Harvesting Commodity Styles: An Integrated Framework

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ABSTRACT

This paper develops a portfolio allocation framework to study the benefits of style integration and to compare the effectiveness of alternative integration methods in commodity futures markets. The framework is flexible enough to be applicable to any asset class for either long-short, long- or short-only styles. We study the naïve equally-weighted integration and sophisticated integrations where the style exposures are estimated by utility maximization, style rotation, volatility-timing, cross-sectional pricing or principal components methods. Considering a "universe" of eleven long-short commodity styles, we demonstrate that the naïve integration improves the reward-to-risk tradeoff and crash risk profile of each individual style. While also achieving multiple-style exposures, the sophisticated integrations are unable to challenge the equally-weighted integration because this naïve approach circumvents estimation risk and perfect-foresight bias. The findings hold after trading costs, various reformulations of the sophisticated integrations, economic sub-period analyses and data snooping tests inter alia.

JEL classifications: G13, G14

Keywords: Style integration; Commodity futures markets; Long-short asset allocation.

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1. Introduction

The commodity futures pricing literature has established that trading on the phases of backwardation and contango captures a sustainable return in excess of the risk-free rate, known as a commodity risk premium. Since backwardation (contango) signals a likely rise (fall) in futures prices, typical investment strategies or "styles" buy backwardated commodities – identified as those with low inventories (Fama and French, 1987; Symeonidis et al., 2012; Gorton et al., 2012), downward sloping forward curves (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Szymanowska et al., 2014; Koijen et al., 2017), good past performance (Erb and Harvey, 2006; Miffre and Rallis, 2007; Asness et al., 2013), net short hedging and net long speculation (Bessembinder, 1992; Basu and Miffre, 2013; Dewally et al., 2013) – and short contangoed commodities identified as those with opposite values for the above signals. Recent studies have shown that long-short style portfolios based on liquidity, open interest, inflation beta, dollar beta, value, volatility or skewness signals can also capture a premium (Hong and Yogo, 2012; Asness et al., 2013; Szymanowska et al., 2014; Fernandez-Perez et al., 2018).

Instead of putting all the eggs in the same basket (i.e., adopting one of the commodity investment styles mentioned above), the present paper is concerned with the idea of forming a long-short commodity portfolio that has exposure to many styles. Style integration has a strong economic appeal. By relying on a composite variable that aggregates information from various signals, the investor ought to predict more reliably the subsequent asset price changes. Relatedly, an integrated portfolio should benefit from signal diversification in the form of less volatile payoffs. Last but not least, a portfolio that integrates many styles is less trading intensive, and thus more cost effective, than holding each style as a separately-managed entity. For the above reasons, one may readily agree that style integration is a sensible approach that may improve performance relative to standalone style portfolios. This, however, begs the question: How shall an investor integrate *K* styles at asset level (i.e., within a unique portfolio)?

Specifically, how may she decide the weights that the integrated portfolio should allocate to each of the individual styles?

This paper makes two contributions to the literature on style integration. Our first contribution is to propose a simple, yet versatile, framework to conduct style integration. By doing this, we provide academics and practitioners alike with a well-structured way to blend multiple styles into a single asset allocation. The proposed framework is very flexible as it is applicable to long-only, short-only, as well as long-short investment styles, for any asset class. The recommended framework nests many integration approaches: a naïve integration approach with time-constant, equal-weights for all styles (Equal-Weighted Integration; EWI) and five sophisticated approaches with time-varying, heterogeneous style exposures determined by different criteria such as utility maximization (Optimized Integration; OI), persistence in performance (Rotation-of-Styles Integration, RSI), volatility (Volatility Timing Integration, VTI), pricing ability (Cross-Sectional Pricing Integration, CSI) and principal components analysis (Principal Components Integration, PCI). In essence, the EWI, OI and RSI methods are not new (e.g., Barberis and Shleifer, 2003; Brandt et al., 2009; Fitzgibbons et al., 2016), but the VTI, CSI and PCI methods have not been considered yet in the style integration literature.

Illustrating the flexibility of the integration framework, our second contribution is to deploy the above approaches in the context of a "universe" of 11 commodity futures investment styles with in mind the idea to assess their relative effectiveness. To our knowledge, no prior study (for any asset class) has conducted such a comprehensive analysis of alternative style-integration approaches. Compared to the 11 standalone portfolios and the other five integrated portfolios, the naïve EWI portfolio stands out as it generates the most attractive reward-to-risk ratio profile (Sharpe, Sortino and Omega ratios) and the lowest crash risk (downside volatility, 99% Value-at-Risk, and maximum drawdown). The failure of more sophisticated integration approaches to outperform the EWI portfolio suggests that the benefits from allowing time-varying and heterogeneous exposures to the K styles are offset by estimation risk and perfect-foresight bias. We adduce evidence that the *de facto* OI approach to integration (see, e.g., Brandt et al., 2009; Barroso and Santa-Clara, 2015; DeMiguel et al., 2017 among others) is not more effective than the simpler EWI, VTI and CSI approaches that do not require solving an optimization problem at each portfolio formation time. These key findings remain unchallenged when we introduce trading costs, alternative style-weighting schemes and commodity scoring schemes, data snooping tests, and economic sub-period analyses.

Our article speaks to a recent, yet growing, literature on style integration for equities (Barberis and Shleifer, 2003; Brandt et al., 2009; Frazzini et al., 2013; Fitzgibbons et al., 2016; DeMiguel et al., 2017), currencies (Kroencke et al., 2014; Barroso and Santa-Clara, 2015), commodities (Fuertes et al., 2010, 2015; Blitz and De Groot, 2014) and across markets (Asness et al., 2013, 2015). Common across these studies is their focus on one integration approach. We complement this literature in two ways. First, we formalize a simple and flexible integration framework that nests not only existing integration approaches (EWI, OI and RSI) but also various other approaches not considered as yet in the style integration literature (VTI, CSI and PCI). Second, we conduct an empirical "horse-race" across various integration methods to investigate their relative effectiveness at harvesting commodity returns and managing commodity risk. To our best knowledge, an empirical exercise of this nature has not been conducted as yet for any asset class.

In adducing empirical evidence that the naïve EWI approach is not surpassed by sophisticated integration approaches, our article speaks to two other literatures. It adds to a voluminous literature on forecast combination where the equal-weights approach has become the benchmark to confront any newly developed forecast combination with (see Timmermann, 2006, for a survey). It also speaks to the literature on asset allocation. DeMiguel et al. (2009) establish empirically that the naïve $1/N$ rule to allocating N assets into a portfolio is at least as good as 14 optimal portfolio allocations in terms of Sharpe ratio, certainty equivalent return and turnover. However, this finding is contested by Kirby and Ostdiek (2012) and Fletcher (2011) through volatility timing strategies.

The paper proceeds as follows. Section 2 presents the asset allocation framework. Section 3 discusses the data and the main empirical findings. Section 4 conducts a battery of robustness tests, before concluding in Section 5.

2. Methodology

2.1. A flexible framework for asset allocation

Let the cross-section of assets be denoted $i = 1, .., N$, the styles $k = 1, \dots, K$, and the portfolio formation times $t = 1, \dots, T$. Bold font is used hereafter to represent matrices and vectors. At each portfolio formation time *t*, the investor allocates wealth to the *N* available assets according to the $N \times 1$ *asset-allocation* (or asset weighting) vector $\boldsymbol{\phi}_t$ constructed as

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

where $\boldsymbol{\Theta}_t$ is a $N \times K$ *score* matrix and $\boldsymbol{\omega}_t$ is a $K \times 1$ *signal- (or style-) weighting* vector that defines the style exposures. The sign of the *i*th asset allocation weight $\phi_{i,t}$ dictates the type of position, i.e., $\phi_{i,t}^L \equiv \phi_{i,t} > 0$, and $\phi_{i,t}^S \equiv \phi_{i,t} < 0$ where *L* denotes long and *S* denotes short.

For most of the study, as regards the $N \times K$ score matrix $\boldsymbol{\Theta}_t$ the focus is on the ternary scoring scheme $\theta_{i,k,t} \in \{-1,0,1\}$ which assigns, according to the *k*th characteristic, a score of 1 (buy) to the quintile of assets with the greatest expected price increase; a score of -1 (sell) to the quintile of assets with the greatest expected price decrease; and a score of 0 to the remaining assets. The next section discusses the construction of the score matrix in our specific commodity futures context.

The proposed framework, Equation (1), allows other scoring schemes. One is defined by the standardized signal $\theta_{i,k,t} \equiv \tilde{x}_{i,k,t} = (x_{i,k,t} - \bar{x}_{k,t})/\sigma_{k,t}^{x}$ where $x_{i,k,t}$ denotes the *k*th characteristic of asset *i* at time *t*. Another is defined by the standardized ranking $\theta_{i,k,t} \equiv \tilde{z}_{i,k,t} = (z_{i,k,t} - \bar{z}_{k,t})/\sigma_{k,t}^{z}$ where $z_{i,k,t} \in \{1, \ldots, N\}$ is the rank of asset *i* at time *t* according to the *k*th characteristic. These scoring schemes are included in our study as part of various other robustness checks.

A key investor decision is which importance to give to the *K* style portfolios at each portfolio formation time *t*. This aspect of the integration is captured by the $K \times 1$ weight vector $\boldsymbol{\omega}_t$ which accommodates time-varying, heterogeneous style-exposures. Section 2.3 formalizes various determination approaches for the style-weights which include extant and new ones.

The portfolio analysis is conducted throughout the paper in an out-of-sample[1] and fully-collateralized experiment that mimics the investor's decisions in real time. The commodity allocations $\phi_{i,t}$ obtained by weighting the scores $\theta_{i,k,t}$ with $\omega_{k,t}$, as formalized in Equation (1), are normalized to ensure a full investment ($\tilde{\phi}_{i,t} = \phi_{i,t}/\sum_{i=1}^{N}|\phi_{i,t}|$ so that $\sum_{i=1}^{N}|\tilde{\phi}_{i,t}| = 1$). Thus $\tilde{\boldsymbol{\Phi}}_t \equiv (\tilde{\phi}_{1,t}, \ldots, \tilde{\phi}_{N,t})$ defines the final commodity allocations at portfolio formation time (month end) *t*. The excess return of the long-short fully-collateralized integrated portfolio held for one month is

$$r_{P,t+1} = \sum_{i=1}^{N} \tilde{\phi}_{i,t} ln \frac{P_{i,t+1}}{P_{i,t}} = \sum_{i=1}^{N} \tilde{\phi}_{i,t} r_{i,t+1} = \sum_i \tilde{\phi}_{i,t}^{L} r_{i,t+1} - \sum_j |\tilde{\phi}_{j,t}^{S}| r_{j,t+1} \quad (2)$$

with $\sum_i \tilde{\phi}_{i,t}^{L} = 0.5$ and $\sum_i \tilde{\phi}_{i,t}^{S} = -0.5$ since each style allocates an equal mandate to the longs and shorts. At time *t*+1 a new commodity allocation vector $\tilde{\boldsymbol{\Phi}}_{t+1}$ is obtained, and so forth.

The commodity allocation framework proposed is very flexible also in that it nests any standalone (*e.g.*, term-structure or momentum) style. For concreteness, the *k*th standalone style

[1] The terminology out-of-sample means in the present context that at each portfolio formation time *t* the investor's allocation vector $\boldsymbol{\Phi}_t$ is constructed from past data.

emerges from Equation (1) for weight vector $\boldsymbol{\omega}_t$ with the *k*th entry set at 1 (all other entries at 0). Constraints can be easily imposed so that the framework nests also long-only ($\theta_{i,k,t} \in \{0,1\}$ with $\omega_{k,t} \geq 0$) and short-only ($\theta_{i,k,t} \in \{0,-1\}$ with $\omega_{k,t} \geq 0$) portfolio construction approaches.

2.2. Individual long-short commodity portfolios

The set of individual styles entertained in the paper is meant to be exhaustive in the sense that it is representative of the commodity investing literature (see Miffre, 2016, for a review).[2] Each individual style buys (shorts) the commodity quintile deemed to appreciate (depreciate) the most. Appendix A lists the specific variables or signals used to predict the commodity futures returns in each style, as well as the supporting studies. Now we motivate the *K*=11 commodity styles that we subsequently integrate.

The *term structure* style builds on the theory of storage (Kaldor, 1939; Working, 1949; Brennan, 1958) which relates the slope of the term structure of commodity futures prices to inventory levels and to the costs/benefits of owning the physical commodity. As empirically shown by Erb and Harvey (2006), Gorton and Rouwenhorst (2006), and Bakshi et al. (2017), a premium can be earned by taking long (short) positions in futures with high (low) roll-yields.

According to the hedging pressure hypothesis developed by Cootner (1960) and Hirshleifer (1988), net long (short) speculators demand a risk premium for taking on the risk of falling (rising) prices that net short (long) hedgers seek to avoid. Evidence of a hedging pressure premium is adduced by Chang (1985), Bessembinder (1992), De Roon et al. (2000) and Basu and Miffre (2013). Two hedging pressure styles arise from two distinct signals -- buy (sell)

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[2] Our usage of the term “style” is somewhat broad to encompass all the long-short commodity strategies employed in the literature to generate returns in excess of the risk free rate (premia). We are agnostic on whether those returns are compensation for exposure to risk factors or a reflection of market anomalies.

futures with high (low) *hedgers' hedging pressure*, or buy (sell) futures with high (low) *speculators' hedging pressure*.

A *momentum* premium in commodity futures markets has been evidenced by Erb and Harvey (2006), Miffre and Rallis (2007), Asness et al. (2013), Gorton et al. (2012) or Bakshi et al. (2017). The well-known momentum style essentially buys past winners and sells past losers.

A *value* premium in commodity futures is documented in Asness et al. (2013) using a long-term mean reversion signal. This style buys long-term losing (high-value or cheap) commodities and sells long-term winning (low-value or expensive) commodities.

A *volatility* premium strategy is motivated by the theory of Dhume (2011) and Gorton et al. (2012) and empirically supported by Szymanowska et al. (2014). In a consumption CAPM framework, Dhume's (2011) model predicts that commodity futures with high volatility correlate positively with durable consumption growth and thus, fail to act as a hedge against intertemporal risk: as a result, investors demand compensation for holding them. Combining aspects from the theories of storage and hedging pressure, the model of Gorton et al. (2012) also predicts that a volatility premium is earned by buying (selling) commodity futures with high (low) volatility.

The *open interest* strategy is motivated by Hong and Yogo (2012) who argue that open interest (OI) is a pro-cyclical indicator of economic activity and hence, unexpected OI changes can predict commodity futures returns. Evidence of a premium obtained by buying-selling commodity futures using open interest changes as the sorting signal is also adduced by Szymanowska et al. (2014).

A *liquidity* premium in commodity futures is evidenced in Szymanowska et al. (2014) using the "Amivest" measure of liquidity as sorting signal (Marshall et al., 2012). The corresponding premium captures the compensation that investors demand in the form of excess returns for taking long positions in commodity futures with relatively low liquidity.

Building on the negative relation between commodity returns and changes in the US$ effective exchange rate index of Erb and Harvey (2006), the US$ beta signal is used by Szymanowska et al. (2014) to capture a *foreign exchange* (FX) premium; the latter reflects the compensation that investors demand for holding commodity futures with low US$ betas.

Commodities are well-known for providing a hedge against inflation shocks (Bodie and Rosansky, 1980; Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). Building on this stylized fact, Szymanowska et al. (2014) document an *inflation* risk premium that reflects the compensation demanded by investors for holding commodity futures with high sensitivity to inflation shocks.

Using total skewness as signal, portfolios that are long (short) in commodity futures with the most negative (positive) skew are shown to capture a sizeable premium by Liu et al. (2017) and Fernandez-Perez et al. (2018). The premium can be rationalized by investors' preferences for skewness under cumulative prospect theory and selective hedging practices.

2.3. Integrated portfolios

We formulate six style-integration approaches within the proposed framework that correspond with six different style-weighting schemes, $\boldsymbol{\omega}_t$, in Equation (1). In the first integration approach the style exposures are time-constant and pre-determined. In the remaining five approaches, the exposures are time-varying, i.e., estimated at each portfolio formation time *t* using prior 60-month data. For now, we focus on the parsimonious score matrix $\boldsymbol{\Theta}_t$ with ternary elements $\theta_{i,k,t} \in \{-1,0,1\}$.

Equally-Weighted Integration (EWI)

By assigning constant and identical exposures to the *K* individual style premia; *i.e.*, $\boldsymbol{\omega}_t = \boldsymbol{\omega} = \left(\frac{1}{K}, \dots, \frac{1}{K}\right)'$, the EWI approach is naïve yet appealing for various related reasons. First, it incurs no *estimation risk* as it does not require weight estimation. Second, it sidesteps *perfect-foresight* *bias* meaning that even in the ideal scenario where estimation risk was negligible and hence, the *K* styles relative past performance was reliably established, good past performance is not guarantee for good future performance. Third, its simplicity reduces the scope for data mining because it does not require ranking the *K* individual styles using past data which requires ad-hoc choices (e.g., length of past data window and specific performance criteria) and multiple testing.

Prior style integration studies employ an equal-weighting scheme similar to EWI; see e.g., Leippold and Rueegg (2017) and Fitzgibbons et al. (2016) for equities, Kroencke et al. (2014) for currencies, and Blitz and De Groot (2014) and Fuertes et al. (2015) for commodities.

Optimal Integration (OI)

The weights that the integrated portfolio assigns to each of the *K* individual style portfolios are defined as those that maximize the conditional expected power utility of the integrated portfolio. This is done by solving at each portfolio formation time *t* the following optimization problem

$$\max_{\boldsymbol{\omega}} \ E_t\left[U\left(r_{P,t+1}\right)\right] = E_t\left[\frac{\left(1+\sum_{i=1}^{N}\tilde{\phi}_{i,t} r_{i,t+1}\right)^{1-\gamma}-1}{1-\gamma}\right], \ \ s.t. \ \omega_k \geq 0 \tag{3}$$

where $\tilde{\phi}_{i,t} = \phi_{i,t}/\sum_{i=1}^{N}\left|\phi_{i,t}\right| = \frac{\sum_{k=1}^{K}\theta_{i,k,t}\omega_k}{\sum_{i=1}^{N}\left|\sum_{k=1}^{K}\theta_{i,k,t}\omega_k\right|}$ are the normalized asset allocations stemming from the style-weighting vector $\boldsymbol{\omega}_t$ that solves Equation (3), and γ is the coefficient of relative risk aversion; we use $\gamma = 5$. By modeling the investor's preferences with power utility, we can parsimoniously capture the higher moments of the return distribution of the integrated portfolio.

