Abstract

In this paper, we propose a portfolio-based framework that treats characteristics as signal processes to handle parameter and model uncertainty in the construction of characteristic-based factors. We reveal that different signal components correspond to distinctive characteristic-related risk premia. A comprehensive trading strategies that combines differentiated constituent portfolios through signal decomposition and transformation of a characteristic substantially improves the performance upon the traditional factor investing by harvesting these unexploited risk premia. The empirical results from asset pricing tests also suggest the existence of hidden risk premia. These findings raise concerns about the measurement errors in factors or omitted risk premia, and new challenges on classical asset pricing models.

Keywords: Risk Premia, Factor Investing, Alpha Decay, Carry, Currencies, Equities, Commodities.

JEL classification: F31, F37, G11, G12, G13, G15.
1 Introduction

Recent decade has witnessed a surge in factor investing and systematic trading in both academic literature and industrial practice. In order to identify return predictors, researchers often rely on linear regressions and construct a spread portfolio \( HML \), the difference between returns on high and low portfolios sorted on one or multiple characteristics, such as momentum and value. The challenge to this approach is that it is difficult to identify characteristics which provide independent information about expected returns (Giglio and Xiu, 2017; Kogan and Tian, 2015; Green, Hand, and Zhang, 2017; Kozak, Nagel, and Santosh, 2019). Moreover, the functional form of characteristics in the expected return mapping function is generally unknown to researchers (Lambert, Fays, and Hubner, 2018; Kozak, 2019).^1

In this paper, we address the latter challenge and ask whether researchers can explore potential relationships between expected returns and a characteristic in order to harvest the unexploited risk premia associated the characteristic. Acknowledging that the selection of factors is intimately associated with the maximum attainable squared Sharpe ratio from characteristic-based factor investing (Fama and French, 2018), it is of paramount importance to measure characteristic-based factors more accurately or completely for characteristic selection.\(^2\) We achieve this goal by incorporating multiple dimensions of a characteristic in portfolio-based factor construction.

We show that understanding the time-series dynamics of a characteristic in a cross-sectional context is crucial for a full spectrum measurement of corresponding characteristic-based factor and factor investing. The existing literature of empirical asset pricing predominately construct cross-sectional long-short portfolios sorted by the magnitudes of characteristics as the proxies for characteristic-based (tradable) factors.

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^1This is also known as parameter and model uncertainty problems, and closely related to the characteristic-based portfolio selection problem (Brandt, Santa-Clara, and Valkanov, 2009; DeMiguel, Martin-Utrera, Nogales, and Uppal, 2018).

^2See Freyberger, Neuhierl, and Weber (2017); Feng, Giglio, and Xiu (2019) for examples in characteristic selection of cash equities.
We illustrate in this paper that there are multiple dimensions of a characteristic and we explore (i) the cross-sectional as well as time-series long-short measurement, (ii) the static as well as dynamic view of characteristics, and (iii) the absolute as well as relative value of characteristics. However, modeling characteristic dynamics could be computationally heavy if it involves a large-scale cross-sectional data set. Therefore, we propose a simple econometric framework that treats a characteristic as a signal process for portfolio-based factor construction. Based on the framework, our portfolio strategies involves using distinctive components of a characteristic as trading signals to uncover the hidden risk premia. We then apply it to a well-known alternative risk premia, carry (see Koijen, Moskowitz, Pedersen, and Vrugt, 2017), in global macro space. Our framework tackles parameter and model uncertainty problems through computationally light signal (characteristic) decomposition and transformation, and hence it allows us to substantially improves the performance upon both cross-sectional and time-series long-short strategies of traditional factor investing.

Specifically, we reveal that the extracted signal components, i.e., static carry, dynamic carry, unexpected dynamic carry, cyclic carry, and unexpected cyclic carry, offer a better overall assessment of the characteristic “carry” and provide distinctive aspects of carry trade risk premia. We find that each of the signal components carries a statistically significant risk premium and has relatively low correlations with others, implying that each component contributes to risk premia in heterogeneous ways. Comprehensive multi-asset cross-sectional and time-series carry trades that optimally combine the constituent strategies constructed using different carry components substantially improve the risk-adjusted return\(^3\) and provide greater downside protection measured by higher moments, maximum drawdown, and Calmar ratio. The trades deliver statistically significant alphas (consistently above 3% and up to 6% per annum with \textit{t}-statistics ranging from 2.8 to 4.8) beyond the conventional carry trade. In particular, the cross-asset comprehensive carry

