A Comprehensive Appraisal of Style-Integration Methods

ABSTRACT

The paper conducts a comprehensive analysis of different style-integration methods in equity index, currency, fixed income and commodity futures markets. We compare empirically the naïve equal-weighting integration (EWI) and various sophisticated style-weighting allocations that determine the style exposures using past data according to utility maximization, style rotation, volatility-timing, cross-sectional pricing, style momentum or principal components criteria inter alia. The analysis conducted per futures market and cross-markets reveals that the naïve equal-weight integrated portfolio is unrivalled in terms of performance by any of the sophisticated style-integrated portfolios. The findings are robust to variants of the sophisticated integrations, longer estimation windows, scoring schemes, data snooping tests, and subperiod analyses.

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1. Introduction

A variety of long-short investment styles have been put forward in the recent literature to capture attractive returns at a relatively low risk, leaving investors somewhat bewildered for a choice of one style over another. The task of selecting one style to pursue is all the more troubling because good past performance is no guarantee of future results. Against this background, academics and practitioners alike have suggested to *integrate* various styles.

Allocating the investor's wealth across K independently-managed style portfolios, known as the 'portfolio mix' strategy, is not practical as it may incur unduly high transaction costs.[1] Instead this paper is concerned with the "style-integration" strategy that combines the information from multiple signals at asset level to form a unique portfolio. The style-integrated portfolio could enhance performance relative to the standalone-style portfolios as it heavily trades the assets that most signals favor and places less or no emphasis on the assets with weak or conflicting signals across styles. However, different methods can be deployed to form a style-integrated portfolio and to date there is no empirical study that appraises them comparatively.

The present paper fills this gap by providing academics and practitioners alike with a well-structured comparison of multiple style-integration approaches: a naïve integration approach that assigns time-constant, equal-weights to the standalone styles (Equal-Weighted Integration, EWI, hereafter) and six other integrations methods that we call "sophisticated" in the sense that they allow for time-varying, heterogeneous style-weights. The six sophisticated integrations have in common that the style-weights are derived from past data but they differ in the criteria adopted which is either utility maximization (Optimized Integration, OI),

[1] In a long-short setting if a portfolio buys x units of asset i and another portfolio sells x units of asset i, the 'portfolio mix' that equally invest into the K style portfolios has zero net exposure to asset i but trading costs are incurred twice. DeMiguel et al. (2018) show analytically and empirically that the turnover required to rebalance a portfolio based on equal-weighting the K characteristics is about $1/\sqrt{K}$ of that required to rebalance all K individual-characteristic separately.

persistence in risk-adjusted performance (Rotation-of-Styles Integration, RSI), volatility (Volatility Timing Integration, VTI), pricing ability (Cross-Sectional Pricing Integration, CSI), factor momentum (Style Momentum Integration, SMI) and principal components analysis (Principal Components Integration, PCI). The EWI, OI, RSI, VTI and SMI strategies are not new (e.g., Barberis and Shleifer, 2003; Brandt et al., 2009; Asness et al., 2015; Fitzgibbons et al., 2016; Arnott et al., 2018), but the CSI and PCI strategies have not been studied as yet, to the best of our knowledge, in the style-integration literature.

This paper contributes to the literature by providing a comprehensive appraisal of the above set of style-integration techniques and variants thereof in a long-short context. Following a branch of the literature (Fleming et al., 2001, 2003, and Moskowitz et al., 2012), we consider a risk-averse investor who, to avoid restrictions on short-selling and minimize transaction costs, implements her allocation decisions by trading futures contracts on multi-asset classes. We study the out-of-sample performance of style-integration methods separately for equity index, currency, fixed income and commodity futures markets. To provide a complete picture, we deploy the horse race also in the context of diversified portfolios that include all futures classes.

The findings suggest that the EWI approach is the most effective integration approach due to the fact that it is easy to deploy as it does not require any parameter estimation while it affords a reward-to-risk profile that is unsurpassed by alternative integration strategies. The inability of the sophisticated integration portfolios to consistently outperform the EWI portfolio suggests indirectly that the benefits from allowing time-varying and heterogeneous style-weights are offset by parameter estimation error and *representativeness heuristic* bias.[2] These findings remain unchallenged in additional analyses which include various re-

[2] As defined by psychologists Amos Tversky and Daniel Kahneman in the early 1970s, when we rely on a representative heuristic, we often wrongly judge that something is more representative than it actually is. In asset management, representative heuristics lead investors to think that future patterns in portfolio behavior (or, in the present context, future patterns in style ranking) will resemble past ones.

formulations of the sophisticated style-integration strategies, increasing the length of the lookback (estimation) period, and conducting tests that are robust to data snooping.

Our article speaks to a recent but quickly growing literature on style integration in equity markets (Barberis and Shleifer, 2003; Brandt et al., 2009; Frazzini et al., 2013; DeMiguel et al., 2018), currency markets (Kroencke et al., 2014; Barroso and Santa-Clara, 2015b), fixed income markets (Brooks et al, 2018), commodity markets (Fuertes et al., 2010, 2015; Blitz and De Groot, 2014) and across markets (Asness et al., 2013, 2015). A feature that is common to many of these studies is their focus on a single style-integration approach. Departing from these studies, our article conducts a comprehensive horse-race of style-integrations methods to inform academics and practitioners alike on their relative performance.

By presenting evidence that the EWI strategy dominates the sophisticated integration strategies, our article speaks to two other literatures. First, it adds to a voluminous literature on forecast combination where the equal-weights forecast combination approach is the de facto benchmark against which any newly developed forecast combination is appraised (see Timmermann, 2006, for a survey). Second, albeit our paper is concerned with style-diversification, it echoes in spirit the findings from a parallel literature concerned with asset-diversification (N assets) instead which has highlighted the effectiveness of the naïve $1/N$ approach (DeMiguel et al., 2009).

The rest of the paper proceeds as follows. Section 2 presents a general allocation framework that nests the standalone styles and style-integration methods, and outlines the evaluation tools and statistical tests. Section 3 presents the data, and Section 4 contains the main results on the out-of-sample performance of different style-integrated portfolios. Section 5 discusses additional tests to assess the robustness of our main findings, before concluding in Section 6.

2. Methodology

2.1 Portfolio allocation framework

To set the stage, we begin by laying out the portfolio allocation framework developed by Brandt et al.'s (2009) to exploit multiple asset characteristics. We particularize the framework, as in Barroso and Santa-Clara (2015b), for assets in zero-net supply given our focus on investors that seek exposure to multiple styles via long-short portfolios of futures contracts.

Let the available cross-section of futures contracts be denoted $i = 1, . . , N$, the investment styles $k = 1, \dots, K$, and the portfolio formation times $t = 1, \dots, T$; thus $x_{i,k,t}$ denotes the value of the k characteristic or signal for the ith futures contract at time t. Bold font is used hereafter to denote matrices and vectors. The investor's asset allocation at time t in the context of style-integration is given by the $N \times 1$ vector $\boldsymbol{\phi}_t$ which can be decomposed as follows

$$\boldsymbol{\phi}_t \equiv \boldsymbol{\Theta}_t \times \boldsymbol{\omega}_t = \begin{pmatrix} \theta_{1,1,t} & \cdots & \theta_{1,K,t} \\ \vdots & \ddots & \vdots \\ \theta_{N,1,t} & \cdots & \theta_{N,K,t} \end{pmatrix} \begin{pmatrix} \omega_{1,t} \\ \vdots \\ \omega_{K,t} \end{pmatrix} = \begin{pmatrix} \phi_{1,t} \\ \vdots \\ \phi_{N,t} \end{pmatrix} \quad (1)$$

where $\boldsymbol{\Theta}_t$ is an $N \times K$ matrix of asset scores that reflects the allocation of style k to asset i. For the main part of our analysis, the elements of the score matrix $\boldsymbol{\Theta}_t$ are the signals appropriately standardized cross-sectionally; namely, $\theta_{i,k,t} \equiv (x_{i,k,t} - \bar{x}_{k,t})/\sigma^x_{k,t}$ where $\bar{x}_{k,t}$ ($\sigma^x_{k,t}$) is the cross sectional mean (standard deviation) of the kth characteristic at time t. Accordingly, the kth strategy longs (shorts) asset i at time t when $\theta_{i,k,t} > 0$ ($\theta_{i,k,t} < 0$) which we refer to as $\theta^L_{i,k,t}$ ($\theta^S_{i,k,t}$) hereafter. Using the standardized signals as scores naturally implies equal long and short investment mandates, $\sum_{i=1}^{N_L} \theta^L_{i,k,t} = \sum_{i=1}^{N_S} \left|\theta^S_{i,k,t}\right|$ per style k, with $N_{\boldsymbol{L}} + N_{\boldsymbol{S}} = N$. At each portfolio formation time t, we work with the original distribution of signals $\{x_{i,k,t}\}_{i=1}^{N}$ per style k; see e.g. Brandt et al. (2009), Barroso and Santa-Clara (2015b), Fischer and Gallmeyer (2016), Ghysels et al. (2016), inter alia. In the robustness tests section, we conduct the horse race of style-integration methods using several outlier-robust scoring schemes including the case where the signals are winsorized prior to standardization as in DeMiguel et al. (2018).

The entries of the $K \times 1$ weight vector $\boldsymbol{\omega}_t$ capture the relative importance given to each of the K styles; unless noted otherwise, the weights are unrestricted. The entries of the $N \times 1$ vector $\boldsymbol{\phi}_t$ represent the solution of the style-integrated portfolio allocation problem; namely, the sign of the allocation, $\phi_{i,t} > 0$ or $\phi_{i,t} < 0$, indicates the specific position, long or short, that the style-integrated portfolio takes on asset i at time t. The vector $\boldsymbol{\phi}_t$ is scaled to $\tilde{\boldsymbol{\phi}}_t$; i.e., $\tilde{\phi}_{i,t} = \phi_{i,t}/\sum_{i=1}^{N}|\phi_{i,t}|$ to ensure 100% investment of the investor's mandate, $\sum_{i=1}^{N}|\tilde{\phi}_{i,t}| = 1$. It follows that, by construction, the final style-integrated portfolio allocates an equal investment mandate to the longs and to the shorts; i.e., $\sum_i \tilde{\phi}_{i,t}^L = \sum_i |\tilde{\phi}_{i,t}^S| = 0.5$. The long/short positions taken at each portfolio formation time t (month-end in our analysis) are held for a month on a fully-collateralized basis; a new $\tilde{\boldsymbol{\phi}}_{t+1}$ is then obtained that defines the style-integrated portfolio over the next month and so on. We adopt an "out-of-sample" or real time approach throughout the paper meaning that at each time t the vector $\boldsymbol{\phi}_t$ is determined using a past window of data.

2.2 Standalone styles

The standalone-style portfolios emerge as particular cases of Equation (1) for a sparse weight vector $\boldsymbol{\omega}_t$ with one entry equal to 1 and the K-1 remaining entries equal to 0. For our implementation of the integration methods we utilize, without loss of generality, the five styles described next that have been proposed in the literature to capture risk premia in various asset classes. Appendix A, Panel A, refers the reader to a few representative studies for each style.[3]

The *momentum* style pursues the trend-continuation principle that the past well-performing assets (or winners) tend to continue outperforming past losers. In our study, the

[3] As in Asness et al. (2013) and Koijen et al. (2018), for each style we define the signals identically (as discussed in Section 2.2) across all the futures classes for the sake of simplicity. This simplification ought not to be a concern since we are not aiming to find the best predictor of returns in each class but instead, for a given futures class and a set of styles, we seek to uncover the best style-integration method.

sorting signal for the cross-section of front-end futures contracts is the average of their daily excess returns in the past year; namely, $x_{i,t} \equiv \frac{1}{D}\sum_{j=0}^{D-1} r_{i,t-j}$ where D denotes the number of days.

The *value* style rests upon the notion of long-run mean reversion. Following Asness et al. (2013) inter alia, the signal is defined as the log of the average D daily front-end futures prices 4.5 to 5.5 years before portfolio formation t over the current front-end futures price*;* namely, $x_{i,t} \equiv ln \frac{\frac{1}{D}\sum_{d=0}^{D-1} f_{i,t-j}^{t_1}}{f_{i,t}^{t_1}}$ where t_1 is the maturity of the front-end contract. The idea is to buy (sell) currently underpriced (overpriced) futures contracts relative to their long-term mean value.

