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A Comprehensive Appraisal of Style-Integration Methods

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ABSTRACT

The paper provides a comprehensive appraisal of style-integration methods in equity index, fixed income, currency, and commodity futures markets. We confront the naïve equal-weight integration (EWI) method with a host of 'sophisticated' style-integrations that derive the style exposures using past data according to utility maximization, style rotation, volatility timing, cross-sectional pricing, style momentum or principal components criteria. The analysis, conducted separately per futures market and cross-markets, reveals that the EWI portfolio is unrivalled in terms of risk-adjusted performance while it sustains a relatively low turnover. The findings are robust to analyses that entertain variants of the sophisticated integrations, longer estimation windows, several asset scoring schemes, data snooping tests, sub-periods evaluation and equities in place of futures.

JEL classifications: G13, G14

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1. Introduction

A variety of long-short investment approaches (or styles) have been put forward in the literature to capture attractive returns at a relatively low risk, leaving investors somewhat bewildered by the possibilities. The task of choosing one style over another is all the more challenging that good performance in the past is no guarantee of good performance in the future. Against this background, since at least the seminal work of Brandt et al. (2009) various studies have suggested to *integrate* styles instead. The idea is to construct a unique portfolio with multiple style exposures that offers a better performance than that of the underlying standalone-style portfolios. However, different methods can be adopted to form a style-integrated portfolio and to date there has been no attempt to appraise them comparatively in a self-contained paper.

The present paper fills this gap by providing academics and practitioners alike with a comprehensive comparison of style-integration methods: the naïve style-integration that assigns time-constant, equal weights to the standalone styles (Equal-Weighted Integration, EWI, hereafter) and six other style-integrations that we term "sophisticated" in the sense that they allow for time-varying, heterogeneous style weights. The six sophisticated style-integrations have in common that the style weights are derived from past style return data but they differ in the criteria adopted: utility maximization (Optimized Integration, OI), 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 and RSI methods have already been employed (e.g., Barberis and Shleifer, 2003; Brandt et al., 2009; Frazzini et al., 2013; Fischer and Gallmeyer, 2016; Fitzgibbons et al., 2016; Ghysels et al., 2016; and DeMiguel et al., 2019), but the VTI, SMI, CSI and PCI methods are new to the style-integration literature, to our best knowledge.

Our paper takes style integration as a valid proposition[1] and contributes to the literature by providing a comprehensive appraisal of the above style-integration methods. To put this differently, given an investor's preference for style integration, we aim to find out the most effective approach he or she shall adopt; this is done by providing a comparative analysis of the out-of-sample performance of various style-integration methods. Our main analysis centers on futures markets (equity, fixed income, currency and commodity) as these markets offer the advantages of deep liquidity, no constraint on shorting and low transaction costs but we provide also robustness evidence from equity markets.

Our conclusions show that EWI is for two reasons the most appealing style-integration method. On the one hand, this approach is very easy to deploy as no parameter estimation is required. On the other hand, as borne out by our findings, the EWI portfolio affords a reward-to-risk profile that is unsurpassed by that of alternative style-integrated portfolios. The inability of the sophisticated style-integration portfolios to outperform the EWI portfolio indirectly suggests that the benefits from allowing time-varying and heterogeneous style-weights are offset by parameter estimation error and representativeness heuristic bias.[2] The key finding that the EWI approach is unsurpassed by sophisticated style-integration methods stems from separate analyses conducted per futures class (equity, fixed income, currency and commodity), across-futures classes and in equity markets. Moreover, the finding is not challenged in a battery of robustness analyses that entertain variants of the sophisticated style-integrations, different

[1] We assume that our representative investor seeks exposure to multiple styles (hereafter, style integration) as opposed to pursuing a single style. This is motivated by recent evidence that establishes the benefits of style-integration for equities (Brandt et al., 2009; Frazzini et al., 2013, Fischer and Gallmeyer, 2016; Fitzgibbons et al., 2016), currencies (Kroencke et al., 2014; Barroso and Santa-Clara, 2015b) and commodity futures (Fuertes et al., 2015).

[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.

asset scoring schemes, data snooping tests, longer lookback windows and different economic sub-periods.

Our article speaks to a recent but quickly growing literature on style-integration in equity markets (Brandt et al., 2009; Frazzini et al., 2013; Fischer and Gallmeyer, 2016; Fitzgibbons et al., 2016; Ghysels et al., 2016; Leippold and Rueegg, 2018; DeMiguel et al., 2019), currency markets (Kroencke et al., 2014; Barroso and Santa-Clara, 2015b) and commodity markets (Fuertes et al., 2015). A common denominator to these studies is their focus on one or at most two style-integration approaches. By contrast, our article conducts a comprehensive horse-race of style-integration methods to inform academics and practitioners alike on their relative risk-adjusted performance.

By providing evidence that the EWI strategy is not challenged by sophisticated style-integration methods, our article speaks to two other literatures. First, it adds to a voluminous literature on forecast combination where the equal-weight forecast combination approach has become 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, our key finding is reminiscent of the evidence in the comprehensive N assets diversification study by DeMiguel et al. (2009) which advocates the naïve $1/N$ heuristic.

The rest of the paper proceeds as follows. Section 2 presents the style-integration framework as adapted to futures contracts, the standalone styles, evaluation tools and statistical tests. Section 3 outlines the data. Section 4 discusses the main results on the out-of-sample performance of the style-integrated portfolios. Section 5 discusses various robustness rests, before concluding in Section 6.

2. Methodology

2.1 Style-integrated futures portfolios

To set the stage, we begin by laying out the portfolio allocation framework developed by Brandt et al. (2009) as adapted to assets in zero-net supply by Barroso and Santa-Clara (2015b). Let the available cross-section of futures contracts be denoted $i = 1,..,N$, the investment styles $k = 1,\ldots,K$, and the portfolio formation times $t = 1,\ldots,T$; 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 captured by the $N \times 1$ vector $\boldsymbol{\phi}_t$ which can be obtained as follows

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

where $\boldsymbol{\Theta}_t$ is an $N \times K$ matrix of asset scores that reflects in the kth column the relative "ranking" of the N assets according to the kth style. For now, the elements of the score matrix $\boldsymbol{\Theta}_t$ are the raw signal values appropriately standardized cross-sectionally (e.g. Brandt et al., 2009, Barroso and Santa-Clara, 2015b, Fischer and Gallmeyer, 2016, Ghysels et al., 2016); 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 style recommends a long (short) position on asset i at time t if $\theta_{i,k,t} > 0$ ($\theta_{i,k,t} < 0$) which we refer to as $\theta^L_{i,k,t}$ ($\theta^S_{i,k,t}$) hereafter. Using the standardized signals as scores naturally implies identical 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 $N_L + N_S = N$.

The $K \times 1$ weight vector $\boldsymbol{\omega}_t$ captures the relative importance given to each of the K styles; unless noted otherwise, these weights are unrestricted ($\boldsymbol{\omega}_t \in R^K$) to allow for the possibility of reversing a style $\left(\omega_{k,t} < 0\right)$ in the aftermath of a temporary crash. Finally, the $N \times 1$ vector $\boldsymbol{\phi}_t$ represents 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 nature of the position, long or short, that the style-integrated portfolio takes on asset i at time t. The vector $\boldsymbol{\phi}_t$ is scaled to $\widetilde{\boldsymbol{\phi}}_t$; 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 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; then $\tilde{\boldsymbol{\phi}}_{t+1}$ is obtained which defines a new style-integrated portfolio, and so forth. We adopt an out-of-sample (or real time) approach throughout the analysis meaning that at each time *t* the final vector $\tilde{\boldsymbol{\phi}}_t$ is determined using a lookback 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 specific entry equal to 1 and the *K*-1 remaining entries equal to 0. For our horse race of style-integration methods we focus, without loss of generality, on a few styles or factors that have been suggested in the literature as sources of risk premia pervasively across asset classes. Appendix A, Panel A lists some 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 sorting signal for the cross section of front-end futures contracts is the average of their daily excess returns in the preceding year; namely, $x_{i,t} \equiv \frac{1}{D}\sum_{j=0}^{D-1} r_{i,t-j}$ where *D* denotes the total 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,

[3] Following Asness et al. (2013) and Koijen et al. (2018), in order to simplify the exposition we define the signals per style identically across all the futures classes. 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 most effective style-integration method.