Brandt et al. (2009) propose an equity portfolio optimization approach based on firm characteristics where the *N* allocations are defined as optimal deviations from a given benchmark (e.g., value-weighted market portfolio) allocations denoted $\bar{\boldsymbol{\phi}}_t \equiv (\bar{\phi}_{1,t}, \dots, \bar{\phi}_{N,t})$. Thus, a simple generalization of our Equation (1) as $\boldsymbol{\phi}_t = \bar{\boldsymbol{\phi}}_t + \frac{1}{N}(\boldsymbol{\Theta}_t \times \boldsymbol{\omega}_t)$ nests, in essence, the Brandt et al. (2009) parametric portfolio approach.[3] In the present application, $\bar{\boldsymbol{\phi}}_{\mathbf{t}} = \mathbf{0}$, as commodity futures are in zero net supply, and the factor $1/N$ is immaterial because it cancels out after the normalization of $\boldsymbol{\phi}_t$ towards $\widetilde{\boldsymbol{\phi}}_t$. Barroso and Santa-Clara (2015) and DeMiguel et al. (2017) deploy the Brandt et al. (2009) style integration method for currencies and stocks, respectively.

Rotation-of-Styles Integration (RSI)

At each month-end, the RSI portfolio has full exposure to the *j*th standalone style with the highest Sharpe ratio ($\omega_{j,t} = 1$). All other styles receive zero weight, $\omega_{k,t} = 0$, for $k = 1, \ldots, K$ $(k \neq j)$. Over time, the RSI strategy aims to exploit persistence in relative style performance.

The RSI approach is motivated by the theoretical style-switching model of Barberis and Shleifer (2003) where investors allocate capital based on relative style performance. Evidence of style-based feedback trading among U.S. equity funds is provided by Frijns et al. (2016).

Volatility Timing Integration (VTI)

In this integration approach, the importance given to the *k*th standalone style is inversely proportional to its risk (proxied by the variance of past monthly returns) as $\omega_{k,t} \equiv \sigma_k^{-2} / \sum_{k=1}^{K} \sigma_k^{-2}$. The approach is inspired by the Kirby and Ostdiek (2012) volatility-timing (or risk-parity) strategy for allocating *N* assets into a portfolio. Specifically, evidence has been adduced to suggest that volatility-timing outperforms the equal-weight $(1/N)$ allocation

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3 Strictly-speaking, in order to nest the Brandt et al. (2009) approach in Equation (1), the score matrix $\boldsymbol{\Theta}_{\mathrm{t}}$ should contain the demeaned and standardized signals; we consider this scoring scheme and alternative ones as robustness checks. As in Brandt et al. (2009), the investor is assumed to maintain constant style-exposures, $\boldsymbol{\omega}$, over the past 60-months used to solve Equation (3). Effectively, by solving the optimization problem at each portfolio formation time *t*, the style exposures are allowed to change over time, $\boldsymbol{\omega}_t$. We deployed the OI approach also for $\gamma = \{3, 10\}$ and the main insights hold.

approach advocated by DeMiguel et al. (2009); see, for instance, Kirby and Ostdiek (2012) for US equities, and Fletcher (2011) for UK equities.

Cross-Sectional Pricing Integration (CSI)

The weights ω_k reflect the ability of the individual style premia to explain the cross-sectional variation of commodity futures returns. The idea is to give higher (lower) weights to the premia that best (worst) price commodity futures contracts. As in Fama-MacBeth (1973), each month-end t we estimate univariate *time-series* OLS regressions per commodity $i = 1, \dots, N$ and style $k = 1, \dots, K$ (a total of $N \times K$ regressions) using the past 60-month window of data

$$r_{i,s} = a_{i,k} + b_{i,k} f_{k,s} + \varepsilon_{i,s}, s = t - 59, \dots, t \qquad (4)$$

where $r_{i,s}$ is the month *s* excess return of commodity *i*, $f_{k,s}$ 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 unknown coefficients to estimate. At step two, we estimate on each month *s* (within the 60-month window) a *cross-sectional* OLS regression

$$r_{i,s} = \lambda_{k,s}^0 + \lambda_{k,s}^1 \hat{b}_{i,k} + \epsilon_{i,s}, i = 1,2, \dots, N \qquad (5)$$

for $s = t - 59, \dots, t$ ($60 \times K$ regressions). The exposure of the CSI portfolio to the *k*th style is given by the average *explanatory power* of the *k*th factor in Equation (5) as $\omega_k \equiv \frac{1}{60} \sum_{s=t-59}^{t} R_{k,s}^2$.

Principal Components Integration (PCI)

At each month-end, we extract the *K* principal components from the covariance matrix of individual style premia. Let $\boldsymbol{L}_j$ denote the *K*-vector of loadings (or *j*th eigenvector) obtained for the *j*th principal component, $j = 1 \dots K$, and e_j its explanatory power. The PCI weights are $\boldsymbol{\omega_t} \equiv \frac{e_1 \boldsymbol{L}_1 + e_2 \boldsymbol{L}_2 + \cdots + e_m \boldsymbol{L}_m}{e_1 + e_2 + \cdots + e_m}$, where *m* is the number of principal components that explain at least τ of the total variation in the individual style premia; we use τ=90% which is arbitrary but conservative.

3. Data and Empirical Results

3.1.Data

The empirical analysis is based on settlement prices, hedgers' and speculators' open interest, total open interest and volume data from *Thomson Reuters Datastream* for 28 commodity futures. The contracts cover all sectors: 12 agricultural (cocoa, coffee, corn, cotton, frozen concentrated orange juice, oats, rough rice, soybeans, soybean meal, soybean oil, sugar 11 and wheat), 6 energies (electricity, gasoline RBOB, heating oil, light sweet crude oil, natural gas and unleaded gas), 4 livestock (feeder cattle, frozen pork bellies, lean hogs, live cattle), 5 metals (high grade copper, gold, palladium, platinum, silver 5000) and lumber. Returns are calculated as changes in the logarithmic (log) prices of front-end contracts up to one month before maturity; the positions are then rolled to the second-nearest contract. The cross-section of commodities is dictated by the availability of data on speculators' and hedgers' open positions as compiled by the Commodity Futures Trading Commission. Data on the US consumer price index and on the USD versus major currency index are also obtained from *Thomson Reuters Datastream.* Although the starting date of our dataset is January 1979, the out-of-sample period that is common to all portfolios, individual and integrated, is from January 1992 to April 2016.

3.2. Performance of individual and integrated styles

Table 1, Panel A summarizes the monthly excess returns of the $K = 11$ long-short portfolios discussed in Section 2.2 over the entire sample period from January 1992 to April 2016 ($T = 292$ months). According to both the reward-to-risk and crash risk profiles, the skewness, speculators' hedging pressure, hedgers' hedging pressure, term structure and momentum portfolios rank top whereas the liquidity, value, open interest and volatility portfolios rank bottom. The certainty equivalent return (CER) which represents the risk-free rate that an investor is willing to accept instead of engaging in a particular risky portfolio strategy, based on power utility preferences with $\gamma = 5$ also confirms the ranking.[4] Despite the poor performance of some of the strategies we include all of them in the subsequent integration exercise for three reasons. First, we want to focus on the "universe" of long-short commodity styles in our analysis in order not to engage in a pre-selection process which might introduce data mining bias. Second, as discussed next, a given strategy may rank poorly over the entire sample period but much more favorably over a specific sub-period; hence, a pre-selection of individual strategies to integrate just the best ones might incur look-ahead bias. Third, a poorly performing style might still play a diversification role in an integrated portfolio if its returns are lowly correlated with those of other styles.

Confirming a common wisdom in the commodity markets literature, we note that any of the long-short styles summarized in Table 1 offers superior reward-to-risk and crash risk profiles than long-only benchmarks such as an equally-weighted, monthly-rebalanced portfolio of the 28 commodities and the S&P-GSCI. The online Annex Table A.I shows that these two portfolios generate a mean excess return of -0.0098 and 0.0007 for a relatively high standard deviation of 0.1266 and 0.2155 (all annualized) and a large maximum drawdown of -0.5672 and -0.8556.

Table 1, Panel B reports the Sharpe ratio of the individual strategies and the corresponding ranking over 5-year non-overlapping rolling windows. Interestingly, the value strategy switches from worse-performing in the 2nd period to top-performing in the last period. Likewise, the momentum strategy is positioned top in the 1st and 2nd periods but is outperformed by at least 6 other styles in the next two periods. The relative performance of the 11 standalone portfolios

[4] The power utility-based certainty equivalent return is defined as $CER = \left(\frac{12}{T}\right)\sum_{t=0}^{T-1}\frac{\left(1+r_{P,t+1}\right)^{1-\gamma}-1}{1-\gamma}$ with $r_{P,t+1}$ the integrated portfolio excess return on month t+1 and T the number of out-of-sample months. $CER > 0$ implies that the risky portfolio is more attractive than the risk-free asset.

varies over time posing a challenge to an investor that seeks to follow a single style. Style integration thus serves as a natural hedge against the underperformance of a given individual style over specific periods.

[Insert Table 1 around here]

Figure 1 plots the Sharpe ratio of the standalone styles deployed cumulatively over time (monthly expanding windows). The first point in each graph is the Sharpe ratio over an initial 5-year investment window [1, t] and the last point in the graph represents the Sharpe ratio accrued over the entire sample period [1, T]. The graph confirms the instability in relative style ranking.

[Insert Figure 1 around here]

Table 2 provides three statistics to gauge the degree of (non)linear dependence across the K standalone styles. Focusing exclusively on linear dependence, Panel A reports the pairwise Pearson correlations across the excess returns of the K individual styles, and Panel B reports the partial coefficient of determination R_k^2 (explanatory power of a regression of the kth style on all other styles). In the interest of robustness, Panel C reports the Spearman rank-order correlation that is able to capture (non)linear association between the K standalone-factor portfolio returns.

[Insert Table 2 around here]

All three statistics suggest that the K styles are mildly correlated with one exception pertaining to the two hedging pressure premia that exhibit a correlation of 66% (and a rank correlation of 65%). Various negative correlations are observed which should help achieve diversification benefits. The value style, which is contrarian in nature, correlates negatively with most other styles. Significant negative correlations are also observed for the momentum style with the open interest and liquidity styles, and between the open interest style and the US$ beta style. The average correlations are low standing at merely 4% (pairwise Pearson correlation), 26% (R_k^2)

and 4% (pairwise rank correlation). This low dependence among the K styles motivates an integrated portfolio approach as a way of managing risk.

We began by studying the performance of the naïve integration strategy, EWI, over the entire January 1992 to April 2016 period with results summarized in Table 3, Panel A, first column. The Sharpe ratio of the EWI portfolio is 0.94 which represents an improvement of at least 16% over each standalone style. The superior risk-adjusted performance of the EWI style is confirmed by more general measures that focus on downside volatility (Sortino ratio) or account for non-normality (Omega ratio). The certainty equivalent return (CER) is also the highest for the EWI portfolio (6.05% *p.a.*) versus the highest 5.87% *p.a.* across individual styles. The EWI portfolio has also lower non-normality risk with insignificant coefficients of skewness and kurtosis. Concerning "crash" risk, as captured by downside volatility, 99% Value-at-Risk, and maximum drawdown measures, the EWI portfolio is also appealing vis-à-vis the standalone-style portfolios.

[Insert Table 3 around here]

To complement the static comparison of the EWI style and individual styles enabled by Table 1, we now plot in Figure 2 the corresponding Sharpe ratios, mean excess returns and volatilities that an investor would obtain cumulatively over time (one-month-expanding windows). The Sharpe ratio (Panel A) of the EWI portfolio is consistently higher than that of the individual strategies. The mean excess return (Panel B) and volatility (Panel C) suggest that while the EWI portfolio does not accrue the largest mean excess return always, it delivers by far the most stable stream of returns which bears out the benefits in terms of style (or signal) diversification.

[Insert Figure 2 around here]

A natural question is whether the sophisticated integrations that allow for time-varying, heterogeneous style exposures improve upon EWI. Table 3, Panel A shows that long-short portfolios constructed by optimal integration (OI), rotation-of-styles integration (RSI), volatility-timing integration (VTI), cross-sectional-pricing integration (CSI) and principal component integration (PCI) are unable to challenge the reward-to-risk and crash risk profiles of the EWI portfolio. Amongst the five sophisticated integrated portfolios, the closest competitors to the EWI portfolio are the VTI and CSI portfolios since they exhibit similar downside risk profiles albeit economically lower reward-to-risk ratios (e.g., Sharpe ratios of 0.83 and 0.82 versus 0.94 for EWI). The OI approach that is becoming the *de facto* approach in the literature on style integration (see. e.g., Brandt et al., 2009; Barroso and Santa-Clara, 2015; DeMiguel et al., 2017 among others) offers a Sharpe ratio that stands at 0.69 merely. The RSI and PCI portfolios close the horse-race by offering the smallest Sharpe ratios of 0.53 and 0.37, respectively, and the most unappealing downside risk profiles.

To assess the statistical relevance of our findings we calculate the Opdyke (2007) p-value for the null hypothesis $H_0: SR_{EWI} \leq SR_j$ versus $H_A: SR_{EWI} > SR_j$ where j denotes a sophisticated integrated portfolio. The p-values, reported in Table 3, Panel A reject the null hypothesis at the 5% or better for the RSI and PCI portfolios, and at the 10% level for OI. The Sharpe ratios of the EWI, VTI and CSI portfolios are statistically identical. Yet given the simplicity of the EWI approach versus the estimation entailed in the VTI and CSI approaches, the former is preferred. Unreported results for the Opdyke test $H_0: SR_{EWI} \leq SR_k$ with k denoting an individual style portfolio reject the null hypothesis at the 5% or 1% in all cases except the skewness portfolio. Thus over the sample period the reward-to-risk trade-off of the EWI style is comparable to that of the skewness style; however, the EWI portfolio remains preferable on account of its more favorable crash risk profile.

In order to account for higher order moments of the return distribution, the last two rows of Table 3, Panel A, report the CER of each integrated portfolio and p-values for the null hypothesis $H_0: CER_{EWI} \leq CER_j$ versus $H_A: CER_{EWI} > CER_j$ where j denotes an integrated portfolio other than the EWI. The p-values solidly reject the null hypothesis at conventional levels confirming the dominance of the EWI approach.[5] Unreported p-values for $H_0: CER_{EWI} \leq CER_k$, with k denoting a given standalone-style portfolio, also reject H_0; the one exception is the skewness portfolio.

Table 3, Panel B provides a dynamic snapshot of the Sharpe ratio of the integrated portfolios over non-overlapping 5-year rolling windows, and associated ranking in parentheses. EWI offers almost the best reward-to-risk ratio throughout. The cumulative performance over an initial 5-year window expanded monthly, shown in Figure 3, confirms this finding.

[Insert Figure 3 around here]

Specifically, the graphs reveal that the outstanding Sharpe ratio of the EWI strategy versus sophisticated integrations is driven both by its effectiveness to capture larger mean excess return and its diversification benefits (lesser volatility) but the former plays a stronger role. Among all integration strategies, the lowest volatility is achieved by VTI, then EWI and CSI (Panel C) but the EWI portfolio clearly excels at capturing large excess returns (Panel B).[6]

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[5] The p-values for the test of significance of the CER differential are obtained through the Politis and Romano (1994) bootstrap method. We obtain B=10,000 pairs of pseudo time-series of excess returns $\{r^*_{EWI,t}, r^*_{j,t}\}$ with the same length, T=292 months, as the actual time-series $\{r_{EWI,t}, r_{j,t}\}$ by resampling blocks of random length from the latter. The block-length is a geometrically distributed variable with expected value $1/q$. For space constraints, we report results for q=0.2; the results for q=0.5 offer similar insights and available from the authors upon request.

[6] A relevant question is whether one might be better off by optimizing the portfolio weights of the 28 individual commodities directly, rather than relying on style-integration which can formally be described as a parametric representation of portfolio weights. To address this question empirically, we optimized the weights of the 28 commodities over the previous 60-month window assuming a power utility and ensuring full investment. Specifically, we set the optimization problem as $\max_{\boldsymbol{\omega}} E_t\left[U\left(r_{P,t+1}\right)\right] = E_t\left[\frac{\left(1+\sum_{i=1}^{N} \omega_{i,t} r_{i,t+1}\right)^{1-\gamma}-1}{1-\gamma}\right], \; s.t. \; \sum_{i=1}^{N}\left|\omega_{i,t}\right| = 1$, where $\omega_{i,t}$ is the weight of commodity ith at portfolio formation time t. With a Sharpe ratio of 0.40 and maximum drawdown of -0.30, the results reported in the online Annex Table A.I. confirm the superiority of most integrated portfolios versus the direct optimization of the individual commodities' weights.

We assess the extent to which the excess returns of the different integrated portfolios reflect exposure to the K underlying styles by estimating OLS regressions of the long-short integrated portfolio excess returns on the long-short excess returns of the K standalone styles. Table 4 reports the results. Two observations can be made as regards the EWI portfolio. First, the K sensitivities are significantly positive and similar in size which suggests that, as it was intended, EWI attains equal style exposures. Second, the time-variation in the returns of the K styles jointly explains 98% of the time-variation in the EWI portfolio returns, bearing out its effectiveness to blend signals.

[Insert Table 4 around here]

As regards the sophisticated integration strategies and consistent with our prior findings, the regressions for the VTI and CSI portfolios reveal that these integrated approaches are the closest to EWI; their R^2 (above 90%) and vectors of sensitivities indirectly suggest that the resulting commodity allocations, $\boldsymbol{\phi}_t$ from Equation (1), are similar across the three integration methods. As expected, the RSI portfolio loads positively on the individual styles that perform best on average (term structure, speculators' hedging pressure, momentum and skewness; c.f. Table 1). Interestingly also, the RSI style is most sensitive to the momentum premia which is aligned with the theoretical prediction from the Barberis and Shleifer (2003) model that style-based investing can generate momentum in individual asset returns at intermediate horizons. With merely 17% of the time-variation in the PCI returns jointly explained by the 11 underlying style portfolios and only two significant sensitivities, the PCI method is the least effective at integrating styles which is not surprising given their mild commonality.

3.3. Role of the number of standalone styles

To examine the effect of increasing the number of styles, K, on the benefits of integration and on the relative efficiency of the integration approaches, Figure 4 presents box-and-whisker plots of the Sharpe ratio, mean excess return and volatility for $K = \{2, \ldots, 11\}$. Panels A1-A3 show

how the performance of the EWI portfolio evolves with K; the two horizontal lines in each graph denote the range of the performance measure at hand across the standalone-style portfolios. Panels B1-F3 show the differential performance of EWI versus OI, RSI, VTI, CSI and PCI portfolios.