Next, we consider the *carry* trade that relies on the roll-yield defined as the difference between the logarithmic front-end futures price and the logarithmic second-nearest futures price; namely, $x_{i,t} \equiv \ln\left(f_{i,t}^{t_1}\right) - \ln(f_{i,t}^{t_2})$ where t_1 and t_2 denote the maturity of the front-end and second-nearest futures contracts. The idea is to buy (sell) futures contracts with negatively (positively) sloped term structure of futures prices to capture the expected increase (decrease) in their price as maturity approaches under the assumption that the futures curve stays the same.

The *liquidity* style captures a risk premium that reflects the compensation that investors demand for holding less liquid assets. Following prior studies (e.g., Szymanowska et al., 2014), we adopt the Amivest liquidity measure which averages the daily dollar volume per absolute return of the front-end futures contract over the past two months (D days); in our paper the signal is defined as the opposite of this measure, $x_{i,t} \equiv -\frac{1}{D}\sum_{j=0}^{D-1} \frac{\$Volume_{i,t-j}}{|r_{i,t-j}|}$, so that positive standardized-signals dictate long positions as formalized in the above framework, Equation (1).

Our final style adopts a *skewness* signal which is motivated by the notion that investors tend to prefer positively-skewed assets. Following prior studies (Fernandez-Perez et al., 2018), the signal is defined as the third moment of the distribution of daily excess returns of the front-end futures contracts in the prior year; again, we use the negative of this measure so that positive standardized-signal values amount to long positions, $x_{i,t} \equiv -\frac{1}{D}\frac{\sum_{j=0}^{D-1}(r_{i,t-j}-\mu_i)^3}{\sigma_i^3}$ with D days.

2.3. Style-integration methods

Next we discuss the seven style-integration methods, particular cases of Equation (1), that arise from different approaches to determine the style-weighting vector $\boldsymbol{\omega}_t$. As discussed next, the first method is based on weights set a priori whereas the other six integration methods are called "sophisticated" because they allow for time-varying and heterogeneous weights $\boldsymbol{\omega}_t$ which are derived from past data in the 60-month window preceding portfolio formation time t.

Equally-Weighted Integration (EWI). The naïve EWI method assigns homogeneous weights to the K signals constantly at each portfolio formation time $t = 1, \ldots, T$; namely, $\boldsymbol{\omega}_t = \boldsymbol{\omega} = (1/K, \ldots, 1/K)'$. EWI is appealing for various reasons. First, it incurs no sampling uncertainty or *estimation risk* as $\boldsymbol{\omega}_t$ is not derived from past data. Second, it sidesteps concerns related to the so-called *representativeness heuristic* which can bias the sophisticated style-integration approaches as they assign more weight to the best styles (where "best" is defined according to some criteria) under the presumption that the past relative ranking of the K styles is a good guide to their future relative ranking. Third, the simplicity of the EWI approach reduces the scope for *data mining* since it circumvents the choices associated with the pre-ranking of the K standalone styles; instances are the specific length of the estimation or lookback period, the ranking or estimation criterion (e.g., investor's utility function) and so forth.

Optimal Integration (OI). This method defines the style-weighting vector $\boldsymbol{\omega}_t$ as the set of weights that maximize the conditional expected utility of the portfolio that exploits all *K* styles. Accordingly, at each portfolio formation time *t*, we solve the following optimization problem $\max_{\boldsymbol{\omega}} E_t\left[U\left(\sum_{k=1}^{K} \omega_k r_{k,t+1}\right)\right]$ with $r_{k,t}$ denoting the month *t* excess return of the *k*th style portfolio. Following DeMiguel et al. (2018), the OI style-weights are determined under an unconstrained mean-variance utility assumption $E_t\left[U\left(r_{P,t+1}\right)\right] = \boldsymbol{\omega}_t'\boldsymbol{\mu}_t - \frac{\gamma}{2}\boldsymbol{\omega}_t'\Sigma_t\boldsymbol{\omega}_t - \gamma\boldsymbol{\omega}_t'\boldsymbol{\sigma}_{bk}$ where the $K \times 1$ vector $\boldsymbol{\mu}_t$ contains the expected standalone-style portfolio excess returns with *k*th entry estimated as $\hat{\mu}_{k,t} = \frac{1}{60}\sum_{j=0}^{60-1} r_{k,t-j}$, $\boldsymbol{\Sigma}_t$ is the corresponding variance-covariance matrix, and $\boldsymbol{\sigma}_{bk}$ is the vector of covariances between the benchmark and standalone-style portfolios which is not needed in the present context of assets in zero-net supply.[4] We employ the closed-form solution, $\boldsymbol{\omega}_t = \frac{1}{\gamma}\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\mu}_t$ with coefficient of relative risk aversion γ=5 and $\boldsymbol{\omega}_t \in \mathrm{R}^K$ (as unrestricted style weights allow for the possibility of taking the opposite of the score obtained for the *k*th style when it crashes; e.g., Daniel and Moskowitz, 2016). This is essentially the OI approach of Brandt et al. (2009) adapted here to assets in zero-net supply as in Barroso and Santa-Clara (2015b). In the robustness checks section of the paper, we consider different utility functions.

Rotation-of-Styles Integration (RSI). At each month-end *t*, the RSI portfolio adopts the *j*th style with the highest past Sharpe ratio ($\omega_{j,t} = 1$) and neglects other styles, $\omega_{k,t} = 0$, $k = 1, \ldots, K$ $(k \neq j)$. RSI is motivated by the theoretical style-switching model of Barberis and Shleifer (2003) and the idea is to exploit any persistence in relative style performance.

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[4] Notwithstanding the potential short-selling and liquidity constraints, as well as the higher trading costs, the long-short style-integrated portfolio strategies appraised in the paper are applicable to assets in positive net supply (e.g., stocks and bonds) simply by modifying Equation (1) as $\boldsymbol{\phi}_t = \overline{\boldsymbol{\phi}}_t + \frac{1}{N}(\boldsymbol{\Theta}_t \times \boldsymbol{\omega}_t)$ where $\overline{\boldsymbol{\phi}}_t$ denotes the benchmark allocations (e.g., market-portfolio weights). In our present analysis, $\overline{\boldsymbol{\phi}}_t = \mathbf{0}$, as futures contracts are in zero-net supply, and the factor $1/N$ cancels out after normalizing $\boldsymbol{\phi}_t$ to $\widetilde{\boldsymbol{\phi}}_t$.

Volatility Timing Integration (VTI). This style-integration method defines the relative exposure to a style as inversely proportional to the variance of its past excess returns, $\omega_{k,t} \equiv 1/\sigma^2_{k,t}$. This approach is inspired by the Kirby and Ostdiek (2012) volatility-timing allocation of *N* assets into a portfolio which can be seen as a restricted (or extreme "shrinkage") mean-variance approach that makes the simplifying assumption of equal means and zero covariances.

Cross-Sectional Pricing Integration (CSI). The style weights in the CSI method reflect the relative ability of the standalone style premia to explain the cross-sectional variation in the asset returns. Higher weights are given to the styles or factors that are better able to price the assets. As in Fama and MacBeth (1973), at each month-end *t* we estimate a univariate *time-series* OLS regressions per futures contract $i = 1, \dots, N$ and style $k = 1, \dots, K$ (a total of $N \times K$ regressions) using the preceding 60-month length window of data

$$r_{i,s} = a_{i,k} + b_{i,k} r_{k,s} + \varepsilon_{i,s}, s = t - 59, \dots, t \tag{2}$$

where $r_{i,s}$ is the month *s* excess return of the *i*th futures contract, $r_{k,s}$ is the month *s* excess return of the *k*th style, $\varepsilon_{i,s}$ is an error term, $a_{i,k}$ and $b_{i,k}$ are the estimated coefficients. At step two, we estimate for each of those 60 months a *cross-sectional* OLS regression

$$r_{i,s} = \lambda^0_{k,s} + \lambda^1_{k,s} \hat{b}_{i,k} + \epsilon_{i,s}, i = 1,2, \dots, N \tag{3}$$

for $s = t - 59, \dots, t$ ($60 \times K$ regressions). The explanatory power of the *k*th factor in Equation (3) determines the weight that the CSI portfolio assigns to the *k*th style, $\omega_{k,t} \equiv \frac{1}{60} \sum_{j=0}^{60-1} R^2_{k,t-j}$.

Style Momentum Integration (SMI). Recent studies document momentum in the styles or factor returns themselves (Ehsani and Linnainmaa, 2017; Arnott et al., 2018). Accordingly, the SMI style-weights at each portfolio formation time *t* are given by the average excess returns of the standalone-style portfolios in the prior 60-month lookback period, $\omega_{k,t} \equiv \frac{1}{60}\sum_{j=0}^{60-1} r_{k,t-j}$.

Principal Components Integration (PCI). This method defines the style weights as a direct function of the eigenvectors associated with the first *m* principal components of the *K* style premia ($m < K$); namely, $\boldsymbol{\omega_t} \equiv \frac{e_{1,t}\boldsymbol{L}_{1,t}+e_{2,t}\boldsymbol{L}_{2,t}+\cdots+e_{m,t}\boldsymbol{L}_{m,t}}{e_{1,t}+e_{2,t}+\cdots+e_{m,t}}$ where $e_{j,t}$ is the explanatory power of the *j*th principal component, $\boldsymbol{L}_{j,t}$ is the corresponding *K*-vector of loadings (or *j*th eigenvector, $j = 1, \ldots, K$), and *m* is the number of PCs that explain at least τ of the total variation in the standalone style premia. We use the conservative threshold τ=90% in our main analysis.

Appendix A, Panel B, refers the reader to studies that deploy the EWI, OI, RSI, VTI or SMI methods. To our knowledge, the CSI and PCI methods are new to the integration literature.

2.4. Everywhere style-integration

The discussion thus far has been implicitly geared towards the construction of futures class-specific portfolios; namely, equity index, fixed income, currency or commodity futures portfolios. Since investors in futures markets may seek diversification across futures classes, we describe now a method for the construction of "everywhere" style-integrated portfolios with a view to appraise their relative effectiveness also in this scenario.

As argued by Barberis and Schleifer (2003), investors have a tendency to classify decisions into categories based on some similarities among them, e.g. asset classes; accordingly, we conceptualize the everywhere style-integrated portfolio construction as involving two sequential decisions: i) how much funds to allocate to each of the four futures classes, and ii) the style exposures within each asset class. More specifically, the everywhere style-integrated portfolio from month t to month t+1 is formalized as a weighted combination of style-integrated portfolios per class

$$R_{P,t+1} = \boldsymbol{\varphi}_t' \boldsymbol{r}_{P,t+1} = \sum_{c=1}^{4} \varphi_t^c \, r_{P,t+1}^c \qquad (4)$$

where φ_t^c represents decisions made at portfolio formation time t based on past data; the subscripts $c = 1,..,4$ denote the equity index, currency, fixed income *and* commodity futures classes, respectively, which receive allocations φ_t^c at each portfolio formation time t, and $r_{P,t}^c = f(\boldsymbol{\omega}_t^c)$, is the month t return of the style-integrated portfolio for the cth futures class which hinges on the choice of style-weighting vector $\boldsymbol{\omega}_t^c$.

The asset manager determines $\boldsymbol{\omega}_t^c$ and $\boldsymbol{\varphi}_t$ using two non-overlapping windows of each 60 monthly observations. The first 60-month window is used to obtain the style-weight vector $\boldsymbol{\omega}_t^c$ separately for each futures class, $c = 1, \ldots, 4$ following the style-integration methods described in Section 2.3. The subsequent 60-month window and the corresponding returns $r_{P,t}^c$ are used to determine the class-weighting vector $\boldsymbol{\varphi_t}$ for an agent with an unconstrained mean-variance utility (DeMiguel et al., 2009). Accordingly, at each portfolio formation time t the investor maximizes the mean-variance utility of the everywhere style-integrated portfolio over the 60-month prior window to derive the class-weights as $\boldsymbol{\varphi}_t \equiv \frac{1}{\gamma}\widetilde{\boldsymbol{\Sigma}}_t^{-1}\widetilde{\boldsymbol{\mu}}_t$ where $\widetilde{\boldsymbol{\mu}}_t$ is the 4×1 vector of expected excess returns for the class-specific style-integrated portfolios and $\widetilde{\boldsymbol{\Sigma}}_t$ is the variance-covariance matrix. As before, we employ the relative risk aversion parameter γ=5. The resulting allocations, $\boldsymbol{\varphi}_t$, are standardized to ensure full investment. In the robustness tests section, we consider other everywhere style-integrations.