\(^3\)The annualized Sharpe ratios are about 1.2 for currencies, 1.5 for equity indices, and 1.4 for commodities, after transaction costs.
trades do not have synchronized drawdowns contrary to the plain vanilla carry trades as described in Koijen, Moskowitz, Pedersen, and Vrugt (2017). The improvements in Sharpe ratios are also robust to Ledoit and Wolf (2008) test with the corresponding annualized active returns (information ratios) ranging from 1.5% (20%) to 7% (100%). Lastly, to avoid data-snooping bias, we test the marginal improvements in Sharpe ratios under different combinations of parameters and models for signal generations, and find that the outperformance of our approach is robust to thousands of parameter and model scenarios.

The economic intuition behind the superior performance of our proposed factor investment approach can be summarized as follows. First, we show that constituent carry strategies offer diversification opportunities through low correlations. Each component of the characteristic corresponds to different sources of risk and/or mispricing. For instance, static carry is the major source of risk premia of cross-sectional currency carry (over 75%) trade but contributes a smaller portion of excess returns to cross-sectional equity carry (about 15%) and commodity carry (about 35%) trades. We find that dynamic carry plays a pivotal role in generating excess returns for equity and commodity carry. While equity and commodity carry trades share similar risk and return profiles, the sources of risk premia between cross-sectional and time-series are different. For the cross-sectional trades, almost all the excess returns across currencies, equity indices, and commodities, can be attributable to the carry component\(^4\). For the time-series trades, however, it is the return component that accounts for over 60% of the excess returns of equity carry trades while carry component still dominates commodity carry trades. Thus, understanding the properties of distinctive components of carry is crucial in constructing an enhanced portfolio strategy and those components should not be treated equally as if those share a common source of risk premia, such as liquidity risk, volatility risk, or crash risk.

Second, we investigate the investment performance in response to the delayed reaction to the trading signals (henceforth, alpha decay) and find that investors are able to capture\(^4\) See definition for different asset classes in the first paragraph of Section 2.
additional alpha by having higher portfolio-rebalancing frequency. Contrary to the most popular cross-sectional currency carry trade which has negligible alpha decay, the alpha decay rates for both cross-sectional and time-series equity (commodity) carry trades are quite (moderately) fast especially in the first 10 trading days. The contribution of static carry or the signal nature of a characteristic is attributable to the speed of alpha decay of the corresponding trading strategy. We find that capturing this variation of alpha decay across asset classes is non-trivial in measuring risk premia even after taking transaction costs into account. Our empirical evidence suggests that higher-frequency implementation is an effective way to discover the hidden risk premia in contrast to the monthly-rebalancing paradigm in the literature.

Third, given our empirical findings that dynamic carry plays a pivotal role for equity and commodity carry, we examine whether it is the expected or unexpected component of carry that drives the risk premia associated with the dynamic trades.\(^5\) We find supportive evidence that the key driver of excess returns is the unexpected carry across asset classes. We further address that cyclical component, especially unexpected cyclic component, also carries a hidden risk premium that provides considerable excess returns with low correlations with other constituent carry strategies. The cyclic carry captures the risk premium unrelated to the level of carry but is closely associated with the economic cycles (annualized Sharpe ratio: about 0.4 for currencies, 1.3 for equity indices, and 1.1 for commodities). The unexpected cyclic carry corresponds to the risk premium interactive with the shocks to the economic cycles and provides annualized Sharpe ratio of approximately 0.8 for currencies, 0.8 for equity indices, and 1.2 for commodities.

The convention in factor risk premia investment that imposes the same parameter restriction on each component of a characteristic. Contrary to this, our empirical results suggest that we should distinguish static effect from dynamic effect, level effect from cyclic effect, and unexpected effect from expected effect in measuring risk premia. Given the statistically significant risk premia and cross-sectional spreads in excess returns of

\(^5\)Note that there is no unexpected carry in static carry.
portfolios sorted by different carry components, we perform standard asset pricing tests on the cross sections of constituent carry portfolios and fail to identify a risk factor that consistently explain the cross-sectional risk premia associated with constituent carry trades. This suggests the existence of hidden carry trade risk premia with low correlations and further gives rise to new challenges on classical asset pricing models due to omitted perspectives in defining factors. More specifically, conventional approaches confine the characteristics-return relations in a certain type of mapping function, ignoring the economically meaningful asymmetric and nonlinear effects from signal decomposition and transformation. The statistical restrictions imposed by conventional approaches impede investors from harvesting the unexploited risk premia associated with a characteristic.