[Insert Figure 4 around here]

Two interesting patterns emerge from Panels A1 to A3. First, the Sharpe ratio of the EWI portfolio improves with K, the number of integrated styles. Second, the mean return of the EWI portfolio rises, and its volatility falls, with K but the latter effect dominates. Hence, it is the risk diversification that drives the Sharpe ratio pattern. Three styles suffice ($K \geq 3$) for the EWI portfolio essentially to be less volatile than all of the single-style portfolios.

The remaining plots show an upward-sloping Sharpe ratio $SR_K^{EWI} - SR_K^j$ in all five comparisons j={OI, RSI, VTI, CSI, PCI} confirming that the reward-to-risk profile of the EWI portfolio improves with K at a faster rate than that of sophisticated integrated portfolios. The mean excess return differential $\mu_K^{EWI} - \mu_K^j$ also rises with K in all five cases, suggesting that the relative superiority of the EWI portfolio at capturing higher mean excess returns rises as we integrate more styles. The volatility differential of EWI versus OI portfolios, VTI portfolios and CSI portfolios has essentially zero slope suggesting that the diversification benefits of all three approaches improve at a similar rate with K. In contrast, the plots of $\sigma_K^{EWI} - \sigma_K^{PCI}$ and $\sigma_K^{EWI} - \sigma_K^{RSI}$ slope downwards suggesting that as K increases the EWI approach is more efficient at providing risk diversification benefits. Figure A.I in the online Annex provides box-and-whisker plots of the reward-to-risk profile (versus K) of each alternative integrated portfolio.

4. Robustness Analysis

We now test whether the dominance of the naïve EWI portfolio withstands the consideration of trading costs, alternative integration approaches and scoring schemes, and economic sub-periods.

4.1. Turnover and transaction costs

To get a sense of how trading intensive each investment (standalone and integrated) strategy is, we measure the portfolio *turnover* (TO) defined as the time average of all the trades incurred

$$TO_j = \frac{1}{T-1}\sum_{t=1}^{T-1}\sum_{i=1}^{N}\left(\left|\tilde{\phi}_{j,i,t+1} - \tilde{\phi}_{j,i,t^+}\right|\right) \tag{6}$$

$t = 1, \dots, T$ denotes each of the (month-end) portfolio formation periods in the sample, $\tilde{\phi}_{j,i,t}$ is the *i*th commodity allocation weight dictated at month *t* by the *j*th style according to Equation (1), $\tilde{\phi}_{j,i,t^+} \equiv \tilde{\phi}_{j,i,t} \times e^{r_{i,t+1}}$ is the actual portfolio weight right *before* the next rebalancing at $t+1$, $r_{i,t+1}$ is the monthly return of the *i*th commodity from month-end t to month-end $t+1$. Thus TO captures the mechanical evolution of the allocation weights due to within-month price dynamics (*e.g.*, $\tilde{\phi}_{j,i,t}$ increases to $\tilde{\phi}_{j,i,t^+}$ when $r_{i,t+1} > 0$). Figure 5, Panel A graphs TO.

[Insert Figure 5 around here]

The integrated portfolios are generally more trading intensive than the individual styles given that the former invest potentially in all *N* commodities whereas the latter invest, by construction, only in 40% of the *N* commodities (i.e., top/bottom quintiles). Two exceptions are the individual term structure and open interest styles which exhibit the highest TO. The trading intensity of EWI is comparable to that of RSI, VTI and CSI; not only OI and PCI are less effective at capturing risk premia (Figure 3) but also they are more trading intensive.

The key question is whether transaction costs (TC) wipe out the outperformance of the EWI portfolio. To address this question, we calculate the net return of each portfolio as

$$\tilde{r}_{P,t+1} = \sum_{i=1}^{N}\tilde{\phi}_{i,t}r_{i,t+1} - TC\sum_{i=1}^{N}\left|\tilde{\phi}_{i,t} - \tilde{\phi}_{i,t-1^+}\right| \tag{7}$$

using proportional trading costs of 8.6 bps (Marshall et al., 2012). Figure 5, Panel B shows that the superior reward-to-risk of the naïve EWI portfolio is not challenged by trading cost considerations.

4.2. Alternative commodity scoring schemes

Thus far, our investigation has focused on a particular aspect of the integration framework, the style-weighting vector $\boldsymbol{\omega}_t$, while maintaining the same ternary scoring scheme $\theta_{i,k,t} \in \{-1,0,1\}$. We now turn our attention to the role played by the scoring scheme by deploying Equation (1) with a matrix $\boldsymbol{\Theta}_t = \{\theta_{i,k,t}\}$ populated by either standardized signals or standardized rankings.[7] For consistency, we again focus on the extreme quintiles and fully collateralize the positions. Table A.II in the online Annex reports a battery of performance measures for the integrated portfolios based on standardized signals and standardized rankings (*c.f.*, Table 3).

A comparison of Table 3 and Table A.II in the online Annex shows that, relative to the weighting scheme, $\boldsymbol{\omega}_t$, the choice of scoring scheme, $\boldsymbol{\Theta}_t$, plays a small role on the relative performance of the integrated portfolios. For instance, there is no clear contrast amongst the EWI portfolios obtained with the various scoring schemes; this is not surprising given that the allocations $\{\phi_{i,t}^{EWI}\}_{t=1}^{T}$ obtained from Equation (1) with the ternary scores {-1,0,1} correlate highly with those obtained with the standardized signals (rankings) at 0.98 (0.85) on average across commodities. With alternative scoring schemes, the EWI portfolio remains the leading integrated portfolio as regards its reward-to-risk tradeoff and downside risk profile.

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[7] As noted in Section 2.3, the OI strategy of Brandt et al. (2009) is a particular case of the framework encapsulated in Equation (1) for a score matrix $\boldsymbol{\Theta}_t$ with elements given by the standardized rankings. The triple-scoring strategy deployed by Frazzini et al. (2013) for stocks, Kroencke et al. (2014) for currencies, and Fuertes et al. (2015) for commodities is an equal-weights style integration that is nested in Equation (1) for a standardized-rankings matrix $\boldsymbol{\Theta}_t$ as well.

4.3. Reformulation of the sophisticated integration strategies

This section reformulates the sophisticated integrations studied thus far. We adhere to the ternary scoring scheme, and the investor decision about the style exposures at each month end, $\boldsymbol{\omega}_t$, is based as before on past 60-month data on each style. The integrated portfolios are held for a month.

We design three alternative OI strategies where the objective function $U(r_{P,t+1})$ is the integrated portfolio's quadratic utility, exponential utility or power utility with disappointment aversion of Gul (1991). Thus the investor solves at each portfolio formation time, respectively

1) $\max_{\boldsymbol{\omega}} [E_t(r_{P,t+1}) - \frac{\gamma}{2} Var_t(r_{P,t+1})]$, where $r_{P,t+1} \equiv \sum_{i=1}^{N} \tilde{\phi}_{i,t} r_{i,t+1}$ is the return of the integrated portfolio, and γ is the relative risk aversion parameter ($\gamma = 5$).

2) $\max_{\boldsymbol{\omega}} \; E_t\left[-e^{-\kappa(1+r_{P,t+1})}/\kappa\right]$ with absolute risk aversion parameter $\kappa = 5$.

3) $\max_{\boldsymbol{\omega}} \; E_t \left\{ \begin{matrix} \frac{(1+r_{P,t+1})^{1-\gamma}-1}{1-\gamma} & if\ r_{P,t+1} > 0 \\ \frac{(1+r_{P,t+1})^{1-\gamma}-1}{1-\gamma} + \left(\frac{1}{A}-1\right)\left[\frac{(1+r_{P,t+1})^{1-\gamma}-1}{1-\gamma}\right] & if\ r_{P,t+1} \leq 0 \end{matrix} \right\}$ where $A \leq 1$ is the coefficient of disappointment aversion that controls the relative steepness of the value function in the gains/losses regions (we report results for A=0.6; similar results are obtained for A=0.8).[8]

Leaving the utility setting aside, we consider an investor who is only concerned about minimizing risk and therefore the style exposures are obtained as $\min_{\boldsymbol{\omega}} \; [Var_t(r_{P,t+1})]$ subject to $\sum_{k=1}^{K} \omega_k = 1$ (to avoid the trivial solution $\omega_k = 0$). For all the OI strategies considered, we consider two cases – non-negativity constraint ($\omega_k \geq 0$) and no sign constraint ($\forall \omega_k$).

Inspired by the cluster combination approach of Aiolfi and Timmermann (2006), we formulate a potentially smoother version of the former RSI strategy based on the three styles

[8] This utility function recognizes that investors are more sensitive to losses than to gains of the same magnitude. A = 1 entails the standard power utility function where there is no loss aversion.

with best past performance, RSI(3) hereafter. At each month-end, the RSI(3) portfolio has equal exposure to the three styles with the highest Sharpe ratio ($\omega_k = 1/3$) and zero exposure to the remaining styles.

We deploy two variants of the earlier VTI strategy inspired by Kirby and Ostdiek (2012). Firstly, the VTI($\eta = 4$) approach that assigns weights inversely proportional to the style variance, $\omega_k = (\sigma_k^{-2})^\eta / \sum_{k=1}^{K} (\sigma_k^{-2})^\eta$, with a stronger timing aggressiveness $\eta = 4$.[9] Secondly, the reward-to-risk timing integration (RRTI) approach with style weights $\omega_k = (\mu_k^+ / \sigma_k^2)^\eta / \sum_{k=1}^{K} (\mu_k^+ / \sigma_k^2)^\eta$ where $\mu_k^+ = \max(0, \mu_k)$, and μ_k is the mean excess return of the kth style; we also adopt $\eta = 4$.

We also consider a version of the CSI strategy that focuses on the first-stage of the Fama-MacBeth (1973) approach (time-series pricing integration, TSI, hereafter). Specifically, we estimate univariate predictive time-series OLS regressions of the excess returns of each commodity $i = 1, \dots, N$ on the past-month style premium $k = 1, \dots, K$ (a total of $N \times K$ regressions)

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

and the exposure to the kth style is given by $\omega_k \equiv \frac{1}{N} \sum_{i=1}^{N} R_{i,k}^2$ where $R_{i,k}^2$ is the predictive power.[10] Finally, we deploy the simplest version of PCI that uses just the first principal component, PCI(1).

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[9] If $\eta = 0$ (no volatility timing), then $\omega_k = 1/K$ for $k = 1, \dots, K$ and we have the EWI approach. If $\eta \to \infty$, (most aggressive volatility timing) the jth style with the lowest past volatility receives all the weight $\omega_j = 1$ ($\omega_k = 0, k \neq j$); this is a volatility-based variant of the RSI approach.

[10] The performance of a TSI strategy based on Equation (8) with contemporaneous factor $f_{k,s}$ is inferior as borne out by a Sharpe ratio of 0.6846, maximum drawdown of -0.1563 and 99% VaR of 0.0519.

Table A.III in the online Annex reports the results. The EWI portfolio still presents the highest Sharpe ratio (0.94), highest CER (6.05%) and a relatively appealing downside risk profile. Another finding is that, consistent with our prior findings, the OI strategies with sign-restricted weights $\omega_k \geq 0$ perform better than the counterpart OIs with free weights. Table A.IV in the online Annex reports results for all of these sophisticated integration variants as regards their effectiveness at allocating commodities into portfolios. The evidence suggests that no integration method poses a challenge to the EWI approach in terms of harvesting large returns and managing risk.

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

Data snooping risk needs to be quantitatively addressed in an empirical analysis of this nature that uses the same dataset repeatedly to implement various investment strategies. We deploy the Superior Predictive Ability test of Hansen (2005) in order to shield the inferences from this bias.

Adopting the EWI strategy as our benchmark we appraise the relative performance of the $M = 31$ long-short investment strategies studied in the paper (eleven standalone styles in Table 1, six integration strategies in Table 3 and fourteen alternative sophisticated integrations in Table A.III). Let $r_{m,t}$ denote the month *t* excess returns of strategy *m* ($m = 1, \dots, M$) and define $r_t^{max} \equiv max(r_{EWI,t}, r_{1,t}, \dots, r_{M-1,t})$. Performance of the *m*th strategy is measured in terms of the expected "loss" modelled as in Hansen (2005) with a linear mathematical function, $L_{m,t} \equiv r_t^{max} - r_{m,t}$, and two nonlinear functions, $L_{m,t} \equiv 1/exp(\lambda r_{m,t})$ with curvature parameter $\lambda = \{1, 2\}$. Likewise, for the benchmark we define the losses as $L_{EWI,t} \equiv r_t^{max} - r_{EWI,t}$ and $L_{EWI,t} \equiv 1/exp(\lambda r_{EWI,t})$, respectively. The expected "loss" of the *m*th strategy relative to the benchmark is therefore $E[d_{m,t}] = E[L_{EWI,t} - L_{m,t}]$ for $t = 1, \dots, T$ months. Strategy m is better than the benchmark (EWI) if and only if $E[d_{m,t}] > 0$. The null hypothesis is that the best of the M strategies incurs a larger "loss" than the benchmark EWI strategy; *i.e.*, $H_0\colon E[d_{m,t}] \leq 0$, for all $m = 1,\ldots,M$.[11]

As shown in Table A.V of the online Annex, the large bootstrap p-values of the test, ranging from 0.3602 to 0.5116 across "loss" functions, are clearly unable to reject the null hypothesis. Thus our main finding that the EWI portfolio is not outperformed by any of the standalone-style portfolios or sophisticated integrated portfolios does not appear to be an artifact of data mining.

4.5. Are the findings sample-specific?

To address this question, we re-evaluate the performance of the standalone and integrated portfolios over different sub-periods defined according to economic criteria. First, we consider high versus low commodity market volatility regimes identified through a GARCH(1,1) model fitted to the monthly excess returns of the long-only (equally-weighted and monthly rebalanced) portfolio of all 28 commodities. The threshold to define the regimes is the average fitted volatility ($\bar{\sigma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\sigma}_t$ =12.25% p.a.). Second, we split the sample in two periods to reflect the so-called financialization of commodity futures markets roughly dated January 2006 (Stoll and Whaley, 2010). Finally, we consider recession versus expansion periods according to the NBER-dated business cycle phases. The results are shown in Table A.VI of the online Annex.

The EWI portfolio obtains a reward-to-risk tradeoff which is as good as (often better than) that of the sophisticated integrated portfolios; according to the Opdyke test and the bootstrap p-values for $H_0\colon CER_{EWI} \leq CER_j$ no individual style significantly outperforms the EWI style. Moreover, the EWI portfolio stands out as regards the battery of crash risk measures considered. The only exception is the NBER-dated recession periods but a caveat to this finding is that the

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[11] The test is based on a statistic with a non-standard (sample dependent) distribution which we approximate using the Politis and Romano (1994) bootstrap method. We obtain B=10,000 pseudo time series $\{d^*_{m,t}\}$ for each investment strategy m by combining random-length sampled blocks from the actual $\{d_{m,t}\}$. The block-length is a geometrically distributed random variable with expected value $1/q$; we consider $q = \{0.2, 0.5\}$.

corresponding sample size is too small (28 months) which weakens the reliability of the estimates.

5. Conclusions

A variety of strategies or "styles" have been proposed in the literature to capture the risk premium of commodity markets using predictive variables such as the roll yield or hedging pressure *inter alia*. This paper investigates the ability of style integration to improve portfolio allocation.

Our first ambition is to help academics and practitioners alike to implement style integration in a well-structured manner. To do this, we formalize an allocation framework that nests any individual style and many integration methods. The flexible framework is illustrated for eleven long-short commodity styles but it has a broader appeal since it is applicable also to long- and short-only styles, as well as to other asset classes. Alternative integration approaches emerge from different ways to define the style exposures at each portfolio formation time such as the naive equal-weighted integration (EWI) and sophisticated integrations based on utility maximization, style rotation, volatility timing, cross-sectional pricing and principal components analysis. From a methodological viewpoint, the portfolio allocation framework proposed is thus useful to get insights as to which free parameters or restrictions are used by the existing integration approaches in the literature, and to provide some structure to develop integration methods such as, for instance, the novel ones that we consider in a commodity futures context.

We conduct an extensive out-of-sample experiment that mimics the investors' decisions in real time to assess the benefits of style integration for commodity futures, and the effectiveness of alternative integration methods on which there is a dearth of research for any asset class. A key finding is that the improvement in reward-to-risk tradeoff and crash risk profiles afforded by the naïve EWI portfolio (vis-à-vis the standalone style portfolios) is not challenged by sophisticated integration methods that allow for time-varying and style-heterogeneous exposures. The rationale is that the gains from the latter are outweighed by estimation noise and "perfect foresight" bias. The findings are robust to trading costs, alternative scoring schemes, economic sub-period analysis and data snooping tests inter alia. Our empirical exercise is ambitious in that it compares the performance of many integration approaches, existing and novel ones, but the list of approaches considered may not be exhaustive.

Our findings suggest that the naïve EWI portfolio is a challenging "benchmark" to confront the performance of newly proposed commodity portfolio strategies with. We hope that the simple yet flexible integration framework proposed instigates further research. Specifically, it would be interesting to see if the EWI approach also dominates the style-integration landscape for other asset classes.

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Appendix A: Standalone long-short styles for commodity futures investing.