2.5. Evaluation criteria and statistical tests

We begin by appraising the portfolio strategies using the well-known Sharpe ratio. To make statistical inferences, we deploy the Opdyke (2007) test for the null hypothesis $H_0{:}\, SR_{P_a} \geq$

SR_{P_b} versus the alternative $H_A: SR_{P_a} < SR_{P_b}$ where P_a and P_b denote two alternative portfolios.[5]

In order to account for non-normality, we also evaluate the relative performance of the portfolios by means of two alternative ratios: the Sortino ratio which scales mean returns by the downside standard deviation, and the Omega ratio which uses as risk measure the probability-weighted ratio of gains versus losses relative to a threshold excess return of zero.

In addition, for each portfolio strategy we compute the certainty equivalent return (CER) which represents the risk-free return that an investor is willing to accept instead of engaging in the risky investment. Adopting the mean-variance utility for now, the CER of portfolio P is calculated as the annualized average realized utility over the evaluation period; namely, $CER_P = \mu_P - \frac{\gamma}{2}\sigma_P^2$ where μ_P and σ_P^2 denote the first two moments of the portfolio excess returns distribution. A strictly positive CER means that the risky portfolio is more appealing than the risk-free asset. Following DeMiguel et al. (2009), we test the superiority of the EWI portfolio over another portfolio j, namely $H_0: CER_{EWI} \geq CER_j$ versus $H_A: CER_{EWI} < CER_j$, by exploiting the asymptotic properties of functional forms of the estimators for means and variances. We also assess the robustness of our findings by calculating the CER measure and corresponding tests for the above H_0 versus H_A hypotheses under a power utility assumption.

To provide a more complete picture of the relative effectiveness of different style-integration methods we compare the EWI and sophisticated style-integrations in terms of the volatility (standard deviation) of their excess returns, and downside risk as measured by the semi standard deviation, maximum drawdown and 99% modified (Cornish-Fisher) VaR that

[5] Opdyke (2007) provides an expression for the asymptotic distribution of differences in Sharpe ratios that is valid under quite general conditions (stationary and ergodicity of returns) thus permitting time-varying conditional volatilities, serial correlation, and other non-iid return behavior.

accounts for skewness and kurtosis. When the returns have negative skewness or fat-tails, the Cornish-Fisher VaR will give a larger estimation for the loss than the traditional VaR.

Finally, even though futures contracts are cheap to trade and therefore transaction costs are unlikely to alter the performance comparison, for completeness we take into account the trading intensity of each strategy. To this end, we measure portfolio *turnover* (TO) as the average of all the trades incurred over the sample evaluation period

$$TO_P = \frac{1}{T-1}\sum_{t=1}^{T-1}\sum_{i=1}^{N}\left(\left|\tilde{\phi}_{P,i,t+1} - \tilde{\phi}_{P,i,t^+}\right|\right) \tag{5}$$

where $\tilde{\phi}_{P,i,t}$ is the allocation to the ith asset at month-end t in the portfolio and $\tilde{\phi}_{P,i,t^+} \equiv \tilde{\phi}_{P,i,t} \times e^{r_{i,t+1}}$ is the actual portfolio weight immediately before the next rebalancing is due at month-end $t+1$, where $r_{i,t+1}$ denotes the realized monthly excess return of the ith futures contract from t to $t+1$. Thus, the above TO measure captures the mechanical evolution of the futures contracts weights due to within-month price dynamics.

3. Data

We collect daily settlement prices, volume and open interest from *Thomson Reuters Datastream* for 131 US-exchanged futures contracts on 45 equity indices, 22 fixed income and interest rates, 21 foreign currencies and 43 commodities, as detailed in Appendix B. The time-series start in April 1982 for equity indices, January 1979 for currencies, October 1975 for fixed income, and January 1979 for commodities. All the time-series end in December 2017.

We deploy the strategies by taking positions on the first nearest-to-maturity contracts as these are the most liquid.[6] Specifically, returns are changes in logarithmic prices of the front-

[6] For the same reason, at each portfolio formation time, we exclude the futures contracts with zero open interest. Qualitatively similar results, shown in Table A.I of the Internet Appendix, are obtained when we restrict our sample to a more liquid universe (the 90% or 80% of contracts with the highest open interest) to provide conservative evidence on an implementable set of trading strategies. The Internet Appendix is available as supplement material with the online version of this article.

end contract up to one month before maturity, then we roll to the second-nearest contract to mitigate the confounding impact of erratic prices and volumes as maturity approaches.

To ensure a reasonable level of diversification across futures contracts in the long-short portfolios held, the initial portfolio formation time in our exercise is dictated by the requirement that any subsequent long-short portfolio formed includes at least six futures contracts. Thus, the start date for the monthly portfolio excess returns that is common across the standalone-styles and style-integrations is September 2001 for equity index futures, December 1991 for fixed income futures, August 1989 for currency futures, and July 1989 for commodity futures.

Futures markets are a sound "laboratory" for the present long-short style-integrated portfolio analysis for quite a few reasons: taking short positions in futures contracts is as feasible as taking long positions (since no short-selling restrictions are imposed), transaction costs implied are relatively low compared to those incurred on the underlying assets, futures contracts at least in the front-end are highly liquid. They also allow investors to leverage their positions and provide them with an exposure similar to that obtained on the underlying asset (in line with the observations made by Moskowitz et al. (2012), Bessembinder (1992) and de Roon et al. (2000), we find that the front-contract futures excess returns are highly correlated with the spot excess returns on the same underlying asset; e.g., the correlation between the monthly S&P500 (CME) futures excess returns and the underlying cash index excess returns is 99%, Euro vs US dollar (CME) futures and the underlying is 99%, or Gold (CMX) futures and the underlying is 97%).

4. Results

4.1. Ranking and correlation structure of standalone-style portfolios

We begin by summarizing the performance of the standalone-style portfolios over the entire sample period in Table 1 to provide a static picture of their relative standing -- per futures class, equity indices (Panel A), fixed income (Panel B), currencies (Panel C) and commodities (Panel D), and cross-class using the unrestricted mean-variance weighting approach described in Section 2.4 (Panel E). The results confirm stylized facts such as that there is pervasive momentum and carry everywhere. The ranking of styles differs across futures classes; for instance, the momentum and skewness premia stand out in commodity futures markets, while the value and carry premia stand out in currency futures markets. Thus, the difficulty of finding one style that is consistently performing across futures classes poses a challenge for investors that seek broad diversification through cross-(futures) class portfolios. This motivates style-integration.

[Insert Table 1 around here]

We observe also that although a few of the standalone styles – liquidity (equity index futures), value (fixed income futures), and skewness (currency futures) – rank bottom as shown in the static snapshot provided by Table 1, their relative ranking reverses over sub-periods. The extent of the instability in the relative ranking of the styles is illustrated in Table 2 which reports over 5-year non-overlapping windows the Sharpe ratios of the standalone strategies and corresponding ranks (where 1 denotes worst performance and 5 best performance). The momentum strategy switches from best to worst in fixed income markets depending on the sub-period considered (Panel B). Similar instability in relative ranking is observed for the value strategy in equity markets (Panel A) and the carry and skewness strategies in commodity markets (Panel D). Hence, time-variation in the relative performance of the standalone-style portfolios poses a challenge for an investor in choosing a "best" style which further motivates style integration. Relatedly, the integration of styles ought to provide investors with some protection against the occasional "crashes" that they may suffer which are difficult to predict in real time; e.g, Barroso and Santa-Clara (2015a) discuss crashes in the momentum style.

[Insert Table 2 around here]

Finally, to grasp the extent of the overlap across the standalone styles, Table 3 shows the correlation structure of their excess returns per futures class in Panels A to D, and in the cross-class setting in Panel E. The pairwise Pearson correlations across styles per futures class are generally small ranging from -0.06 (commodities) to 0.16 (fixed income) on average. This is echoed by the pairwise correlations across the cross-class style portfolios. The value style, which is contrarian in nature, typically correlates negatively with the other styles. This mild correlation structure across styles additionally motivates the notion of style-integrated portfolio allocation. The key idea is that, by aggregating the information from multiple signals at asset level, the investor ought to obtain a more reliable (composite) signal and a better allocation.

[Insert Table 3 around here]

4.2 Performance of style-integrated portfolios

What is the most effective way for an investor to construct a unique portfolio that is exposed to multiple styles? Table 4 answers this question by summarizing the seven style-integrated portfolio strategies discussed in Section 2.3 per futures class and across futures classes. As revealed by Panels A to D for the equity index, currency, fixed income and commodity futures, respectively, the naïve EWI portfolio is often unrivalled in terms of performance – as measured either by the Sharpe ratio, Omega ratio, Sortino ratio or CER – by the sophisticated style-integrated portfolios. For example, across integration strategies EWI presents the highest Sharpe ratios in Panels A, B and D and comes close second after VTI in terms of Sharpe ratio in Panel C and E. Moreover, the EWI strategy is also well positioned vis-à-vis the sophisticated style-integrations regarding trading turnover, as Figure 1 illustrates.

[Insert Figure 1 around here]

To add statistical significance to these findings, we assess the statistical superiority of the EWI strategy relative to the sophisticated portfolios through the Opdyke test. The null hypothesis is $H_0: SR_{EWI} \geq SR_j$ where j denotes a sophisticated style-integrated strategy. The test *p*-values are large across all futures classes and hence, they suggest that the Sharpe ratio of the EWI portfolio is unsurpassed by the Sharpe ratio of sophisticated style-integrated portfolios. Consistent with this finding, the *p*-values for the test that assesses the relative effectiveness of the EWI strategy using the CER as criteria, $H_0: CER_{EWI} \geq CER_j$, unambiguously fail to reject the null hypothesis and hence, endorse the simple EWI method for style integration.[7]

[Insert Table 4 around here]

Since investors often seek broad diversification across multiple asset classes, it is also important to compare the effectiveness of the alternative style-integration methods in the context of "everywhere" portfolios of equity index, fixed income, currency and commodity futures. The results of this additional horse race are shown in Panel E of Table 4. Reassuringly, as borne out by the Opdyke test ($H_0: SR_{EWI} \geq SR_j$) and CER test ($H_0: CER_{EWI} \geq CER_j$), we find that in a cross-class context the EWI approach is not challenged either.

Table 5 reports the Sharpe ratios, and corresponding Opdyke test *p*-values, over 5-year non-overlapping rolling windows. With only one exception, the Sharpe ratio of the EWI portfolio remains superior to that of sophisticated style-integration portfolios as borne out by

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[7] These main findings are not challenged under a power utility assumption, that is, by calculating $CER = \left(\frac{12}{T}\right)\sum_{t=0}^{T-1}\frac{(1+r_{P,t+1})^{1-\gamma}-1}{1-\gamma}$ with $r_{P,t+1}$ the portfolio excess return on month *t*+1; we use $\gamma = 5$. The test for differences in CERs with power utility is based on the Politis and Romano (1994) bootstrap method using *B*=10,0000 iterations. We construct bootstrap time-series of returns for the EWI portfolio and each competing integrated portfolio, $\{r^*_{EWI,t}, r^*_{j,t},\}$, by combining random blocks of length *l* sample from the original time-series of returns. The block-length *l* is geometrically distributed with expected value $1/q$. We use $q = \{0.2, 0.5\}$. Results are provided in Table A.II of the Internet Appendix.

large Opdyke test *p*-values across all the subperiods. A dynamic comparison of the style-integration methods is also conducted by ranking their performance. Specifically, we start off by assigning a top (bottom) rank of 7 (1) to the integrated strategy with the highest (lowest) Sharpe ratio. This is done for each of the 5-year non-overlapping periods, as well as for each of the class of futures (Panels A to D) and across classes (Panel E). We then average the ranks thus obtained per integrated strategy and calculate the standard deviation of these ranks, as well as the ratio of the mean rank to its standard deviation. The results, presented at the bottom of Table 5, suggest that the naïve EWI portfolio has a relatively high volatility-adjusted expected rank which suggests that it offers sizeable risk-adjusted returns consistently across subperiods and futures classes. Endorsing our prior findings, the sophisticated two-step CSI strategy acquires a similar volatility-adjusted mean rank as the naïve EWI; given that the latter is much simpler to deploy as it does not require parameter estimation, it is the preferred strategy overall.