The rest of this paper is organized as follows: In Section 2, we introduce a theoretical foundation for regarding characteristics as signal processes in trading futures or forwards, followed by an integrated framework of signal modeling and portfolio strategy construction in Section 3. Section 4 describes the data set used in this paper and relevant procedures of signal and portfolio . Section 5 presents a systematic view of carry trade risk premia with performance evaluation and robustness checks on the corresponding constituent portfolio strategies. Section 6 provides the methodologies and risk factors employed for cross-sectional asset pricing tests and discussions on relevant empirical results. We draw a conclusion in Section 7. We delegate data sources, technical details, and complementary findings to the online appendix.

2 The Dynamics of Asset Prices, Carry, and Risk Premia

In this section, we explore how our signal processing procedure is applicable to carry trades in global macro space. Futures are liquid standardized forward contracts widely used as trading instruments in the financial industry for multiple asset classes. The
valuation of futures under no-arbitrage condition takes a general form of $F_{i,t} = S_{i,t} (1 - y_{i,t})$, where $S_{i,t}$ is the spot price, $F_{i,t}$ is the futures price with the same time-to-maturity of $\tau$ as $y_{i,t}$. $y_{i,t}$ is asset-specific: dividend yield for equity index futures in excess of risk-free interest rate of contract denominated currency $r_{i,t}$, cost of carry in excess of convenience yield for commodity futures, $r_{i,t} (1 + r_{i,t} / S_{i,t})$ in excess of $r$ for the treasury bond futures, and $(r_{i,t} - r_{i,t+1}) / (1 + r_{i,t})$ for currency futures/forwards, where * denotes foreign variables. The returns to trading the futures are given by:

$$ R^{(j)}_{i,t+1} = \frac{E_{i,t}^{(j)}}{E_{i,t}^{(j)}} \cdot \left[ \left( \frac{F_{(j)}^{(j)}}{F_{(j)}^{(j)}} - 1 \right) + \left( \text{Rolling Spread} \right) \right] - 1 $$

where $\iota_{t+1}$ is 1 if $t + 1$ is the day to roll the current contract $j$ over to the next contract $j + 1$, and 0 otherwise. The roll-over trade is assumed to be executed at the end of the day. The sign of the roll spread depends on the slope of two contracts. If we have a long (short) position on the contract, the roll return is positive (negative) for backwardation and negative (positive) for contango. The roll date is not necessarily the expiry date, as investors can set their own roll rules depending on the market conditions. We can rewrite Equation (1) in logarithm:

$$ E_{t+1}^{(j)}(y_{i,t+1}) = E_{t}^{(j)}(s_{i,t+1}) - s_{i,t+1} \cdot r_{i,t+1} - E_{t+1}^{(j)}(s_{i,t+1}) - y_{i,t+1} \cdot y_{i,t+1} \cdot \tau_{i,t+1}$$

where $\tau_{i,t+1} = \tau_{i,t+1} - 1$. Let $\tau^{(j)}$, $\tau^{(j+1)}$ be the maturity to the roll date of contract $j$, and $j + 1$, respectively. It is clear that two key components affecting the future returns. The first component is currency return $\Delta s_{i,t+1}$, which is related to the risk premium associated with movements in spot price. The second component is carry $y_{i,t+1} - y_{i,t+1}$, and if $t + 1$ is a roll date, there is an addition carry component — implied carry $y_{i,t+1}^{(j+1)} - y_{i,t+1}^{(j)}$ for time from $t + \tau^{(j)}_{i,t+1}$ to $t + \tau^{(j+1)}_{i,t+1} - 1$. $\tau^{(j)}_{i,t+1}$ equals to the number days before the expiry of contracts

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$B_{i,t}^{*}$ is the present value of coupons over $\tau$ periods, the futures contract’s maturity.
defined by the roll rule on the roll date. After iterating Equation (2) from time $t$ (the end of the roll date) forward for $\tau(j) - 1$ periods, summing up, and rearranging, we have:

$$s_{i,t+\tau(j)-1} - \mathbb{E}_t[s_{i,t+\tau(j)-1}] = \sum_{k=0}^{\tau(j)-1} \mathbb{E}_t[y_{i,t+k\psi} - y_{i,t+1+k\psi}] + \sum_{k=0}^{\tau(j)-1} \mathbb{E}_t[r_{i,t+1+k\psi}]$$