	Style name	Acronym		Signal	Scoring scheme $\Theta_t = \{-1,0,1\}$	References
1)	Term structure	TS	Roll yield or basis defined as difference in log month-end prices of front-end contract (spot price) and next maturity contract	$Roll_{it} \equiv \ln(f_{i,t}^{front}) - \ln(f_{i,t}^{second})$	{Low,Medium,High}	Kaldor (1939), Working (1949), Brennan (1958), Erb and Harvey (2006), Gorton and Rouwenhorst (2006), Szymanowska et al. (2014), Bakshi et al. (2017)
2)	Hedgers' hedging pressure	Hedgers' HP	Net short open interest (short minus long) over total open interest of hedgers during the last 12 months	$HP_{H,it} \equiv \left(\frac{1}{12}\right)\sum_{j=0}^{12-1}\frac{Short_{H,it-j} - Long_{H,it-j}}{Long_{H,it-j} + Short_{H,it-j}}$	{Low,Medium,High}	Cootner (1960), Hirshleifer (1988), De Roon et al. (2000), Basu and Miffre (2013), Dewally et al. (2013)
3)	Speculators' hedging pressure	Speculators' HP	Net long open interest (long minus short) over total open interest of speculators during the last 12 months	$HP_{S,it} \equiv \left(\frac{1}{12}\right)\sum_{j=0}^{12-1}\frac{Long_{S,it-j} - Short_{S,it-j}}{Long_{S,it-j} + Short_{S,it-j}}$	{Low,Medium,High}	Cootner (1960), Chang (1985), Hirshleifer (1988), Bessembinder (1992), Basu and Miffre (2013), Dewally et al. (2013)
4)	Momentum	Mom	Average excess daily return of the commodity during the recent past 12 months (D days)	$Mom_{it} \equiv \frac{1}{D}\sum_{j=0}^{D-1} r_{i,t-j}$	{Low,Medium,High}	Erb and Harvey (2006), Miffre and Rallis (2007), Fuertes et al. (2010), Asness et al. (2013), Bakshi et al. (2017), Szymanowska et al. (2014)
5)	Value	Value	Log of the average daily front-end futures prices 4.5 to 5.5 years ago (D days) divided by the front-end futures price at time t	$Value_{it} \equiv ln\frac{\frac{1}{D}\sum_{d=1}^{D} f_{i,d}^{front}}{f_{i,d}^{front}}$	{Low,Medium,High}	Asness et al. (2013)
6)	Volatility	Volatility	Coefficient of variation (variance-per-absolute-mean daily futures return) during prior 36 months	$CV_{it} \equiv \sigma_{it}^2/\lvert\mu_{it}\rvert$	{Low,Medium,High}	Dhume (2011), Gorton et al. (2012), Szymanowska et al. (2014)
7)	Open interest	Open Interest	Change in current month total open interest along entire term structure	$\Delta OI_{it} \equiv OI_{it} - OI_{it-1}$	{Low,Medium,High}	Hong and Yogo (2012), Szymanowska et al. (2014)
8)	Liquidity	Liquidity	Amivest measure of liquidity or dollar daily volume over absolute daily return during the prior 2 months (D days)	$LR_{it} = \frac{1}{D}\sum_{d=1}^{D}\frac{\$Volume_{id}}{\lvert r_{id}\rvert}$	{High,Medium,Low}	Marshall et al. (2012), Szymanowska et al. (2014)
9)	US$ beta	US$ beta	Slope of regression of monthly commodity futures returns on effective US dollar changes (prior 60 months)	$r_{is} = \alpha_i + \beta_{i,t}^{US\$},\Delta US\$_s + \varepsilon_{is}, s = t-59, \dots, t$	{High,Medium,Low}	Erb and Harvey (2006), Szymanowska et al. (2014)
10)	Inflation beta	Inflation beta	Slope of regression of 60-month commodity futures returns on unexpected inflation modeled as changes in monthly inflation	$r_{is} = \alpha_i + \beta_{i,t}^{CPI}\Delta CPI_s + \varepsilon_{is}, s = t-59, \dots, t$	{Low,Medium,High}	Bodie and Rosansky (1980), Erb and Harvey (2006), Gorton and Rouwenhorst (2006), Szymanowska et al. (2014)
11)	Skewness	Skewness	Third moment of daily return distribution during the prior 12 months (D days)	$SK_{it} \equiv \frac{\sum_{d=1}^{D}(r_{i,d} - \mu_i)^3/D}{\sigma_i^3}$	{High,Medium,Low}	Fernandez-Perez et al. (2017), Liu et al. (2017)

Figure 1. Cumulative reward-to-risk ratio of standalone styles.

The figure graphs the annual Sharpe ratio of the *K*=11 standalone-style portfolios (see Appendix A) over sequential time windows expanded by one month at a time. The first plotted Sharpe ratio is based on monthly excess returns from January 1992 to Dec. 1996 and the last one on monthly excess returns over the full sample period from January 1992 to April 2016. HP denotes hedging pressure.

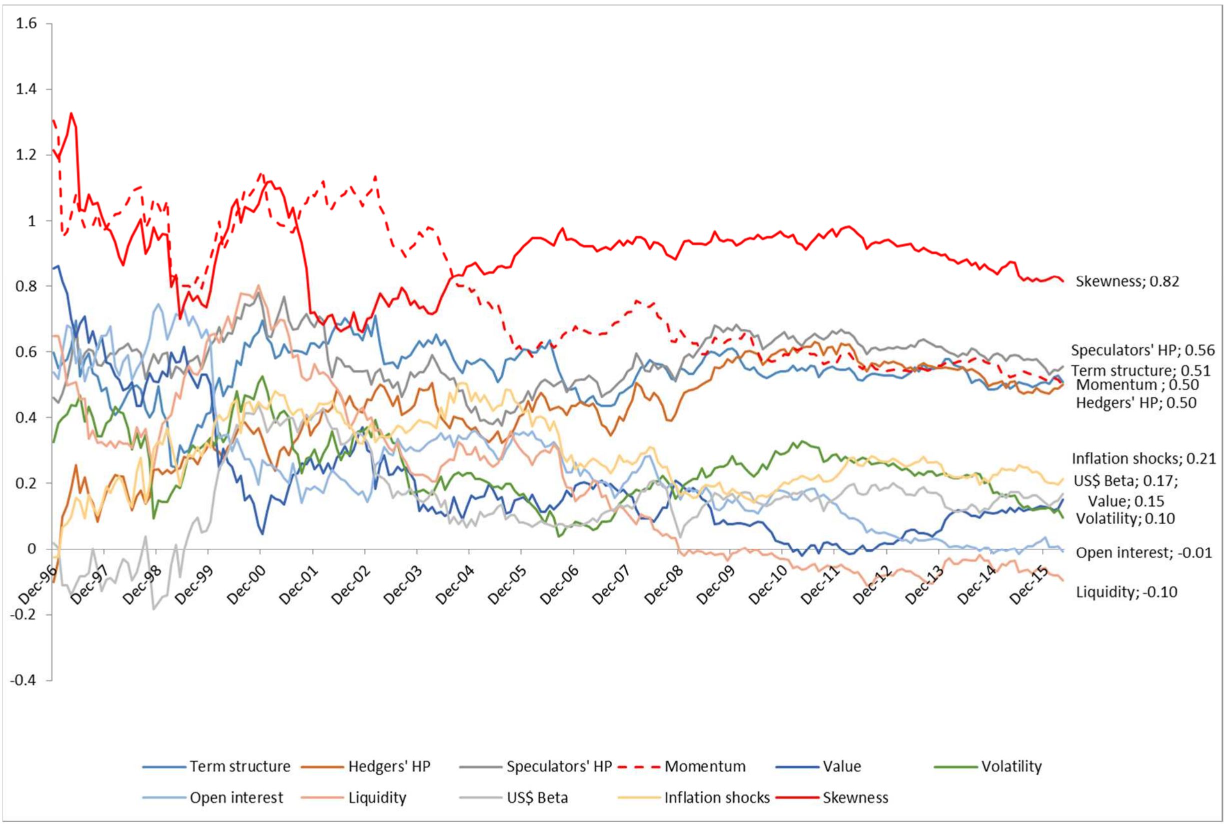
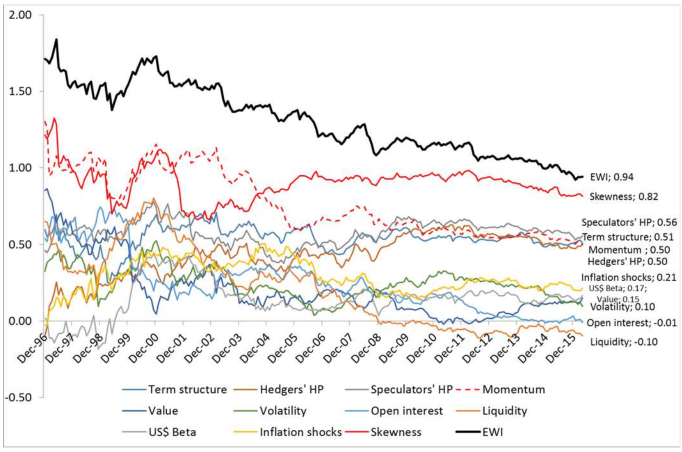


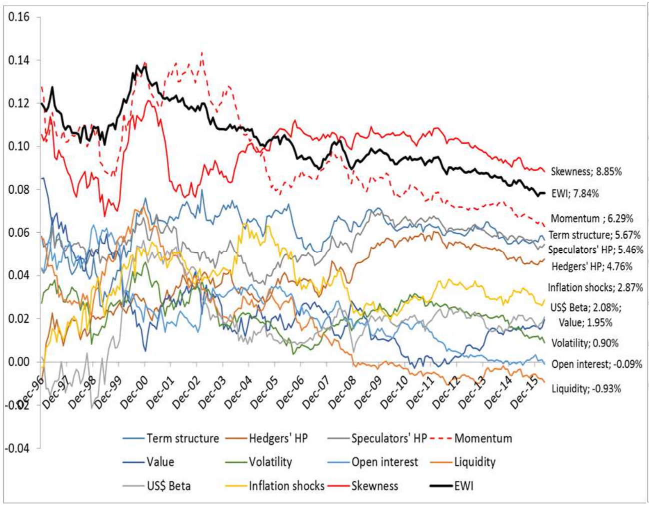
Figure 2. Performance of standalone styles and EWI strategy.

The figure graphs cumulative Sharpe ratios, mean returns and standard deviations (all annualized) of the K=11 standalone long-short portfolios and the equally-weighted integrated portfolio (EWI) described in Section 2.3. The statistics are computed over windows expanded by one month at a time. The first point in each graph is based on monthly excess returns from January 1992 to Dec. 1996, and the last point covers the full sample period from January 1992 to April 2016. HP denotes hedging pressure.

Panel A: Sharpe ratio



Panel B: Mean return



Panel C: StDev

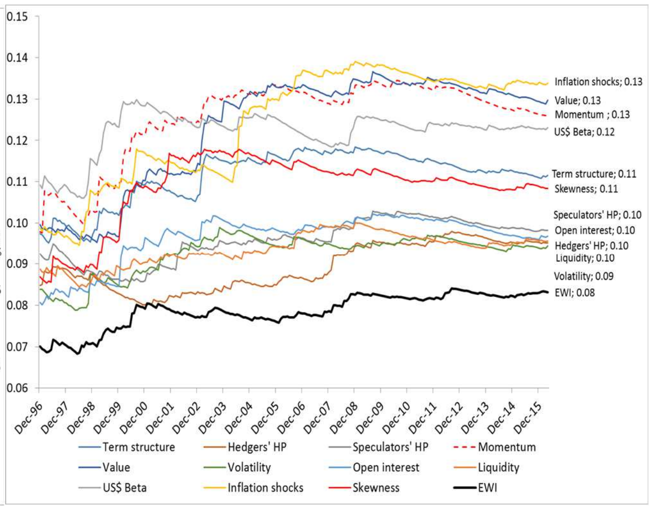
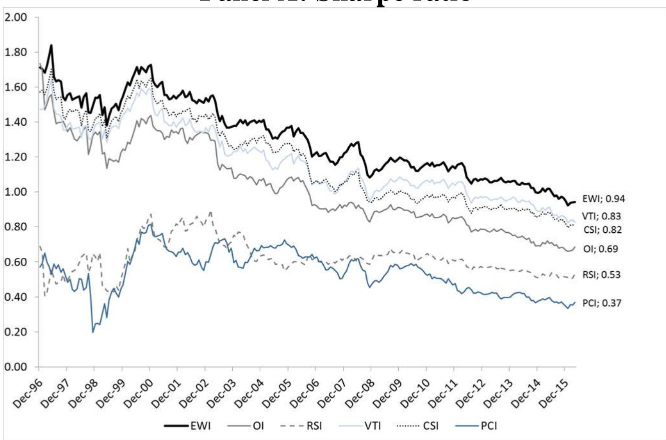


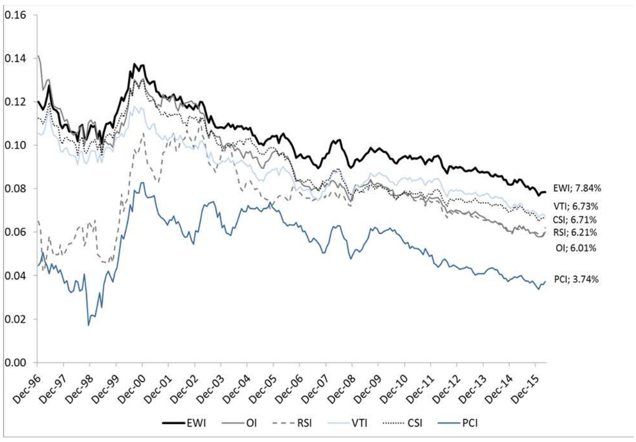
Figure 3. Performance of EWI portfolio and alternative integrated portfolios.

The graphs plot cumulative Sharpe ratios, mean returns and standard deviations (all annualized) over windows expanded by one month at a time. The first point is based on monthly excess returns from January 1992 to Dec. 1996, and the last point on the January 1992 to April 2016 period. EWI is equally-weighted integration, OI is optimal-integration, RSI is rotation-of-styles integration, VTI is volatility-timing integration, CSI is cross-sectional pricing integration and PCI is principal components integration.

Panel A: Sharpe ratio



Panel B: Mean return



Panel C: StDev

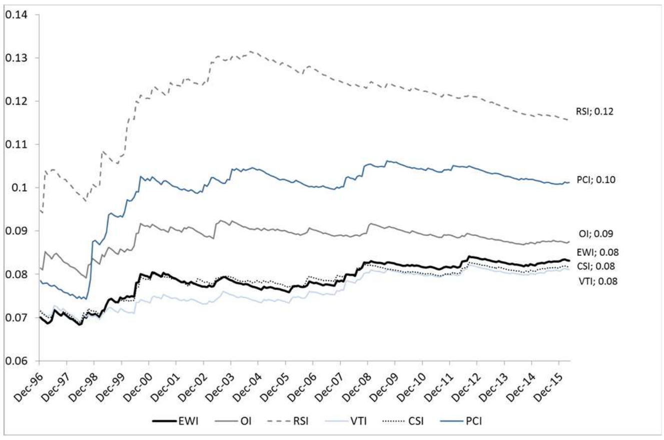


Figure 4. Number of styles and relative reward-to-risk profile of integrated portfolios.

This figure reports box-and-whisker plots of the January 1992 – April 2016 Sharpe ratio, mean return and volatility (all annualized; vertical axis) of the equally-weighted integrated (EWI) portfolio and differential with sophisticated integrated portfolios versus the number of styles K (horizontal axis). OI is optimal-integration, RSI is rotation-of-styles integration, VTI is volatility-timing integration, CSI is cross-sectional pricing integration and PCI is principal components integration. The dash lines are the maximum and minimum of the performance measure across the 11 style portfolios. In each plot the rectangular area for each K represents the interquartile (25^{th}-75^{th}) range, the middle line represents the median and the crosses beyond the whiskers represents outliers defined as points outside the 1^{th}-99^{th} percentiles.

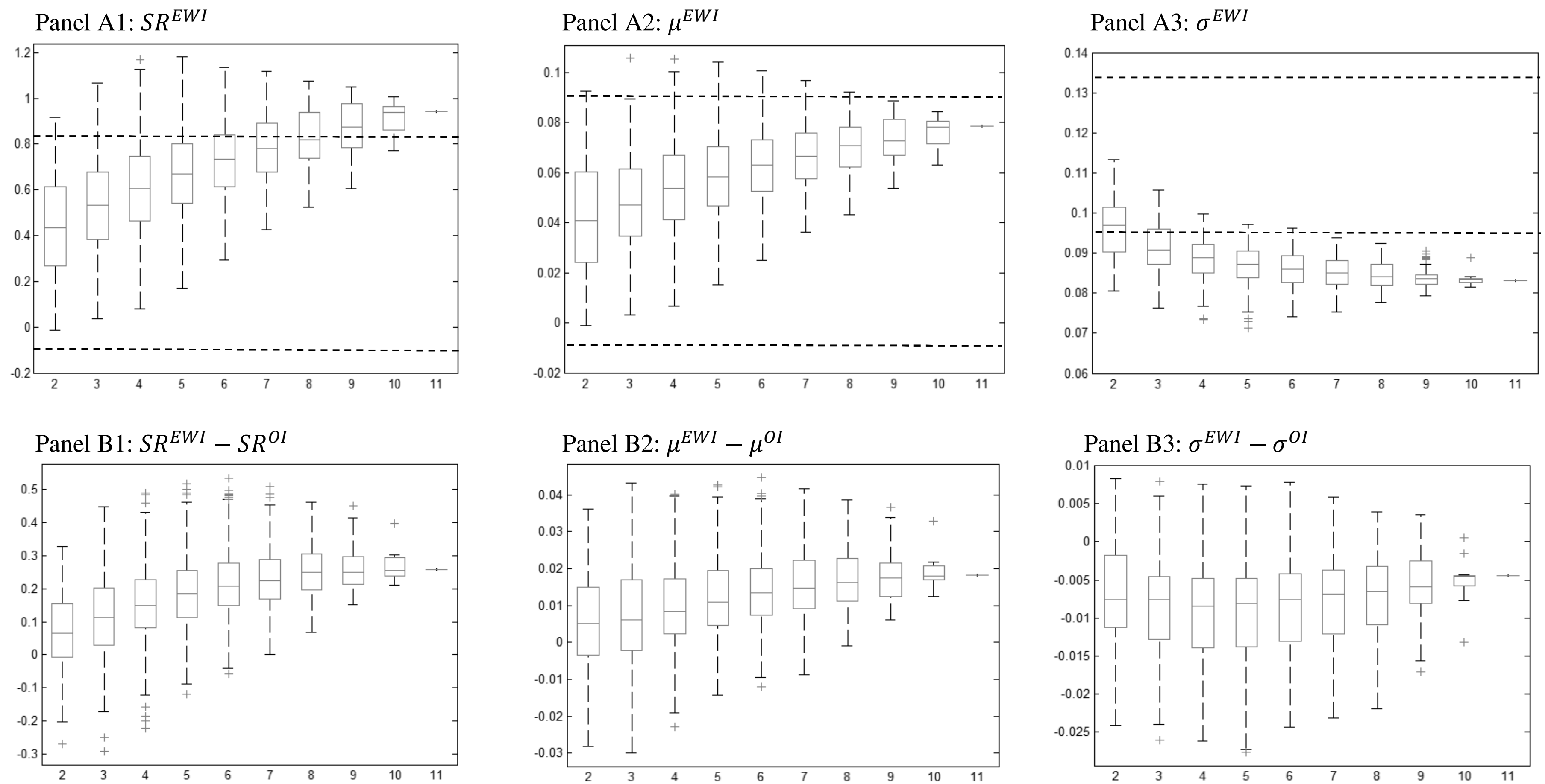


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Figure 4. Number of styles and relative reward-to-risk profile of integrated portfolios.