$x_{i,t} \equiv ln\frac{\frac{1}{D}\sum_{d=0}^{D-1} f_{i,t-j}^{t_1}}{f_{i,t}^{t_1}}$ 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.

We consider the *carry* style that relies on the roll-yield defined as the difference between the logarithmic front- and second-nearest futures prices, $x_{i,t} \equiv \ln\left(f_{i,t}^{t_1}\right) - \ln(f_{i,t}^{t_2})$ where t_1 and t_2 denote the corresponding contract maturity. The idea is to buy (sell) those futures contracts with negatively (positively) sloped term structure 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, $x_{i,t} \equiv -\frac{1}{D}\frac{\sum_{j=0}^{D-1}\left(r_{i,t-j}-\mu_i\right)^3}{\sigma_i^3}$ with *D* days.

2.3. Style-integration methods

Now we discuss several style-integration methods that arise from Equation (1) under different criteria to determine the style-weights vector, $\boldsymbol{\omega}_t$. As explained next, the first method is based on fixed style weights, whereas the other six style-integration methods are called "sophisticated" in our paper because they allow for time-varying and heterogeneous style weights that are estimated using 60 months of prior data at each portfolio formation time *t*.

Equal-Weight Integration (EWI). The naïve EWI method assigns fixed homogeneous weights to the K signals at each portfolio formation time $t = 1, \dots, T$; namely, $\boldsymbol{\omega}_t = \boldsymbol{\omega} = (1/K, \dots, 1/K)'$. 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). The style-weighting vector $\boldsymbol{\omega}_t$ at each portfolio formation time *t* is the solution of the investor's utility-maximization 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 standalone-style portfolio. Following DeMiguel et al. (2019), the OI style weights are determined under an unconstrained mean-variance utility assumption; namely, $E_t\left[U\left(r_{P,t+1}\right)\right] = \boldsymbol{\omega}_t'\boldsymbol{\mu}_t - \frac{\gamma}{2}\boldsymbol{\omega}_t'\boldsymbol{\Sigma}_t\boldsymbol{\omega}_t - \gamma\boldsymbol{\omega}_t'\boldsymbol{\sigma}_{bk,t}$ where the $K \times 1$ vector $\boldsymbol{\mu}_t$ contains the expected standalone-style portfolio excess returns with the *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 $\boldsymbol{\sigma}_{bk,t}$ is the $K \times 1$ vector of covariances between the benchmark portfolio and standalone-style portfolios. $\boldsymbol{\sigma}_{bk,t}$ is redundant in the context of futures contracts in zero-net supply but is considered when studying equity integration (Section 5.6). We use the closed-form solution

$\boldsymbol{\omega}_t \equiv \frac{1}{\gamma}\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\mu}_t$ with relative risk aversion coefficient γ=5. This is essentially the OI approach of Brandt et al. (2009) adapted to zero net supply assets as in Barroso and Santa-Clara (2015b).

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 ignores the remaining 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 the performance ranking of the styles.

Volatility Timing Integration (VTI). This method is inspired by the Kirby and Ostdiek (2012) volatility-timing allocation of *N* assets into a portfolio. It defines the relative exposure to a style as inversely proportional to the variance of its past excess returns, $\omega_{k,t} \equiv 1/\sigma_{k,t}^2$ and hence, it is a restricted (or extreme "shrinkage") version of the mean-variance OI approach that makes the assumption of equal expected returns for the individual styles and zero covariances.

Cross-Sectional Pricing Integration (CSI). The style-weighting scheme in the CSI method reflects the relative ability of the standalone styles (or factors) to explain the cross-sectional variation in the $i = 1, \ldots, N$ futures contracts. Higher weights are given to the styles or factors with superior pricing ability. As in Fama and MacBeth (1973), at each month-end *t* we estimate a univariate *time-series* OLS regression per futures contract $i = 1, \ldots, N$ and style $k = 1, \ldots, K$ (a total of $N \times K$ regressions) using the preceding 60-month window of data

$$r_{i,s} = a_{i,k} + b_{i,k} r_{k,s} + \varepsilon_{i,s}, s = t - 59, \ldots, t \quad (2)$$

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 in each of those 60 months a *cross-sectional* OLS regression

$$r_{i,s} = \lambda_{k,s}^0 + \lambda_{k,s}^1 \hat{b}_{i,k} + \epsilon_{i,s}, i = 1,2, \ldots, N \quad (3)$$

where $s = t - 59, \dots, t$ ($60 \times K$ regressions). The explanatory power of the *k*th factor in Equation (3) defines the weight of the *k*th style in the CSI portfolio as $\omega_{k,t} \equiv \frac{1}{60}\sum_{j=0}^{60-1} R_{k,t-j}^2$.

Style Momentum Integration (SMI). The thrust of this approach is to exploit any continuation or momentum over time in the performance of the standalone styles. Accordingly, the style weights at each portfolio formation time *t* are dictated by the average excess returns of the standalone-style portfolios over a 60-month lookback period as $\omega_{k,t} \equiv \frac{1}{60}\sum_{j=0}^{60-1} r_{k,t-j}$.[4]

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, $j = 1, \dots, K$), and *m* is the number of principal components that explain at least τ of the total variation in the standalone-style premia. We use the conservative threshold value τ=90%.

Appendix A, Panel B lists a few representative studies that deploy the EWI, OI and RSI methods; by contrast, to our best knowledge, the VTI, CSI, SMI or PCI methods have not been considered in any style-integration study as yet. The discussion has hitherto 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 discuss next the construction of "everywhere" style-integrated portfolios with a view to appraise their relative effectiveness also in this scenario.

2.4. Everywhere style-integration

[4] We thank an anonymous referee for this suggestion. The former RSI can be seen as an extreme shrinkage version of SMI; namely, at each portfolio formation time it assigns all the weight to one style. The two methods also differ in their reliance on past risk-adjusted mean returns and mean returns, respectively.

As argued by Barberis and Shleifer (2003), investors have a tendency to classify decisions into categories to facilitate investment decision making. In a cross-market style-integration setting such as ours, this translates into two sequential decisions. The first decision pertains to the formation of style-integrated portfolios within a given class of futures (as discussed in Section 2.3). The second decision concerns the weighting of the class-specific integrated portfolios which we formalize by writing the excess returns of the everywhere integrated portfolio as a weighted combination of the class-specific style-integrated portfolio returns

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

where $\varphi_t^c,\ c = 1,..,4$ are the class weights that capture the desired importance given by the investor to the equity index, fixed income, currency and commodity futures markets, respectively, at each portfolio formation time *t*, and $r_{t+1}^c = f(\boldsymbol{\omega}_{t+1}^c)$ is the excess return from month *t* to *t*+1 of the *c*th futures class integrated portfolio which hinges on the choice of style-weighting vector $\boldsymbol{\omega}_t^c$. We consider the following three schemes to determine $\boldsymbol{\varphi_t}$.

Mean-variance weights. The class-weighting vector, $\boldsymbol{\varphi_t}$, is obtained at each portfolio formation time *t* by maximizing the mean-variance utility of the “everywhere” style-integrated portfolio; namely, $\boldsymbol{\varphi}_t \equiv \frac{1}{\gamma}\mathbf{S}_t^{-1}\mathbf{L}_t$ where $\mathbf{L}_t$ is the 4×1 vector of expected excess returns for the class-specific style-integrated portfolios over the past 60 months and $\mathbf{S}_t$ is the corresponding variance-covariance matrix. As before, the relative risk aversion parameter γ is set to 5.

