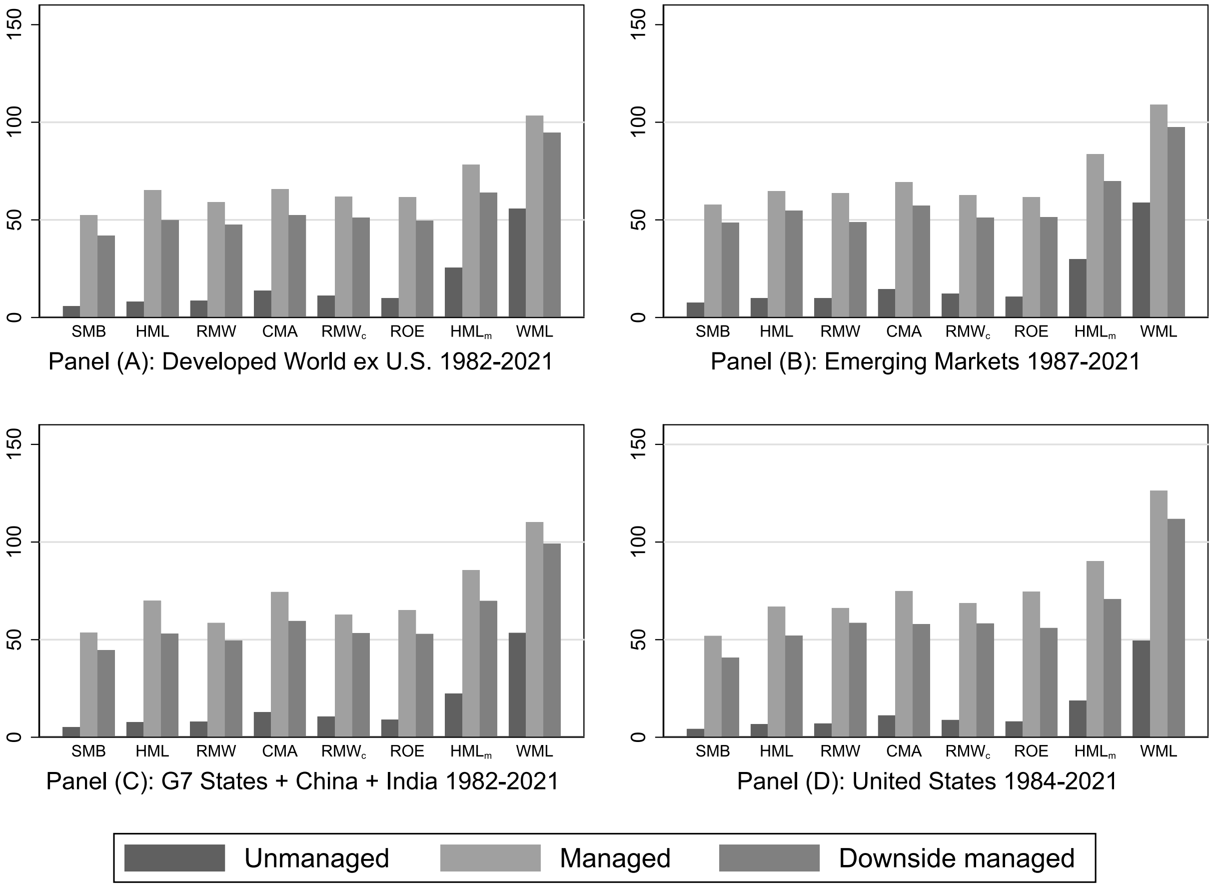

Fig. 2. Turnover of unmanaged and (downside) volatility-managed factors. The figure shows the equal-weighted monthly average turnover for the unmanaged, managed and downside managed factors across the respective countries in a given region. Panels A, B, C, and D, respectively, present the average turnover (% per month) for the non-market equity factors by region over the respective sample period.

(RMW^{σ}) to 9.4% (WML^{σ}), respectively. The U.S. also lies in a comparable range with annual absolute transaction costs ranging from 4.8% (RMW^{σ}) to 9.5% (WML^{σ}).

The relative increase of the annual transaction costs of the annually (monthly) rebalanced factors through total volatility management is almost the same for the emerging markets and the developed markets ex U.S. as both increase the transaction costs of the original factors by a factor ranging from 4 (1.5) to 5.9 (2.4) and 4.4 (1.7) to 7.4 (2.6), respectively. The G7+ region is also in a comparable relative increase range ranging from 5.2 (1.8) to 8.4 (3.2). Interestingly, the U.S. has the biggest relative increase in annual (monthly) transaction costs, ranging from 6.1 (2.3) to 10.1 (3.7). In other words, the U.S. loses its relative transaction cost advantage in the original factor construction when volatility management is applied.

As with turnover, the implications for the absolute as well as the relative transaction cost increases are transferable for the downside volatility strategies at a lower level. In conclusion, it can be stated that the higher absolute performance of the volatility- and downside volatility-managed equity factor strategies goes along with a significant increase in transaction costs, which impacts the after-cost performance of the volatility-managed factors more than the downside volatility-managed factors[12] and is especially high in emerging markets.

Table 4 reports performance statistics for each volatility-managed equity factor country combination after considering transaction costs.

The results clearly show that the transaction costs imposed by volatility management erode almost the entire gross performance of all total volatility-managed equity factors. Only the total volatility-managed market (MKT^{σ}) and momentum (WML^{σ}) portfolios still show a noteworthy number of positive generalized net-of-costs alpha point estimates. The total volatility-managed market factor and the total volatility-managed momentum factor have 25 and 39 positive generalized net-of-costs alpha point estimates, with 4 and 9 of them being statistically significant at the five-percent level, respectively. The higher transaction costs for the emerging

[12] Assessing the transaction cost increases of downside and total volatility-managed strategies based on comparable scaling factors, i.e., both approaches scale with e.g., variance and downside variance, reveals a higher relative transaction cost increase for downside volatility-managed strategies.