(3)

where $\tau_{i,t+k\psi} = \tau(j) - k$ and $\tau_{i,t+k\psi}$ is reset to $\tau(j)$ on the end of roll date ($k = 0$). We define

$$\lim_{k \to \infty} y_{i,t+k\psi} = \bar{y}_i, \quad \lim_{k \to \infty} \sum_{k=1}^{\infty} \Delta y_{i,t+k\psi} = 0, \quad \lim_{k \to \infty} \sum_{k=0}^{\infty} \left( t_{i+1+k} - t_{i+1+k} \right) \cdot \bar{y}_i = \bar{y}_i^*$$

and $\lim_{k \to \infty} \tau_{i,t+k\psi} = \bar{r}_i$ that are not contract $(j)$ dependent, and $\eta = \bar{r}_i - \bar{y}_i$. Then Equation (3) can be written as:

$$s_{i,t+\eta} = \mathbb{E}_t[s_{i,t+k\psi}] + k \cdot \eta = \sum_{k=0}^{\infty} \mathbb{E}_t[y_{i,t+k\psi} - \bar{y}_i] + \sum_{k=0}^{\infty} \mathbb{E}_t[r_{i,t+1+k\psi} - \bar{r}_i]$$

(4)

Equation (4) indicates that the payoff to trading futures is driven by prospective carry and prospective underlying return, which can also be related to other sources of risk premia and/or mispricing, such as momentum and value. We focus on carry in this paper. If there is no time variation in carry, spot and futures returns are directly predictable by original carry signals. Nevertheless, carry is shown to fluctuate with drift or around their long-run mean. Investors evaluate the relation of the observed fluctuations (such as the trend, cycle, or even seasonality) with the economic cycles and incorporate dynamic information of these fluctuations into their trading decision-making process.

3 Characteristics-Based Risk Premia

In previous section, we introduce a framework of the carry-return relation for systematic futures trading in order to demonstrate that our signal processing procedure conforms with the economic implications of the framework. In this section, accordingly,
we propose a portfolio-based framework that models characteristics as signal processes that alleviates the issue of parameter and model uncertainty in the characteristic-return relation. By doing so, we also relate alpha uncertainty and alpha decay of the characteristic-based factor to the signal nature of characteristics, via signal decomposition and transformation.

3.1 Characteristics as Signal Processes

Given a characteristic $x_{i,t}$ for asset $i$ at time $t$, we define the conditional aggregate mean $\bar{x}_{i,t} = \frac{1}{N} \sum_{t=1}^{T} x_{i,t}$, the unconditional asset-specific mean $\bar{x}_i = \mathbb{E}[x_i]$, and the unconditional aggregate mean $\bar{x} = \mathbb{E}[\bar{x}]$. Nevertheless, we can only observe $\bar{x}_{i,t}$ and $\bar{x}$ conditionally, i.e., $\bar{x}_{i,t}^e = \frac{1}{T} \sum_{t=1}^{T} x_{i,t}$, and $\bar{x}^e = \frac{1}{NT} \sum_{t=1}^{T} \sum_{i=1}^{N} x_{i,t}$. Without loss of generality, we assume, for simplicity, that the signal process of a characteristic follows an AR(1) structure:

$$x_{i,t} - \bar{x}_{i,t}^e = \delta_i (x_{i,t-1} - \bar{x}_{i,t}^e) + u_{i,t}$$  \hspace{1cm} (5)

where $\delta_i$ is the AR(1) coefficient. Then, $\bar{x}_{i,t}^e$ is static carry, $\delta_i (x_{i,t-1} - \bar{x}_{i,t}^e)$ is the expected dynamic carry, denoted by $d_{i,t}$, and the unexpected dynamic carry is represented by the residual $u_{i,t}$.

By combining Equation (5) with Equation (6), we have:

$$x_{i,t} = \bar{x}_{i,t}^e + \bar{d}_{i,t}^e + t_{i,t} + (\bar{x}_{i,t}^e - \bar{x}_{i,t}^e) + (d_{i,t}^e - d_{i,t}^e) + (u_{i,t} - \bar{u}_{i,t})$$  \hspace{1cm} (7)

7See also Hassan and Mano (2019) that propose a panel decomposition framework to analyze the coefficient of Fama (1984) regression.