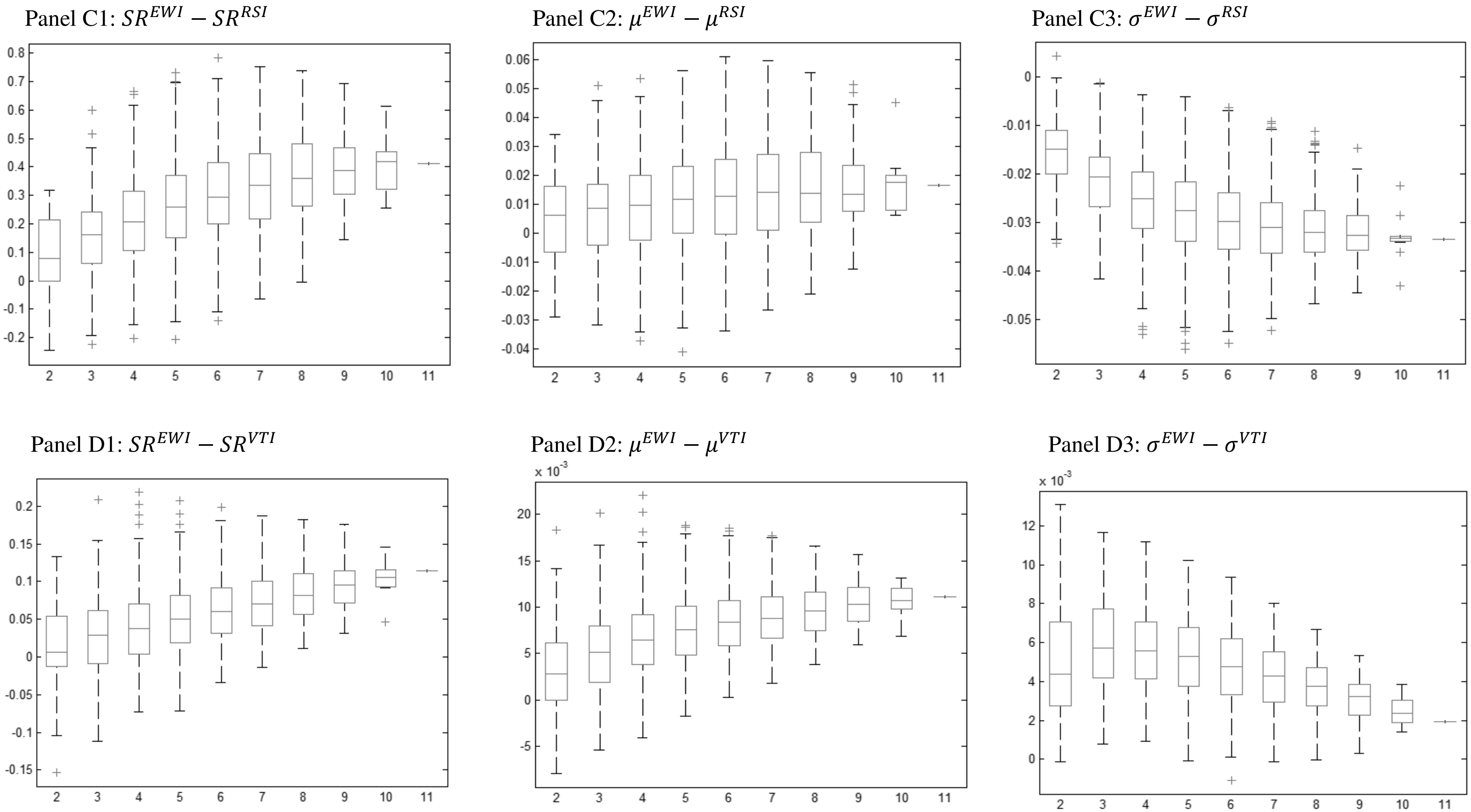

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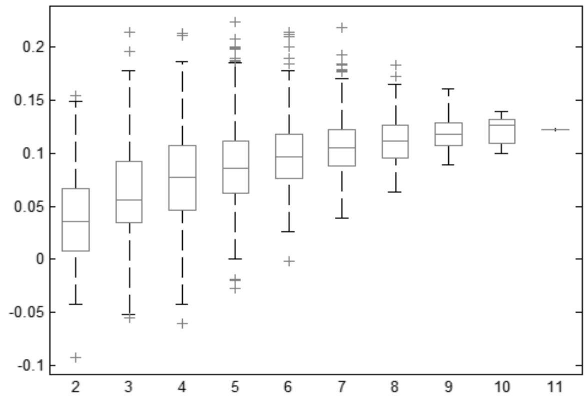
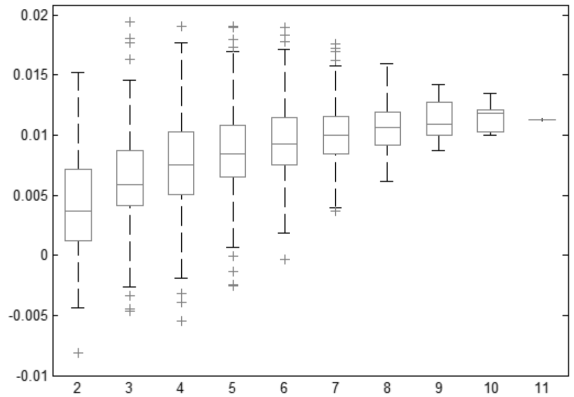
Figure 4. Number of styles and relative reward-to-risk profile of integrated portfolios.

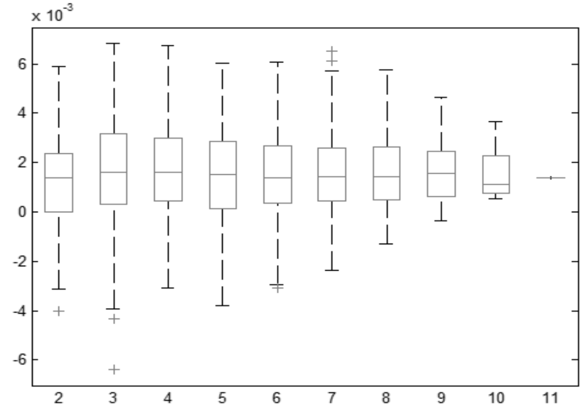
Panel E1: $SR^{EWI} - SR^{CSI}$



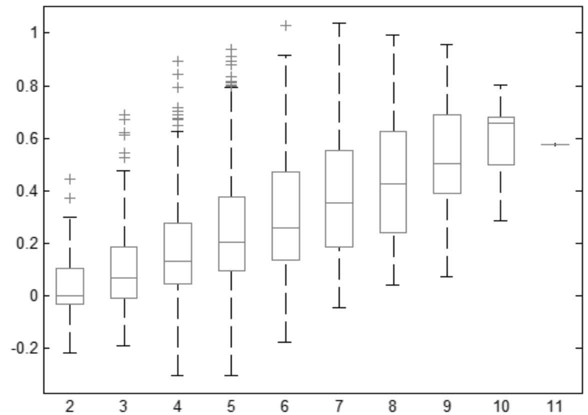
Panel E2: $\mu^{EWI} - \mu^{CSI}$



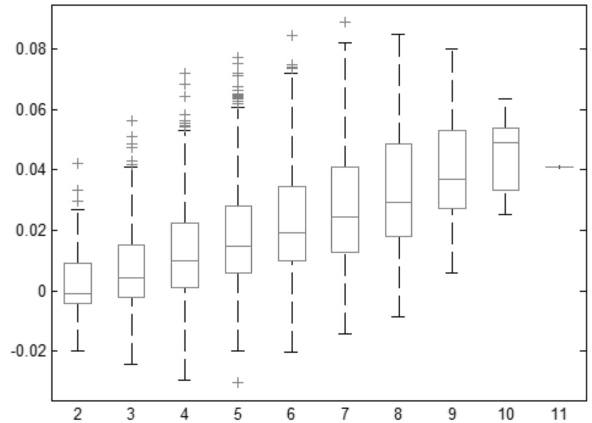
Panel E3: $\sigma^{EWI} - \sigma^{CSI}$



Panel F1: $SR^{EWI} - SR^{PCI}$



Panel F2: $\mu^{EWI} - \mu^{PCI}$



Panel F3: $\sigma^{EWI} - \sigma^{PCI}$

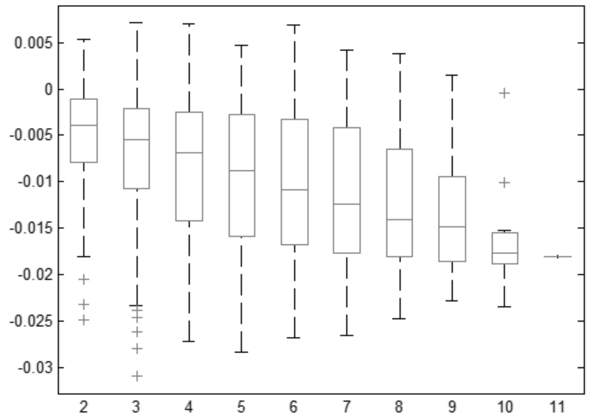
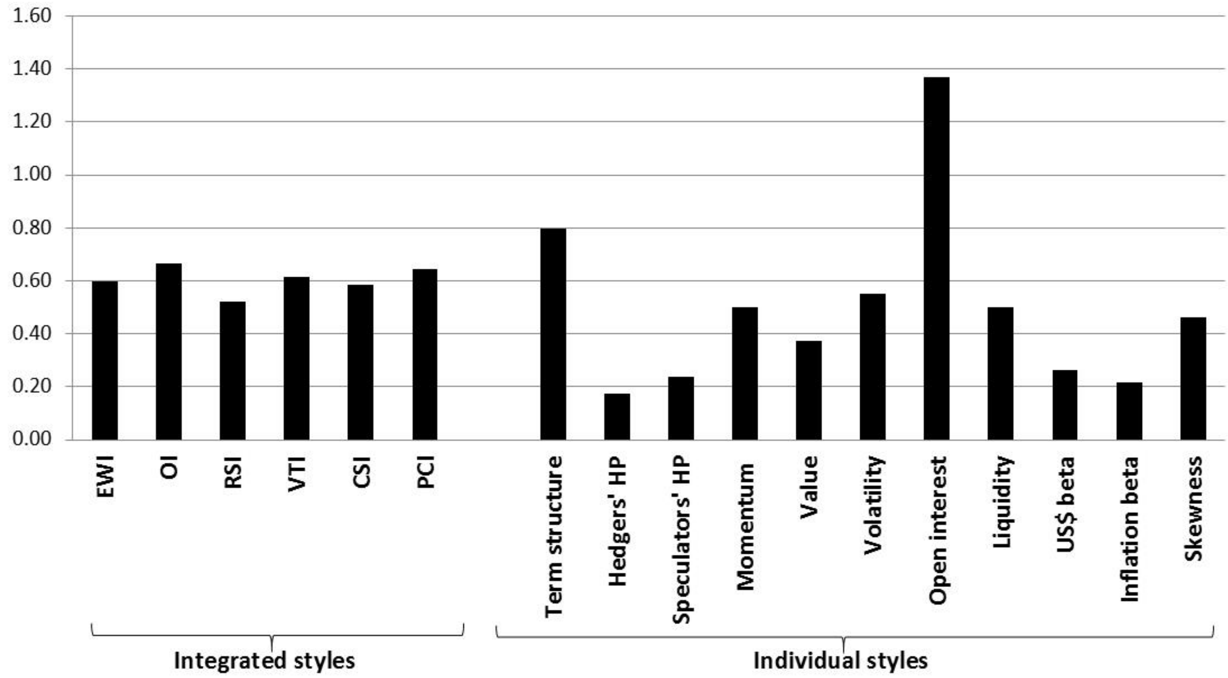


Figure 5. Turnover and net Sharpe ratio of individual and integrated portfolios.
Panel A graphs the portfolio turnover. Panel B graphs the annual Sharpe ratio before and after 8.6 bps proportional costs per trade. HP denotes hedging pressure. EWI is equally-weighted integration, OI is optimal-integration, RSI is rotation-of-styles integration, VTI is volatility-timing integration, CSI is cross-sectional pricing integration and PCI is principal components integration.

Panel A. Turnover



Panel B. Sharpe ratio

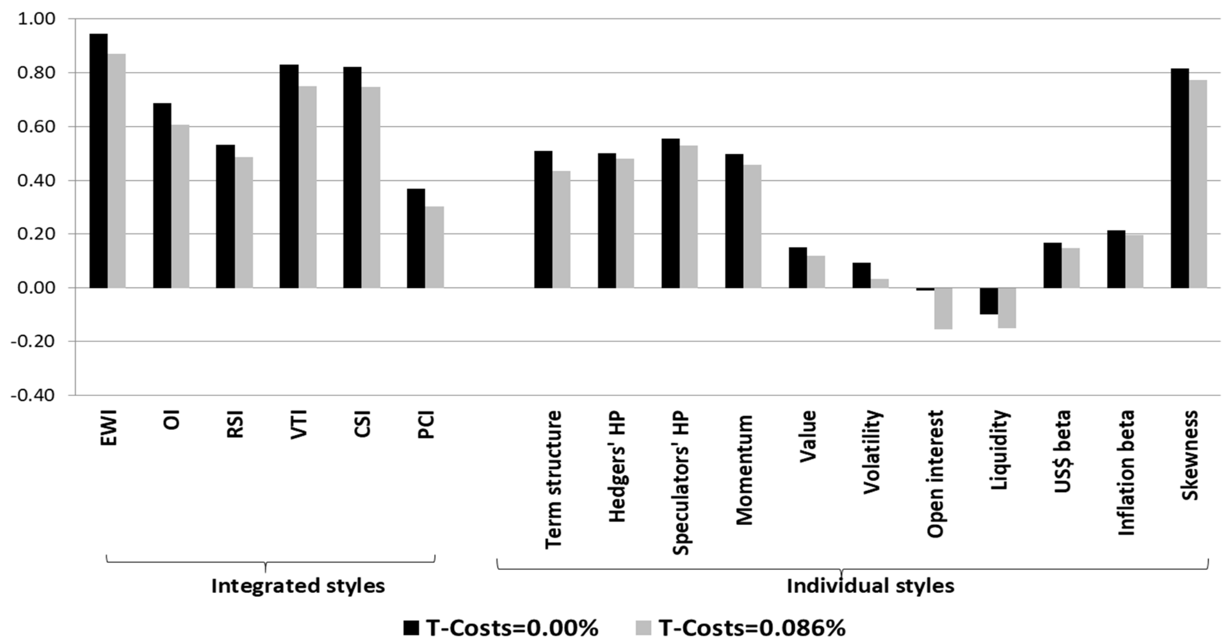


Table 1. Performance of commodity investment styles.
The table summarizes the performance of K=11 long-short investment styles based on the predictive signals stated in the first row (see Appendix A). The portfolios are fully collateralized and held for one month. HP stands for hedging pressure. Panel A reports statistics for the monthly portfolio excess returns over the full sample period from January 1992 to April 2016. Mean and standard deviation (StDev) are annualized. Newey-West significance t-statistics are reported in parentheses. CER is the annualized certainty-equivalent return based on power utility preferences (with CRRA parameter $\gamma = 5$). Panel B reports the annual Sharpe ratio of each style over 5-year non-overlapping rolling windows; the number in parenthesis is the 1 (top) to 11 (bottom) ranking.

	Term structure	Hedgers' HP	Speculators' HP	Momentum	Value	Volatility	Open interest	Liquidity	US$ beta	Inflation beta	Skewness
Panel A: Performance over entire sample Jan 1992 - April 2016											
Mean	0.0567	0.0476	0.0546	0.0629	0.0195	0.0090	-0.0009	-0.0093	0.0208	0.0287	0.0885
	(2.55)	(2.46)	(2.83)	(2.30)	(0.72)	(0.45)	(-0.05)	(-0.43)	(0.80)	(1.13)	(3.70)
StDev	0.1115	0.0951	0.0983	0.1261	0.1297	0.0945	0.0968	0.0957	0.1231	0.1338	0.1084
Skewness	0.2766	0.3220	0.2138	-0.0106	-0.1562	-0.2222	-0.0912	0.0290	-0.4687	0.3147	0.1167
	(1.93)	(2.25)	(1.49)	(-0.07)	(-1.09)	(-1.55)	(-0.64)	(0.20)	(-3.27)	(2.20)	(0.81)
Excess Kurtosis	0.7300	0.3939	0.3710	0.7627	0.8919	0.3781	0.6243	0.5368	0.6785	1.4308	0.8216
	(2.55)	(1.37)	(1.29)	(2.66)	(3.11)	(1.32)	(2.18)	(1.87)	(2.37)	(4.99)	(2.87)
JB normality test p-value	0.0133	0.0331	0.1149	0.0316	0.0113	0.1017	0.0646	0.1380	0.0038	0.0010	0.0188
Downside volatility (0%)	0.0643	0.0502	0.0520	0.0803	0.0842	0.0625	0.0625	0.0604	0.0891	0.0814	0.0639
99% VaR (Cornish-Fisher)	0.0682	0.0549	0.0590	0.0862	0.0973	0.0691	0.0710	0.0679	0.0959	0.0900	0.0686
% of positive months	53.77%	52.74%	55.48%	55.82%	54.11%	52.74%	50.00%	49.32%	55.82%	50.68%	58.56%
Maximum drawdown	-0.2440	-0.1720	-0.1892	-0.4117	-0.5081	-0.3374	-0.4416	-0.6114	-0.4052	-0.4301	-0.2746
Sharpe ratio	0.5086	0.5001	0.5553	0.4985	0.1504	0.0950	-0.0097	-0.0969	0.1691	0.2144	0.8160
Sortino ratio (0%)	0.8822	0.9487	1.0487	0.7833	0.2318	0.1437	-0.0150	-0.1536	0.2337	0.3523	1.3836
Omega ratio	1.4719	1.4432	1.4975	1.4610	1.1193	1.0730	0.9929	0.9296	1.1353	1.1791	1.8591
CER	0.0261	0.0253	0.0306	0.0229	-0.0234	-0.0137	-0.0247	-0.0324	-0.0185	-0.0153	0.0587
Panel B: Sharpe ratio (relative position) of individual styles over 5-year non-overlapping subsamples											
Jan 1992 - Dec 1996	0.5971 (5)	-0.1004 (11)	0.4614 (7)	1.3031 (1)	0.8539 (3)	0.3257 (8)	0.5387 (6)	0.6481 (4)	0.0196 (9)	-0.0267 (10)	1.2154 (2)
Jan 1997 - Dec 2001	0.6477 (6)	0.8762 (3)	0.9062 (2)	0.9492 (1)	-0.2511 (11)	0.2826 (9)	-0.0550 (10)	0.4797 (7)	0.7212 (5)	0.7632 (4)	0.4425 (8)
Jan 2002 - Dec 2006	0.2855 (4)	0.5535 (2)	0.2534 (5)	0.0066 (8)	0.1337 (6)	-0.3072 (9)	0.4046 (3)	-0.5667 (10)	-0.7009 (11)	0.0315 (7)	1.4008 (1)
Jan 2007 - Dec 2011	0.7328 (5)	0.9636 (3)	1.0268 (1)	0.2335 (7)	-0.5042 (10)	0.9034 (4)	-0.2168 (9)	-0.7526 (11)	0.3868 (6)	0.1415 (8)	1.0062 (2)
Jan 2012 - Apr 2016	0.2887 (2)	0.0599 (7)	-0.0059 (8)	0.0893 (6)	0.9701 (1)	-0.9790 (11)	-0.9157 (10)	-0.2804 (9)	0.2265 (3)	0.1863 (4)	0.1243 (5)

Table 2. Dependence between commodity investment styles.