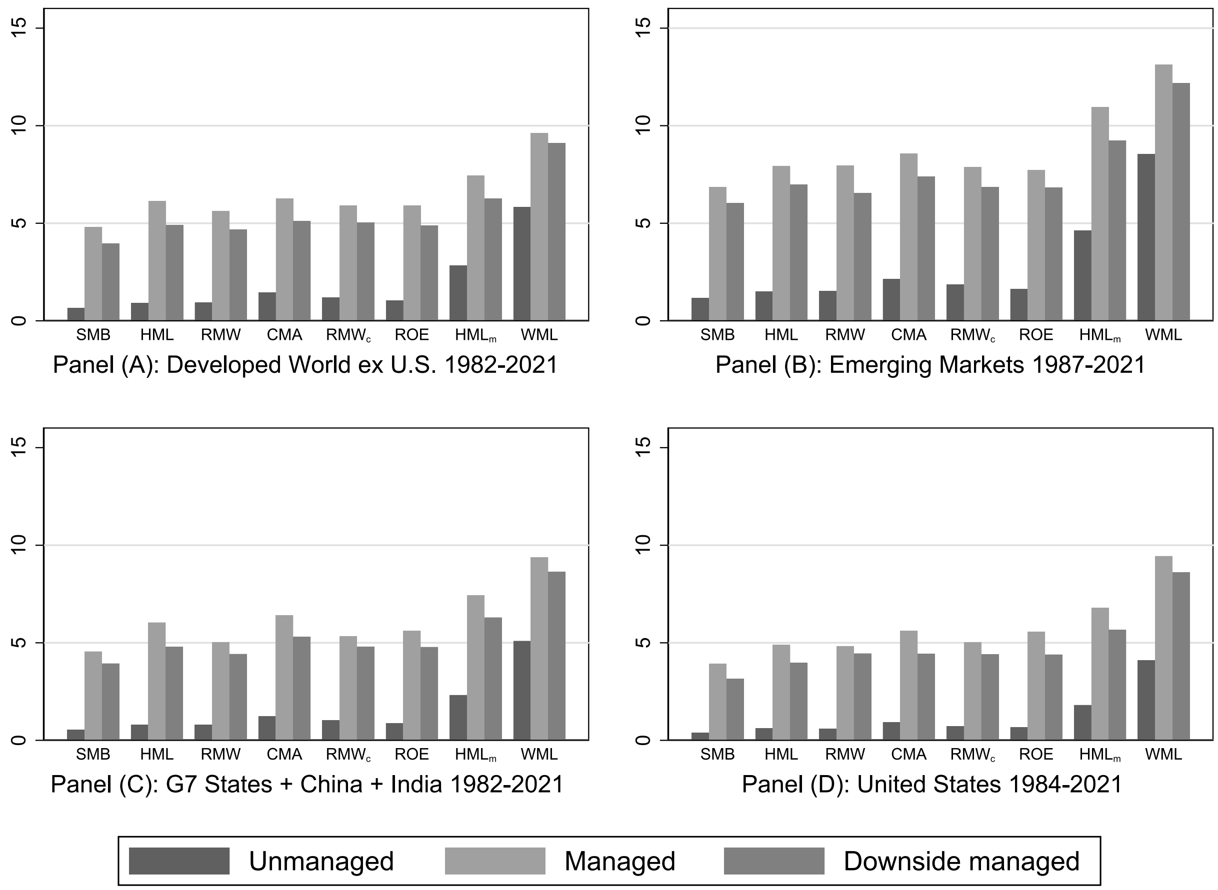

Fig. 3. Transaction costs of unmanaged and (downside) volatility-managed factors. The figure shows the equal-weighted annual average transaction costs for the unmanaged, managed and downside managed factors across the respective countries in a given region. Panels A, B, C, and D, respectively, present the average transaction costs (% per year) for the non-market equity factors by region over the respective sample period.

markets are clearly visible for the managed momentum factor, as 7 of the 9 significant generalized net-of-costs alpha estimates are from the developed markets. It should be noted that the estimated transaction costs for total volatility-managed market portfolios could potentially be reduced to a very modest level through the use of country-level ETFs. Selling just one security (the ETF) instead of a couple hundred or even thousand stocks can avoid a lot of transaction costs if country-level ETFs are able to capture the benefits of volatility management. The corresponding ETF analysis is presented in Table A.11 (Panel A) of Appendix A.5 and suggests that it would have been rather difficult to attain the benefits of total volatility-managed market portfolios through existing ETFs.

Judging the after-cost performance of total volatility-managed equity factors based on direct Sharpe ratio comparisons suggests an even more devastating picture, as most of the factors, with the exception of MKT^{σ} and WML^{σ}, have more than 27 significant Sharpe ratio decreases. Only the managed momentum factor is able to attain 4 significant Sharpe ratio improvements. The results suggest that the performance of the total volatility-managed equity factors is not robust to the transaction cost estimations.

Table 5 reports performance statistics for each downside volatility-managed equity factor country combination after considering transaction costs.

The after-cost results for the downside volatility-managed equity factors are slightly better than the after-cost results of the total volatility-managed factors but still very poor overall. Likewise, only the downside volatility-managed market ($MKT^{d\sigma}$) and momentum ($WML^{d\sigma}$) portfolios show positive generalized net-of-costs alpha point estimates. The downside volatility-managed market factor and the downside volatility-managed momentum factor have 34 and 35 positive generalized net-of-costs alpha point estimates, with 3 and 8 of them being statistically significant at the five-percent level, respectively. Looking at the direct Sharpe ratio comparisons confirms the poor after-cost performance as all factors besides $MKT^{d\sigma}$ and $WML^{d\sigma}$ show no positive, but at least over 22 negative significant Sharpe ratio decreases. The downside volatility-managed market factor is able to attain 1 positive significant z-statistic. The downside volatility-managed momentum factor is able to attain 4 positive significant z-statistics.

The results suggest that the better gross performance of the downside volatility-managed equity factors is also not robust to the transaction cost estimations. Neither the combination investment strategy nor the direct investment strategy seems promising after considering transaction costs. The corresponding ETF analysis for the downside volatility-managed market portfolios is presented in Table A.11 (Panel B) of Appendix A.5 and suggests that it would have been rather difficult to attain the benefits of downside

Table 4
Net-of-costs performance of volatility-managed factors.

		MKT	SMB	HML	HML_m	CMA	RMW	RMW_c	ROE	WML
Australia	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.15
	$z(SR(f^{\sigma}_{net}))$	−1.20	−4.68	−4.60	−4.37	−4.90	−3.91	−4.97	−3.71	0.23
Austria	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.51
	$z(SR(f^{\sigma}_{net}))$	−0.56	−3.68	−2.24	−2.80	−1.64	−4.99	−3.82	−6.02	0.53
Belgium	α_{net}	3.13	0.00	0.53	0.00	0.00	0.00	0.00	0.00	3.64
	$z(SR(f^{\sigma}_{net}))$	0.32	−2.30	0.02	−0.84	−3.16	−4.77	−2.91	−1.91	0.51
Canada	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.51
	$z(SR(f^{\sigma}_{net}))$	−2.00	−4.57	−2.66	−4.22	−4.77	−1.99	−1.99	−3.46	0.14
Denmark	α_{net}	4.68**	0.00	−0.87	0.00	0.00	0.00	0.00	0.00	2.77
	$z(SR(f^{\sigma}_{net}))$	0.91	−1.99	−0.22	−0.82	−4.22	−2.64	−3.14	−4.78	0.18
Finland	α_{net}	2.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.24
	$z(SR(f^{\sigma}_{net}))$	−0.21	−1.99	−3.76	−2.62	−3.46	−2.15	−1.84	−1.28	1.05
France	α_{net}	0.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.38**
	$z(SR(f^{\sigma}_{net}))$	−0.85	−1.99	−4.08	−4.85	−2.87	−2.67	−3.74	−2.81	1.83
Germany	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.02***
	$z(SR(f^{\sigma}_{net}))$	−0.62	−2.53	−2.86	−3.20	−5.85	−4.97	−5.09	−3.83	1.66
Hong Kong	α_{net}	6.85**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.29**
	$z(SR(f^{\sigma}_{net}))$	1.14	−2.34	−2.13	−3.35	−4.75	−3.21	−3.70	−3.77	2.24
Israel	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.79*
	$z(SR(f^{\sigma}_{net}))$	−1.98	−3.30	−1.17	−1.25	−2.22	−4.20	−3.83	−3.56	1.31
Italy	α_{net}	1.58	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.67***
	$z(SR(f^{\sigma}_{net}))$	0.12	−0.72	−1.16	−1.75	−3.88	−4.53	−3.16	−3.75	1.75
Japan	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	−2.20	−3.67	−2.94	−2.21	−4.20	−5.87	−3.61	−5.32	−0.83
Netherlands	α_{net}	3.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.78*
	$z(SR(f^{\sigma}_{net}))$	0.28	−1.78	−0.52	−1.10	−1.37	−3.19	−2.03	−1.73	1.08
New Zealand	α_{net}	3.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.52
	$z(SR(f^{\sigma}_{net}))$	0.23	−4.68	−2.75	−2.61	−4.05	−2.85	−2.74	−1.86	−0.68
Norway	α_{net}	2.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.86
	$z(SR(f^{\sigma}_{net}))$	0.11	−2.33	−2.85	−3.09	−2.71	−3.79	−3.97	−4.53	0.70
Portugal	α_{net}	4.04	0.00	0.31	0.00	0.00	0.00	0.00	0.00	2.51
	$z(SR(f^{\sigma}_{net}))$	0.72	−2.85	−0.13	−1.62	−2.63	−4.16	−3.78	−3.49	0.02
Singapore	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.40
	$z(SR(f^{\sigma}_{net}))$	−1.25	−4.49	−4.52	−4.26	−4.43	−3.40	−5.80	−3.61	1.01
Spain	α_{net}	0.68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.47
	$z(SR(f^{\sigma}_{net}))$	−0.41	−2.84	−1.93	−2.28	−2.89	−0.75	−2.09	−1.50	0.41
Sweden	α_{net}	1.68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.35**
	$z(SR(f^{\sigma}_{net}))$	−0.45	−2.27	−2.80	−3.21	−4.02	−4.34	−3.66	−3.46	1.48
Switzerland	α_{net}	1.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.14*
	$z(SR(f^{\sigma}_{net}))$	−0.17	−1.98	−2.64	−2.53	−1.39	−0.47	−1.86	−0.93	0.81
U.K.	α_{net}	1.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.46***
	$z(SR(f^{\sigma}_{net}))$	−0.16	−1.12	−2.10	−3.38	−2.37	−2.97	−3.88	−2.81	2.44
U.S.	α_{net}	2.28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.05
	$z(SR(f^{\sigma}_{net}))$	−0.49	−3.88	−2.84	−2.53	−4.83	−3.00	−3.97	−4.55	0.89
Brazil	α_{net}	6.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.04
	$z(SR(f^{\sigma}_{net}))$	−0.31	−0.26	−2.85	−1.43	−1.57	−2.41	−2.61	−2.29	1.08
Chile	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.84
	$z(SR(f^{\sigma}_{net}))$	−1.93	−2.17	−4.66	−3.37	−1.94	−2.33	−1.89	−1.90	0.21
China	α_{net}	0.00	0.00	0.00	0.40	0.00	−0.23	0.00	0.00	2.27
	$z(SR(f^{\sigma}_{net}))$	−1.07	−4.67	−0.40	−0.42	−4.11	0.13	−4.06	−0.78	1.79
Egypt	α_{net}	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.00	1.39
	$z(SR(f^{\sigma}_{net}))$	−1.06	−2.45	−0.14	0.33	−2.41	−2.46	−3.83	−1.78	0.74
Greece	α_{net}	4.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.64
	$z(SR(f^{\sigma}_{net}))$	0.64	−3.52	−3.82	−3.26	−3.14	−2.07	−3.48	−1.52	1.61
India	α_{net}	3.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	11.92***
	$z(SR(f^{\sigma}_{net}))$	−0.16	−1.80	−2.50	−2.57	−2.19	−2.30	−2.45	−2.69	1.98
Indonesia	α_{net}	5.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.39
	$z(SR(f^{\sigma}_{net}))$	0.19	−2.28	−2.16	−2.94	−0.81	−3.37	−3.79	−2.47	0.94
Korea	α_{net}	0.00	0.00	2.22	0.00	0.00	0.00	0.00	0.00	1.25
	$z(SR(f^{\sigma}_{net}))$	−0.74	−2.77	−0.42	−1.22	−1.51	−4.71	−4.10	−4.86	0.91
Malaysia	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.53**
	$z(SR(f^{\sigma}_{net}))$	−0.53	−4.43	−4.68	−4.97	−5.84	−3.07	−4.94	−3.92	2.23
Mexico	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.70
	$z(SR(f^{\sigma}_{net}))$	−1.01	−0.97	−4.40	−1.46	−2.57	−0.34	−2.02	−2.22	0.90
Pakistan	α_{net}	0.00	1.40	0.00	−28.19	0.00	0.00	−9.61	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	−1.99	0.15	−1.94	−0.70	−0.61	−3.16	−0.33	−0.53	0.64