Risk-parity weights. At each portfolio formation time *t*, the weight of the *c*th class-specific style-integrated portfolio is inversely proportional to its expected volatility, $\varphi_t^c \equiv 1/\sigma_t^c$. This heuristic seeks to achieve identical contributions of each class-specific style-integrated portfolio to the risk of the “everywhere” style-integrated portfolio, ignoring correlations. Following Natixis (2015) and Moskowitz et al. (2012) inter alia, we obtain σ_t^c using the forward-looking Exponentially Weighted Moving Average (EWMA) model of *Riskmetrics*, a specific case of GARCH(1,1) model that does not require parameter estimation

$$\sigma_t^c = \sqrt{(1-\lambda)\sum_{j=0}^{m-1}\lambda^j(r_{t-j}^c - \bar{r}_t^c)^2} \tag{5}$$

where $\bar{r}_t^c$ is the average excess return over the past $m = 60$ months. We use the smoothing parameter $\lambda = 0.97$ as recommended by the *Riskmetrics* framework for monthly data.

Constant weights. Inspired by Jacobs et al. (2010) and Asness et al. (2015) inter alia, the weights assigned to the equity index, fixed income, currency and commodity style-integrated portfolios are predetermined, $\boldsymbol{\varphi_t} \equiv \boldsymbol{\varphi}$, and rebalanced to that level at each portfolio formation time *t*; specifically, we adopt the fixed weights 40%, 40%, 10% and 10%, respectively.[5]

In each of the above three settings, the weights assigned to the everywhere portfolios are standardized to ensure full investment and the performance appraisal is conducted over a common sample which acknowledges the fact that 120 months of past data are consumed in the mean-variance and risk-parity approaches: 60 months to determine the asset allocations within the class-specific style-integrated portfolios, and another 60 months to obtain the class weights.

Finally, we consider a direct approach to constructing the everywhere style-integrated portfolio which is a one-step 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, $\phi_{i,t},\ i = 1, \ldots, N$ $(N = 131)$ and scale each by the expected volatility of the corresponding futures contract using the EWMA model. Thus, the final allocations in the direct "everywhere" style-integrated portfolio are $\breve{\phi}_{i,t} = \frac{\phi_{i,t}}{\sigma_{i,t}}, i = 1, \ldots, N$ $(N = 131)$ which, to ensure full investment for consistency with the rest of the analysis, are subsequently standardized.[6]

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[5] We also considered 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.

[6] The *two-step* and *direct* risk-parity approaches to constructing everywhere style-integrated portfolios differ primarily in that the former controls for differences in volatility among the class-specific style-integrated portfolios while the direct approach accounts for differences in

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.[7] As in DeMiguel et al. (2009, 2019), we also test the null hypothesis above using the Jobson and Korkie (1981) test with the correction in Memmel (2003) and the Ledoit and Wolf (2008) test.

In order to account for non-normality, we further gauge the risk-adjusted performance of the different portfolios by means of 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 for a threshold excess return target of zero

In addition, we calculate the certainty equivalent return (CER) of each portfolio strategy 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, 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. Following DeMiguel et al. (2009), we test the superiority of the portfolio P_a over another portfolio P_b, namely $H_0: CER_{P_a} \geq CER_{P_b}$ versus $H_A: CER_{P_a} < CER_{P_b}$, by exploiting the asymptotic properties of functional forms of the estimators for means and variances. To account for higher order moments (non-normality), we also obtain the CER measure and corresponding tests for the above H_0 versus H_A hypotheses under a power utility assumption.

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volatility of the futures contracts within (and across) classes; for instance, natural gas versus gold in the commodities class.

[7] 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.

Finally, even though futures contracts are cheap to trade and therefore transaction costs are unlikely to influence the outcome of the horse-race of style-integrated portfolios, for completeness we account for their trading intensity. For this purpose, we measure portfolio *turnover* (TO) as the average of all the trades incurred over the sample evaluation period

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

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 allocations in the style-integrated portfolio due to within-month price changes.

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, October 1975 for fixed income, January 1979 for currencies 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.[8] Specifically, excess returns are changes in logarithmic prices of the front-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.

[8] For the same reason, at each portfolio formation time *t* 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). The Internet Appendix is available as supplement material with the online version of this paper.

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; this number is arbitrary but conservative. Thus, the first monthly excess return commonly available across the standalone-style portfolios and style-integrated portfolios pertains to September 2001 for equity index futures, December 1991 for fixed income futures, August 1989 for currency futures, July 1989 for commodity futures and September 2006 for the "everywhere" futures.

Following Fleming et al. (2001, 2003) or Moskowitz et al. (2012) inter alia, we implement most of our analysis in futures markets. We see futures contracts as the implementation vehicle of choice for several reasons: relatively high liquidity, low transaction costs and no restriction on short selling. Besides, standard no-arbitrage arguments under the cost-of-carry model imply that fully-collateralized futures positions provide similar exposure to the underlying spot assets as the spot positions themselves and thus, the use of futures can be seen as a fair substitute to that of spot assets.[9] These points notwithstanding, we also provide evidence pertaining to U.S. equity markets in the robustness section.

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 to provide a static picture of their relative standing. The results are presented in Table 1 per class of futures: equity indices (Panel A), fixed income (Panel B), currencies (Panel C) and commodities (Panel D). The results confirm the stylized fact that the momentum and

[9] In line with Moskowitz et al. (2012), we find that front-end futures returns are highly correlated with spot excess returns on the same underlying; e.g., 99% correlation between the monthly S&P500 (CME) futures returns and the underlying cash index excess returns, 99% correlation between the Euro vs US dollar (CME) futures and its underlying, or 97% between the Gold (CMX) futures and its underlying.

carry premia are very pervasive across asset classes. However, the ranking of styles differs across futures classes; e.g., the momentum and skewness premia stand out in commodity futures markets, while the value and carry premia stand out in currency futures markets.

[Insert Table 1 around here]

We observe also that, although a few of the 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, the relative standing of a given style can be subject to dramatic swings over non-overlapping 5-year sub-periods as the results in Table 2 show. For instance, in fixed income markets the momentum strategy switches from best (rank 5) in the 1996/12-2001/11 period to worst (rank 1) in the 2001/12-2006/11 period (Panel B), in equity futures markets the value strategy switches from worst (rank 1) in the 2001/09-2006/08 period to best (rank 5) in the 2006/09-2011/08 period (Panel A). Such fluctuations in the relative performance of the standalone-style portfolios pose a challenge for an investor seeking to choose one style, which further motivates style integration. The idea is that, by constructing a style-integrated portfolio with exposure to multiple styles, the investor ought to gain some protection against occasional crashes of the individual styles which are difficult to predict in real time; see e.g., Barroso and Santa-Clara (2015a) and Daniel and Moskowitz (2016) for a discussion of momentum crashes.

[Insert Table 2 around here]

Finally, to grasp the extent of the overlap across the five styles we examine the correlation structure of their excess returns. As shown in Table 3, the pairwise Pearson correlations across styles per futures class are fairly small with average values ranging from -0.06 (commodities) to 0.16 (fixed income). The value style typically correlates negatively with the other styles, confirming its contrarian nature. The mild correlation structure across individual styles additionally motivates the notion of style integration; namely, the idea is that, by aggregating the information from multiple signals at asset level, the investor obtains a composite signal that ought to be more reliable, leading to a better allocation.

[Insert Table 3 around here]

4.2. Performance of class-specific 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. The results suggest that pervasively across equity index, fixed income, currency and commodity futures markets the naïve EWI portfolio is a strong competitor to the sophisticated style-integrated portfolios as suggested by various risk-adjusted performance measures – Sharpe ratio, Omega ratio, Sortino ratio and CER. In each futures class, the EWI portfolio is also well positioned vis-à-vis the sophisticated style-integrated portfolios regarding trading turnover, as Figure 1 illustrates.