8Note that $\bar{u}_i = \frac{1}{T} \sum_{t=1}^{T} u_{i,t} = 0$ and $\bar{u}_t = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} u_{i,t} = 0$ from estimations.
This is essentially signal decomposition, and thereby can be applied to other trading signals and asset classes for the purpose of portfolio construction of systematic strategies. As shown in Equation (7), trading signals consist of six components:

- $\bar{x}^e$: unconditional aggregate mean in both cross section and time series.

- $\bar{d}_t^e$: expected conditional aggregate deviation at time $t$, which is conditional aggregate mean $\bar{x}_{t,\psi}$ in excess of $\bar{x}$. This term captures the expected temporary deviation from unconditional aggregate mean $\bar{x}^e$.

- $\bar{u}_t$: unexpected conditional aggregate deviation or simply aggregate shock at time $t$, which is the aggregate level of shocks in the cross section. This term captures the unexpected temporary deviation from unconditional aggregate mean $\bar{x}^e$.

- $\bar{x}_{t,\psi}^e - \bar{x}^e$: unconditional dispersion, which is unconditional asset-specific mean $\bar{x}_{t,\psi}$ in excess of $\bar{x}^e$. This term represents the permanent component in the cross-sectional dispersion $x_{i,t,\psi} - \bar{x}_{t,\psi}$.

- $d_{t,\psi}^e - \bar{d}_t^e$: expected conditional dispersion at time $t$, which is the expected dynamic component $d_{i,t,\psi}^e$ in excess of expected conditional aggregate deviation $\bar{d}_t^e$. This term corresponds to the expected transitory component in the cross-sectional dispersion $x_{i,t,\psi} - \bar{x}_t$.

- $u_{i,t,\psi} - \bar{u}_t$: unexpected conditional dispersion at time $t$, which is the deviation of $u_{i,t,\psi}$ from unexpected conditional aggregate deviation or aggregate shock $\bar{u}_t$. This term corresponds to the unexpected transitory component in the cross-sectional dispersion $x_{i,t,\psi} - \bar{x}_t$.

### 3.2 Signal-Based Decomposition of Portfolio Strategies

We construct portfolio strategies using the aforementioned signal decomposition framework. To avoid look-ahead bias, we assume that investors place trade orders at the
end of time \( t + 1 \) on the information obtained at the end of time \( t \), and the corresponding return of the trading instrument \( i \) is realized at the end of time \( t + 2 \), denoted by \( r_{i,t+2} \). To construct trading strategies that incorporates both time-series and cross-sectional dimensions of the characteristics, we systematically assign portfolio weights proportional to the signal strength relative to the unconditional aggregate mean of characteristics. Similarly, the portfolio weights of constituent trading strategies are proportional to the decomposed signals.

\[
\sum_{t,\psi}[r_{i,t+2}(x_{i,t\psi} - \bar{x}_e)] = \sum_{i,t}[r_{i,t+2}(\bar{x}_{i\psi} - \bar{x}_e)]
\]

(8)

The signal-based decomposition of portfolio strategies is given by Equation (8) above. It reveals five basic elements of trading strategies. The first category, static trade (ST) invests in (funded by) assets that are expected to have high (low) expected signals relative to the unconditional aggregate mean. It benefits from the persistence of signal-related risk premia over investment horizons. Thus, it captures the permanent component of characteristic-related risk premia. The second category, dynamic trade (DT) reacts to the temporary cross-sectional differential or time-series deviation (between-time-and-asset variation) in the signals. It buys (sells) assets with high (low) levels of the signals not only relative to the cross-sectional mean but also relative to its own asset-specific historical mean. It essentially capture temporary cross-sectional and time-series signal deviations from long-run means. It can be further decomposed into expected dynamic trade (EDT) and unexpected dynamic trade (UDT) with respective to temporary asset-specific deviations. Moreover, due to the transitory nature of the dynamic signal component, the dynamic trade is closely associated with the alpha decay, which is the sensitivity.
of returns to the speed in arrival of information about the characteristics. The third category, market-timing trade (MT) takes long or short position of the whole market according to the short-run deviation of aggregate signal from its long-run mean. It can also be further decomposed into expected market-timing trade (EMT) and unexpected market-timing trade (UMT) with respective to temporary aggregate deviations.