[Insert Table 5 around here]

Next we compare the full-sample performance of the standalone-style portfolios in Table 1 and the EWI portfolio in Table 4 under all the scenarios (four separate futures classes and cross-class) while bearing in mind the turnover shown in Figure 1. The results presented in Table A.III of the Internet Appendix indicate that EWI statistically delivers superior out-of-sample performance than the standalone style. Further to compare the style portfolios and the EWI portfolio we rank all six of them over 5-year non-overlapping subperiods and across scenarios, as explained above. The results shown suggest that the volatility-adjusted expected rank is highest for EWI. Moreover, the EWI portfolio offers a shield against the downside risk of standalone-style portfolios as borne out by the risk measures shown in Table A.IV of the Internet Appendix. These findings are not new but serve to confirm (in the context of wide cross-sections of futures contracts for four instruments) prior studies advocating style-integration (e.g., Brandt et al., 2009; Asness et al., 2013; Barroso and Santa-Clara, 2015b; DeMiguel et al., 2018).

As a byproduct of our analysis, we can compare the performance of the dominant EWI strategy when it is deployed for individual futures classes and cross-classes. Since the performance measures reported in Table 4 for those different contexts are based on samples of returns starting on different periods, for this comparison to be informative, we recalculate the same measures over the longest sample period that is common (September 2006 to December 2017). The results reported in Table A.V of the Internet Appendix confirm the broad diversification benefits of cross-class style integration.[8] For instance, with a Sharpe ratio of 1.03 and 99% VaR of 0.0138, the cross-class EWI portfolio is more attractive than the single futures-class EWI portfolios with Sharpe ratios ranging from 0.17 (fixed income) to 0.97 (equity index), and 99% VaRs ranging from 0.0224 (fixed income) to 0.1234 (equity index).

Finally, leaving the dominant EWI method aside for a moment, we draw comparisons across the remaining style-integrated strategies in terms of several performance measures over the entire sample period (Table 4) and Sharpe ratio-based ranking over subperiods (Table 5). We observe that the CSI portfolio strategy inspired by the two-step Fama-MacBeth methodology affords relatively high performance in a fairly consistent manner across scenarios (futures classes and cross-class) and over time. Both the OI and the statistically-motivated PCI lie at the other end of the spectrum with the least attractive performance.

5. Robustness tests

The purpose of this section is primarily to assess the robustness of our main finding that the naïve EWI strategy is unrivalled by sophisticated style-integration strategies to: reformulations of the sophisticated style-integration strategies, longer estimation windows,

[8] The diversification benefits of deploying the EWI portfolios in an everywhere (cross-class) fashion stem from the low correlations between the EWI excess returns across futures classes which ranges from -0.23 (equity index and fixed income portfolios) to 0.20 (equity index and foreign exchange portfolios).

different sub-periods, and deploying the "reality check" test in Hansen (2005) to mitigate data snooping concerns. To preserve length, the tabulated tests for differences in performance focus on the Sharpe ratio; tests based on the CER measure produced qualitatively similar results.

5.1. Reformulations of the "sophisticated" style-integration methods

We begin by considering four alternative OI strategies where the objective function to optimize is: i) the mean-variance utility with shrinkage of the covariance matrix (Ledoit and Wolf, 2004) which is an asymptotically optimal convex linear combination of the sample covariance matrix with the identity matrix, ii) the power utility $U(r_{P,t+1}) = \frac{(1+r_{P,t+1})^{1-\gamma}-1}{1-\gamma}$, iii) the exponential utility $U(r_{P,t+1}) = -\frac{e^{-\kappa(1+r_{P,t+1})}}{\kappa}$, and iv) the power utility with disappointment aversion (Gul, 1991) $U(r_{P,t+1}) = \frac{(1+r_{P,t+1})^{1-\gamma}-1}{1-\gamma}$ if $r_{P,t+1} > 0$ and $\frac{(1+r_{P,t+1})^{1-\gamma}-1}{1-\gamma} + \left(\frac{1}{A} - 1\right)\left[\frac{(1+r_{P,t+1})^{1-\gamma}-1}{1-\gamma}\right]$ if $r_{P,t+1} \leq 0$. γ and κ are the relative and absolute risk aversion parameters, respectively, and $A \leq 1$ is the coefficient of disappointment aversion that controls the relative steepness of the value function in the gains/losses regions; we use $\gamma = \kappa = 5$ and A=0.6.[9]

Next we consider an investor who is only concerned about risk, measured by the variance, and therefore she obtains the style exposures as the solution of the problem $min_{\boldsymbol{\omega}} \left[Var_t(r_{P,t+1})\right]$ subject to $\sum_{k=1}^{K} \omega_k = 1$ (to avoid the trivial solution $\omega_k = 0$). The minimum variance portfolio can be cast as a special case of the mean-variance portfolios by assuming equal means.

[9] The power utility with disappointment aversion embeds the behavioral notion that investors are more sensitive to losses than to gains of equal size. A=1 implies the standard power utility function without loss aversion. We solved the OI problem using A=0.8 and the main insights also hold.

For each of the above reformulations of the OI strategy, we deploy a restricted ($\omega_k \geq 0$) version and an unrestricted ($\forall\omega_k$) version. We also deploy now a constrained ($\omega_k \geq 0$) version of our earlier mean-variance utility OI approach, for completeness.

Inspired by the cluster combination approach of Aiolfi and Timmermann (2006), we deploy a smoother version of the RSI strategy based on the three styles with the best past performance. Specifically, at each month-end the resulting RSI(3) portfolio has equal exposure to the top three styles according to the Sharpe ratio ($\omega_k = 1/3$) and no exposure to the remaining styles.

Next, the earlier VTI strategy inspired by Kirby and Ostdiek (2012) is reformulated in two ways. First, by considering the more general VTI(η) strategy with style weights $\omega_{k,t} = \left(1/\sigma_{k,t}^2\right)^\eta$ where timing-aggressiveness is dictated by the parameter η.[10] Second, by considering the reward-to-risk timing integration (RRTI) with style weights $\omega_{k,t} = \left(\hat{\mu}_{k,t}^+/\sigma_{k,t}^2\right)^\eta$ where $\hat{\mu}_{k,t}^+ = \max\left(0, \hat{\mu}_{k,t}\right)$, and $\hat{\mu}_{k,t}$ is the mean excess return of the *k*th style. We use $\eta = 4$.

As a variant of the earlier CSI approach, we formulate a time-series pricing integration (TSI) that solely focuses on the first-stage of Fama-MacBeth (1973). Accordingly, at each portfolio formation time *t*, the TSI strategy estimates $N \times K$ predictive OLS regressions of the monthly excess returns of each asset $i = 1, \dots, N$ on the past-month style premium $k = 1, \dots, K$

$$r_{i,s} = a_{i,k} + b_{i,k} f_{k,s-1} + \varepsilon_{i,s}, s = t - 59, \dots, t \tag{8}$$

and the *k*th style weight is defined as the average predictive power $\omega_{k,t} \equiv \frac{1}{N}\sum_{i=1}^{N} R_{i,k,t}^2$ based on the regression's coefficient of determination $R_{i,k,t}^2$. Finally, we deploy a very parsimonious

[10] For $\eta = 0$, there is no volatility-timing, $\omega_k = 1/K$ for $k = 1, \dots, K$ and the EWI strategy arises. For $\eta = 1$, the baseline VTI strategy arises. For $\eta \to \infty$, the most aggressive volatility-timing strategy arises such that the jth style with the lowest past variance receives weight $\omega_j = 1$ ($\omega_k = 0, k \neq j$).

version of the earlier PCI approach that focuses on the 1st principal component, denoted PCI(1).

Table A.VI of the Internet Appendix reports results for these reformulations of the sophisticated style-integrations deployed per futures class and cross-classes. The performance of these reformulated style-integration strategies, as measured by the Sharpe ratio, does not challenge the performance of the much easier-to-construct EWI portfolio. This is formally confirmed by large Opdyke test *p*-values which fail to reject $H_0\colon SR_{EWI} \geq SR_j$ throughout.

5.2. Alternative scoring schemes

Our analysis thus far has relied on the standardized signals, as entries of the scoring matrix $\mathbf{\Theta}_t$ in Equation (1), to rank the cross-section of futures contracts according to each style. We now turn attention to three alternative scoring schemes. Following DeMiguel et al. (2018), the first seeks to mitigate the biases induced by noise (outliers) in the individual signals by first winsorizing the signals, and then standardizing the resulting winsorized signals. Specifically, at each portfolio formation time for each signal $k = 1, \ldots, 5$, we shrink all signal values above the upper threshold $Q_{3,k} + 3 \cdot R_k$ to that upper threshold value, and any signal values below the lower threshold $Q_{1,k} - 3 \cdot R_k$ to that lower threshold value; $Q_{1,k}$ and $Q_{3,k}$ are the first and third quartiles of the distribution $\{x_{i,k}\}_{i=1}^{N}$ and R_k is the interquartile range.

The second scoring scheme is based on standardized rankings, $\theta_{i,k,t} \equiv \tilde{z}_{i,k,t} = (z_{i,k,t} - \bar{z}_{k,t})/\sigma_{k,t}^{z}$ where $z_{i,k,t} \in \{1, \ldots, N\}$ is the *i*th asset rank at time *t* according to $x_{i,k,t}$ (i.e., a rank *N* is assigned to the best candidate, and 1 to the worst candidate). By transforming the signals onto rankings, this approach ought to mitigate the effects of potential outliers in the individual signals while it still differentiates among the candidate assets for the long and short positions.

A very parsimonious scheme sorts the candidate futures contracts according to the signals, $\{x_{i,k,t}\}_{i=1}^{N}$ and assigns those with a signal value above (below) the median signal a score of +1(-1). As the final allocations $\phi_{i,t}$ resulting from Equation (1) will not add to zero in this scheme when the available futures contracts N is an odd number, we center them before scaling, i.e., $\tilde{\phi}_{i,t} = (\phi_{i,t} - E_i(\phi_{i,t}))/\sum_{i=1}^{N}\left|\phi_{i,t} - E_i(\phi_{i,t})\right|$ to ensure 100% fulfilment of the investor's mandate. This simple heuristic is also robust to noise but it may lose information by mapping the signals onto just two scores; namely, it does not discriminate among the candidate assets for the long positions; likewise as regards the short positions.

Finally, inspired by the asset management literature we consider three schemes that at each portfolio formation time consider only the assets bucketed into the extreme (top and bottom) quintiles according to the signal at hand, and ignore the assets in the intermediate quintiles. Specifically, the quintile version of the standardized signals scheme, the standardized rankings scheme and the binary {-1, +1} scheme described above; in all of them, the number of contracts in the top and bottom quintiles is *N*/5 (rounded up to the closest integer). For consistency with our earlier portfolio formation approaches, we ensure full investment of the investor's mandate and allocate an equal investment mandate to the longs and to the shorts throughout.

The main finding is that for all of the alternative scoring schemes, the EWI strategy remains unchallenged by the sophisticated style-integrations, as borne out by the Sharpe ratios and Opdyke test p-values for the hypothesis: $H_0\!: SR_{EWI} \geq SR_j$ where j is the sophisticated integrated portfolio at hand. Table A.VII of the Internet Appendix reports the results.

As a byproduct of this analysis, the comparison across scoring schemes suggests that exploiting the full cross-section of signals (instead of merely the signals provided by extreme quintiles) results in better performance across integration methods, futures classes and cross-class. The average Sharpe ratio of the integrated portfolios indeed stands at 0.67 when $\theta_{i,k,t}$ considers the whole cross-section of signals and drops to 0.58 when $\theta_{i,k,t}$ is only populated with the signals delivered by extreme quintiles. This implies that the scoring approaches that exploit the whole cross section of available futures enable a more informative composite signal.