[Insert Table 4 and 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 $H_0\colon SR_{EWI} \geq SR_j$ where j denotes a sophisticated style-integrated portfolio. The test *p*-values are large and imply that the Sharpe ratio of the EWI portfolio is statistically at least as attractive as that of a sophisticated style-integrated portfolio. These results are confirmed by alternative Sharpe ratio tests suggested in the literature as shown in the Internet Appendix Table A.II. Consistent with this finding, the *p*-values of the counterpart tests based on the CER measure, $H_0\colon CER_{EWI} \geq CER_j$, uniformly fail to reject the null hypothesis and hence, suggest that the EWI portfolio is unsurpassed by sophisticated style-integrated portfolios.[10]

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[10] These key findings are not challenged under a power utility assumption, that is, by measuring $CER = \left(\frac{12}{T}\right)\sum_{t=0}^{T-1}\frac{\left(1+r_{P,t+1}\right)^{1-\gamma}-1}{1-\gamma}$ 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

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-integrated portfolios as borne out by large Opdyke test p-values across all the sub-periods. A dynamic comparison of the style-integration methods is also conducted by ranking their performance. Specifically, we begin by assigning a rank of 7 (1) to the style-integrated portfolio with the highest (lowest) Sharpe ratio in each of the 5-year non-overlapping periods and for each futures class (Panels A to D). We then average the ranks thus obtained per style-integrated portfolio 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, show that the naïve EWI portfolio stands out with a relatively high volatility-adjusted expected rank consistently across sub-periods and futures classes.

[Insert Table 5 around here]

Leaving aside the EWI method, just for now, to draw a comparison across the remaining style integrations over the full sample period (Table 4) and sub-periods (Table 5) we observe that the CSI portfolio strategy inspired by the two-step Fama-MacBeth methodology fares quite well. Both the OI and PCI methods lie at the other extreme with the least attractive performance.

It is interesting also to compare the Sharpe ratios of the standalone styles and EWI portfolio over the full sample period (Tables 1 and 4), as well as over 5-year non-overlapping periods (Tables 2 and 5). As Table A.IV of the Internet Appendix shows, the test p-values for $H_0: SR_{EWI} \geq SR_j$ indicate that the Sharpe ratio of the EWI portfolio is not surpassed by that of the standalone styles. Moreover, the sub-period analysis suggests that the volatility-adjusted expected rank of the EWI strategy is the highest at 4.26 and compares very favorably to that of

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(1994) bootstrap method. We obtain bootstrap time-series of excess returns for the EWI portfolio and a given style-integrated portfolio, $\{r^*_{EWI,t}, r^*_{j,t},\}$, by pooling random blocks of $2 \times l$ dimension sampled from the original time-series of excess returns. The block-length l is geometrically distributed with expected value $1/q$. We use $q = \{0.2, 0.5\}$ and B=10,000 iterations. Table A.III of the Internet Appendix shows the results.

the best standalone style (carry) at 2.65. These findings serve to reinforce prior studies that advocate style integration (e.g., Brandt et al., 2009; Barroso and Santa-Clara, 2015b; Fitzgibbons et al., 2016 to name only a few).[11]

4.3. Do common factors drive the class-specific style-integrated portfolios?

Is the performance of the four class-specific style-integrated portfolios (constructed according to each of the methods described in Section 2.2) driven by common forces? To address this question, we begin by examining the correlation structure of their excess returns over the available common period from September 2001 to December 2017. As Table 6, Panel A, shows the correlations are small; namely, the average of the absolute correlations equals 0.12 for the EWI method and ranges from 0.07 to 0.16 for the sophisticated integration methods. This weak correlation structure does not support the notion that the style-integrated portfolio excess returns of the four futures classes are compensation for exposure to common risk factors.

[Insert Table 6 around here]

Next we conduct a principal component analysis (PCA). For each of seven style-integration methods studied, we extract the PCs of the class-specific style-integrated portfolio excess returns. As Panel B of Table 6 shows, on average the first principal component merely explains 32.1% of the total variation in the excess returns of the class-specific style-integrated portfolios. This result further indicates that the style-integrated portfolio excess returns do not compensate investors for exposure to some underlying factors that are common across futures classes.

[11] The volatility-adjusted expected rank of EWI is much higher in commodity futures markets (15.5) than in currency or fixed income futures markets (3.41 and 4.90, respectively). Thus while style-integration seems to be a valid proposition across classes of futures, its benefits are stronger in commodity futures markets. Additional unreported results suggest that the superior style-integration benefits of EWI in commodity markets stem both from its ability to capture a larger mean excess return and a more attractive risk profile (e.g., lower downside volatility, 99% VaR). Corroborating the evidence in Fitzgibbons et al., (2016) the latter relates to the lower correlations observed across styles in Table 3, Panel D.

Finally, focusing on four possible global risks that might drive the excess returns of the style-integrated portfolios we address the initial question with a regression analysis. Following Asness et al. (2013) and Koijen et al. (2018) inter alia, we consider innovations to: *i*) Kilian (2018) index of global real economic activity, *ii*) global market liquidity L_t, *iii*) global funding liquidity TED_t and *iv*) global volatility v_t.[12] The results shown in Table 6, Panel C, do not reveal a common reaction of the four class-specific style-integrated portfolios to those global factors. Altogether, there is no evidence to suggest that the excess returns of the style-integrated portfolios of the four classes reflect compensation for exposure to common risk factors.

4.4 Performance of "everywhere" style-integrated portfolios

The weak correlation structure of the style-integrated portfolios per futures class is appealing from a broad diversification perspective; namely, it motivates the "everywhere" (cross-class) style-integrated portfolios. Hence, using the construction approaches described in Section 2.4, we obtain everywhere style-integrated portfolios, and conduct the horse race of style-integration methods in this additional setting. Table 7 presents in Panel A the cross-class portfolios based on the two-step construction approaches while Panel B pertains to the direct (pooling) method. The appraisal is conducted over the largest common period of portfolio returns available from September 2006 to December 2017. Figure 2 shows the turnover measures.

[Insert Table 7 and Figure 2 around here]

Two observations can be made. First, the EWI method is not challenged by any of the sophisticated style-integrations in an everywhere setting either. This is borne out by the large

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[12] The index of global economic activity is obtained from Killian's website. Global market liquidity L_t is an average of the Amivest liquidity measure $L_{i,t}$ (as described in Section 2.2) across all futures i=1,..,N (N=131). Funding liquidity is proxied by the monthly TED spread (3-month interbank LIBOR minus 3-month T-bill rate) from the Federal Reserve Bank of St. Louis. Global volatility v_i is the square root of an average across all futures contracts of their monthly realized variance (measured as the sum of daily squared excess returns). As in Asness et al. (2013) the innovations or shocks to these variables are defined as the residuals from an AR(2) model; similar results are obtained with an AR(3) model.

p-values of the Opdyke test ($H_0\colon SR_{EWI} \geq SR_j$) and CER test ($H_0\colon CER_{EWI} \geq CER_j$) together with the relatively low turnover of the EWI portfolio. Second, although comparing among the four methods used to construct everywhere portfolios goes beyond the scope of the paper, we observe that the *mean-variance* class-weights and the *constant* class-weights (40% Equity; 40% FI; 10% FX; 10% Commodities) are quite effective in terms of performance and turnover.

5. Robustness tests

This section assesses the robustness of our key finding that the EWI method is highly effective. We consider reformulations of the sophisticated style-integration methods, different scoring schemes, data snooping tests, longer estimation windows, different economic sub-periods, as well as equities in place of futures.