Panels A and B report Pearson pairwise correlations and multiple correlations as linear dependence measures among the monthly excess returns of K=11 long-short investment styles. Panel C reports the non-parametric Spearman rank-order correlation as a (non)linear dependence measure. HP stands for hedging pressure. Bold denotes significant correlations at the 10% level or better. The monthly excess returns span the period from January 1992 to April 2016.

	Term structure	Hedgers' HP	Speculators' HP	Momentum	Value	Volatility	Open interest	Liquidity	US$ beta	Inflation beta	Skewness
Panel A: pairwise Pearson correlations											
Hedgers' HP	**0.13**										
Speculators' HP	**0.24**	**0.66**									
Momentum	**0.39**	**0.29**	**0.45**								
Value	**-0.39**	**-0.24**	**-0.33**	**-0.46**							
Volatility	**0.16**	0.00	-0.01	0.06	**-0.29**						
Open interest	0.08	0.01	-0.07	**-0.22**	0.07	0.05					
Liquidity	0.01	-0.01	-0.06	**-0.10**	-0.04	**0.13**	**0.11**				
US$ beta	-0.01	0.08	**0.15**	0.08	**-0.16**	**0.18**	**-0.15**	0.02			
Inflation beta	**0.10**	**0.16**	**0.16**	0.04	**-0.38**	0.02	-0.02	**0.21**	**0.14**		
Skewness	**0.13**	**0.26**	**0.20**	0.09	**-0.14**	0.07	-0.04	0.00	0.09	**0.15**	
Panel B: partial R^2 of regressions of each individual style premia on all other style premia (multiple Pearson correlations)											
	0.25	0.47	0.53	0.41	0.44	0.16	0.11	0.08	0.10	0.24	0.09
Panel C: pairwise Spearman rank correlations											
Hedgers' HP	**0.10**										
Speculators' HP	**0.21**	**0.65**									
Momentum	**0.36**	**0.27**	**0.43**								
Value	**-0.35**	**-0.23**	**-0.31**	**-0.40**							
Volatility	**0.13**	0.00	-0.01	0.04	**-0.23**						
Open interest	0.05	0.04	-0.04	**-0.20**	0.06	0.06					
Liquidity	-0.01	-0.01	-0.04	-0.08	-0.03	0.08	0.06				
US$ beta	0.05	**0.12**	**0.20**	0.06	**-0.17**	**0.18**	-0.09	0.03			
Inflation beta	**0.13**	**0.21**	**0.21**	**0.10**	**-0.40**	0.01	-0.03	**0.16**	**0.19**		
Skewness	**0.10**	**0.22**	**0.18**	0.06	**-0.10**	0.09	0.02	0.01	**0.10**	**0.12**	

Table 3. Performance of integrated portfolio approaches.

The table summarizes integration approaches nested in Equation (1) that differ in the determination of the style-exposures. EWI is equally-weighted integration and the other five sophisticated integration approaches allow for time-varying, heterogeneous style exposures: optimal integration (OI); rotation-of-styles integration (RSI); volatility-timing integration (VTI); cross-sectional pricing integration (CSI); principal components integration (PCI). Panel A reports statistics for monthly excess returns of fully-collateralized portfolios from January 1992 to April 2016. CER is annualized certainty-equivalent return with power utility preferences (CRRA parameter $\gamma = 5$). The asymptotic p-values of the Opdyke (2007) test are for $H_0: SR_{EWI} \leq SR_j$ versus $H_A: SR_{EWI} > SR_j$ where j is a sophisticated integrated style. The bootstrap p-values of the CER test are for $H_0: CER_{EWI} \leq CER_j$ versus $H_A: CER_{EWI} > CER_j$. Mean and standard deviation (StDev) are annualized. Newey-West robust t-statistics are shown in parenthesis. Panel B reports the annual Sharpe ratio of each integrated portfolio over 5-year non-overlapping rolling windows and the number in parenthesis is the 1 (top) to 6 (bottom) ranking.

	EWI	OI	RSI	VTI	CSI	PCI
Panel A: Performance over entire sample period						
Mean	0.0784	0.0601	0.0621	0.0673	0.0671	0.0374
	(4.40)	(3.30)	(2.58)	(3.90)	(3.96)	(1.54)
StDev	0.0831	0.0875	0.1167	0.0812	0.0817	0.1013
Skewness	0.0707	0.1399	0.2014	0.1217	0.0751	0.0509
	(0.49)	(0.98)	(1.40)	(0.85)	(0.52)	(0.36)
Excess Kurtosis	0.0076	0.4066	1.0501	-0.1061	-0.0227	0.7327
	(0.03)	(1.42)	(3.66)	(-0.37)	(-0.08)	(2.56)
JB normality test p-value	0.5000	0.1895	0.0044	0.5000	0.5000	0.0363
Downside volatility (0%)	0.0436	0.0510	0.0703	0.0423	0.0424	0.0603
99% VaR (Cornish-Fisher)	0.0480	0.0534	0.0759	0.0461	0.0478	0.0688
% of positive months	61.30%	56.16%	53.77%	58.90%	60.27%	55.14%
Maximum drawdown	-0.1635	-0.1552	-0.2683	-0.1532	-0.1477	-0.2935
Sharpe ratio	0.9432	0.6865	0.5319	0.8294	0.8211	0.3691
Opdyke test p-value (H_0: SR_{EWI}-$SR_j \leq 0$)	-	0.0737	0.0331	0.1720	0.1615	0.0140
Sortino ratio (0%)	1.7994	1.1791	0.8826	1.5924	1.5843	0.6193
Omega ratio	1.9662	1.6719	1.5145	1.8131	1.7936	1.3172
CER	0.0605	0.0408	0.0283	0.0505	0.0501	0.0118
CER bootstrap p-value (H_0: CER_{EWI}-$CER_j \leq 0$)	-	0.0585	0.0565	0.0069	0.0186	0.0119
Panel B: Sharpe ratio of integrated styles and relative position over 5-year non-overlapping subsamples						
Jan 1992 - Dec 1996	1.7118 (2)	1.7335 (1)	0.6873 (5)	1.4713 (4)	1.5725 (3)	0.5701 (6)
Jan 1997 - Dec 2001	1.4263 (1)	1.0070 (4)	0.9146 (5)	1.3081 (3)	1.3511 (2)	0.7326 (6)
Jan 2002 - Dec 2006	0.5765 (1)	0.1060 (6)	0.2510 (5)	0.4559 (3)	0.3129 (4)	0.5703 (2)
Jan 2007 - Dec 2011	0.9035 (2)	0.6103 (4)	0.5995 (5)	0.9706 (1)	0.6639 (3)	0.0796 (6)
Jan 2012 - Apr 2016	0.1442 (2)	-0.1356 (5)	0.0956 (3)	-0.0469 (4)	0.2409 (1)	-0.2159 (6)

Table 4. Integration effectiveness.

The table reports coefficients, Newey-West robust *t*-ratios and explanatory power (coefficient of determination R^2) for regressions of the January 1992 - April 2016 monthly excess returns of each integrated portfolio on those of the *K* standalone portfolios summarized in Table 1. The integration methods differ in the determination of the style-exposures; equally-weighted integration (EWI), optimal-integration (OI), rotation-of-styles integration (RSI), volatility-timing integration (VTI), cross-sectional pricing integration (CSI) and principal components integration (PCI). All portfolios are fully collateralized.

	Standalone style portfolios												
Integration methods	Intercept	Term structure	Hedgers' HP	Speculators' HP	Momentum	Value	Volatility	Open interest	Liquidity	US$ beta	Inflation shocks	Skewness	R^2
EWI	**0.0003**	**0.1943**	**0.2090**	**0.2088**	**0.1884**	**0.1918**	**0.1889**	**0.2014**	**0.1987**	**0.1890**	**0.1963**	**0.1930**	97.59%
	(2.14)	(20.96)	(15.85)	(20.10)	(18.94)	(20.23)	(16.07)	(22.72)	(22.28)	(21.96)	(21.02)	(22.16)	
OI	**-0.0019**	**0.1204**	0.0565	**0.2772**	**0.2999**	**0.3857**	**0.1264**	**0.0992**	0.0357	**0.0941**	**0.2078**	**0.2671**	68.13%
	(-2.34)	(2.27)	(1.25)	(4.84)	(4.92)	(8.62)	(2.98)	(2.59)	(0.77)	(2.62)	(6.02)	(6.69)	
RSI	-0.0003	**0.1359**	0.0586	**0.1325**	**0.5354**	0.0373	-0.0396	-0.0470	-0.0094	0.0666	0.0168	**0.1405**	55.68%
	(-0.28)	(2.13)	(0.82)	(1.74)	(6.32)	(0.57)	(-0.65)	(-0.85)	(-0.17)	(1.49)	(0.32)	(1.96)	
VTI	0.0003	**0.1658**	**0.2645**	**0.2221**	**0.1157**	**0.1225**	**0.2231**	**0.2186**	**0.2493**	**0.1401**	**0.1157**	**0.1633**	94.88%
	(0.98)	(11.24)	(12.84)	(12.14)	(7.75)	(8.36)	(14.04)	(16.78)	(16.28)	(9.82)	(10.51)	(10.31)	
CSI	-0.0004	**0.1821**	**0.1797**	**0.1388**	**0.1656**	**0.2714**	**0.2319**	**0.1985**	**0.2033**	**0.2046**	**0.2425**	**0.2036**	90.96%
	(-0.95)	(8.32)	(7.16)	(5.14)	(9.10)	(13.03)	(7.95)	(10.52)	(12.12)	(12.59)	(14.09)	(9.64)	
PCI	0.0006	0.0602	-0.1195	0.0935	0.0123	0.1052	**0.2592**	0.0632	0.0482	0.1247	0.0068	**0.2234**	16.90%
	(0.35)	(0.93)	(-1.05)	(0.92)	(0.17)	(1.62)	(3.15)	(0.87)	(0.67)	(1.60)	(0.09)	(3.16)	

On-line Annex

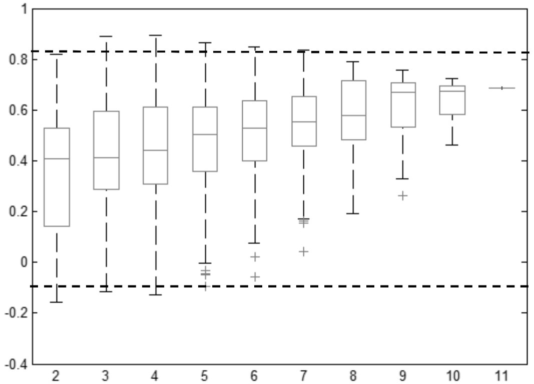
Harvesting Commodity Styles: An Integrated Framework

November 21, 2017

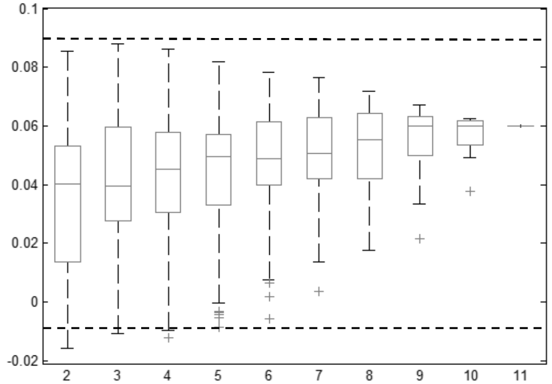
Figure A.I. Number of styles and return-to-risk profile of sophisticated integration strategies.

This figure reports box-and-whisker plots of the Jan. 1992 – Apr. 2016 Sharpe ratio, mean return and volatility (all annualized; vertical axis) of sophisticated integrated portfolios versus the number of styles K (horizontal axis). OI is optimal-integration, RSI is rotation-of-styles integration, VTI is volatility-timing integration, CSI is cross-sectional pricing integration and PCI is principal-components integration. The dash lines are the maximum and minimum of the performance measure across the 11 style portfolios. In each plot the rectangular area for each K denotes the interquartile (25th-75th) range, the middle line represents the median and the crosses beyond the whiskers represents outliers defined as points outside the 1th-99th percentiles.

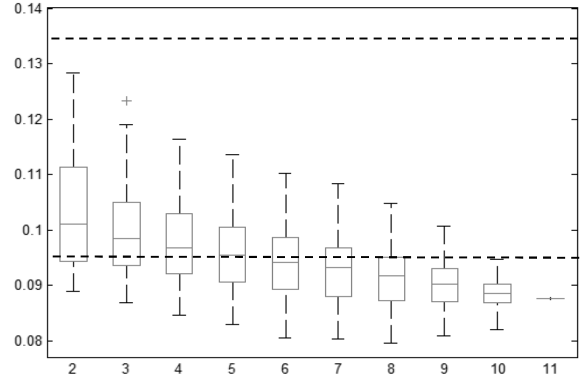
Panel A1: SR^{OI}



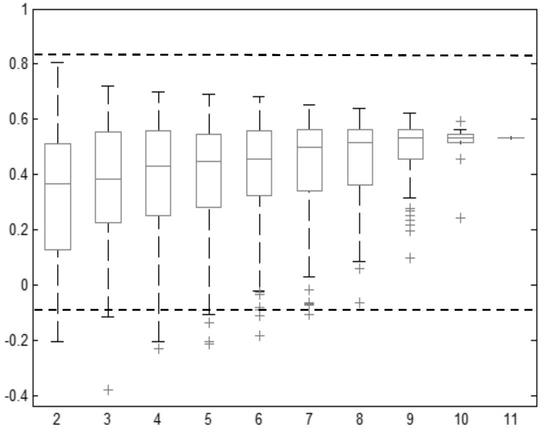
Panel A2: μ^{OI}



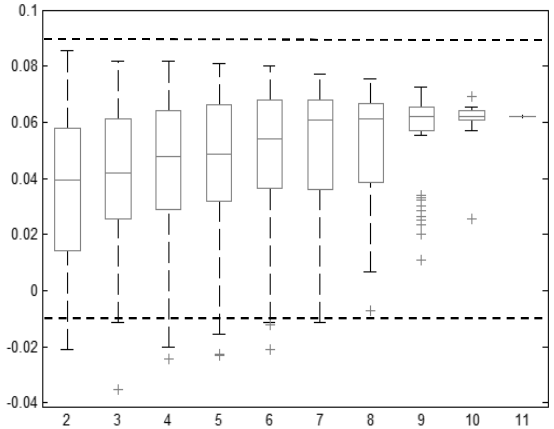
Panel A3: σ^{OI}



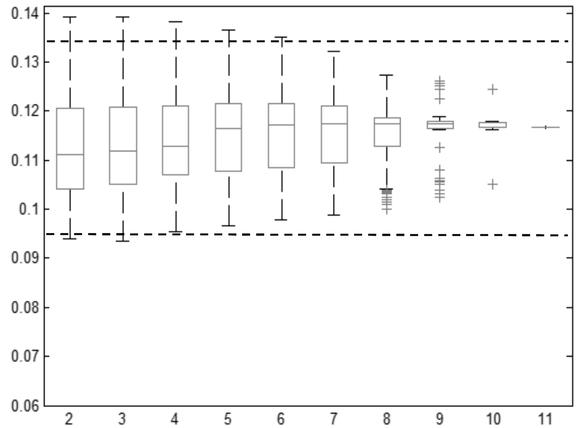
Panel B1: SR^{RSI}



Panel B2: μ^{RSI}

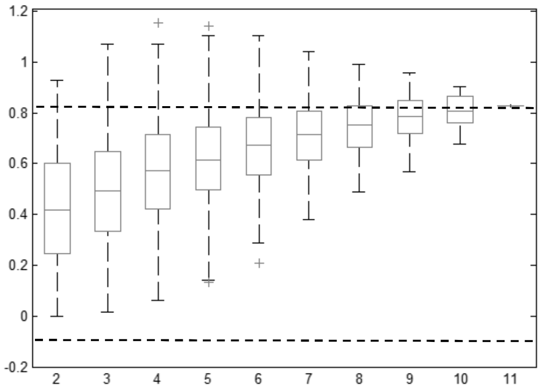


Panel B3: σ^{RSI}

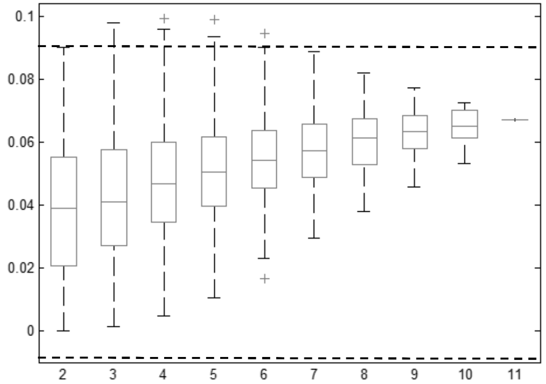


(*Cont.*) Figure A.I. Number of styles and return-to-risk profile of sophisticated integration strategies.