5.3 Other class-weighting methods for the "everywhere" style-integrated portfolios

To assess the robustness of our prior findings as regards the comparison of style-integration methods in an "everywhere" (cross futures class) context, we now deploy Equation (4) using two simple heuristics to determine the class-weights $\boldsymbol{\varphi}_t$ as an alternative to the mean-variance optimization deployed earlier.

Constant weights. Following common practice among academics and practitioners, we form global portfolios by assigning predetermined time-constant weights to each futures class, i.e. $\boldsymbol{\varphi_t} \equiv \boldsymbol{\varphi}$ in Equation (4); see e.g. Jacobs et al. (2010) and Asness et al. (2015). Specifically, the equity index, fixed income, currency and commodity building blocks (class-specific style-integrated portfolios) are given weights 40%, 40%, 10% and 10%, respectively, towards the everywhere style integrated portfolio. The weights are rebalanced at each portfolio formation time t to its original mix to accommodate within-month movements in the value of the asset class.[11]

Risk-parity (EWMA) weights. Risk parity has gained prominence among practitioners to aggregate asset classes into a global risk-balanced portfolio due to its parsimony and effectiveness (Ang, 2014). This simple heuristic seeks to achieve identical contributions of the each asset class to the risk of the global portfolio, ignoring correlations. Specifically, the importance given to each futures class, $c = 1, \ldots, 4,$ at each portfolio formation time t is inversely proportional to the expected volatility of the asset class, $\varphi_t^c \equiv 1/\sigma_t^c$ in Equation (4). Following Natixis (2015) and Moskowitz et al. (2012) inter alia, we obtain the volatility σ_t^c using the forward-looking Exponentially Weighted Moving Average (EWMA) model of

[11] We also used 50%, 30%, 10% and 10% weights for equity index, fixed income, currency and commodity futures, respectively, or equal class weights. The key findings remain unchallenged.

Riskmetrics' tool, a specific case of GARCH(1,1) model that does not require parameter estimation

$$\sigma_t^c = \sqrt{(1-\lambda)\sum_{j=0}^{m-1}\lambda^j (r_{c,t-j} - \bar{r}_{c,t})^2}$$

where $m = 60$ months in our context and $\bar{r}_{c,t}$ is the average return over those past 60 months. We use the smoothing parameter value $\lambda = 0.97$ as recommended by Riskmetrics for monthly data. The resulting allocations are also standardized to ensure full investment.

Finally, we consider a direct approach to constructing the everywhere style-integrated portfolio which is a one-stage version of the above risk-parity approach as deployed by Moskowitz et al. (2012). At each portfolio formation time *t*, we apply the methods discussed in Section 2.3 to the entire cross-section of futures contracts to obtain the style-integrated allocations, $\phi_{i,t},\ i = 1, \dots, N$ $(N = 131)$ and scale each by the expected volatility of the corresponding futures contract using the EWMA model. Thus, the everywhere style-integrated portfolio uses the allocations $\breve{\phi}_{i,t} = \frac{\phi_{i,t}}{\sigma_{i,t}}$, $i = 1, \dots, N$ $(N = 131)$. These allocations are finally standardized to ensure full investment, that is, $\tilde{\breve{\phi}}_{i,t} = \breve{\phi}_{i,t} / \sum_{i=1}^{N} \left|\breve{\phi}_{i,t}\right|$ where $\sum_{i=1}^{N} \tilde{\breve{\phi}}_{i,t} = 1$.

The latter approaches to constructing everywhere style-integrated portfolios – the two stage approach and the direct approach -- have in common their risk-parity flavour. They differ primarily in that the two-stage approach allows for distinct style weights per futures class, $\boldsymbol{\omega}_{t(c)}$, the direct approach accounts for differences in volatility in the instruments within each futures class; for instance, natural gas versus gold or wheat in the commodity futures class.

As Table A.VIII of the Internet Appendix reveals, the main finding of our paper as regards the unrivalled performance of the EWI strategy is not challenged by the choice of the class-weighting approach. Although it goes beyond the scope of the paper, we compare for a given style-integration strategy, the Sharpe ratios obtained using the four class-weighting schemes entertained in the paper. While we do not claim that either of these schemes is optimal, we observe that the simplest heuristic that assigns constant weights to the four futures classes is the most effective in line with previous findings in the literature (Jacobs et al., 2014). In particular, the everywhere EWI portfolio based on constant weights 40% (equity index), 40% (fixed income), 10% (currencies) and 10% (commodities) stands out with a Sharpe ratio of 1.13, while the next most effective approach to select the class weights is the unrestricted mean-variance approach leading to an everywhere EWI portfolio with a Sharpe ratio of 1.03. The naïve risk-parity schemes (two-stage in Panel B or one-stage in Panel C of Table A.VIII) are the least effective.

5.4 Is the superior economic performance of EWI due to data snooping?

Employing the same dataset repetitively to test the performance of many investment strategies can trigger false discoveries -- this is the data snooping issue as it is understood by practitioners. Now we conduct the Superior Predictive Ability test of Hansen (2005) based on Sharpe ratio differences, as outlined next, to alleviate the impact of data snooping on our empirical inference.

Adopting the EWI portfolio strategy as benchmark, we appraise the $M = 27$ portfolio strategies studied in the paper (five standalone styles discussed in Section 2.2, six sophisticated style-integration strategies discussed in Section 2.3 and 16 variants thereof as discussed in Section 5.1). Let SR_j denote the Sharpe ratio of the *j*th portfolio strategy ($j = 1, \dots, M$) and define SR_{EWI} as the Sharpe ratio of the EWI strategy. Relative performance is measured in terms of differences between both Sharpe ratios, $d_j \equiv SR_j - SR_{EWI}$. The expected "loss" of the *j*th strategy relative to the benchmark is therefore $E[d_j] = E[\, SR_j - SR_{EWI}]$. Strategy j is better in terms of Sharpe ratio than the benchmark (EWI) if and only if

$E[d_j] > 0$. The null hypothesis is that the best of the M strategies does not obtain a superior Sharpe ratio than the benchmark EWI strategy; *i.e.*, H_0: $max_{j=1,\ldots,M} E[SR_j] \leq E[SR_{EWI}]$.[12]

The bootstrap p-values of the test, reported in Table A.IX of the Internet Appendix, ranging from 0.65 to 0.97 across all futures classes and cross class, are consistently unable to reject H_0. Thus, we can assert that the key finding that the EWI portfolio is unsurpassed by the sophisticated style-integrated portfolios is robust to data snooping biases.

5.5 Longer estimation windows

The sophisticated style-integration approaches, unlike the EWI approach which is parameter-free, suffer from estimation error. It is therefore natural for us to investigate whether the EWI portfolio can be "easily" beaten by simply increasing the length of the lookback (or estimation) window as the estimation error ought to diminish on average with longer estimation windows. To do this, instead of the fixed 60-month rolling windows used thus far to estimate the style-weighting vector $\boldsymbol{\omega}_t$ in Equation (1) we now use: i) recursive windows expanded one month at a time (starting from 60 months) and ii) fixed 120-month length rolling windows. As Table A.X of the Internet Appendix shows, none of sophisticated integrated portfolios significantly outperforms the simpler-to-construct EWI portfolio.

5.6 Are the findings time-specific?

To address this question, we conduct now a sub-period comparison of the style-integration methods based on two economic criteria. We split the sample months into months pertaining to: *i*) high versus low volatility regimes specific to each futures class,[13] and *ii*) recession versus expansion months according to the NBER-dated business cycle phases. We report

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[12] The test is based on a statistic with a non-standard distribution that we approximate using the Politis and Romano (1994) random-length bootstrap method described earlier in Section 4.2. The block-length l is geometrically distributed with expected value $1/q$. We use $q = \{0.2, 0.5\}$.

[13] The regimes per futures class (and cross-class) are obtained by fitting a GARCH(1,1) model to the monthly excess returns of a long-only equally-weighted monthly-rebalanced portfolio of all futures contracts. The cut-off points are the means of the fitted annualized volatilities: 12.15% for equity indices, 3.50% for fixed income, 7.67% for currencies, 10.86% for commodities, and 3.40% for cross-class (where the cross-class portfolio is that obtained by an unconstrained mean-variance optimizer).

Sharpe ratios and test the null hypothesis that EWI is unchallenged by the sophisticated style-integrated portfolio at hand. We also report the rank of each strategy in each sub-sample -- a number ranging between 1 (lowest Sharpe ratio) and 7 (highest Sharpe ratio) – and the instability-adjusted mean rank, as earlier. Notwithstanding the small number of months in some of the regimes (e.g., recessions) the results, presented in Table A.XI of the Internet Appendix, suggest that the Sharpe of the EWI portfolio remains superior to that of the alternative integrated portfolios as borne out by large Opdyke test p-values for $H_0: SR_{EWI} \geq SR_j$; the only exception is the low-volatility regime for the equity futures cross-section where the SMI portfolio significantly outperforms the EWI portfolio at the 10% level. As regards the performance ranking, the highest instability-adjusted mean rank is clearly achieved by the EWI portfolio strategy which is thus confirmed as the preferred one followed by the CSI strategy, in line with our earlier findings.

6. Conclusions

The asset pricing literature has identified a set of long-short investment strategies, termed styles, backed by reasonable economic intuition and out-of-sample tests that deliver attractive long-term risk-adjusted returns pervasively across asset classes and different markets. However, as past performance is not necessarily a good guide for future performance, choosing one style over another may be bewildering for investors, particularly, those interested in broad diversification across multiple asset classes. Following a recent literature, this article studies style-integration defined as the combination of multiple asset characteristics with a view to construct a unique portfolio with simultaneous exposures to many styles. We contribute to the literature by providing a comprehensive analysis of the effectiveness of various existing style-integrations and novel ones. Specifically, we confront the naïve equal-weight-integration (EWI) approach that assigns time-constant and homogeneous weights to the different styles, with a set of "sophisticated" approaches with time-varying and heterogeneous style weights that are estimated from past data according to some criteria such as utility maximization, style rotation, volatility timing, cross-sectional pricing, style momentum and principal components.

Employing cross-sections of futures contracts on equity indices, fixed income, currency and commodity futures to sidestep short-sale constraints and to keep transaction costs low, we construct long-short portfolios according to the aforesaid methods in various scenarios: per futures class and cross-class. The risk-adjusted performance of the naïve EWI portfolio is unrivalled by that of any of the sophisticated style-integrated portfolios consistently in all scenarios. This finding is robust to trading costs, reformulations of the sophisticated integration methods, sub-period analysis, data snooping tests and longer estimation windows.

Our study is ambitious in that it confronts the EWI portfolio with seven sophisticated style-integrated portfolio strategies and variants thererof. Given that new integration methods may be put forward in future research, the main takeaway from our paper is that the naïve EWI approach lends itself as a challenging benchmark to confront any style-integration method with.

References

Aiolfi, M., Timmermann, A., 2006. Persistence in forecasting performance and conditional combination strategies. Journal of Forecasting 135, 31–53.

Amaya, D., Christoffersen, P., Jacobs, K., Vasquez, A., 2015. Does realized skewness predict the cross-section of equity returns? Journal of Financial Economics 118, 135-167.

Amihud, Y., H. Mendelson, L. Pedersen, 2005, Liquidity and asset prices: Foundations and Trends in Finance 1:4, NOW Publishers, Hanover, MA.

Ang, A., 2014. *Asset management: A systematic approach to factor investing*. Oxford University Press.

Arnott, R., Clements, M., Kalesnik, V., Linnainmaa, J., 2018. Factor momentum. University of Southern California working paper.

Asness, C., Moskowitz, T., Pedersen, L., 2013. Value and momentum everywhere. Journal of Finance 68, 929-985.

Asness, C., Ilmanen, A., Israel, R., Moskowitz, T., 2015. Investing with style. Journal of Investment Management 13, 27-63.

Barberis, N., Shleifer, A., 2003. Style investing. Journal of Financial Economics 68, 161-199.

Barroso, P., Santa-Clara, P., 2015a. Momentum has its moments. Journal of Financial Economics 116, 111-120.

Barroso, P., Santa-Clara, P., 2015b. Beyond the carry trade: Optimal currency portfolios. Journal of Financial and Quantitative Analysis 50, 1037-1056.

Blitz, D., De Groot, W., 2014. Strategic Allocation to Commodity Factor Premiums. Journal of Alternative Investments 17, 103-115.