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

We entertain other OI strategies where the style-weighting vector, $\boldsymbol{\omega}_t$ in Equation (1), is derived by maximizing: i) the mean-variance utility as in the main section of the paper but with covariance matrix estimator based on the shrinkage approach of Ledoit and Wolf (2004) to reduce estimation error, ii) the power utility $U\left(r_{P,t+1}\right) = \frac{\left(1+r_{P,t+1}\right)^{1-\gamma}-1}{1-\gamma}$, iii) the exponential utility $U\left(r_{P,t+1}\right) = -\frac{e^{-\kappa\left(1+r_{P,t+1}\right)}}{\kappa}$, and iv) the power utility with disappointment aversion (Gul, 1991) $U\left(r_{P,t+1}\right) = \frac{\left(1+r_{P,t+1}\right)^{1-\gamma}-1}{1-\gamma}$ if $r_{P,t+1} > 0$ and $\frac{\left(1+r_{P,t+1}\right)^{1-\gamma}-1}{1-\gamma} + \left(\frac{1}{A} - 1\right)\left[\frac{\left(1+r_{P,t+1}\right)^{1-\gamma}-1}{1-\gamma}\right]$ 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 $A = 0.6$.[13]

[13] 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.

We also consider an OI investor that is only concerned about risk (measured by the variance); accordingly, she derives the style weights by minimizing $\boldsymbol{\omega}_t'\boldsymbol{\Sigma}_t\boldsymbol{\omega}_t$ where $\boldsymbol{\Sigma}_t$ is the variance-covariance matrix of the K style portfolio excess returns. We impose the restriction $\sum_{k=1}^{K}\omega_k = 1$ to avoid the trivial solution $\omega_k = 0$. For each of the above reformulations of the OI strategy, we deploy a restricted ($\boldsymbol{\omega}_t \in \mathrm{R}^+$) version and an unrestricted ($\boldsymbol{\omega}_t \in \mathrm{R}^K$) version. We also study a restricted ($\boldsymbol{\omega}_t \in \mathrm{R}^+$) 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, our earlier VTI strategy inspired by Kirby and Ostdiek (2012) is reformulated in two ways; first, we deploy a more general VTI(η) strategy with style weights $\omega_{k,t} = \left(1/\sigma_{k,t}^2\right)^\eta$ where timing aggressiveness[14] is dictated by the parameter η; second, we deploy a reward-to-risk timing integration (RRTI) strategy with style weights $\omega_{k,t} = \left(\mu_{k,t}^+/\sigma_{k,t}^2\right)^\eta$ where $\mu_{k,t}^+ = \max\left(0, \mu_{k,t}\right)$, and $\mu_{k,t}$ is the mean excess return of the kth 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 $i = 1, \ldots, N$ on the past-month style premium $k = 1, \ldots, K$

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

[14] For $\eta = 0$, there is no volatility-timing, $\omega_k = 1/K$ for $k = 1, \ldots, K$ 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 all the weight, $\omega_j = 1$ ($\omega_k = 0, k \neq j$).

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

Table A.V of the Internet Appendix reports results for the above variants of the sophisticated style integrations, deployed again per futures class and cross-class. Their risk-adjusted performance as measured, for instance, by the Sharpe ratio, does not challenge the performance of the much easier-to-construct EWI portfolio. This is formally confirmed by the Opdyke test p-values which strongly fail to reject the null hypothesis $H_0\colon SR_{EWI} \geq SR_j$ 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). We now turn our attention to other scoring schemes. Following DeMiguel et al. (2019), the first scheme seeks to mitigate the biases induced by outliers in the individual signals by winsorizing the signals prior to standardizing them. Specifically, at each portfolio formation time per signal $k = 1, \ldots, 5$, we shrink all observations $\{x_{i,k,t}\}_{i=1}^{N}$ above the upper threshold $Q_{3,k} + 3 \cdot R_k$ to this upper threshold value, and all signal values below the lower threshold $Q_{1,k} - 3 \cdot R_k$ to this lower threshold value; $Q_{1,k}$ and $Q_{3,k}$ are the first and third quartiles of the distribution $\left\{x_{i,k,t}\right\}_{i=1}^{N}$ and R_k is the interquartile range.

The second alternative scoring matrix $\mathbf{\Theta}_t$ is populated with 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 ith 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 mapping the signals onto rankings, this approach also mitigates the effects of potential outliers while it still differentiates among the candidate futures contracts for the long and short positions.

Third, we consider a parsimonious scheme that for each signal (or style) $k = 1, \ldots, K$ sorts the cross section of futures contracts according to the observed signal values, $\left\{x_{i,k,t}\right\}_{i=1}^{N}$, and assigns those with a value above (below) the median $x_{k,t}^{0.50}$ a score of +1 (-1). The final allocations $\phi_{i,t}$ from Equation (1) will not add to zero when the total number of available futures contracts N is an odd number; hence, we center them before scaling, $\tilde{\phi}_{i,t} = (\phi_{i,t} - E_i(\phi_{i,t}))/\sum_{i=1}^{N}|\phi_{i,t} - E_i(\phi_{i,t})|$ to ensure 100% investment of the client's mandate.[15]

Finally, we consider sparse versions of the above score matrices $\mathbf{\Theta}_t$ that at each portfolio formation time *t* only consider the futures contracts classified into the extreme (top and bottom) quintiles according to the signal at hand, and ignore ($\theta_{i,k,t} = 0$) those in the intermediate quintiles. Thus, we have quintile versions of the i) standardized signals, ii) standardized rankings, and iii) the binary {-1, +1} schemes 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 equal mandates to the longs and the shorts.

Table A.VI of the Internet Appendix shows that the key finding that the EWI method is unsurpassed by the sophisticated style-integration methods remains unchallenged when we employ different score matrices $\mathbf{\Theta}_t$ in Equation (1). As a byproduct, the comparison among score matrices reveals that by exploiting the full cross section of observed signal values (instead of just the extreme values in the top/bottom quintiles) the style-integrated portfolios generally afford better risk-adjusted performance.

5.3 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.

[15] This heuristic is robust to noise but it may lose information by mapping the signals onto two scores; namely, it does not discriminate among the candidate assets for the long/short positions.

We now 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.

The data mining checks are conducted, separately, per class of futures and in an "everywhere" context by comparing the Sharpe ratio of a given style-integration strategy j ($j = 1, \ldots, M$) to that of the EWI portfolio. M is the total number of alternative style-integration strategies against which the performance of the EWI portfolio is appraised.[16] Relative performance is measured by the Sharpe ratio differential, $d_j \equiv SR_j - SR_{EWI}$. The expected "loss" of the jth 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: $max_{j=1,\ldots,M} E[SR_j] \; \leq \; E[SR_{EWI}]$.[17]

The bootstrap p-values of the test, reported in Table A.VII of the Internet Appendix, range from 0.65 to 0.97 in all five settings (four futures classes and everywhere) and they are thus consistently unable to reject H_0. Thus, our key finding that the EWI portfolio is unsurpassed by the sophisticated style-integrated portfolios is robust to data snooping biases.

5.4 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 "easily" be beaten by simply increasing the length of the lookback (or estimation)

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[16] $M = 27$ for each of the four class-specific style-integration strategies which consist of the 5 standalone styles of Section 2.2, the 6 sophisticated style-integration strategies of Section 2.3 and 16 variants thereof as discussed in Section 5.1. M = 22 for the "everywhere" portfolios which consist of the 6 sophisticated style-integration strategies of Section 2.3 and 16 variants thereof as discussed in Section 5.1.

[17] 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 $q = \{0.2, 0.5\}$.

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.VIII of the Internet Appendix shows, none of sophisticated style-integrated portfolios significantly outperforms the simpler-to-construct EWI portfolio.

5.5 Are the findings time-specific?

To address this question, we conduct 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,[18] and *ii*) recession versus expansion months according to the NBER-dated business cycle phases. We report 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 volatility-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.IX of the Internet Appendix, suggest that the Sharpe ratio of the EWI portfolio is at least as good as that of the alternative style-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 volatility-

[18] The volatility regimes are obtained via a GARCH(1,1) model fitted to the monthly excess returns of a long-only equally-weighted monthly-rebalanced portfolio of futures contracts. The threshold is the mean of the fitted annualized volatility at 12.15% (equity indices), 3.50% (fixed income), 7.67% (currencies), and 10.86% (commodities). In the everywhere (cross-class) context, the model is fitted to the excess returns of the mean-variance-optimized combination of class-specific long-only portfolios (3.49% threshold).