(*continued on next page*)

Table 4 (*continued*).

Peru	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	−1.21	−1.49	−2.28	−1.86	−2.69	−1.69	−0.44	−0.58	−1.23
Philippines	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.02
	$z(SR(f^{\sigma}_{net}))$	−1.45	−3.69	−3.70	−4.41	−3.04	−5.03	−4.05	−4.37	0.67
Poland	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.45
	$z(SR(f^{\sigma}_{net}))$	−2.33	−4.43	−4.06	−2.82	−3.49	−2.87	−3.08	−2.66	0.47
Russia	α_{net}	5.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.90
	$z(SR(f^{\sigma}_{net}))$	0.24	−2.50	−4.01	−4.64	−2.52	−1.89	−0.74	−0.66	0.76
Saudi Arabia	α_{net}	9.30**	0.00	0.00	0.00	0.00	0.00	0.00	0.21	4.15*
	$z(SR(f^{\sigma}_{net}))$	1.71	−2.11	−0.58	−2.92	−1.42	−0.17	−1.58	0.37	1.76
South Africa	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.77
	$z(SR(f^{\sigma}_{net}))$	−0.80	−0.40	−5.64	−5.42	−3.32	−1.22	−1.99	−0.59	0.30
Taiwan	α_{net}	6.71*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.63
	$z(SR(f^{\sigma}_{net}))$	0.67	−2.57	−1.87	−2.77	−1.12	−1.94	−2.46	−2.10	1.34
Thailand	α_{net}	10.91**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.12
	$z(SR(f^{\sigma}_{net}))$	1.55	−4.05	−3.36	−4.79	−3.44	−2.78	−2.73	−1.83	0.46
Turkey	α_{net}	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.14
	$z(SR(f^{\sigma}_{net}))$	−1.09	−3.73	−0.06	−0.08	−2.07	−0.66	−0.99	−1.00	0.71
U.A.E.	α_{net}	2.58	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	−0.08	−3.92	−1.82	−1.65	−1.70	−2.77	−1.66	−3.76	−0.84
Morocco	α_{net}	2.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	0.38	−5.03	−4.11	−2.65	−3.12	−3.15	−4.60	−3.18	−1.06
Jordan	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f^{\sigma}_{net}))$	−0.54	−1.68	−4.21	−3.24	−4.40	−1.64	−1.27	−1.72	−1.52
Total $\alpha_{net} > 0$ [Signif.]		25 [4]	1 [0]	4 [0]	2 [0]	0 [0]	0 [0]	0 [0]	1 [0]	39 [9]
	DM	15 [2]	0 [0]	2 [0]	0 [0]	0 [0]	0 [0]	0 [0]	0 [0]	21 [7]
	EM	10 [2]	1 [0]	2 [0]	2 [0]	0 [0]	0 [0]	0 [0]	1 [0]	18 [2]
Total $\alpha_{net} < 0$ [Signif.]		20 [0]	44 [0]	41 [0]	43 [0]	45 [0]	45 [0]	45 [0]	44 [0]	6 [0]
	DM	7 [0]	22 [0]	20 [0]	22 [0]	22 [0]	22 [0]	22 [0]	22 [0]	1 [0]
	EM	13 [0]	22 [0]	21 [0]	21 [0]	23 [0]	23 [0]	23 [0]	22 [0]	5 [0]
Total $z(SR(f^{\sigma}_{net})) > 0$ [Signif.]		15 [0]	1 [0]	1 [0]	1 [0]	0 [0]	1 [0]	0 [0]	1 [0]	39 [4]
	DM	8 [0]	0 [0]	1 [0]	0 [0]	0 [0]	0 [0]	0 [0]	0 [0]	20 [2]
	EM	7 [0]	1 [0]	0 [0]	1 [0]	0 [0]	1 [0]	0 [0]	1 [0]	19 [2]
Total $z(SR(f^{\sigma}_{net})) < 0$ [Signif.]		30 [5]	44 [35]	44 [30]	44 [30]	45 [34]	44 [34]	45 [35]	44 [27]	6 [0]
	DM	14 [3]	22 [19]	21 [15]	22 [16]	22 [19]	22 [20]	22 [20]	22 [16]	2 [0]
	EM	16 [2]	22 [16]	23 [15]	22 [14]	23 [15]	22 [14]	23 [15]	22 [11]	4 [0]

The table reports performance statistics after considering transaction costs for each volatility-managed equity factor country combination over the 1982 to 2021 sample period. Table B.4 of the Online Appendix reports the net returns. $\alpha_{net}(\%)$ denotes the generalized net-of-costs alpha following Novy-Marx and Velikov (2016) and $z(SR(f^{\sigma}_{net}))$ denotes the z-statistic from the Jobson and Korkie (1981) test of the null hypothesis that $SR(f^{\sigma}_{net}) - SR(f_{net}) = 0$. All alphas (%) are annualized. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

volatility-managed market portfolios through existing ETFs. Overall, the results suggest that only managed market portfolios could potentially be systematically robust to transaction costs if successfully implemented through the use of ETFs.