Blitz, D., Van Vliet, P., 2008. Global Tactical Cross-Asset Allocation: Applying Value and Momentum Across Asset Classes. Journal of Portfolio Management 35, 23-38.

Brandt, M., Santa-Clara, P., Valkanov, R., 2009. Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. Review of Financial Studies 22, 3444-3447.

Brooks, J., Palhares, D. and Richardson. S., 2018. Style investing in fixed income. Journal of Portfolio Management, *forthcoming.*

Brunnermeier, M.K., Nagel, S., Pedersen, L.H., 2009. Carry trades and currency crashes. NBER Macroeconomics Annual 23, 313–347.

Chiang, I-H., 2016. Skewness and coskewness in bond returns. The Journal of Financial Research 39, 145–178.

Daniel, K., and T., Moskowitz (2016). Momentum crashes. Journal of Financial Economics, 122 (2), 221-247.

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

DeMiguel, V., Martín-Utrera, A., Nogales, F.J., Uppal, R., 2018. A portfolio perspective on the multitude of firm characteristics. London Business School working paper.

Ehsani, S., Linnainmaa, J. T., 2017. Factor momentum and the momentum factor. USC Marshall School of Business Working Paper

Erb, C., Harvey, C., 2006. The strategic and tactical value of commodity futures. Financial Analysts Journal 62, 69-97.

Fama, E., 1984, Forward and spot exchange rates, Journal of Monetary Economics, 14, 319-338

Fama, E., MacBeth, J., 1973. Risk, returns, and equilibrium: empirical tests. Journal of Political Economy 81, 607-636.

Fischer M., and Gallmeyer. M.F., 2016. Heuristic portfolio trading rules with capital gain taxes. Journal of Financial Economics 119, 611–625

Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., Miffre, J., 2018. The skewness of commodity futures returns. Journal of Banking and Finance 86, 143-158.

Fleming, J., Kirby, C., Ostdiek, B., 2001. The economic value of volatility timing. Journal of Finance 56, 329-352.

Fleming, J., Kirby, C., Ostdiek, B., 2003. The economic value of volatility timing using "realized" volatility. Journal of Financial Economics 67, 473-509.

Fitzgibbons, S., Friedman, J., Pomorski, L., Serban, L., 2016. Long-only style investing: Don't just mix, integrate. AQR Capital Management white paper June 2016.

Frijns, B., Gilbert, A., Zwinkels, R., 2016. On the style-based feedback trading of mutual fund managers. Journal of Financial and Quantitative Analysis 51, 771-800.

Frazzini, A., Israel, R., Moskowitz, T., Novy-Marx, R., 2013. A new core equity paradigm: Using value, momentum and quality to outperform markets. AQR Capital Management white paper March 2013.

Fuertes, A.-M., Miffre, J., Rallis, G., 2010. Tactical allocation in commodity futures markets: Combining momentum and term structure signals. Journal of Banking and Finance 34, 10, 2530–2548

Fuertes, A.-M., Miffre, J., Fernandez-Perez, A., 2015. Commodity strategies based on momentum, term structure and idiosyncratic volatility. Journal of Futures Markets 35, 3, 274-297.

Ghysels, E., Plazzi, A., and Valkanov, R., 2016. Why Invest in Emerging Markets? The Role of Conditional Return Asymmetry. Journal of Finance 71, 2145-2192.

Gorton, G., Rouwenhorst, G., 2006. Facts and fantasies about commodity futures. Financial Analysts Journal 62, 47-68.

Gul, F., 1991. A theory of disappointment aversion. Econometrica 59, 667–686.

Hansen, P.R., 2005. A test for superior predictive ability. Journal of Business and Economic Statistics 23, 365-380.

Jacobs, H., Muller, S. Weber, M., 2014. How should individual investors diversify? An empirical evaluation of alternative asset allocation policies. Journal of Financial Markets 19, 62-85.

Kirby, C., Ostdiek, B., 2012. It's all in the timing: Simple active portfolio strategies that outperform naïve diversification. Journal of Financial and Quantitative Analysis 47, 437-467.

Koijen, R., Moskowitz, T., Pedersen, L., Vrugt, E., 2018. Carry. Journal of Financial Economics, 127, 197-225.

Kroencke, T., Schindler, F., Schrimpf, A., 2014. International diversification benefits with foreign exchange investment styles. Review of Finance 18, 1847–1883.

Ledoit, O., Wolf, M., 2004. A well-conditioned estimator for large-dimensional co-variance matrices. Journal of Multivariate Analysis 88, 365-411.

Leippold, M., Rueegg, R., 2017. The mixed vs the integrated approach to style investing: Much ado about nothing. European Financial Management, forthcoming.

Lin H., Wang, J, and Wu, C., 2011, Liquidity risk and expected corporate bond returns, Journal of Financial Economics, 99, 3, 628-650.

Mancini L., Ranaldo A., and Wrampelmeyer J., 2013. Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums. Journal of Finance 68, 1805-1841

Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A., 2012. Carry Trades and Global Foreign Exchange Volatility. Journal of Finance 67, 681-718.

Miffre, J., and Rallis, G., 2007. Momentum strategies in commodity futures markets. Journal of Banking and Finance 31, 6, 1863-1886.

Moskowitz, T.J., Ooi, Y. H., and Pedersen, L. H., 2012. Time series momentum. Journal of Financial Economics 104, 228-250.

Natixis (2015). Risk parity: choosing a risk-based approach. Natixis Asset Management.

Opdyke J.D., 2007., Comparing Sharpe ratios: So, where are the p-values? Journal of Asset Management 8, 308–336.

Pastor, L., and Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Politis, D.N., Romano, J.P., 1994. The stationary bootstrap. Journal of the American Statistical Association 89, 1303–1313.

Shleifer, A., Summers, L., 1990, The noise trader approach to finance, Journal of Economic Perspectives 4, 19–33.

Szymanowska, M., De Roon, F., Nijman, T., Van Den Goorbergh, R., 2014. An anatomy of commodity futures risk premia. Journal of Finance 69, 453-482.

Timmermann, A., 2006. Forecast combinations. In G. Elliott, C. W. J. Granger, and A. G. Timmermann (Eds., Handbook of Economic Forecasting. Amsterdam: North Holland Press.

Appendix A. Background studies on standalone styles and style-integrations

	Equities	Fixed income	Currencies	Commodities	Across classes
Panel A: Individual-style strategies					
Momentum	Asness et al. (2013, 2015)	Asness et al. (2013, 2015)	Asness et al. (2013, 2015)	Asness et al. (2013, 2015)	Asness et al. (2013, 2015)
	Jegadeesh and Titman (1993)	Brooks et al. (2018)	Menkhoff et al. (2012)	Erb and Harvey (2006)	
	Moskowitz et al. (2012)		Shleifer and Summers (1990)	Miffre and Rallis (2007)	
Value	Asness et al. (2013, 2015)	Asness et al. (2013, 2015)	Asness et al. (2013, 2015)	Asness et al. (2013, 2015)	Asness et al. (2013, 2015)
	DeBondt and Thaler (1985, 1987)	Brooks et al. (2018)			
Carry	Asness et al. (2015)	Asness et al. (2015)	Asness et al. (2015)	Asness et al. (2015)	Asness et al. (2015)
	Koijen et al. (2018)	Brooks et al. (2018)	Fama (1984)	Erb and Harvey (2006	Koijen et al. (2018)
		Koijen et al. (2018)	Koijen et al. (2018)	Koijen et al. (2018)	
			Menkhoff et al. (2012)	Gorton and Rouwenhorst (2006)	
Liquidity	Amihud et al. (2005)	Amihud et al. (2005)	Koijen et al. (2018)	Koijen et al. (2018)	
	Pastor and Stambaugh (2003)	Lin et al. (2011)	Mancini et al. (2013)	Szymanowska et al. (2014)	
Skewness	Amaya et al. (2015)	Chiang (2016)	Brunnermeier et al. (2009)	Fernandez-Perez et al. (2018)	
Panel B: Style-integrated strategies					
EWI	Asness et al. (2013)	Asness et al. (2013)	Asness et al. (2013)	Asness et al. (2013)	
	Blitz and van Kliet (2008)	Brooks et al. (2018)	Kroencke et al. (2014)	Blitz and De Groot (2014)	
	Fitzgibbons et al. (2016)	Blitz and van Kliet (2008)		Fuertes et al. (2015)	Blitz and van Kliet (2008)
	Leippold and Rueegg (2017)				
OI	Brandt et al. (2009)		Barroso and Santa-Clara (2015b)		
	DeMiguel et al. (2018)				
RSI	Barberis and Shleifer (2003)				
	Frijns et al. (2016)				
VTI	Asness et al. (2015)	Asness et al. (2015)	Asness et al. (2015)	Asness et al. (2015)	Asness et al. (2015)
SMI	Arnott et al. (2018)				

Appendix B. Cross-sections of futures contracts

Panel A: 45 equity index futures

Dow-Jones Industrial Average	MSCI Russia	Russell 1000 Value	S&P Industrial
E-mini Dow-Jones Industrial Average	MSCI Taiwan	Russell 2000	S&P Information Technology
E-Mini S&P500	MSCI Thailand	Russell 2000 Growth	S&P Materials
Euro Stoxx 50	MSCI USA	Russell 2000 Value	S&P Small Capitalization
Eurotop 100	MSCI World	Russell 3000	S&P Utilities
Eurotop 300	Nasdaq 100	S&P Citigroup Growth	S&P400 Mid Capitalization
Major Market Index	Nasdaq Biotechnology	S&P Citigroup Value	S&P500
MSCI Asia	Nikkei 225	S&P Consumer Discretionary	Value Line
MSCI EAFE	NYSE composite	S&P Consumer Staples	VIX
MSCI Emerging Markets	PSE Technology	S&P Energy	
MSCI Emerging Markets Latin America	Russell 1000	S&P Finance	
MSCI India	Russell 1000 Growth	S&P Health	

Panel B: 22 fixed Income and interest rate futures

1-Month Eurodollar	30-Year U.S. Treasury Bond
30-Day FED Funds	BC U.S. Aggregate
90-Day U.S. Treasury Bill	Brazil 'C' Barra Index
3-Month CD	Brazil 'EI' Bond Index
3-Month Eurodollar	GNMA Constant Default Rate
3-Month Euromark	Mexican Brady Bond Index
2-Year U.S. Treasury Note	Moody's Bond Index
3-Year U.S. Treasury Note	Municipal Bond Index
5-Year Eurodollar Bundle	Ultra 10-Year U.S. Treasury Note
5-Year U.S. Treasury Note	Ultra Treasury Bond Index
10-Year Agency Note	
10-Year U.S. Treasury Note	

Panel C: 21 currency futures

Australian Dollar	Mexican Peso
Brazilian Real	New Zealand Dollar
Canadian Dollar	Norwegian Krona
Chinese Renmimbi	Polish Zloty
Czech Koruna	Russian Rouble
Deutsche Mark	South African Rand
Euro	Sterling
French Franc	Swedish Krona
Hungarian Forint	Swiss Franc
Israeli Shekel	
Japanese Yen	
Korean Won	

Panel D: 43 Commodity futures

BFP Milk	Frozen Concentrated Orange Juice	NY Harbor ULSD	Sugar Number 14
Brent Crude Oil	Frozen Pork Bellies	Oats	Unleaded Gas
Butter Cash	Gold 100 oz (CBT)	Palladium	Wheat (CBT)
Cheese Cash	Gold 100 oz (CMX)	Platinum	Wheat (KCBT)
Coal	High Grade Copper	RBOB Gasoline	Wheat (MGE)
Cocoa	HR Coil Steel	Rough Rice	White Wheat
Coffee C	Lean Hogs	Silver 1000 oz	WTI Crude Oil
Corn	Light Crude Oil	Silver 500 oz	
Cotton Number 2	Live Cattle	Soyabean Meal	
Electricity JPM	Lumber	Soyabean Oil	
Ethanol	Mini-Soyabeans	Soyabeans	
Feeder Cattle	Natural Gas	Sugar Number 11	

Figure 1. Turnover of standalone-style portfolios and style-integrated portfolios.