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.

5.6 Do the findings apply to equities?

Setting aside the liquidity constraints and higher trading costs of equities, this section tests whether the evidence thus far obtained in futures markets also extends to equity markets. Following the seminal work of Brandt et al. (2009), for this purpose we modify Equation (1) to $\boldsymbol{\phi}_t = \overline{\boldsymbol{\phi}}_t + \frac{1}{N}(\boldsymbol{\Theta}_t \times \boldsymbol{\omega}_t)$ where $\overline{\boldsymbol{\phi}}_t$ denotes the benchmark allocations (i.e., value-weights or equal-weights). The $N \times 1$ vector $\boldsymbol{\phi}_t$ represents the solution of the style-integrated portfolio allocation problem which is decomposed into: *i*) the weights of the stocks in the benchmark portfolio or the passive weights of the style-integrated portfolio, denoted $\overline{\boldsymbol{\phi}}_t$, and *ii*) the deviations of the optimal portfolio weights from this benchmark or the active weights of the style-integrated portfolio, denoted $\frac{1}{N}(\boldsymbol{\Theta}_t \times \boldsymbol{\omega}_t)$.

For consistency with the main analytical framework in the paper, the elements of the score matrix $\boldsymbol{\Theta}_t$ are the raw signals appropriately standardized cross-sectionally, the weights $\boldsymbol{\omega}_t$ are unrestricted ($\boldsymbol{\omega}_t \in R^K$), the positions $\boldsymbol{\phi}_t$ taken at each month-end t are held for one month, the investor's mandate is assumed to be fully invested (i.e., $\phi_{i,t} \geq 0$ and $\sum_{i=1}^{N} \phi_{i,t} = 1$),[19] and the sample period is the longest feasible in the paper from July 1989 to December 2017.

We focus on the size, value and momentum styles employed in Brandt et al. (2009) and follow their methodology in constructing the corresponding standalone-style portfolios. We download from the CRSP database the holding period returns of the S&P 500 composite index stocks and from the CRSP/Compustat merged database the corresponding book-to-market and market capitalization of each stock. As in Fama and French (1993) or Brandt et al. (2009), the

[19] To do so, we follow Brandt et al. (2009) and re-scale the optimal weights as $\tilde{\phi}_{i,t} = \frac{\max(0,\phi_{i,t})}{\sum_{j=1}^{N_t} \max(0,\phi_{j,t})}$.

stocks included in the style-integrated portfolios meet the following criteria: *i*) they have been available in the CRSP/Compustat database for at least 2 consecutive years, *ii*) they have non-negative book-to-market values, *iii*) they have data for all three signals and *iv*) they are amongst the 80% largest in terms of market capitalization. The cross-section of stocks thus considered for the analysis ranges from 1,170 in July 1989 to 1,896 in July 2005 with an average at 1,639.

Table A.X of the Internet Appendix reports the Sharpe ratios of the seven equity-based style-integrated portfolios, the test p-values for the hypothesis $H_0: SR_{EWI} \geq SR_j$ and the relative rankings of performance from 7 (top) to 1 (bottom). The results are reported for the value-weighted benchmark in Panel A, for the equally-weighted benchmark in Panel B, over the full sample, and the six consecutive 5-year sub-samples. The bottom row summarizes the relative performance of the style-integrated strategies by reporting their volatility-adjusted expected ranks. Altogether the key finding of our paper that the EWI approach is the most effective among a host of style-integration methods survives in the equities scenario. Over the full period and in most sub-periods, the large Opdyke test p-values for $H_0: SR_{EWI} \geq SR_j$ reveal that the Sharpe ratio of the EWI portfolio is at least as good as that of the sophisticated style-integrated portfolios. EWI also obtains the highest volatility-adjusted expected rank. In sum, the equity EWI portfolio, aside from being much simpler to construct than the sophisticated alternatives, also comes across as very effective in terms of performance and attractive in terms of risk.

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. Following a recent literature, this article studies style integration defined as the combination of multiple characteristics or signals at asset level with a view to construct a portfolio with simultaneous exposure to many styles. We contribute to the literature by providing a comprehensive appraisal of style-integration methods. 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 style return data according to utility maximization, style rotation, volatility timing, cross-sectional pricing, style momentum and principal components criteria.

Using futures to represent multiple asset classes – equities, fixed income, currencies and commodities – to sidestep liquidity concerns and short-sale constraints while keeping transaction costs low, we construct long-short portfolios according to the different style-integration methods. Consistently across scenarios (per futures class and cross-class) we find that the risk-adjusted performance of the naïve EWI portfolio is unrivalled by that of any of the sophisticated style-integrated portfolios. This key finding withstands a battery of robustness checks that entertain variants of the sophisticated style-integration methods, different asset scoring schemes, data snooping tests, longer estimation windows, sub-period analyses and the consideration of equities in place of futures.

Our study is ambitious in that it confronts the EWI method with several sophisticated style-integration (extant and new) methods. Overall, a clear implication from the evidence is that any style-integration put forward in future research should be subject to a "reality check" of its relevance by comparing it with the easy-to-deploy but highly effective naïve EWI method.

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

	Equities	Fixed income	Currencies	Commodities
Panel A: Standalone-style strategies				
Momentum	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)			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)
	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)
	Koijen et al. (2018)	Brooks et al. (2018)	Koijen et al. (2018)	Erb and Harvey (2006)
		Koijen et al. (2018)	Menkhoff et al. (2012)	Koijen et al. (2018)
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	Frazzini et al. (2013)			Fuertes et al. (2015)
	Fitzgibbons et al. (2016)			
	Leippold and Rueegg (2018)			
OI	Brandt et al. (2009)		Barroso and Santa-Clara (2015b)	
	Fischer and Gallmeyer (2016)		Kroencke et al. (2014)	
	Ghysels et al. (2016)			
	DeMiguel et al. (2018)			
RSI	Barberis and Shleifer (2003)			

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 class-specific style-integrated portfolios

The figure plots the turnover, measured as in Equation (5), for each of the class-specific style-integrated portfolios. EWI is equal-weight 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.