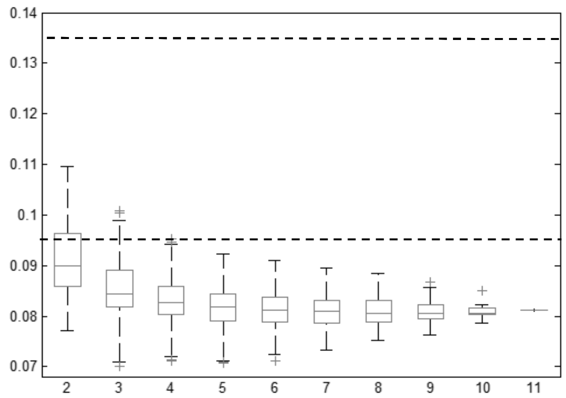
Panel C1: SR^{VTI}



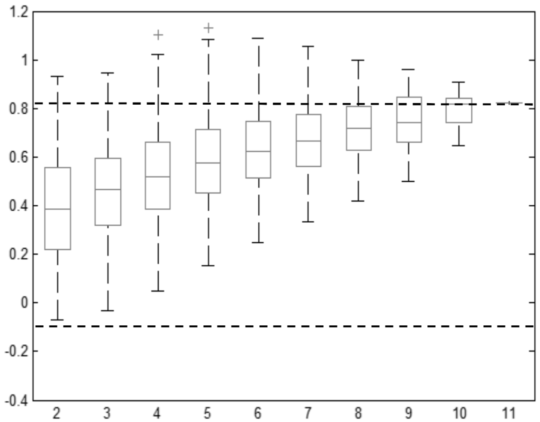
Panel C2: μ^{VTI}



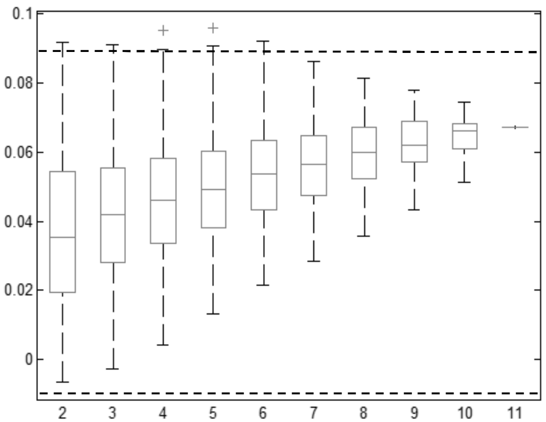
Panel C3: σ^{VTI}



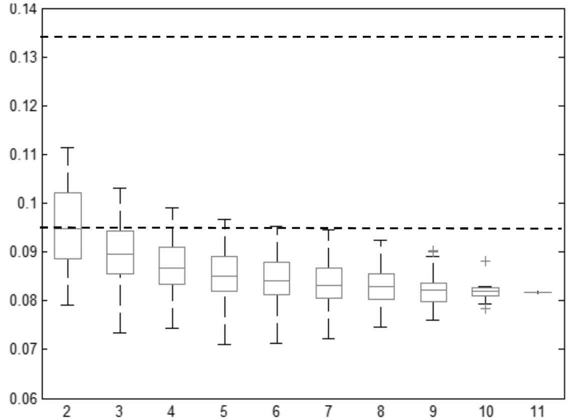
Panel D1: SR^{CSI}



Panel D2: μ^{CSI}

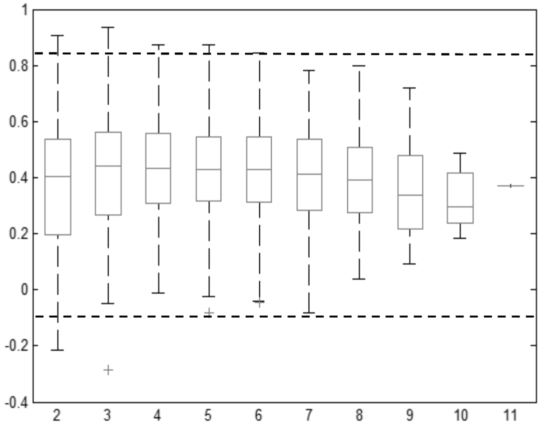


Panel D3: σ^{CSI}

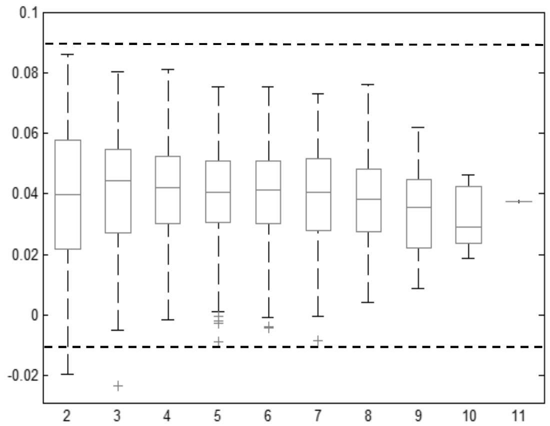


(*Cont.*) Figure A.I. Number of styles and return-to-risk profile of sophisticated integration strategies.

Panel E1: SR^{PCI}



Panel E2: μ^{PCI}



Panel E3: σ^{PCI}

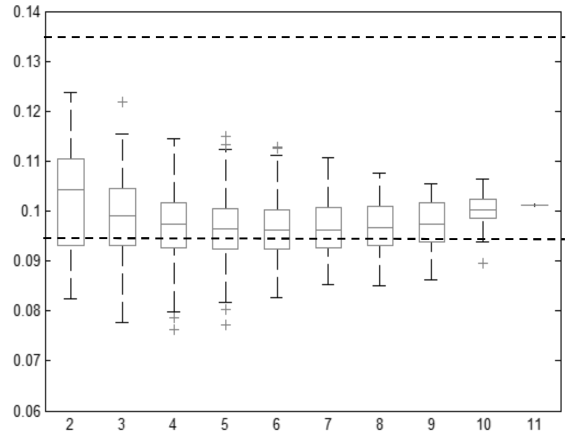


Table A.I. Performance of long-only commodity benchmarks and individual-weight-optimized portfolio.

The table reports statistics on the performance of an equally-weighted monthly rebalanced portfolio of the 28 commodities (EW), the S&P-GSCI, and the portfolio based on the optimization of the individual commodity weights using power utility (and ensuring full investment). All portfolios are fully-collateralized. Panel A reports statistics for monthly excess returns obtained over the entire sample period from Jan. 1992 to Ap. 2016. Mean and standard deviation (StDev) are annualized. Robust Newey-West significance *t*-statistics for mean excess returns are reported in parentheses. CER is the annualized certainty-equivalent return based on power utility preferences ($\gamma = 5$). Panel B reports the annual Sharpe ratio of each portfolio over 5-year non-overlapping rolling periods and the number in parenthesis is the overall ranking among the eleven individual styles reported in Table 1.

	EW		S&P GSCI		Power utility with individual commodities	
Panel A: Performance over entire sample period Jan. 1992 to Apr. 2016						
Mean	-0.0098		0.0007		0.0603	
	(-0.32)		(0.01)		(2.05)	
StDev	0.1266		0.2155		0.1511	
Skewness	-0.8438		-0.6714		0.1253	
	(-5.89)		(-4.68)		(0.87)	
Excess Kurtosis	3.9732		2.4723		1.3349	
	(13.86)		(8.62)		(4.66)	
JB normality test *p*-value	0.0010		0.0010		0.0014	
Downside volatility (0%)	0.1012		0.1638		0.0902	
99% VaR (Cornish-Fisher)	0.1326		0.2007		0.1058	
% of positive months	52.74%		54.45%		53.08%	
Maximum drawdown	-0.5672		-0.8556		-0.2990	
Sharpe ratio	-0.0776		0.0032		0.3993	
Sortino ratio (0%)	-0.0971		0.0043		0.6690	
Omega ratio	0.9399		1.0025		1.3518	
CER	-0.0557		-0.1405		0.0033	
Panel B: Sharpe ratio over 5-year non-overlapping subsamples						
Jan 1992 - Dec 1996	0.6581	(4)	0.5935	(6)	0.1610	(9)
Jan 1997 - Dec 2001	-0.7941	(12)	-0.0228	(10)	0.4475	(8)
Jan 2002 - Dec 2006	0.5637	(2)	0.5489	(3)	-0.1318	(9)
Jan 2007 - Dec 2011	-0.0934	(9)	-0.0940	(9)	0.8393	(5)
Jan 2012 - Apr 2016	-0.5484	(10)	-0.8561	(10)	0.5399	(2)

Table A.II. Style-integration approaches based on standardized signals or standardized rankings.

The table summarizes the performance of style-integration approaches nested in Equation (1) for a scoring matrix $\mathbf{\Theta}_t$ with standardized-signals (Panel A) or standardized-rankings (Panel B). EWI is equally-weighted integration and the other (sophisticated) integrations allow for time-varying, heterogeneous style exposures: optimal integration (OI); rotation-of-styles integration (RSI); volatility-timing integration (VTI); cross-sectional pricing integration (CSI); principal components integration (PCI). CER is the annualized certainty-equivalent return for an investor with power utility preferences (CRRA parameter $\gamma = 5$). The asymptotic p-values of the Opdyke (2007) test are for $H_0: SR_{EWI} \leq SR_j$ vs $H_A: SR_{EWI} > SR_j$ where j is a sophisticated integration. The CER bootstrap p-values are for $H_0: CER_{EWI} \leq CER_j$ vs $H_A: CER_{EWI} > CER_j$. Mean and standard deviation (StDev) are annualized. Newey-West robust t-statistics are shown in parenthesis. The monthly excess returns of the fully-collateralized integrated portfolios span the Jan. 1992 to Apr. 2016 period.

	Panel A: Standardized-signals						Panel B: Standardized-rankings					
	EWI	OI	RSI	VTI	CSI	PCI	EWI	OI	RSI	VTI	CSI	PCI
Mean	0.0798	0.0724	0.0497	0.0660	0.0712	0.0273	0.0777	0.0647	0.0681	0.0667	0.0655	0.0267
	(4.55)	(3.74)	(1.98)	(4.03)	(4.22)	(1.08)	(4.40)	(3.49)	(2.83)	(3.89)	(3.87)	(1.09)
StDev	0.0861	0.0976	0.1297	0.0813	0.0855	0.1095	0.0826	0.0916	0.1223	0.0811	0.0820	0.1010
Skewness	0.0113	-0.1496	-0.0346	0.1233	-0.0994	0.1886	0.0575	0.1273	0.2086	0.1316	0.0361	0.0517
	(0.08)	(-1.04)	(-0.24)	(0.86)	(-0.69)	(1.32)	(0.40)	(0.89)	(1.46)	(0.92)	(0.25)	(0.36)
Excess Kurtosis	0.2263	0.1766	0.5737	0.0380	0.1664	1.3339	0.0934	0.4720	0.8656	-0.0865	0.0674	0.6995
	(0.79)	(0.62)	(2.00)	(0.13)	(0.58)	(4.65)	(0.33)	(1.65)	(3.02)	(-0.30)	(0.24)	(2.44)
JB normality test p-value	0.5000	0.4366	0.1059	0.5000	0.5000	0.0013	0.5000	0.1415	0.0104	0.5000	0.5000	0.0445
Downside volatility (0%)	0.0489	0.0583	0.0829	0.0432	0.0498	0.0672	0.0436	0.0532	0.0717	0.0421	0.0431	0.0614
99% VaR (Cornish-Fisher)	0.0522	0.0635	0.0889	0.0471	0.0542	0.0763	0.0485	0.0564	0.0776	0.0460	0.0493	0.0692
% of positive months	59.25%	57.88%	54.45%	59.59%	60.62%	50.34%	61.64%	58.56%	52.40%	58.90%	59.93%	52.74%
Maximum drawdown	-0.1721	-0.1708	-0.3996	-0.1441	-0.1930	-0.3554	-0.1689	-0.1409	-0.2650	-0.1523	-0.1680	-0.3055
Sharpe ratio	0.9275	0.7418	0.3834	0.8112	0.8328	0.2496	0.9411	0.7056	0.5566	0.8228	0.7994	0.2645
Opdyke test p-value (H_0: SR_{EWI}-SR_j≤0)	-	0.1527	0.0066	0.2144	0.2200	0.0025	-	0.0920	0.0407	0.1670	0.1250	0.0042
Sortino ratio (0%)	1.6320	1.2408	0.5994	1.5283	1.4304	0.4066	1.7817	1.2143	0.9497	1.5862	1.5190	0.4352
Omega ratio	1.9740	1.7168	1.3380	1.7916	1.8318	1.2124	1.9649	1.6938	1.5380	1.8044	1.7633	1.2182
CER	0.0607	0.0480	0.0075	0.0491	0.0524	-0.0024	0.0601	0.0435	0.0310	0.0500	0.0484	0.0013
CER bootstrap p-value (H_0: CER_{EWI}-CER_j≤0)	-	0.1852	0.0088	0.0574	0.0380	0.0009	-	0.0953	0.0799	0.0115	0.0087	0.0015

Table A. III. Performance of additional sophisticated integrated portfolios.

The table summarizes variants of the sophisticated integration approaches reported in Table 3. OI is optimal-integration, RSI(3) is rotation-of-styles integration that focuses (equal-weights) on the three best styles, VTI is volatility-timing integration, RRTI is reward-to-risk timing integration, TSI is time-series integration, PCI(1) is first principal component integration. DA denotes disappointment aversion and η is a tuning parameter that captures timing aggressiveness. CER is annualized certainty-equivalent return with power utility preferences (CRRA parameter $\gamma = 5$). The asymptotic p-values of the Opdyke (2007) test are for $H_0: SR_{EWI} \leq SR_j$ versus $H_A: SR_{EWI} > SR_j$ where j is the integrated style at hand. The CER bootstrap p-values are for $H_0: CER_{EWI} \leq CER_j$ versus $H_A: CER_{EWI} > CER_j$. Mean and standard deviation (StDev) are annualized. Newey-West t-statistics are in parenthesis. The last two rows report the portfolio turnover and the Sharpe ratio after 8.6 bps proportional costs per trade. The monthly excess returns of the fully-collateralized integrated portfolios span the Jan. 1992 to Apr. 2016 period.

	OI ($\omega \geq 0$)				OI ($\forall \omega$)					RSI(3)	VTI (η=4)	RRTI (η=4)	TSI	PCI(1)
	Mean-variance utility	Exponential utility	Power utility with DA	Variance	Power utility	Mean-variance utility	Exponential utility	Power utility with DA	Variance					
Mean	0.0606	0.0610	0.0552	0.0483	0.0432	0.0429	0.0429	0.0387	0.0248	0.0596	0.0464	0.0401	0.0713	0.0257
	(3.31)	(3.32)	(3.24)	(3.10)	(2.40)	(2.40)	(2.38)	(2.19)	(1.88)	(2.99)	(2.67)	(2.55)	(4.11)	(1.13)
StDev	0.0881	0.0882	0.0862	0.0736	0.0862	0.0859	0.0860	0.0845	0.0684	0.0959	0.0811	0.0880	0.0813	0.1014
Skewness	0.1504	0.1517	0.1144	0.0142	0.2913	0.2977	0.2908	0.3922	0.0240	0.5483	0.0738	0.1738	0.1526	0.0209
	(1.05)	(1.06)	(0.80)	(0.10)	(2.03)	(2.08)	(2.03)	(2.74)	(0.17)	(3.82)	(0.51)	(1.21)	(1.06)	(0.15)
Excess Kurtosis	0.4555	0.4120	0.2821	0.0357	0.5061	0.5263	0.5093	0.9852	-0.1571	1.2522	0.0994	0.8465	0.1208	0.5189
	(1.59)	(1.44)	(0.98)	(0.12)	(1.77)	(1.84)	(1.78)	(3.44)	(-0.55)	(4.37)	(0.35)	(2.95)	(0.42)	(1.81)
JB normality test p-value	0.1325	0.1676	0.4046	0.5000	0.0300	0.0262	0.0298	0.0023	0.5000	0.0010	0.5000	0.0133	0.4843	0.1576
Downside volatility (0%)	0.0509	0.0511	0.0491	0.0433	0.0470	0.0469	0.0468	0.0464	0.0398	0.0519	0.0468	0.0505	0.0426	0.0630
99% VaR (Cornish-Fisher)	0.0538	0.0535	0.0527	0.0453	0.0511	0.0509	0.0511	0.0507	0.0428	0.0533	0.0498	0.0572	0.0465	0.0691
% of positive months	56.85%	56.16%	58.22%	59.93%	51.71%	51.71%	51.37%	53.08%	54.11%	54.79%	55.48%	51.03%	60.27%	53.77%
Maximum drawdown	-0.1551	-0.1557	-0.1495	-0.1936	-0.2136	-0.2146	-0.2339	-0.2558	-0.1994	-0.1560	-0.1484	-0.1616	-0.1632	-0.2528
Sharpe ratio	0.6883	0.6915	0.6398	0.6570	0.5013	0.4991	0.4990	0.4574	0.3630	0.6213	0.5721	0.4552	0.8775	0.2529
Opdyke test p-value (H_0: SR_{EWI}-$SR_j \leq 0$)	0.0126	0.0778	0.0389	0.0761	0.0131	0.0741	0.0124	0.0075	0.0111	0.0359	0.0159	0.0048	0.2951	0.0081
Sortino ratio (0%)	1.1900	1.1926	1.1236	1.1163	0.9188	0.9148	0.9172	0.8327	0.6235	1.1480	0.9914	0.7933	1.6756	0.4075
Omega ratio	1.6741	1.6793	1.6087	1.6262	1.4561	1.4548	1.4529	1.4181	1.3030	1.6188	1.5178	1.4063	1.8878	1.2105
CER	0.0411	0.0414	0.0365	0.0346	0.0248	0.0246	0.0246	0.0211	0.0132	0.0370	0.0299	0.0208	0.0544	0.0000
CER bootstrap p-value (H_0: CER_{EWI}-$CER_j \leq 0$)	0.0644	0.0615	0.0253	0.0364	0.0037	0.0057	0.0052	0.0031	0.0040	0.0413	0.0049	0.0038	0.0632	0.0077
Turnover	0.6694	0.6688	0.6766	0.6837	0.7161	0.7159	0.7176	0.7507	0.7634	0.6208	0.6009	0.5632	0.6253	0.5294
Sharpe ratio (TC=0.086%)	0.6092	0.6126	0.5581	0.5614	0.4153	0.4130	0.4126	0.3651	0.2497	0.5544	0.4955	0.3892	0.7979	0.1990

Table A.IV. Effectiveness of additional sophisticated integration strategies.

The table reports coefficients, Newey-West robust t-ratios and explanatory power (coefficient of determination R^2) for regressions of the Jan. 1992 to Apr. 2016 monthly excess returns of each additional sophisticated integrated portfolio on the excess returns of the K=11 standalone-style portfolios. The integration methods differ in the determination of the style-exposures as discussed in Section 4 of the paper. OI is optimal-integration, RSI(3) is rotation-of-styles integration (equal-weights) of the three best styles, VTI is volatility-timing integration, RRTI is reward-to-risk timing integration, TSI is time-series integration, PCI(1) is 1st principal component integration. The parameter η captures the timing aggressiveness of the VTI and RRTI strategies. HP is hedging pressure. DA is disappointment aversion. All portfolios are fully collateralized.