4.3. After-cost performance using cost-mitigation strategies

The two baseline strategies, i.e., using realized total variance and realized downside volatility as a leverage (scaling) factor, are not necessarily the most cost-efficient implementations of (downside) volatility-managed equity factor strategies. Next, I apply a set of cost-mitigation strategies suggested by Barroso and Santa-Clara (2015), Moreira and Muir (2017) and Barroso and Detzel (2021) which all try to mitigate costs by slowing down trading or by filtering out expensive to trade stocks. Specifically, I apply the following five cost-mitigation strategies for the total volatility-managed equity factors: (i) capping leverage of the baseline strategy at 150%, (ii) scaling by prior month realized standard deviation (volatility) instead of variance, (iii) scaling by expected realized variance instead of realized variance, (iv) scaling by realized standard deviation (volatility) over a prior six-month rolling window, and (v) excluding small caps in the baseline strategy. Detailed calculations of the alternative scaling factors are provided in Appendix A.10.

Overall, the results of the cost-mitigation strategies suggest that it is really difficult for marginal traders to benefit from total volatility-managed equity factor strategies after considering transaction costs. In international equity markets, only total volatility-managed momentum factors scaled by six-month volatility and total volatility-managed market portfolios, if successfully implemented through ETFs, promise potential after-cost benefits for marginal traders. The after-cost results of the cost-mitigation strategies are presented in Table A.8 of Appendix A.3. The cost-saving potential is illustrated in Fig. A.1 of Appendix A.3.

For the downside volatility-managed equity factors, I apply the following four cost-mitigation strategies: (i) capping leverage of the baseline strategy (downside volatility) at 150%, (ii) scaling by realized downside standard deviation (downside volatility) over

Table 5
Net-of-costs performance of downside volatility-managed factors.

		MKT	SMB	HML	HML_m	CMA	RMW	RMW_c	ROE	WML
Australia	α_{net}	0.62	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.94
	$z(SR(f_{net}^{d\sigma}))$	−0.36	−5.65	−3.44	−2.38	−4.03	−1.93	−4.07	−1.41	0.16
Austria	α_{net}	2.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.78
	$z(SR(f_{net}^{d\sigma}))$	0.70	−2.84	−2.52	−2.37	−1.56	−3.86	−4.01	−5.39	0.82
Belgium	α_{net}	2.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.98**
	$z(SR(f_{net}^{d\sigma}))$	0.38	−3.63	−0.34	−0.83	−2.31	−4.24	−3.76	−0.96	1.16
Canada	α_{net}	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.47
	$z(SR(f_{net}^{d\sigma}))$	−0.40	−3.46	−1.60	−4.15	−3.97	−1.03	−1.43	−2.74	0.51
Denmark	α_{net}	2.18	0.00	0.52	0.00	0.00	0.00	0.00	0.00	2.00
	$z(SR(f_{net}^{d\sigma}))$	0.19	−1.42	0.38	−0.74	−4.03	−4.55	−4.32	−4.80	0.60
Finland	α_{net}	4.09*	0.00	0.00	0.00	0.00	0.00	0.00	−0.31	0.78
	$z(SR(f_{net}^{d\sigma}))$	1.01	−2.21	−3.32	−1.90	−3.54	−2.07	−1.57	−0.36	0.14
France	α_{net}	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.48**
	$z(SR(f_{net}^{d\sigma}))$	−0.71	−2.66	−2.60	−3.00	−2.05	−3.55	−5.54	−2.17	1.76
Germany	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.70*
	$z(SR(f_{net}^{d\sigma}))$	−0.61	−3.47	−1.81	−3.05	−5.58	−4.14	−5.73	−4.71	1.13
Hong Kong	α_{net}	4.09*	0.00	−0.21	0.00	0.00	0.00	0.00	0.00	6.49***
	$z(SR(f_{net}^{d\sigma}))$	1.07	−1.48	−0.44	−1.83	−4.28	−2.58	−4.36	−3.18	3.15
Israel	α_{net}	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	2.96
	$z(SR(f_{net}^{d\sigma}))$	−0.80	−2.19	0.04	0.75	−1.57	−4.27	−3.64	−3.93	1.10
Italy	α_{net}	0.95	−0.57	0.00	0.00	0.00	0.00	0.00	0.00	3.77**
	$z(SR(f_{net}^{d\sigma}))$	0.12	−0.27	−0.33	−0.68	−4.02	−3.77	−3.99	−4.00	1.38
Japan	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f_{net}^{d\sigma}))$	−0.55	−3.39	−1.69	−1.66	−3.80	−7.61	−6.46	−6.51	−1.55
Netherlands	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.91***
	$z(SR(f_{net}^{d\sigma}))$	−0.84	−1.53	−0.84	−2.27	−1.50	−3.87	−2.65	−2.49	2.24
New Zealand	α_{net}	1.84	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.71
	$z(SR(f_{net}^{d\sigma}))$	0.23	−4.32	−2.91	−2.41	−3.46	−2.74	−3.00	−3.04	−0.02
Norway	α_{net}	1.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.92
	$z(SR(f_{net}^{d\sigma}))$	−0.10	−2.14	−1.31	−1.18	−2.94	−3.58	−3.96	−4.71	0.67
Portugal	α_{net}	5.88***	0.00	0.00	−1.01	0.00	0.00	0.00	0.00	3.42*
	$z(SR(f_{net}^{d\sigma}))$	2.03	−2.69	−0.44	−0.05	−0.32	−4.01	−4.25	−3.86	1.09
Singapore	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.96
	$z(SR(f_{net}^{d\sigma}))$	−1.18	−3.89	−4.91	−4.41	−4.96	−2.96	−6.09	−2.77	1.31
Spain	α_{net}	1.42	0.00	0.00	0.00	0.00	0.24	0.00	0.00	2.08
	$z(SR(f_{net}^{d\sigma}))$	−0.05	−2.52	−2.00	−2.17	−3.13	−0.30	−1.48	−1.77	0.74
Sweden	α_{net}	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.88
	$z(SR(f_{net}^{d\sigma}))$	−0.57	−2.99	−1.59	−1.79	−4.40	−5.28	−4.44	−4.43	0.83
Switzerland	α_{net}	1.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.30***
	$z(SR(f_{net}^{d\sigma}))$	0.36	−2.28	−2.07	−1.40	−1.96	−1.28	−3.02	−1.13	1.93
U.K.	α_{net}	0.00	0.00	1.16	0.00	0.00	0.00	0.00	0.00	7.80***
	$z(SR(f_{net}^{d\sigma}))$	−0.45	−0.40	0.24	−1.17	−2.87	−2.97	−4.21	−2.34	2.54
U.S.	α_{net}	1.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21
	$z(SR(f_{net}^{d\sigma}))$	−0.30	−4.53	−0.71	−1.28	−3.48	−2.56	−4.03	−3.58	0.16
Brazil	α_{net}	3.60	0.00	0.00	0.95	0.00	0.00	0.00	0.00	2.36
	$z(SR(f_{net}^{d\sigma}))$	0.18	−1.21	−2.33	−0.08	−1.68	−2.49	−3.90	−2.41	1.48
Chile	α_{net}	2.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30
	$z(SR(f_{net}^{d\sigma}))$	0.39	−2.41	−5.91	−4.87	−3.26	−0.83	−2.08	−4.06	−0.69
China	α_{net}	2.87	0.00	0.37	0.00	0.00	0.08	0.00	0.00	2.45
	$z(SR(f_{net}^{d\sigma}))$	0.71	−3.73	−0.13	−0.67	−4.82	0.14	−3.25	−0.88	1.75
Egypt	α_{net}	0.27	0.00	0.00	6.24	0.00	0.00	0.00	0.00	−1.11
	$z(SR(f_{net}^{d\sigma}))$	−0.18	−1.52	0.31	1.47	−2.10	−4.49	−5.19	−2.18	−0.13
Greece	α_{net}	7.97**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.18
	$z(SR(f_{net}^{d\sigma}))$	1.85	−3.31	−5.20	−3.72	−3.57	−1.57	−3.82	−2.03	0.59
India	α_{net}	5.16*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.44**
	$z(SR(f_{net}^{d\sigma}))$	0.73	−2.89	−2.18	−1.72	−2.14	−1.35	−2.59	−1.07	1.52
Indonesia	α_{net}	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	1.50
	$z(SR(f_{net}^{d\sigma}))$	−0.04	−2.01	−1.83	−2.62	−0.37	−2.91	−4.07	−1.75	0.66
Korea	α_{net}	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	−0.65
	$z(SR(f_{net}^{d\sigma}))$	−0.22	−2.16	−0.48	−0.77	−1.63	−4.66	−4.31	−4.86	0.18
Malaysia	α_{net}	4.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.62*
	$z(SR(f_{net}^{d\sigma}))$	0.80	−4.69	−4.08	−4.85	−7.26	−4.18	−5.77	−4.67	2.02
Mexico	α_{net}	3.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f_{net}^{d\sigma}))$	0.41	−2.08	−3.53	−0.26	−2.26	−0.80	−2.16	−2.06	−0.04
Pakistan	α_{net}	−2.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f_{net}^{d\sigma}))$	−1.03	−1.14	−3.77	−3.11	−1.55	−0.90	−1.41	−0.79	0.34