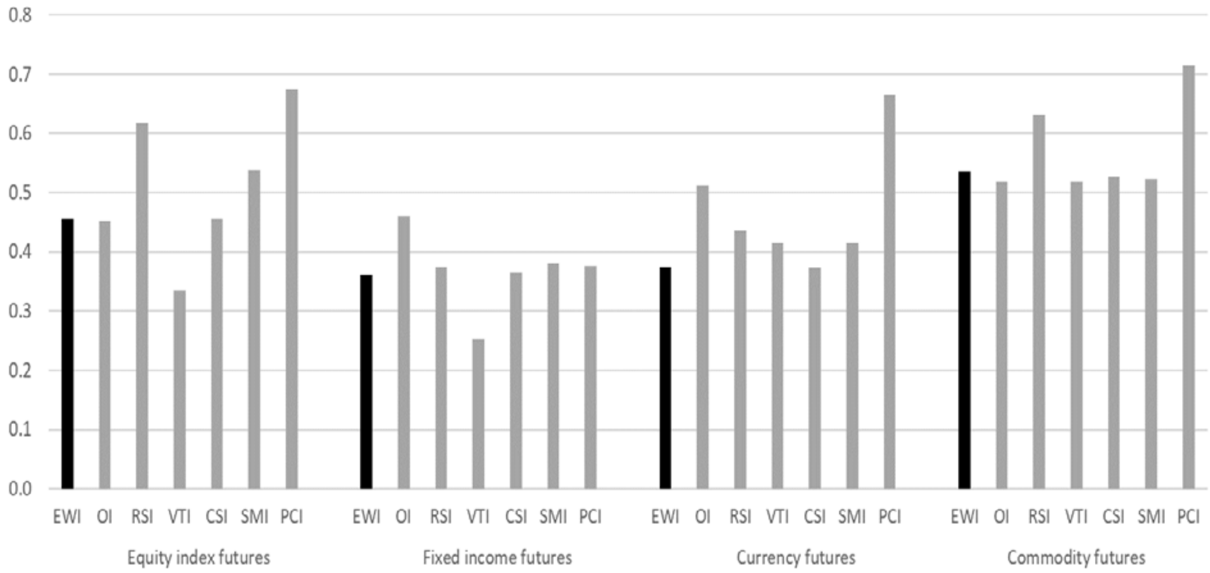

Figure 2. Turnover of "everywhere" style-integrated portfolios

The figure plots the turnover, measured as in Equation (5), for everywhere (cross-class) style-integrated portfolios constructed using two-step (mean-variance, risk-parity, and constant class-weights) approaches and a direct approach that pools all *N*=131 contracts and inversely-weighs them by their volatilities. The constant class-weights are 40% (equity indices), 40% (fixed income), 10% (currencies) and 10% (commodities). EWI is equal-weight 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.

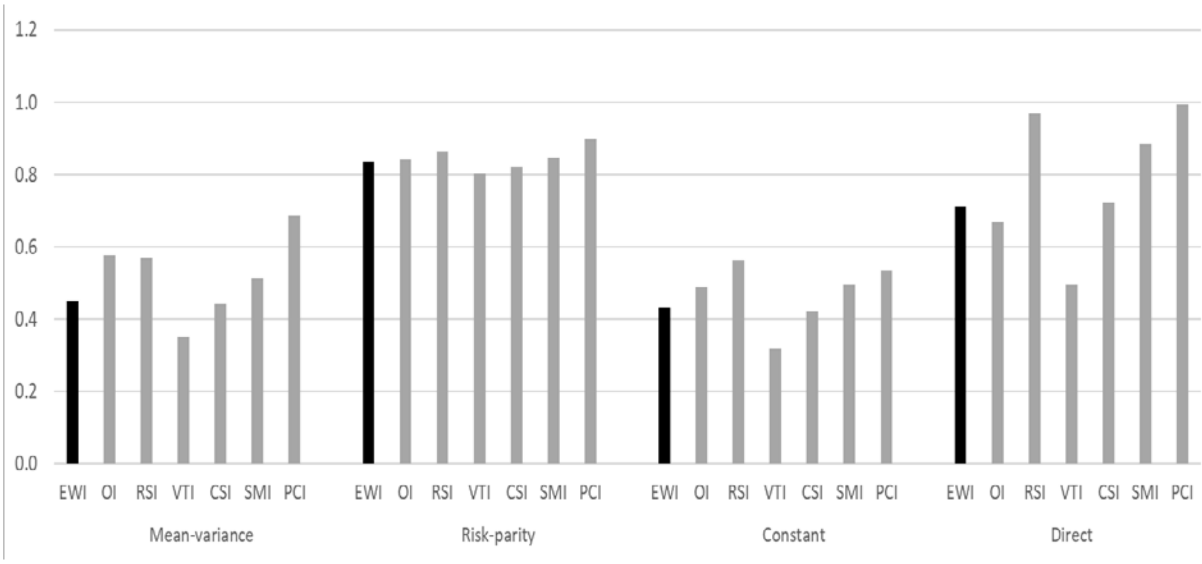

Table 1. Performance of standalone-style portfolios

The table summarizes the risk-adjusted performance of five long-short portfolio strategies based on the predictive signals stated in the first row. The results pertain to four futures classes – equity index (Panel A), fixed income (Panel B), currency (Panel C) and commodity (Panel D); the portfolio excess returns span the period indicated in parentheses. CER is the annualized certainty-equivalent return based on unconstrained mean-variance utility with relative risk aversion parameter $\gamma = 5$.

	Momentum	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

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 and volatility of the ranks, and corresponding ratio across time periods and class-specific portfolios; a larger ratio for a given style indicates a higher volatility-adjusted expected rank.

	Momentum		Value		Carry		Liquidity		Skewness	
	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
Mean rank		3.32		2.68		3.55		3.00		2.45
StDev rank		1.52		1.46		1.34		1.48		1.10
Mean/Stdev rank		*2.18*		*1.84*		*2.65*		*2.03*		*2.23*

Table 3. Correlation structure of standalone-style portfolios

This table reports Pearson pairwise correlations of the excess returns of the five styles. Bold denotes significance at the 5% significance level or better. The sample periods are indicated in parentheses.

	Momentum	**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**

Table 4. Performance of style-integrated portfolios

The table summarizes the style-integrated portfolios per futures class – equity indices (Panel A), fixed income (Panel B), currencies (Panel C) and commodities (Panel D). EWI is equal-weight 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.

	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	-	(0.81)	(0.58)	(1.00)	(0.66)	(0.57)	(0.71)
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	-	(0.95)	(0.54)	(1.00)	(0.86)	(0.48)	(0.78)
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	-	(0.90)	(0.88)	(0.50)	(0.59)	(0.94)	(0.92)
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	-	(0.95)	(0.85)	(0.82)	(0.74)	(0.95)	(0.92)
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	-	(0.89)	(0.99)	(0.27)	(0.43)	(0.97)	(0.98)
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	-	(0.90)	(0.99)	(0.34)	(0.32)	(0.97)	(0.98)
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	-	(0.90)	(0.99)	(0.86)	(0.85)	(0.95)	(1.00)
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	-	(0.91)	(0.99)	(0.98)	(0.98)	(0.93)	(1.00)

Table 5. Subsample analysis of style-integrated portfolios

The table reports per style-integration strategy the annual Sharpe ratio (SR) over 5-year non-overlapping 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-integration method, and their rank from 7 (top) to 1 (bottom). EWI is equal-weight 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. The last rows report the mean and volatility of the ranks, and corresponding ratio across time periods and class-specific portfolios; a larger ratio for a given strategy indicates a higher volatility-adjusted expected 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
Mean rank		5.23			3.05			3.77			4.45			4.82			3.82			2.86
StDev rank		1.66			1.89			2.05			2.26			1.33			1.87			1.88
Mean/Stdev rank		*3.15*			*1.61*			*1.84*			*1.97*			*3.62*			*2.04*			*1.52*

Table 6. Can a common factor structure explain the performance of the class-specific style-integrated portfolios?

Panel A reports Pearson correlations between the excess returns of the style-integrated portfolios per class of futures: equity indices (Eq), fixed income (FI), currencies (FX) and commodities (Comm). EWI is equal-weight 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. Panel B reports the percentage of the total variation of the excess returns of the four class-specific style-integrated portfolios that each principal component explains. Panel C reports slope coefficients, Newey-West *t*-statistics (in parentheses) and adjusted-R^2 from regressions of each style-integrated portfolio excess returns on innovations to the Kilian (2018) index of global real economic activity, global market liquidity (L), global funding liquidity (TED) and global volatility (v). Bold means significant at the 10% level or better. The analysis is conducted over the common sample period September 2001- December 2017.