The figure plots the turnover of the standalone-style momentum, value, carry, liquidity and skewness portfolios discussed in Section 2.2, and the style-integrated portfolios discussed in Section 2.3, measured as in Equation (5). EWI is equally-weighted integration, OI is optimized (mean-variance) integration, RSI is rotation-of-styles integration, VTI is volatility-timing integration, CSI is cross-sectional pricing integration, SMI is style momentum integration and PCI is principal components integration.

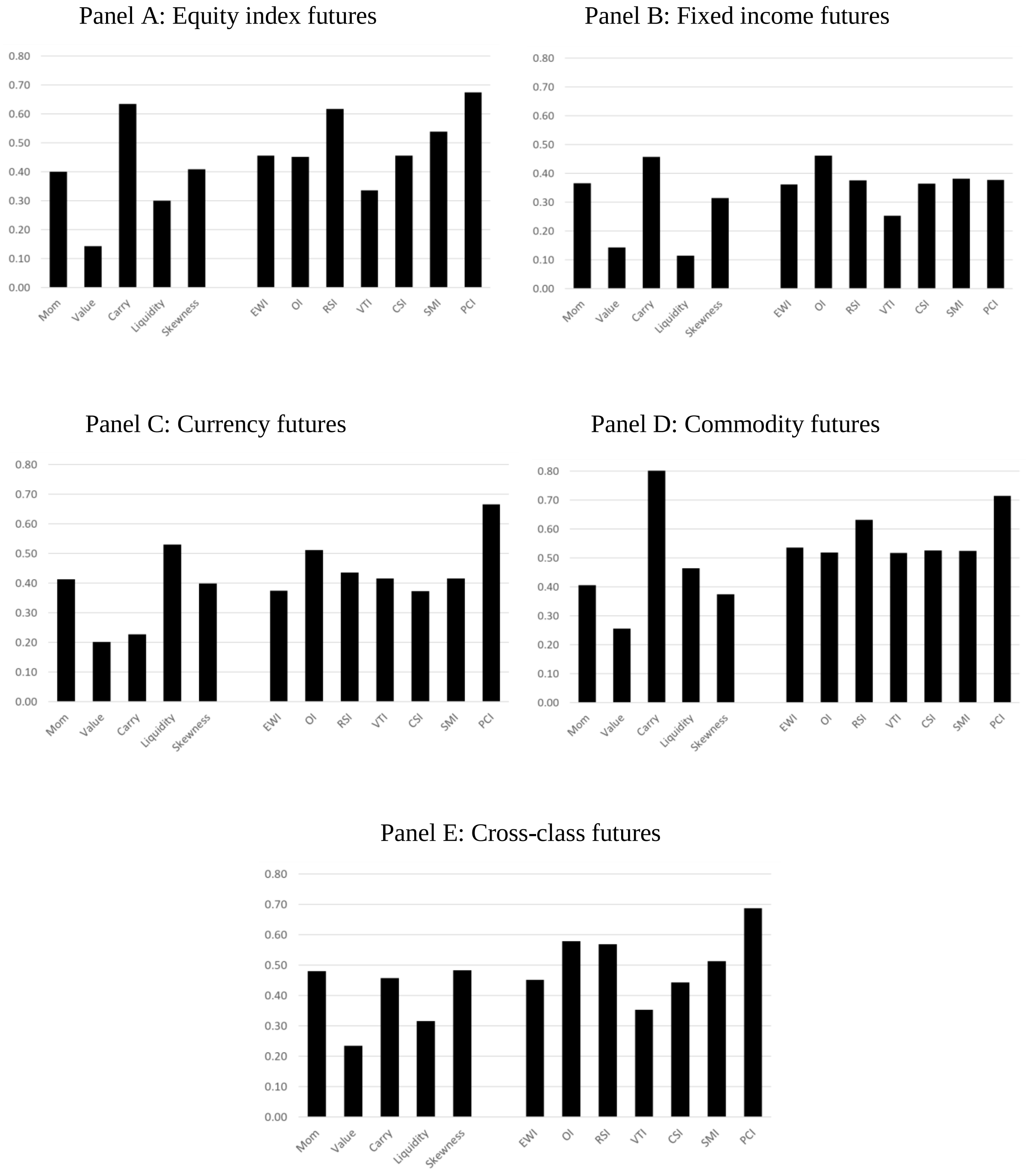

Table 1. Performance of standalone-style portfolios.

The table summarizes the performance of the five long-short standalone style portfolios based on the predictive signals stated in the first row. The results are reported per class of futures in Panels A to D and cross-class in Panel E; the portfolio excess returns span the period indicated in parentheses. The class-weights in Panel E are determined by unconstrained mean-variance optimization. CER is the annualized certainty-equivalent return based on unconstrained mean-variance utility with coefficient of relative risk aversion parameter $\gamma = 5$.

	Mom	Value	Carry	Liquidity	Skewness
	Panel A: Equity index futures (2001/09-2017/12)				
Sharpe ratio	0.8932	0.1246	1.0505	-0.7804	0.2719
Sortino ratio (<0%)	1.2933	0.2001	1.3581	-1.2695	0.3182
Omega ratio (=0%)	2.0009	1.1146	2.4199	0.5699	1.2550
CER	0.0794	-0.0291	0.1076	-0.0195	-0.0032
	Panel B: Fixed income futures (1991/12-2017/12)				
Sharpe ratio	0.3091	-0.0734	0.4149	0.4872	0.2971
Sortino ratio (<0%)	0.4891	-0.1126	0.6075	0.7252	0.4616
Omega ratio (=0%)	1.2880	0.9469	1.3829	1.4574	1.2570
CER	0.0086	-0.0054	0.0112	0.0078	0.0057
	Panel C: Currency futures (1989/08-2017/12)				
Sharpe ratio	0.1069	0.6653	0.4090	0.2938	-0.0381
Sortino ratio (<0%)	0.1246	1.0541	0.3956	0.4461	-0.0421
Omega ratio (=0%)	1.0986	1.6874	1.4622	1.2826	0.9658
CER	-0.0042	0.0249	0.0166	0.0078	-0.0107
	Panel D: Commodity futures (1989/07-2017/12)				
Sharpe ratio	0.5893	0.2672	0.3480	0.1635	0.4532
Sortino ratio (<0%)	1.0498	0.4334	0.5745	0.2298	0.7032
Omega ratio (=0%)	1.5373	1.2192	1.3190	1.1373	1.4030
CER	0.0333	0.0025	0.0089	-0.0016	0.0201
	Panel E: Cross-class futures (2006/09-2017/12)				
Sharpe ratio	0.5768	0.5523	1.2176	0.9328	0.1978
Sortino ratio (<0%)	0.7775	0.8606	1.5814	1.2284	0.2758
Omega ratio (=0%)	1.5637	1.5679	2.5190	2.0342	1.1632
CER	0.0240	0.0187	0.0396	0.0135	0.0034

Table 2. Subsample analysis of standalone-style portfolios.

This table reports per style the annual Sharpe ratio (SR) over 5-year non-overlapping rolling windows and the corresponding rank from 5 (top) to 1 (bottom). The final rows report for each style the mean ranking and volatility of rankings (and corresponding ratio) across time periods and class-specific or cross-class portfolios; a larger ratio for a given style indicates a higher instability-adjusted rank.

	Mom		**Value**		**Carry**		**Liquidity**		**Skewness**	
Time period	SR	Rank	SR	Rank	SR	Rank	SR	Rank	SR	Rank
Panel A: Equity index futures										
2001/09 - 2006/08	1.2795	4	-0.2215	1	1.6372	5	0.1536	3	-0.1891	2
2006/09 - 2011/08	0.3236	3	1.0464	5	0.8137	4	-0.5828	1	-0.1287	2
2011/09 - 2016/08	1.0230	5	-0.3182	2	0.7782	4	-1.8730	1	0.7493	3
2016/09 - 2017/12	5.4843	5	-3.1300	1	4.6561	4	-2.5801	2	2.9219	3
Panel B: Fixed income futures										
1991/12 - 1996/11	0.5833	5	-0.6139	1	0.4169	4	0.2152	2	0.4041	3
1996/12 - 2001/11	0.7551	5	0.5748	3	0.5585	2	0.7452	4	0.4518	1
2001/12 - 2006/11	0.1514	1	0.5142	3	0.3532	2	0.6601	5	0.6330	4
2006/12 - 2011/11	0.1266	3	-0.3075	1	0.7191	5	0.6318	4	0.0554	2
2011/12 - 2016/11	-0.0648	4	-0.2825	1	-0.1496	3	0.2212	5	-0.2005	2
2016/12 - 2017/12	-0.7183	2	-1.0747	1	1.1983	5	0.8280	3	1.0408	4
Panel C: Currency futures										
1989/08 - 1994/07	0.1851	3	0.4200	4	0.0755	2	-0.7263	5	-0.7884	1
1994/08 - 1999/07	-0.1729	1	1.1903	5	0.0911	2	0.6183	4	0.3948	3
1999/08 - 2004/07	1.0640	4	0.6464	3	1.1690	5	0.2163	2	-0.7779	1
2004/08 - 2009/07	0.0211	1	0.7798	5	0.7388	4	0.3671	2	0.5843	3
2009/08 - 2014/07	-0.2424	1	0.5759	4	0.2684	3	0.7323	5	-0.0648	2
2014/08 - 2017/12	0.0166	2	0.3618	3	0.6775	4	0.7944	5	-0.0333	1
Panel D: Commodity futures										
1989/07 - 1994/06	0.8591	5	0.6487	3	-0.4347	1	0.7287	4	0.3838	2
1994/07 - 1999/06	0.5297	3	0.5958	4	-0.2062	1	0.5172	2	1.2560	5
1999/07 - 2004/06	0.9427	5	-0.3016	1	0.4278	4	0.1621	2	0.3983	3
2004/07 - 2009/06	0.4198	4	0.3302	2	0.8936	5	-0.3320	1	0.4004	3
2009/07 - 2014/06	0.5322	5	0.1649	2	0.3199	4	-0.0971	1	0.1863	3
2014/07 - 2017/12	-0.0587	2	0.4616	4	0.8379	5	0.4155	3	-0.3024	1
Panel E: Cross-class futures										
2006/09 - 2011/08	0.1581	5	0.5676	4	0.9810	5	0.0041	1	0.2015	3
2011/09 - 2016/08	0.6218	3	0.4278	2	0.8815	4	1.9385	5	-0.0375	1
2016/09 - 2017/12	3.7915	4	1.3892	2	4.2846	5	2.9284	3	1.1550	1
Mean rank		3.40		2.68		3.68		3.00		2.36
StDev rank		1.47		1.41		1.31		1.50		1.11
Mean/Stdev rank		*2.31*		*1.91*		*2.80*		*2.00*		*2.12*

Table 3. Correlation structure of standalone-style portfolios.

This table reports Pearson pairwise correlations of the excess returns of the standalone-style portfolios. Bold figures denote significant correlations at the 5% significance level or better. The sample periods that the style premia correlation matrices refer to are indicated in parentheses.

	Mom	Value	Carry	Liquidity
Panel A: Equity index futures (2001/09-2017/12)				
Value	-0.11			
Carry	**0.60**	**-0.12**		
Liquidity	**-0.27**	-0.09	**-0.23**	
Skewness	**0.37**	**0.31**	**0.22**	**-0.36**
Panel B: Fixed income futures (1991/12-2017/12)				
Value	**-0.34**			
Carry	**0.63**	**-0.34**		
Liquidity	**0.61**	**-0.45**	**0.81**	
Skewness	**0.21**	**-0.18**	**0.34**	**0.31**
Panel C: Currency futures (1989/08-2017/12)				
Value	**-0.23**			
Carry	**0.15**	**0.40**		
Liquidity	**0.13**	**0.30**	**0.17**	
Skewness	**0.00**	**-0.01**	**0.24**	**0.12**
Panel D: Commodity futures (1989/07-2017/12)				
Value	**-0.51**			
Carry	**0.37**	**-0.27**		
Liquidity	**-0.07**	**0.00**	**-0.13**	
Skewness	**-0.02**	**-0.04**	**-0.06**	**0.14**
Panel E: Cross-class futures (2006/09-2017/12)				
Value	**0.26**			
Carry	**0.29**	**0.09**		
Liquidity	**0.04**	**-0.02**	**0.36**	
Skewness	**0.11**	**-0.05**	**0.25**	**0.03**

Table 4. Performance of style-integrated portfolios.