(*continued on next page*)

Table 5 (*continued*).

Peru	α_{net}	3.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f_{net}^{d\sigma}))$	0.66	−1.11	−3.02	−2.39	−4.18	−2.86	−1.84	−1.58	0.24
Philippines	α_{net}	2.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f_{net}^{d\sigma}))$	0.63	−4.62	−4.45	−4.13	−3.75	−4.37	−3.33	−4.34	−0.66
Poland	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.76
	$z(SR(f_{net}^{d\sigma}))$	−1.74	−3.02	−4.56	−2.88	−3.52	−3.94	−3.90	−3.21	0.43
Russia	α_{net}	8.74*	0.00	0.00	0.00	0.00	0.00	0.79	0.00	2.17
	$z(SR(f_{net}^{d\sigma}))$	0.82	−1.64	−3.78	−5.11	−2.80	−1.69	0.48	−0.50	0.33
Saudi Arabia	α_{net}	5.39	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.86
	$z(SR(f_{net}^{d\sigma}))$	1.08	−0.94	−0.40	−1.81	−2.32	0.01	−1.64	−0.01	1.37
South Africa	α_{net}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.27
	$z(SR(f_{net}^{d\sigma}))$	−1.52	−1.71	−4.91	−3.34	−3.56	−1.64	−2.03	−1.71	0.75
Taiwan	α_{net}	5.26*	0.70	0.00	0.00	0.00	0.00	0.00	0.00	1.24
	$z(SR(f_{net}^{d\sigma}))$	1.35	0.47	−0.95	−2.33	−1.99	−2.01	−3.14	−2.51	0.33
Thailand	α_{net}	9.46**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.22
	$z(SR(f_{net}^{d\sigma}))$	1.75	−4.93	−2.30	−2.41	−2.75	−1.36	−1.79	−1.33	0.59
Turkey	α_{net}	3.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f_{net}^{d\sigma}))$	0.41	−2.79	−2.12	−0.56	−1.91	−1.96	−1.86	−1.35	0.24
U.A.E.	α_{net}	4.87	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.47
	$z(SR(f_{net}^{d\sigma}))$	0.59	−3.26	−1.97	−0.35	−2.16	−2.13	−1.98	−3.92	−0.23
Morocco	α_{net}	2.78	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f_{net}^{d\sigma}))$	0.87	−6.06	−4.19	−1.62	−4.03	−3.67	−5.04	−2.93	−1.91
Jordan	α_{net}	1.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	$z(SR(f_{net}^{d\sigma}))$	0.69	−2.06	−4.91	−2.53	−5.39	−1.37	−1.94	−0.76	−2.18
Total $\alpha_{net} > 0$ [Signif.]		34 [3]	1 [0]	5 [0]	2 [0]	1 [0]	2 [0]	1 [0]	0 [0]	35 [8]
	DM	16 [1]	0 [0]	3 [0]	0 [0]	0 [0]	1 [0]	0 [0]	0 [0]	21 [7]
	EM	18 [2]	1 [0]	2 [0]	2 [0]	1 [0]	1 [0]	1 [0]	0 [0]	14 [1]
Total $\alpha_{net} < 0$ [Signif.]		11 [0]	44 [0]	40 [0]	43 [0]	44 [0]	43 [0]	44 [0]	45 [0]	10 [0]
	DM	6 [0]	22 [0]	19 [0]	22 [0]	22 [0]	21 [0]	22 [0]	22 [0]	1 [0]
	EM	5 [0]	22 [0]	21 [0]	21 [0]	22 [0]	22 [0]	22 [0]	23 [0]	9 [0]
Total $z(SR(f_{net}^{d\sigma})) > 0$ [Signif.]		26 [1]	1 [0]	4 [0]	2 [0]	0 [0]	2 [0]	1 [0]	0 [0]	36 [4]
	DM	9 [1]	0 [0]	3 [0]	1 [0]	0 [0]	0 [0]	0 [0]	0 [0]	20 [3]
	EM	17 [0]	1 [0]	1 [0]	1 [0]	0 [0]	2 [0]	1 [0]	0 [0]	16 [1]
Total $z(SR(f_{net}^{d\sigma})) < 0$ [Signif.]		19 [0]	44 [32]	41 [25]	43 [22]	45 [36]	43 [30]	44 [35]	45 [29]	9 [1]
	DM	13 [0]	22 [17]	19 [8]	21 [9]	22 [18]	22 [18]	22 [19]	22 [17]	2 [0]
	EM	6 [0]	22 [15]	22 [17]	22 [13]	23 [18]	21 [12]	22 [16]	23 [12]	7 [1]

The table reports performance statistics after considering transaction costs for each downside volatility-managed equity factor country combination over the 1982 to 2021 sample period. Table B.5 of the Online Appendix reports the net returns. $\alpha_{net}(\%)$ denotes the generalized net-of-costs alpha following Novy-Marx and Velikov (2016) and $z(SR(f_{net}^{d\sigma}))$ denotes the z-statistic from the Jobson and Korkie (1981) test of the null hypothesis that $SR(f_{net}^{d\sigma}) - SR(f_{net}) = 0$. All alphas (%) are annualized. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

a prior six-month rolling window, (iii) scaling by expected realized downside variance, and (iv) excluding small caps in the baseline strategy (downside volatility). Detailed calculations of the alternative scaling factors are provided in Appendix A.10.

The after-cost performance of cost-mitigated downside volatility-managed portfolios is similar to the after-cost performance of cost-mitigated total volatility-managed portfolios at my estimated levels of transaction costs. This is evident in the baseline approach and all cost-mitigation strategies. Once again, it appears that only downside volatility-managed momentum factors scaled by six-month downside volatility and ETF implemented downside volatility-managed market portfolios promise potential after-cost benefits for marginal traders in international equity markets. This appears to be possible since these two factors show the greatest absolute benefits (alphas) from volatility-timing among all equity factors tested, although, relative to all other equity factor strategies, the momentum (WML) and market (MKT) portfolios experience some of the lowest relative transaction cost increases from volatility-timing. The detailed after-cost results of the cost-mitigation strategies for the downside volatility-managed portfolios are presented in Table A.9 of Appendix A.3. The cost-saving potential is illustrated in Fig. A.2 of Appendix A.3. As noted in Wang and Yan (2021), the superior before-cost performance of downside volatility-managed equity factors could just be due to limits to arbitrage.

In summary, it can be stated that my results substantiate the U.S. findings of Barroso and Detzel (2021), namely that transaction costs may also explain the performance persistence of international (downside) volatility-managed equity factor strategies.