		Intercept	Term structure	Hedgers' HP	Speculators' HP	Momentum	Value	Volatility	Open interest	Liquidity	US$ beta	Inflation beta	Skewness	R^2
OI with ω≥0														
	Mean-variance utility	**-0.0025**	**0.1069**	0.0087	**0.1633**	**0.3111**	**0.3107**	**0.1325**	0.0516	-0.0331	**0.0835**	**0.2010**	**0.2523**	53.23%
		(-2.61)	(2.02)	(0.13)	(2.08)	(4.33)	(6.06)	(2.70)	(1.06)	(-0.59)	(2.10)	(4.82)	(5.66)	
	Exponential utility	**-0.0019**	**0.1240**	0.0571	**0.2779**	**0.3005**	**0.3889**	**0.1301**	**0.1006**	0.0369	**0.0933**	**0.2079**	**0.2699**	67.98%
		(-2.31)	(2.29)	(1.26)	(4.69)	(4.83)	(8.61)	(3.05)	(2.61)	(0.79)	(2.56)	(5.94)	(6.74)	
	Power utility with DA	**-0.0025**	**0.1446**	**0.1183**	**0.2519**	**0.2905**	**0.4035**	**0.1450**	**0.1343**	0.0678	**0.0847**	**0.1654**	**0.2692**	71.71%
		(-3.15)	(2.86)	(2.44)	(4.42)	(5.01)	(9.25)	(3.51)	(3.42)	(1.57)	(2.48)	(5.08)	(6.95)	
	Variance	0.0006	**0.1135**	0.0779	**0.1652**	**0.1614**	**0.3128**	**0.2154**	**0.1652**	**0.2199**	**0.1095**	**0.0954**	0.0165	50.12%
		(0.62)	(2.59)	(1.39)	(3.51)	(3.60)	(8.66)	(4.79)	(3.69)	(4.68)	(2.83)	(2.53)	(0.48)	
OI with ∀ω														
	Power utility	**-0.0024**	**0.1075**	0.0098	**0.1625**	**0.3135**	**0.3109**	**0.1325**	0.0522	-0.0318	**0.0825**	**0.2011**	**0.2524**	53.18%
		(-2.59)	(2.02)	(0.15)	(2.06)	(4.30)	(6.00)	(2.72)	(1.07)	(-0.56)	(2.05)	(4.84)	(5.63)	
	Mean-variance utility	**-0.0020**	**0.1208**	0.0662	**0.2706**	**0.3042**	**0.3944**	**0.1329**	**0.0979**	0.0350	**0.0993**	**0.2088**	**0.2707**	68.87%
		(-2.43)	(2.32)	(1.49)	(4.85)	(5.15)	(8.95)	(3.09)	(2.54)	(0.75)	(2.81)	(6.04)	(6.80)	
	Exponential utility	**-0.0025**	**0.1067**	0.0115	**0.1657**	**0.3203**	**0.3100**	**0.1291**	0.0567	-0.0380	**0.0825**	**0.2002**	**0.2492**	54.12%
		(-2.64)	(2.04)	(0.18)	(2.12)	(4.42)	(6.02)	(2.69)	(1.19)	(-0.67)	(2.06)	(4.89)	(5.60)	
	Power utility with DA	**-0.0027**	**0.1290**	0.0340	**0.1708**	**0.2879**	**0.3163**	**0.1510**	0.0575	-0.0673	**0.0737**	**0.1564**	**0.2316**	51.00%
		(-2.68)	(2.37)	(0.49)	(2.12)	(3.96)	(5.72)	(2.92)	(1.08)	(-1.18)	(1.81)	(3.85)	(5.22)	
	Variance	0.0048	0.0179	0.0728	0.0815	**0.0974**	**0.1845**	**0.1945**	0.0693	0.0898	0.0170	0.0104	-0.0013	17.40%
		(0.38)	(0.37)	(1.18)	(1.35)	(2.14)	(4.06)	(4.30)	(1.28)	(1.59)	(0.56)	(0.29)	(-0.03)	
RSI(3)		-0.0150	**0.1678**	**0.0932**	**0.2476**	**0.2210**	0.0480	0.0385	0.0001	**0.0800**	**0.0955**	**0.0717**	**0.3244**	64.90%
		(-1.29)	(3.03)	(1.85)	(3.94)	(3.71)	(1.01)	(0.85)	(0.00)	(1.97)	(2.63)	(1.90)	(7.20)	
VTI	η=4	0.0007	**0.0949**	**0.3263**	**0.1746**	0.0144	0.0192	**0.2698**	**0.1800**	**0.2915**	**0.0763**	-0.0060	**0.0646**	71.84%
		(0.89)	(3.22)	(5.98)	(3.62)	(0.48)	(0.54)	(6.26)	(5.47)	(6.98)	(2.67)	(-0.25)	(2.08)	
RRTI	η=4	**-0.0229**	0.0450	**0.2789**	**0.1884**	**0.1769**	0.0547	0.0422	0.0459	**0.0795**	**0.0610**	-0.0041	**0.2708**	58.93%
		(-1.97)	(1.00)	(4.86)	(3.45)	(3.28)	(1.17)	(0.95)	(0.97)	(1.81)	(1.67)	(-0.11)	(5.01)	
TSI		0.0021	**0.1583**	**0.1767**	**0.2527**	**0.1592**	**0.1561**	**0.1840**	**0.2132**	**0.1545**	**0.1842**	**0.1774**	**0.1815**	92.40%
		(0.56)	(8.81)	(7.43)	(10.65)	(8.00)	(9.68)	(9.67)	(12.15)	(8.34)	(11.29)	(13.38)	(12.40)	
PCI(1)		0.0052	0.0320	**-0.2113**	0.0960	0.0601	**0.1488**	**0.1610**	0.0102	-0.0781	**0.1709**	-0.0780	**0.1497**	14.93%
		(0.24)	(0.49)	(-2.04)	(0.93)	(0.72)	(2.10)	(1.96)	(0.12)	(-1.01)	(2.05)	(-1.11)	(2.22)	

Table A.V. Data-snooping-robust test for superior performance.

The table reports bootstrap *p*-values for the Superior Predictive Ability test of Hansen (2005) to control for data snooping risk in the comparison among the *M*=31 long-short portfolios (11 standalone-style portfolios and 20 integrated portfolios altogether considered in the paper). The empirical distribution of the *t*-statistic is constructed by a random-length block bootstrap simulation with *B*=10,000 replications. The null hypothesis is that the best of the *M* portfolios incurs a larger "loss" than the benchmark EWI portfolio.

Benchmark	**Loss function**	**Expected block length 1/q**	
		q=0.2	*q=0.5*
EWI	Linear	0.5106	0.5116
	Exp(λ = 1)	0.4197	0.4430
	Exp(λ = 2)	0.3602	0.3767

Table A.VI. Economic sub-period analysis of standalone-style portfolios and integrated portfolios.

The table reports statistics on the performance of the K=11 standalone-style portfolios and the integrated portfolios over sub-periods defined according to economic criteria: high versus low commodity market volatility periods determined by a GARCH(1,1) model fitted to the monthly excess returns of a long-only equally-weighted portfolio of 28 commodities (Panel A), pre- and post-financialization periods (Panel B), NBER-dated recession and expansion periods (Panel C). HP denotes hedging pressure. EWI is equally-weighted integration, OI is optimal-integration, RSI is rotation-of-styles integration, VTI is volatility-timing integration, CSI is cross-sectional pricing integration and PCI is principal-components integration. The length of each sub-period is indicated in parenthesis next to the title. Mean and standard deviation (StDev) of monthly excess returns are annualized. CER is the annualized certainty-equivalent return with power utility preferences (CRRA parameter $\gamma = 5$). The asymptotic p-values of the Opdyke (2007) test pertain to the hypotheses $H_0: SR_{EWI} \leq SR_j$ versus $H_A: SR_{EWI} > SR_j$ where j denotes a given integrated style. The final row reports bootstrap p-values for the hypotheses $H_0: CER_{EWI} \leq CER_j$ versus $H_A: CER_{EWI} > CER_j$.

	Individual styles											Integrated Styles					
	Term structure	Hedgers' HP	Speculators' HP	Momentum	Value	Volatility	Open interest	Liquidity	US$ beta	Inflation beta	Skewness	EWI	OI	RSI	VTI	CSI	PCI
Panel A: Commodity market volatility regimes																	
	High volatility regime (T1= 100 months)																
Mean	0.0291	0.0737	0.0637	-0.0319	0.0407	0.0164	-0.0314	-0.0339	0.0524	0.0098	0.0370	0.0442	0.0184	0.0201	0.0422	0.0346	0.0036
StDev	0.1075	0.1011	0.1024	0.1281	0.1296	0.0935	0.1000	0.0909	0.1341	0.1321	0.1066	0.0946	0.0952	0.1141	0.0910	0.0906	0.1083
Maximum drawdown	-0.2199	-0.1461	-0.1295	-0.3140	-0.4248	-0.2344	-0.3685	-0.3784	-0.2959	-0.3026	-0.2515	-0.1635	-0.2036	-0.2557	-0.1532	-0.1477	-0.2817
Sharpe ratio	0.2712	0.7291	0.6219	-0.2487	0.3143	0.1757	-0.3141	-0.3733	0.3912	0.0745	0.3472	0.4666	0.1937	0.1757	0.4638	0.3822	0.0331
Opdyke test p-value (H_0: SR_{EWI}-SR_i≤0)	0.2981	0.8184	0.6940	0.0287	0.3953	0.2560	0.0386	0.0213	0.4095	0.1269	0.3533	-	0.1392	0.1771	0.4916	0.2352	0.1757
CER	0.0006	0.0484	0.0380	-0.0738	-0.0010	-0.0054	-0.0574	-0.0555	0.0055	-0.0341	0.0091	0.0219	-0.0040	-0.0123	0.0217	0.0144	-0.0257
CER bootstrap p-value (H_0: CER_{EWI}-CER_j≤0)	0.3158	0.8535	0.6942	0.0014	0.3358	0.2197	0.0148	0.0068	0.3662	0.0868	0.3982	-	0.0780	0.1442	0.5181	0.1478	0.1000
	Low-volatility regime (T2=192 months)																
Mean	0.0710	0.0340	0.0498	0.1122	0.0085	0.0051	0.0149	0.0036	0.0044	0.0385	0.1152	0.0963	0.0818	0.0839	0.0804	0.0840	0.0550
StDev	0.1136	0.0919	0.0963	0.1230	0.1301	0.0953	0.0951	0.0981	0.1171	0.1349	0.1088	0.0762	0.0828	0.1178	0.0756	0.0765	0.0973
Maximum drawdown	-0.2001	-0.1720	-0.2297	-0.3774	-0.4859	-0.3062	-0.2967	-0.4434	-0.3832	-0.3832	-0.2717	-0.1163	-0.1226	-0.2256	-0.1249	-0.1600	-0.1537
Sharpe ratio	0.6256	0.3696	0.5174	0.9122	0.0652	0.0535	0.1570	0.0365	0.0372	0.2854	1.0595	1.2630	0.9876	0.7125	1.0643	1.0982	0.5650
Opdyke test p-value (H_0: SR_{EWI}-SR_i≤0)	0.0135	0.0004	0.0018	0.1315	0.0011	0.0000	0.0004	0.0000	0.0001	0.0003	0.2589	-	0.1413	0.0370	0.1495	0.2071	0.0152
CER	0.0393	0.0133	0.0267	0.0734	-0.0351	-0.0180	-0.0076	-0.0204	-0.0311	-0.0055	0.0845	0.0807	0.0642	0.0494	0.0655	0.0686	0.0313
CER bootstrap p-value (H_0: CER_{EWI}-CER_j≤0)	0.0179	0.0009	0.0106	0.4609	0.0035	0.0000	0.0003	0.0000	0.0001	0.0010	0.5316	-	0.1956	0.1591	0.0002	0.0417	0.0315

(*Cont.*) Table A.VI. Economic sub-period analysis of standalone-style portfolios and integrated portfolios

	Individual styles											Integrated Styles					
	Term structure	Hedgers' HP	Speculators' HP	Momentum	Value	Volatility	Open interest	Liquidity	US$ beta	Inflation beta	Skewness	EWI	OI	RSI	VTI	CSI	PCI
Panel B: Pre-and post-financialization regimes																	
Pre-financialization (Jan 1992-Dec 2005; T1= 168 months)																	
Mean	0.0706	0.0349	0.0433	0.0796	0.0211	0.0159	0.0350	0.0278	0.0101	0.0540	0.1058	0.1040	0.0972	0.0739	0.0888	0.0988	0.0707
StDev	0.1163	0.0849	0.0959	0.1333	0.1329	0.0943	0.0983	0.0942	0.1253	0.1300	0.1148	0.0760	0.0899	0.1284	0.0735	0.0771	0.1017
Maximum drawdown	-0.1731	-0.1720	-0.1892	-0.4036	-0.3870	-0.2145	-0.2967	-0.3477	-0.3666	-0.2731	-0.2746	-0.0761	-0.1183	-0.2683	-0.0711	-0.0852	-0.1615
Sharpe ratio	0.6068	0.4108	0.4517	0.5973	0.1589	0.1688	0.3561	0.2946	0.0808	0.4154	0.9215	1.3679	1.0811	0.5754	1.2070	1.2802	0.6956
Opdyke test p-value (H_0: $SR_{EWI}-SR_i \le 0$)	0.0090	0.0008	0.0007	0.0065	0.0019	0.0001	0.0027	0.0005	0.0001	0.0014	0.0864	-	0.1581	0.0058	0.2403	0.3552	0.0293
CER	0.0374	0.0169	0.0203	0.0347	-0.0247	-0.0065	0.0108	0.0062	-0.0304	0.0141	0.0717	0.0882	0.0759	0.0325	0.0743	0.0827	0.0446
CER bootstrap p-value (H_0: $CER_{EWI}-CER_j \le 0$)	0.0115	0.0014	0.0009	0.0599	0.0033	0.0000	0.0091	0.0001	0.0000	0.0031	0.2965	-	0.2661	0.0338	0.0032	0.1578	0.0685
Financialization (Jan 2006-April 2016; T2=124 months)																	
Mean	0.0379	0.0648	0.0698	0.0401	0.0173	-0.0004	-0.0496	-0.0594	0.0353	-0.0056	0.0649	0.0437	0.0098	0.0461	0.0383	0.0243	-0.0078
StDev	0.1047	0.1077	0.1016	0.1158	0.1259	0.0951	0.0934	0.0961	0.1205	0.1387	0.0991	0.0912	0.0824	0.0990	0.0901	0.0864	0.0996
Maximum drawdown	-0.2440	-0.1506	-0.1221	-0.2000	-0.4248	-0.3374	-0.4361	-0.5087	-0.2959	-0.3736	-0.1135	-0.1635	-0.1552	-0.1418	-0.1532	-0.1477	-0.2935
Sharpe ratio	0.3615	0.6020	0.6869	0.3465	0.1378	-0.0045	-0.5314	-0.6187	0.2931	-0.0404	0.6554	0.4793	0.1195	0.4654	0.4246	0.2808	-0.0787
Opdyke test p-value (H_0: $SR_{EWI}-SR_i \le 0$)	0.3551	0.6915	0.7883	0.3512	0.2580	0.1108	0.0057	0.0023	0.2645	0.0430	0.7124	-	0.0520	0.4803	0.3114	0.0465	0.0882
CER	0.0107	0.0367	0.0445	0.0071	-0.0217	-0.0234	-0.0728	-0.0846	-0.0025	-0.0552	0.0410	0.0231	-0.0068	0.0226	0.0183	0.0058	-0.0326
CER bootstrap p-value (H_0: $CER_{EWI}-CER_j \le 0$)	0.3654	0.6836	0.7902	0.2800	0.2580	0.0846	0.0013	0.0006	0.2282	0.0261	0.7093	-	0.0422	0.3986	0.2347	0.0386	0.0423
Panel C: NBER-dated recession and expansions																	
Recession regime (T1=28 months)																	
Mean	0.1574	0.1642	0.1891	0.0532	0.0453	0.0214	-0.0127	-0.1317	0.0473	-0.0532	-0.0489	0.0855	0.0914	0.1427	0.0984	0.0424	0.0439
StDev	0.1135	0.1306	0.1332	0.1596	0.1461	0.1083	0.1212	0.0909	0.1588	0.1380	0.1355	0.1034	0.1005	0.1159	0.1042	0.0894	0.1287
Maximum drawdown	-0.0900	-0.1345	-0.0920	-0.2000	-0.1841	-0.1389	-0.1860	-0.3012	-0.2959	-0.2859	-0.2471	-0.1635	-0.1022	-0.0627	-0.1532	-0.1477	-0.2112
Sharpe ratio	1.3871	1.2576	1.4199	0.3332	0.3103	0.1977	-0.1051	-1.4482	0.2981	-0.3858	-0.3609	0.8270	0.9093	1.2308	0.9445	0.4748	0.3407
Opdyke test p-value (H_0: $SR_{EWI}-SR_i \le 0$)	0.7898	0.7231	0.8050	0.2434	0.3418	0.2163	0.1369	0.0076	0.2210	0.0337	0.0616	-	0.5512	0.6962	0.6176	0.1515	0.1115
CER	0.1241	0.1212	0.1433	-0.0072	-0.0034	-0.0077	-0.0492	-0.1570	-0.0188	-0.1026	-0.0960	0.0588	0.0674	0.1097	0.0715	0.0227	0.0033
CER bootstrap p-value (H_0: $CER_{EWI}-CER_j \le 0$)	0.9730	0.8536	0.8819	0.2336	0.3528	0.2699	0.0378	0.0033	0.1837	0.0013	0.1475	-	0.5968	0.7840	0.8792	0.0182	0.0464
Expansion regime (T2=264 months)																	
Mean	0.0460	0.0352	0.0403	0.0639	0.0168	0.0077	0.0003	0.0037	0.0180	0.0374	0.1030	0.0777	0.0568	0.0535	0.0640	0.0697	0.0367
StDev	0.1110	0.0902	0.0932	0.1224	0.1282	0.0932	0.0942	0.0956	0.1191	0.1334	0.1046	0.0809	0.0862	0.1167	0.0785	0.0810	0.0982
Maximum drawdown	-0.2440	-0.1720	-0.2039	-0.4117	-0.5469	-0.3374	-0.4412	-0.4657	-0.3745	-0.3577	-0.1183	-0.1270	-0.1552	-0.2683	-0.1371	-0.1418	-0.3372
Sharpe ratio	0.4144	0.3905	0.4324	0.5220	0.1309	0.0823	0.0034	0.0388	0.1513	0.2803	0.9853	0.9597	0.6586	0.4585	0.8153	0.8606	0.3736
Opdyke test p-value (H_0: $SR_{EWI}-SR_i \le 0$)	0.0113	0.0031	0.0053	0.0365	0.0067	0.0005	0.0003	0.0001	0.0007	0.0019	0.5417	-	0.0512	0.0152	0.1285	0.2276	0.0226
CER	0.0157	0.0151	0.0187	0.0261	-0.0255	-0.0143	-0.0221	-0.0192	-0.0185	-0.0061	0.0751	0.0607	0.0380	0.0197	0.0483	0.0530	0.0127
CER bootstrap p-value (H_0: $CER_{EWI}-CER_j \le 0$)	0.0086	0.0058	0.0071	0.0949	0.0074	0.0004	0.0001	0.0000	0.0010	0.0027	0.7372	-	0.0336	0.0207	0.0017	0.0552	0.0205