The table summarizes the style-integrated portfolios in five scenarios – individual futures classes and in Panels A to D and cross-class in Panel E. EWI is equally-weighted integration, OI is optimized (mean-variance) integration, RSI is rotation-of-styles integration, VTI is volatility-timing integration, CSI is cross-sectional pricing integration, SMI is style momentum integration and PCI is principal components integration. CER is the annualized certainty-equivalent return with unconstrained mean-variance utility and CRRA parameter $\gamma = 5$. The p-values of the Opdyke (2007) test are for the null hypothesis $H_0: SR_{EWI} \geq SR_j$ versus $H_A: SR_{EWI} < SR_j$ where j is the sophisticated style-integrated portfolio at hand. The asymptotic p-values of the CER test are for $H_0: CER_{EWI} \geq CER_j$ versus $H_A: CER_{EWI} < CER_j$. The sample periods in each panel are shown in parentheses. The class-weights in the portfolio in Panel E are determined by unconstrained mean-variance optimization of the everywhere style-integrated portfolio.

	EWI	OI	RSI	VTI	CSI	SMI	PCI
	Panel A: Equity index futures (2001/09-2017/12)						
Sharpe ratio	1.0043	0.7576	0.9566	-0.0056	0.9368	0.9680	0.8709
Opdyke test p-value	-	(0.8082)	(0.5789)	(0.9985)	(0.6626)	(0.5742)	(0.7052)
Sortino ratio (<0%)	1.3146	1.0831	1.2546	-0.0094	1.1667	1.4914	1.0785
Omega ratio (=0%)	2.2440	1.9771	2.1244	0.9953	2.1008	2.1788	2.0381
CER	0.0919	0.0420	0.0884	-0.0033	0.0796	0.0935	0.0693
CER asymptotic p-value	-	(0.9514)	(0.5389)	(0.9969)	(0.8583)	(0.4771)	(0.7819)
	Panel B: Fixed income futures (1991/12-2017/12)						
Sharpe ratio	0.4564	0.2141	0.2863	0.4542	0.4442	0.2596	0.2156
Opdyke test p-value	-	(0.9021)	(0.8830)	(0.4996)	(0.5908)	(0.9424)	(0.9199)
Sortino ratio (<0%)	0.6561	0.3239	0.4377	0.6369	0.6378	0.3721	0.2992
Omega ratio (=0%)	1.4742	1.2015	1.2772	1.4414	1.4642	1.2365	1.1813
CER	0.0125	0.0034	0.0074	0.0097	0.0122	0.0059	0.0044
CER asymptotic p-value	-	(0.9513)	(0.8510)	(0.8249)	(0.7358)	(0.9514)	(0.9239)
	Panel C: Currency futures (1989/08-2017/12)						
Sharpe ratio	0.4037	0.1845	0.1055	0.4540	0.4125	0.1479	0.0378
Opdyke test p-value	-	(0.8869)	(0.9911)	(0.2698)	(0.4318)	(0.9695)	(0.9760)
Sortino ratio (<0%)	0.4246	0.1953	0.0897	0.5630	0.4340	0.1446	0.0398
Omega ratio (=0%)	1.4114	1.1722	1.1121	1.4440	1.4232	1.1414	1.0344
CER	0.0152	0.0029	-0.0046	0.0169	0.0158	-0.0006	-0.0066
CER asymptotic p-value	-	(0.8967)	(0.9927)	(0.3393)	(0.3175)	(0.9739)	(0.9813)
	Panel D: Commodity futures (1989/07-2017/12)						
Sharpe ratio	0.9738	0.7440	0.4367	0.8391	0.8498	0.6691	0.0051
Opdyke test p-value	-	(0.8965)	(0.9929)	(0.8579)	(0.8462)	(0.9477)	(0.9999)
Sortino ratio (<0%)	1.6011	1.2161	0.7428	1.2682	1.2656	1.2377	0.0077
Omega ratio (=0%)	2.1059	1.7593	1.3921	1.8763	1.9182	1.6420	1.0038
CER	0.0571	0.0413	0.0190	0.0460	0.0474	0.0379	-0.0169
CER asymptotic p-value	-	(0.9101)	(0.9863)	(0.9849)	(0.9760)	(0.9277)	(0.9999)
	Panel E: Cross-class futures (2006/09-2017/12)						
Sharpe ratio	1.0255	0.2323	0.7245	1.1664	0.8129	0.7378	0.5925
Opdyke test p-value	-	(0.9864)	(0.8041)	(0.3329)	(0.8707)	(0.8116)	(0.8563)
Sortino ratio (<0%)	1.4870	0.3442	0.9770	1.9371	1.0321	1.1670	0.9089
Omega ratio (=0%)	2.1072	1.1941	1.7690	2.3526	1.8548	1.7166	1.5874
CER	0.0264	0.0041	0.0300	0.0172	0.0213	0.0284	0.0217
CER asymptotic p-value	-	(0.9956)	(0.3931)	(0.9152)	(0.9695)	(0.4286)	(0.6263)

Table 5. Subsample analysis of style-integrated portfolios.

This table reports per style-integrated approach the annual Sharpe ratio (SR) over 5-year non-overlapping rolling windows, the Opdyke test p-value for the hypothesis $H_0: SR_{EWI} \geq SR_j$ versus $H_A: SR_{EWI} < SR_j$ where j is a sophisticated style-integrated portfolio strategy, and the corresponding rank from 7 (top) to 1 (bottom). The final rows report for each style the mean ranking and volatility of rankings (and corresponding ratio) across time periods and class-specific or cross-class portfolios; a larger ratio for a given style indicates a higher instability-adjusted rank.

	EWI		OI			RSI			VTI			CSI			SMI			PCI		
	SR	Rank	SR	*p*-value	Rank	SR	*p*-value	Rank	SR	*p*-value	Rank	SR	*p*-value	Rank	SR	*p*-value	Rank	SR	*p*-value	Rank
Panel A: Equity index futures																				
2001/09 - 2006/08	1.2919	7	0.8566	(0.81)	1	1.1301	(0.65)	4	1.0255	(0.73)	2	1.2793	(0.52)	6	1.1281	(0.65)	3	1.2198	(0.56)	5
2006/09 - 2011/08	0.7042	5	0.8201	(0.39)	7	0.7310	(0.47)	6	-0.5730	(0.97)	1	0.6425	(0.61)	4	0.6327	(0.61)	3	0.4484	(0.72)	2
2011/09 - 2016/08	0.9760	7	0.2414	(0.84)	2	0.7782	(0.70)	5	-1.8422	(1.00)	1	0.7567	(0.79)	4	0.8950	(0.58)	6	0.5157	(0.90)	3
2016/09 - 2017/12	4.5240	4	4.3826	(0.51)	2	4.7692	(0.49)	6	-1.6522	(1.00)	1	4.5054	(0.50)	3	5.0228	(0.47)	7	4.6243	(0.50)	5
Panel B: Fixed income futures																				
1991/12 - 1996/11	0.4145	3	0.4591	(0.45)	4	0.6252	(0.28)	7	0.3444	(0.64)	1	0.4094	(0.52)	2	0.5123	(0.30)	5	0.5564	(0.32)	6
1996/12 - 2001/11	0.8761	7	0.3559	(0.88)	1	0.7551	(0.66)	4	0.8572	(0.49)	5	0.8590	(0.53)	6	0.6369	(0.77)	3	0.4508	(0.91)	2
2001/12 - 2006/11	0.5544	5	0.4461	(0.61)	3	0.3088	(0.78)	1	0.6312	(0.33)	7	0.5555	(0.50)	6	0.4151	(0.78)	2	0.4768	(0.69)	4
2006/12 - 2011/11	0.4978	6	0.4202	(0.58)	4	-0.3565	(0.97)	1	0.5559	(0.38)	7	0.4587	(0.61)	5	-0.2821	(0.99)	3	-0.3429	(0.93)	2
2011/12 - 2016/11	-0.2309	2	-0.5827	(0.77)	1	-0.0771	(0.33)	5	-0.1761	(0.41)	4	-0.2171	(0.43)	3	0.1217	(0.16)	7	-0.0183	(0.33)	6
2016/12 - 2017/12	0.9705	4	0.1349	(0.75)	2	0.8280	(0.58)	3	0.9771	(0.50)	6	0.9713	(0.50)	5	-0.9757	(0.95)	1	1.0817	(0.44)	7
Panel C: Currency futures																				
1989/08 - 1994/07	-0.3765	1	0.9101	(0.02)	7	-0.2471	(0.39)	5	-0.2632	(0.24)	4	-0.3328	(0.35)	3	0.3401	(0.08)	6	-0.3386	(0.46)	2
1994/08 - 1999/07	0.3256	6	-0.3387	(0.97)	2	-0.2253	(0.98)	3	0.5837	(0.07)	7	0.2658	(0.81)	5	-0.3993	(0.98)	1	0.2200	(0.68)	4
1999/08 - 2004/07	1.0883	6	0.2327	(0.97)	1	0.4490	(0.91)	3	0.7127	(0.85)	5	1.1123	(0.47)	7	0.5108	(0.93)	4	0.2616	(0.91)	2
2004/08 - 2009/07	0.7606	6	0.2993	(0.92)	2	0.7388	(0.54)	4	0.7210	(0.57)	3	0.7898	(0.45)	7	0.7505	(0.52)	5	-0.2452	(0.95)	1
2009/08 - 2014/07	0.4159	4	0.3742	(0.52)	3	0.0665	(0.77)	2	0.4770	(0.34)	7	0.4593	(0.37)	5	0.4764	(0.44)	6	-0.0283	(0.87)	1
2014/08 - 2017/12	0.6402	5	0.0650	(0.87)	2	0.7576	(0.37)	7	0.6508	(0.48)	6	0.6327	(0.51)	4	0.0061	(0.94)	1	0.1571	(0.73)	3
Panel D: Commodity futures																				
1989/07 - 1994/06	1.0356	6	1.0837	(0.46)	7	0.6507	(0.74)	2	0.7817	(0.81)	3	0.8823	(0.71)	4	0.8924	(0.61)	5	0.3543	(0.94)	1
1994/07 - 1999/06	1.3206	5	1.2672	(0.55)	3	0.2652	(0.99)	1	1.4259	(0.40)	7	1.3734	(0.45)	6	1.3111	(0.50)	4	0.5958	(0.91)	2
1999/07 - 2004/06	0.9890	7	0.6849	(0.78)	4	0.1962	(0.91)	1	0.7905	(0.73)	5	0.8331	(0.69)	6	0.5545	(0.82)	3	0.3121	(0.87)	2
2004/07 - 2009/06	1.0264	7	0.6759	(0.85)	4	0.2725	(0.93)	2	0.8585	(0.70)	6	0.7722	(0.76)	5	0.5298	(0.90)	3	-0.8601	(1.00)	1
2009/07 - 2014/06	0.6247	6	0.1511	(0.84)	3	0.3367	(0.74)	4	0.6697	(0.42)	7	0.5208	(0.70)	5	0.1173	(0.86)	2	-0.2333	(0.89)	1
2014/07 - 2017/12	0.7818	6	0.3425	(0.76)	2	1.1298	(0.30)	7	0.4163	(0.89)	3	0.6787	(0.64)	5	0.5711	(0.63)	4	-0.1518	(0.92)	1
Panel E: Cross-class futures																				
2006/09 - 2011/08	0.7699	7	0.2331	(0.84)	2	0.2035	(0.85)	1	0.5911	(0.69)	5	0.6307	(0.71)	6	0.2874	(0.83)	3	0.3021	(0.80)	4
2011/09 - 2016/08	0.8271	6	-0.1564	(0.97)	1	0.8182	(0.51)	5	1.5241	(0.09)	7	0.5312	(0.91)	4	0.4991	(0.76)	3	-0.0139	(0.90)	2
2016/09 - 2017/12	3.8211	5	3.5351	(0.54)	4	4.0695	(0.47)	7	2.0412	(0.82)	1	3.8908	(0.49)	5	3.1786	(0.60)	2	3.3378	(0.57)	3
Mean rank		5.32			2.96			3.84			4.44			4.84			3.68			2.88
StDev rank		1.60			1.84			2.12			2.29			1.28			1.80			1.79
Mean/Stdev rank		*3.33*			*1.61*			*1.82*			*1.94*			*3.78*			*2.05*			*1.61*