5. Mechanism analysis – Slow trading hypothesis

5.1. Cross-country analysis – Culture dimensions

The literature offers a variety of possible explanations for the outperformance of volatility-managed strategies. However, these have only been tested in the circumstances of the U.S. equity market. Exploiting the heterogeneity of performance across different countries, a cross-country analysis allows to test whether country-specific characteristics may explain the variation in performance. Subsequently, the cross-country analysis aims to access whether a slower trading response (henceforth, slow trading hypothesis) can explain performance differences in international volatility-managed equity factors.

I test the slow trading hypothesis first proposed by Moreira and Muir (2017) as a direct driver in the creation of the mispricing that eventually enables the outperformance. The slow trading hypothesis assumes that investors have slow moving expectations about volatility (see, Lochstoer and Muir, 2022) and consequently might react (trade) slowly in response to volatility shocks. Another paper by Moreira and Muir (2019) shows that long-term investors might react less strongly to an increase in volatility in high volatility times, which could also lead to a slower response to volatility shocks. The international data set potentially allows testing both these hypotheses using cross-country characteristics which proxy for the degree of slow moving expectations or the degree of long-term orientation of investors across countries. In a similar rationale to Dou et al. (2016), I argue that investors from countries with a higher degree of uncertainty avoidance (i.e., a dislike for uncertainty ≈ volatility) will update their expectations about volatility quicker than investors with a lower degree of uncertainty avoidance (i.e., an acceptance for uncertainty) and consequently trade faster in response to volatility shocks. Thus, under the slow moving expectation hypothesis, the outperformance of volatility-managed strategies should be particularly strong in countries where investors are more accepting of uncertainty. Additionally, in a similar rationale to Docherty and Hurst (2018), I argue that culture can influence the degree of investor myopia within a country. Thus, myopic investors, i.e., investors in more short-term orientated countries, will be more focused on short-run rather than long-run deviations in prices. Myopic investors will consequently update their expectations about volatility (relative to long-term oriented investors) faster, which leads to a faster trading reaction. Additionally, I argue that countries with a more long-term-oriented culture are more likely to have a higher proportion of long-term investors. Hofstede (2001) defines long-term orientation as “fostering of virtues orientated toward future rewards” and short-term orientation as “fostering of virtues related to the past and present”, which I argue is in line with the typical views of long-term and short-term-oriented investors. Thus, both under the slow moving expectation hypothesis and under the long-term investor hypothesis, the outperformance of volatility-managed strategies should be particularly strong in countries where investors are more long-term oriented as both channels suggest a slower trading response in reaction to changes in volatility.

In the following, I explain the reasoning behind the selection of each variable in the cross-country analysis. Detailed variable descriptions and summary statistics for the cross-country variables are provided in Table A.15 of Appendix A.8. The chosen country characteristics serve as proxies for cultural differences. In particular, I use the uncertainty avoidance index UAI and the long-term orientation measure LTO from Hofstede (2001). The data is obtained from Hofstede’s personal website. The uncertainty avoidance index UAI expresses the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity. A high uncertainty avoidance index indicates a low tolerance for uncertainty and ambiguity. The long-term orientation measure LTO considers the extent to which society views its time horizon. Long-term-oriented cultures focus on the future and delay short-term success to achieve long-term goals, whereas short-term-oriented cultures focus on the near future, short-term success and generally place a stronger emphasis on the present than the future.

The cross-country analysis aims to identify cross-country differences that are able to explain the varying outperformance of the combination strategies, i.e., portfolios consisting of an optimal combination of volatility-managed and unmanaged equity factors, across countries. Thus, the variable of interest is the country-level before cost alpha from the spanning regressions in Tables 1 and 2, which has a cross-sectional data structure with only a country dimension. Hence, using the spanning regression alpha as the dependent variable solely allows investigating the cross-country relation between the time-averaged outperformance measure of volatility-managed strategies and the time-invariant values of the country characteristics. Therefore, the cross-sectional regressions that are applied in the following are designed to measure the between-country effect.

Table 6 reports the empirical results of the cross-country relation between the time-averaged outperformance measure (alpha) of (downside) volatility-managed strategies and the time-invariant culture dimension proxies. If the slow trading hypothesis is a promising driver of the outperformance of (downside) volatility-managed equity factor strategies, one would expect to see signs of the cultural dimension proxies that indicate a greater outperformance in countries that are associated with a slower reaction in response to changes in volatility. In particular, consistent with the slow trading hypothesis, one would expect UAI to take negative values and LTO to take positive values, respectively. Panels A and B of Table 6 report the results of the cross-sectional regressions for the volatility-managed and the downside volatility-managed equity factor strategies, respectively. The univariate regressions of Panel A show overall promising results in line with the slow trading hypothesis across all 9 equity factor strategies. UAI and LTO have 2 (0) and 6 (3) positive (significant) and 7 (1) and 3 (0) negative (significant) values, respectively. Therefore, the point estimates of the univariate regressions suggest that the outperformance of volatility-managed strategies is greater in countries associated with a lower uncertainty avoidance and a higher long-term orientation. The volatility-managed HML^{σ}, HML_m^{σ} and CMA^{σ} factors each have positive significant LTO estimates, suggesting that some of the outperformance across these factors could potentially be explained by a slower trading reaction in countries where investors are more long-term oriented. The volatility-managed WML^{σ} factor has a negative significant UAI estimate, suggesting that some of the outperformance in this factor could potentially be explained by a slower trading reaction in countries where investors are more accepting of uncertainty. Interestingly, two well-performing factors, particularly the WML^{σ} and the HML^{σ} factors, have significant point estimates that are consistent with the predictions of the slow trading hypothesis. Evaluating the factors individually based on the multiple regressions, it appears that at least the signs across the two cultural proxies for a slower trading response suggest that all factors besides the three volatility-managed profitability factors (RMW^{σ}, RWM_c^{σ} and ROE^{σ}) show a greater outperformance in countries associated with a slower trading response. In the multiple regression models, only the HML^{σ} factor can maintain its significance on the LTO coefficient, while the coefficients (UAI/LTO) for the HML_m^{σ}, CMA^{σ} and WML^{σ} factors show only marginal significance in this setting.

Table 6
Cultural dimensions cross-country analysis of (downside) volatility-managed equity factors.

Panel A: Volatility-managed

	MKT			SMB			HML			HML_m			CMA		
UAI	−0.001		−0.001	−0.001		−0.001	−0.001		−0.001	−0.000		−0.000	−0.001		−0.001
	(−0.41)		(−0.40)	(−0.41)		(−0.39)	(−0.89)		(−0.78)	(−0.13)		(−0.03)	(−0.99)		(−0.93)
LTO		0.000	0.000		0.000	0.001		0.004**	0.004**		0.004**	0.004*		0.003**	0.003*
		(0.22)	(0.13)		(0.20)	(0.33)		(2.44)	(2.20)		(2.15)	(2.00)		(2.05)	(2.01)
Intercept	0.305**	0.226*	0.291*	−0.048	−0.099	−0.076	0.247***	−0.067	0.040	−0.016	−0.246**	−0.228	0.104	−0.119	−0.051
	(2.46)	(1.91)	(1.75)	(−0.43)	(−1.03)	(−0.66)	(2.70)	(−0.71)	(0.30)	(−0.14)	(−2.40)	(−1.49)	(1.32)	(−1.59)	(−0.59)
R^2	0.003	0.001	0.003	0.004	0.001	0.006	0.019	0.135	0.141	0.000	0.086	0.080	0.017	0.097	0.110
	RMW			RMW_c			ROE			WML					
UAI	−0.000		−0.000	0.002*		0.002*	0.002		0.002	−0.006**		−0.006*			
	(−0.06)		(−0.08)	(1.76)		(1.74)	(1.22)		(1.16)	(−2.06)		(−1.97)			
LTO		−0.001	−0.001		−0.002	−0.001		−0.001	−0.001		0.005*	0.004*			
		(−0.65)	(−0.58)		(−1.17)	(−1.05)		(−0.82)	(−0.66)		(1.76)	(1.77)			
Intercept	0.099	0.141**	0.142	−0.101*	0.099	−0.026	−0.040	0.153	0.026	1.192***	0.560***	0.962***			
	(1.26)	(2.04)	(1.40)	(−1.75)	(1.34)	(−0.29)	(−0.44)	(1.46)	(0.20)	(5.89)	(3.66)	(3.93)			
R^2	0.000	0.012	0.010	0.076	0.045	0.113	0.035	0.020	0.049	0.119	0.059	0.169			