Panel A: Correlation analysis

	EWI			OI			RSI			VTI			CSI			SMI			PCI		
	Eq	FI	FX	Eq	FI	FX	Eq	FI	FX	Eq	FI	FX	Eq	FI	FX	Eq	FI	FX	Eq	FI	FX
FI	**-0.23**			0.00			-0.03			0.03			**-0.25**			-0.06			0.03		
FX	**0.20**	**-0.19**		0.06	-0.10		0.08	-0.13		0.00	**-0.22**		**0.21**	**-0.18**		0.10	**-0.16**		**0.14**	0.00	
Comm	-0.01	-0.10	0.00	-0.07	-0.10	0.10	**-0.14**	0.00	-0.04	0.07	-0.11	0.02	0.05	**-0.16**	0.08	-0.09	0.02	0.02	-0.02	0.09	-0.10

Panel B: Principal component analysis (% var explained)

EWI				OI				RSI				VTI				CSI				SMI				PCI			
PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4
35.5	25.7	20.4	18.4	29.8	26.3	22.7	21.2	30.4	26.6	21.7	21.2	31.3	26.4	23.4	18.9	37.2	24.3	20.5	18.0	30.7	26.3	22.6	20.4	29.7	27.0	22.6	20.8

Panel C: Regression analysis

	EWI				OI				RSI				VTI				CSI				SMI				PCI			
	Eq	FI	FX	Comm	Eq	FI	FX	Comm	Eq	FI	FX	Comm	Eq	FI	FX	Comm	Eq	FI	FX	Comm	Eq	FI	FX	Comm	Eq	FI	FX	Comm
β_{Kilian}	**-0.04**	0.00	0.00	-0.01	-0.01	**0.00**	**0.01**	-0.01	-0.02	0.00	**0.01**	-0.01	0.00	0.00	0.00	-0.01	**-0.03**	0.00	0.01	-0.01	-0.05	0.00	0.01	-0.01	**-0.02**	0.00	0.00	0.00
	(-1.99)	(1.07)	(1.43)	(-0.84)	(-1.04)	(2.48)	(1.86)	(-0.78)	(-0.62)	(0.82)	(4.29)	(-1.15)	(0.52)	(0.15)	(1.28)	(-0.87)	(-1.90)	(1.08)	(1.50)	(-0.90)	(-1.49)	(0.64)	(1.43)	(-1.19)	(-1.76)	(0.23)	(-0.68)	(-0.39)
β_L	0.46	**-0.25**	**0.24**	-0.01	0.27	-0.12	**0.18**	-0.01	0.31	**-0.20**	**0.19**	-0.34	**-0.14**	**-0.20**	**0.22**	0.08	0.61	**-0.26**	**0.25**	0.23	0.29	**-0.25**	**0.26**	-0.21	0.55	-0.17	0.05	0.20
	(1.03)	(-2.38)	(2.00)	(-0.03)	(1.18)	(-1.29)	(2.03)	(-0.05)	(0.43)	(-1.73)	(2.01)	(-0.86)	(-1.75)	(-2.08)	(1.84)	(0.26)	(1.37)	(-2.48)	(2.05)	(0.74)	(0.45)	(-2.25)	(2.23)	(-0.67)	(1.38)	(-1.49)	(0.40)	(0.53)
β_{TED}	**-2.29**	-0.01	-0.07	0.10	**-1.06**	-0.05	0.14	0.22	-2.19	-0.24	-0.13	**-1.26**	-0.13	0.02	-0.37	0.37	**-3.23**	-0.04	-0.07	0.50	**-3.95**	-0.21	-0.09	-0.38	-0.60	-0.11	**-1.26**	**0.92**
	(-2.57)	(-0.09)	(-0.16)	(0.23)	(-2.45)	(-0.36)	(0.33)	(0.56)	(-1.30)	(-0.74)	(-0.29)	(-2.04)	(-0.65)	(0.09)	(-1.10)	(0.74)	(-3.46)	(-0.26)	(-0.16)	(1.02)	(-2.13)	(-1.20)	(-0.21)	(-0.94)	(-0.59)	(-0.51)	(-3.34)	(1.92)
β_v	-0.21	0.00	**-0.07**	-0.02	0.05	0.01	**-0.06**	-0.03	-0.18	-0.01	**-0.09**	-0.02	0.00	0.00	**-0.06**	-0.04	-0.12	0.01	**-0.08**	0.01	-0.08	0.01	**-0.07**	**-0.07**	**-0.20**	0.01	**-0.05**	0.01
	(-1.23)	(0.20)	(-3.15)	(-0.52)	(0.64)	(0.61)	(-2.03)	(-0.67)	(-0.93)	(-0.53)	(-3.05)	(-0.37)	(-0.12)	(0.17)	(-2.73)	(-1.02)	(-0.68)	(0.30)	(-3.12)	(0.24)	(-0.28)	(0.61)	(-2.65)	(-1.95)	(-2.01)	(0.60)	(-1.96)	(0.18)
Adj-R^2	0.10	0.04	0.09	0.00	0.03	0.04	0.07	0.00	0.03	0.02	0.15	0.02	0.01	0.03	0.08	0.01	0.11	0.04	0.09	0.01	0.05	0.03	0.09	0.02	0.08	0.02	0.08	0.01

Table 7. Performance of everywhere style-integrated portfolios

The table summarizes the risk-adjusted performance of "everywhere" style-integrated portfolios constructed in a two-step (mean-variance, risk-parity, and constant class weights) approach, and in a direct approach that pools all N=131 contracts while adjusting for their different volatilities. EWI is equal-weight 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 $H_0: SR_{EWI} \geq SR_j$ vs $H_A: SR_{EWI} < SR_j$ where j is a sophisticated style-integrated portfolio. The asymptotic p-values of the CER test are for $H_0: CER_{EWI} \geq CER_j$ vs $H_A: CER_{EWI} < CER_j$. The appraisal covers the common period September 2006 to December 2017.

	EWI	OI	RSI	VTI	CSI	SMI	PCI
Panel A: Two-step approaches							
Mean-variance class weights							
Sharpe ratio	1.0255	0.2323	0.7245	1.1664	0.8129	0.7378	0.5925
Opdyke test p-value	-	(0.99)	(0.80)	(0.33)	(0.87)	(0.81)	(0.86)
Sortino ratio	1.4870	0.3442	0.9770	1.9371	1.0321	1.1670	0.9089
Omega ratio	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	-	(1.00)	(0.39)	(0.92)	(0.97)	(0.43)	(0.63)
Risk-parity class weights							
Sharpe ratio	0.7217	0.5697	0.7341	-0.1444	0.7176	0.8034	0.2419
Opdyke test p-value	-	(0.66)	(0.50)	(1.00)	(0.51)	(0.40)	(0.93)
Sortino ratio	1.1420	1.0955	0.7712	-0.1678	1.1119	1.1091	0.3520
Omega ratio	1.7254	1.5657	1.9454	0.8873	1.7095	1.9381	1.2174
CER	0.0194	0.0109	0.0285	-0.0042	0.0203	0.0272	0.0056
CER asymptotic p-value	-	(0.81)	(0.23)	(1.00)	(0.43)	(0.22)	(0.90)
Constant class weights (40%Eq;40%FI;10%FX;10%Comm)							
Sharpe ratio	1.1283	0.7225	1.0122	-0.1116	1.0156	0.9931	0.6246
Opdyke test p-value	-	(0.88)	(0.65)	(1.00)	(0.70)	(0.70)	(0.94)
Sortino ratio	1.5562	0.9861	1.3285	-0.1523	1.3179	1.4763	0.7133
Omega ratio	2.3471	1.8742	2.1172	0.9181	2.1505	2.1443	1.6670
CER	0.0604	0.0201	0.0771	-0.0023	0.0500	0.0695	0.0281
CER asymptotic p-value	-	(0.99)	(0.20)	(1.00)	(0.94)	(0.27)	(0.97)
Panel B: Direct approach							
Sharpe ratio	0.4102	0.5549	0.6198	0.1099	0.5334	0.3708	0.3018
Opdyke test p-value	-	(0.30)	(0.23)	(0.91)	(0.18)	(0.57)	(0.65)
Sortino ratio	0.5079	0.9508	0.7576	0.1334	0.6827	0.4440	0.3479
Omega ratio	1.4603	1.7989	1.6928	1.1419	1.5815	1.3649	1.3317
CER	0.0072	0.0089	0.0257	0.0011	0.0099	0.0100	0.0064
CER asymptotic p-value	-	(0.37)	(0.08)	(0.93)	(0.10)	(0.34)	(0.55)