Panel B: Downside volatility-managed

	MKT			SMB			HML			HML_m			CMA		
UAI	0.002		0.002	−0.000		0.000	−0.003**		−0.003*	−0.001		−0.001	−0.001		−0.001
	(1.06)		(1.00)	(−0.04)		(0.08)	(−2.13)		(−2.02)	(−0.63)		(−0.60)	(−0.70)		(−0.63)
LTO		−0.001	−0.002		0.002*	0.002*		0.004***	0.003**		0.001	0.000		0.002	0.002
		(−0.90)	(−1.05)		(1.70)	(1.82)		(2.88)	(2.70)		(0.36)	(0.24)		(1.65)	(1.64)
Intercept	0.260***	0.424***	0.343**	0.026	−0.048	−0.061	0.352***	−0.019	0.172*	0.158*	0.081	0.139	0.100	−0.032	0.005
	(2.72)	(5.15)	(2.64)	(0.55)	(−0.90)	(−0.90)	(4.35)	(−0.25)	(1.80)	(1.90)	(1.10)	(1.09)	(1.62)	(−0.56)	(0.09)
R^2	0.027	0.015	0.049	0.000	0.058	0.068	0.114	0.160	0.254	0.006	0.002	0.007	0.010	0.063	0.072
	RMW			RMW_c			ROE			WML					
UAI	0.000		0.000	0.001		0.000	0.000		0.000	−0.005**		−0.005**			
	(0.02)		(0.00)	(0.75)		(0.67)	(0.14)		(0.12)	(−2.51)		(−2.43)			
LTO		−0.001	−0.000		−0.001	−0.001		−0.001	−0.000		0.004**	0.003**			
		(−0.49)	(−0.44)		(−1.18)	(−1.05)		(−0.43)	(−0.37)		(2.03)	(2.09)			
Intercept	0.104	0.132**	0.128	0.002	0.091*	0.054	0.084	0.124*	0.109	0.910***	0.403***	0.738***			
	(1.43)	(2.44)	(1.41)	(0.04)	(1.94)	(0.74)	(1.12)	(1.76)	(1.14)	(5.88)	(4.16)	(4.01)			
R^2	0.000	0.006	0.005	0.010	0.036	0.041	0.001	0.005	0.004	0.165	0.068	0.222			

The table reports the results of the cross-country regressions that examine the relation between cultural dimensions and the benefits of volatility management. The dependent variables are the within-country alphas of the 45 countries from the spanning regressions in Tables 1 and 2. Panels A and B report the regression results for all volatility-managed and downside volatility-managed equity factors, respectively. The explanatory variables are the cultural dimensions uncertainty avoidance UAI and long-term orientation LTO developed by Hofstede (2001) which are explained in detail in Appendix A.8. The t-statistics reported in parentheses are computed using robust standard errors. Statistical significance at the ten-, five- and one-percent level is indicated by *, **, and ***, respectively.

The univariate regressions of Panel B show overall inconclusive results with respect to the slow trading hypothesis across all 9 equity factor strategies. UAI and LTO have 4 (0) and 5 (2) positive (significant) and 5 (2) and 4 (0) negative (significant) values, respectively. However, the point estimates of the univariate regressions for the downside volatility-managed $HML^{d\sigma}$ and $WML^{d\sigma}$ factors suggest that the outperformance is greater in countries associated with a slower response to changes in downside volatility. The downside volatility-managed $HML^{d\sigma}$ and $WML^{d\sigma}$ factors each have negative significant UAI and positive significant LTO estimates, suggesting that some of the outperformance across these factors could potentially be explained by a slower trading reaction in countries in which investors are more long-term-oriented and more accepting of uncertainty. Evaluating the factors individually based on the multiple regressions, it appears that at least the signs across the two cultural proxies for a slower trading response suggest that the downside volatility-managed $HML^{d\sigma}$, $HML_m^{d\sigma}$, $CMA^{d\sigma}$ and $WML^{d\sigma}$ factors show a greater outperformance in countries associated with a slower trading response. In the multiple regression models, only the $WML^{d\sigma}$ factor can maintain its significance on both the UAI and LTO coefficients. The $HML^{d\sigma}$ factor maintains the significant point estimate on the LTO coefficient, while the UAI coefficient shows only marginal significance in the multiple regression framework.

Overall, the results suggest that a significant portion of the cross-country differences in the outperformance of the best-performing (downside) volatility-managed factors (HML and WML) may be attributable to a slower trading response as suggested by the slow trading hypothesis. However, the proxies for a slower trading response are only able to explain differences in the outperformance of the best-performing factors and only show much weaker evidence with respect to the mediocre to poor-performing factors. Therefore, I suggest that the slow trading hypothesis contributes in part to creating mispricing that enables the outperformance of (downside) volatility-managed equity factor strategies, but the slower trading reaction does not appear to be the sole force behind the emergence of the mispricing.

Additional cross-country analyzes are presented in Tables A.16 and A.17 of Appendix A.9 and suggest that differences in informational efficiency and limits to arbitrage across countries do not explain the varying international outperformance of (downside) volatility-managed equity factor strategies.

Furthermore, an additional analysis suggests that the international performance of (downside) volatility-managed market portfolios is more concentrated in high sentiment periods. The results presented in Table A.13 of the Appendix partially substantiate the sentiment explanation of Barroso and Detzel (2021) which is a refinement of the unconditional slow trading hypothesis of Moreira and Muir (2017) suggesting that, in line with the sentiment theory of Yu and Yuan (2011), sentiment traders underreact to volatility.

5.2. Performance following high and low volatility periods

To further investigate the slow trading hypothesis as a potential mechanism that drives the emergence of the documented benefits of volatility management, I test whether the benefits cluster in time following low and moderate volatility as suggested by the slow trading hypothesis.

Table 7
Performance of volatility-managed factors following periods of high and low volatility.

Panel A: Volatility-managed										
		MKT	SMB	HML	HML_m	CMA	RMW	RMW_c	ROE	WML
Total $\alpha > 0$ [Signif.]	High	22[1]	22[2]	20[2]	19[1]	19[0]	27[2]	24[1]	29[0]	36[9]
	Low	32[4]	20[0]	28[7]	15[2]	22[1]	28[5]	20[0]	33[5]	44[31]
	High-Low	13[1]	28[3]	16[0]	28[1]	21[0]	17[2]	26[0]	16[2]	6[0]
Total $\alpha < 0$ [Signif.]	High	23[1]	23[0]	25[1]	26[1]	26[1]	18[0]	21[0]	16[0]	9[0]
	Low	13[1]	25[6]	17[1]	30[3]	23[0]	17[2]	25[1]	12[1]	1[0]
	High-Low	32[3]	17[0]	29[3]	17[0]	24[1]	28[2]	19[0]	29[4]	39[17]
Panel B: Downside volatility-managed										
		MKT	SMB	HML	HML_m	CMA	RMW	RMW_c	ROE	WML
Total $\alpha > 0$ [Signif.]	High	26[0]	24[3]	17[0]	17[0]	23[0]	22[2]	23[2]	22[1]	32[7]
	Low	39[10]	29[1]	33[10]	26[4]	27[2]	32[9]	29[2]	37[10]	43[26]
	High-Low	6[0]	16[0]	9[0]	14[0]	19[2]	14[0]	17[1]	13[0]	12[0]
Total $\alpha < 0$ [Signif.]	High	19[0]	21[1]	28[1]	28[2]	22[0]	23[2]	22[1]	23[1]	13[0]
	Low	6[0]	16[0]	12[0]	19[1]	18[2]	13[1]	16[2]	8[1]	2[0]
	High-Low	39[6]	29[2]	36[10]	31[4]	26[3]	31[5]	28[1]	32[9]	33[11]

The table reports the number of aggregate positive and negative point estimates of spanning regression alphas following high and low volatility periods over the 1982 to 2021 sample period. Panels A and B report the results for volatility-managed and downside volatility-managed equity factors, respectively. Tables B.11 and B.12 of the Online Appendix report the respective country-level results underlying the aggregation. High volatility is defined as having a realized total (downside) volatility in the previous month that is greater than the expanding rolling quintile over the entire history of realized total (downside) volatility. Statistical significance at the five- and one-percent level is counted for the aggregation.

The slow trading hypothesis suggests that investors are slow to react to increases in volatility, which leads to a slower adjustment of current prices, and thus in the short run to lower expected returns. This reaction then creates low risk-return trade-offs immediately following increases in volatility as the risk is high, but the expected return is still low because of the slower trading response. Consequently, this slower trading response then leads to higher expected returns, which are then mainly realized in times following low or moderate volatility. Therefore, if the slow trading response plays a determining role in creating the benefits of volatility management, we would expect to see high alphas especially following low and moderate volatility periods. The volatility-timing strategy delevers exposure to the factors in times following high volatility, i.e., in times – contradicting traditional finance theory – with surprisingly low risk-return trade-offs, which might be created through an initially slower trading response to the increased volatility. Hence, we would expect to see most of the benefits when the volatility-timing strategy levers exposure to the factors, i.e., in times following low and moderate volatility, where the risk-return trade of might now be superior, as the initial slow trading response might increase the expected returns with a delay in times following low or moderate volatility.

Testing whether the benefits of volatility management cluster predominantly in times following low or moderate volatility can at least be interpreted as suggestive evidence favoring the slow trading hypothesis. Table 7 reports spanning regression alphas following high- and low-volatility periods, respectively. High volatility is defined as having a realized total (downside) volatility in the last month that is greater than the expanding rolling quintile over the entire history of realized total (downside) volatility. The results are relatively comparable when using tercile splits. Table 7 aggregates the number of positive and negative point estimates after high and low volatility, their significance, and a test for a significant high-low difference for total (Panel A) and downside (Panel B) volatility-managed portfolios, respectively. I report the country-level results for total and downside volatility-managed portfolios in Tables B.11 and B.12 of the Online Appendix, respectively.

Judging the sample splits results following high and low volatility periods for Panel A (volatility-managed) relative to the unconditional performance documented in Table 1, reveals that all market (MKT) and value (HML) factor results are in line with the prediction of the slow trading hypothesis. Of the 6 (MKT) and 10 (HML) positive significant alphas in Table 1, 3 and 5 show positive significant alphas following low volatility. Furthermore, 2 other HML factors show positive significant alpha estimates following low volatility periods, which at least showed marginally significant alphas in Table 1. Similar results can be observed for the RMW and ROE factors, for which 7 and 6 positive significant alphas in Table 1 show 5 and 3 positive significant alpha estimates following low volatility periods, respectively. Furthermore, 2 other ROE factors show positive significant alpha estimates following low volatility periods for which at least one showed marginally significant alphas in Table 1. The WML factor also shows strong results in line with the prediction of the slow trading hypothesis, i.e., almost all positive significant alphas in Table 1 show positive significant alphas following low volatility. The 39 negative high-low differences, of which 17 are significant, indicate that the momentum factor performance is better following low volatility.

Overall, the results suggest that the total volatility-managed factors that performed well unconditionally earn the majority of their performance following periods of low volatility.

Judging the sample splits results following high and low volatility periods for Panel B (downside volatility-managed) relative to the unconditional performance documented in Table 2, reveals that all market (MKT) and value (HML) factor results are in line with the prediction of the slow trading hypothesis. Of the 14 (MKT) and 17 (HML) positive significant alphas in Table 2, 9 in each case show positive significant alphas following low volatility. Furthermore, 1 other HML factor shows positive significant alpha estimates following low volatility periods, which at least showed marginally significant alphas in Table 2. Again, similar results can be observed for the RMW and ROE factors, for which 12 and 8 positive significant alphas in Table 2 show 8 and 6 positive significant alpha estimates following low volatility periods, respectively. Furthermore, 1 other RMW and 3 other ROE factors show positive significant alpha estimates following low volatility periods, which at least showed marginally significant alphas in Table 2. The WML factor also shows strong results in line with the prediction of the slow trading hypothesis for downside volatility management, i.e., almost all positive significant alphas in Table 2 show positive significant alphas following low volatility. The 33 negative high-low differences, of which 11 are significant, indicate that the momentum factor performance is better following low volatility. Additionally, the 36 and 32 negative high-low differences, of which 10 and 9 are significant, respectively, indicate that profitability factors also perform better following low volatility.

Overall, the results suggest that the downside volatility-managed factors that performed well unconditionally earn the majority of their performance following periods of low volatility. Hence, the results of both the total and downside volatility-managed factors support the conjecture that a slow trading response to increases in volatility might create the benefits of volatility management.

6. Conclusion

This paper studies the international performance of total and downside volatility-managed equity factor strategies for a total of 45 developed and emerging equity markets and for the majority of countries over a sample period of 30 years (max. 1982–2021). I document that (downside) volatility management is not a panacea to improve all equity factor-based strategies. The international outperformance of volatility management is only truly convincing for managed momentum strategies[13] and shows at least promising results for many managed market, value, and profitability factor-based strategies. The applied spanning regressions show that downside volatility management enhances especially the international gross performance of total volatility-managed market and value factor-based strategies.

Using an aggregated effective spread estimate to proxy for the costs faced by a marginal trader confirms that the international performance of all total and downside volatility-managed equity factor-based strategies is not robust to transaction costs in the baseline approaches. Volatility management significantly increases the turnover of both total and downside volatility-managed equity factor strategies. Applying a set of cost-mitigation techniques only changes the results for the total and downside volatility-managed momentum strategies as scaling by six-month volatility and six-month downside volatility, respectively, proves to be a valid strategy to slow down trading while still capturing the benefits of volatility management. Since volatility-managed momentum strategies only have very limited capacities for new capital inflows in the U.S. (see, Barroso and Detzel, 2021), it remains questionable whether a marginal trader would be able to capture the promised outperformance of volatility-managed momentum strategies around the globe. The promising cost-efficient implementation of volatility-managed market portfolios through the use of ETFs, as suggested by Moreira and Muir (2017), proves to be much more difficult to implement outside the U.S. equity market. International volatility-managed market and momentum portfolios appear to be most promising as they deliver both the absolute greatest benefits from volatility-timing and at the same time allow these benefits to be realized at the relatively lowest transaction cost increases. Overall, my results suggest that most of the international performance persistence of the total volatility- and downside volatility-managed equity factors can be explained by the most obvious market friction, namely transaction costs.

Using cross-country analysis, I tested the slow trading hypothesis as a potential cause of the emergence of mispricing that enables the outperformance of (downside) volatility-managed equity factor strategies. The analysis revealed that cultural differences across countries associated with a possible slower trading response can explain a significant portion of the cross-country differences in the outperformance of the best-performing factors (value and momentum). A performance decomposition of the volatility management benefits revealed that the performance for most equity factors clusters mainly in times following low and moderate volatility which supports the conjecture that a slow trading response to increases in volatility might create the benefits of volatility management. Therefore, I conclude that a slower trading reaction in response to changes in volatility contributes in part to the creation of mispricing that strengthens the outperformance of (downside) volatility-managed equity factor strategies.

Examining international volatility-managed multi-factor strategies and extending the analysis to include other return predictors (anomalies) would be an interesting extension of my research. I leave this topic for future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jempfin.2024.101560.

[13] This substantiates the international evidence of (enhanced) momentum strategies from Barroso and Santa-Clara (2015) and Hanauer and Windmüller (2023). A promising explanation for this finding could be the pronounced conditionality in the momentum premium. Barroso and Wang (2022) show that underreaction is the most promising explanation for momentum returns as it is able to explain both its unconditional and conditional performance. They show that momentum performs best in safe periods, i.e., during low volatility periods, when underreaction is more prevalent.

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