If a trading strategy is constructed solely based on the signal strength relative to the conditional cross-sectional mean, it becomes classical portfolio-sorting approach where portfolios are rebalanced according to the cross-sectional dispersion of signals at each point of time. It takes advantage of the cross-sectional predictability — a positive or negative predictive relation between signal levels and future asset returns. Under our framework, the resulting cross-sectional long-short (CS-LS) strategy can be understood as a combination of static trade, expected and unexpected dynamic trades.

\[
\sum_{i,t} [r_{i,t+2}(x_{i,t} - \bar{x}_t)] = \sum_{i,t} [r_{i,t+2}(\bar{x}^e_{i,t} - \bar{x}^e_t)] + \sum_{i,t} [r_{i,t+2}(d_{i,t}^e - \bar{d}_{i,t}^e)] + \sum_{i,t} [r_{i,t+2}(u_{i,t} - \bar{u}_t)]
\]

X X
\[
\sum_{i,t} [r_{i,t+2}(x_{i,t} - \bar{x}_t)] = \sum_{i,t} [r_{i,t+2}(\bar{x}^e_{i,t} - \bar{x}^e_t)] + \sum_{i,t} [r_{i,t+2}(d_{i,t}^e - \bar{d}_{i,t}^e)] + \sum_{i,t} [r_{i,t+2}(u_{i,t} - \bar{u}_t)]
\]

Using different combination of constituent portfolio strategies, we can also reconstruct a time-series long-short (TS-LS) strategy where portfolio weights are allocated according to the signal relative to its own history. The portfolio elements are expected and unexpected components for dynamic as well as market-timing trades.

\[
\sum_{i,t} [r_{i,t+2}(x_{i,t} - \bar{x}_t)] = \sum_{i,t} [r_{i,t+2}(\bar{x}^e_{i,t} - \bar{x}^e_t)] + \sum_{i,t} [r_{i,t+2}(d_{i,t}^e - \bar{d}_{i,t}^e)] + \sum_{i,t} [r_{i,t+2}(u_{i,t} - \bar{u}_t)]
\]

X X
\[
\sum_{i,t} [r_{i,t+2}(x_{i,t} - \bar{x}_t)] = \sum_{i,t} [r_{i,t+2}(\bar{x}^e_{i,t} - \bar{x}^e_t)] + \sum_{i,t} [r_{i,t+2}(d_{i,t}^e - \bar{d}_{i,t}^e)] + \sum_{i,t} [r_{i,t+2}(u_{i,t} - \bar{u}_t)]
\]

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\[
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\]
3.3 Signal-Based Transformation of Portfolio Strategies

The signal uncertainty inevitably induces unnecessary trades and leads to an unproportionate increase in transaction costs, which arise from not only the uncertainty in signal-alpha relation but also low signal-to-noise ratio as a result of unfavorably high signal volatility.\(^9\) Hence, we focus on the signal uncertainty (volatility of signals) rather than the return uncertainty (volatility of returns). We demonstrate that characteristic volatility-managed (or signal uncertainty-managed) dynamic trade has important time-series long-short implications, even though it is a cross-sectional long-short portfolio strategy. It can be interpreted as trading on the cyclic components of the characteristics.

\[
\sum_{i,t} \left\{ T_i,t+2 \left[ \frac{x_i,t_{-t_{-t_{-t}}}}{x_i,t_{-t_{-t_{-t}}}} \sigma_{x_i,t_{-t_{-t_{-t}}}} \right] \right\} = \frac{1}{c} \sum_{i,t} \left\{ T_i,t+2 \left[ z_i,t_{-t_{-t_{-t}}}- \mu_{z_i,t_{-t_{-t_{-t}}}} \right] \right\} = 0 \tag{11}
\]

where \( z_{i,t_{-t_{-t_{-t}}}} = \frac{x_{i,t_{-t_{-t_{-t}}}} - \bar{x}_{i,t_{-t_{-t_{-t}}}}} {\sigma_{x_i,t_{-t_{-t_{-t}}}}} \), \( c = \frac{1}{\sigma_{x_i,t_{-t_{-t_{-t}}}}} \), and \( \sigma_{x_i,t_{-t_{-t_{-t}}}} \) is the target or favorable level of signal volatility.

As shown in Equation (11), characteristic volatility-managed (V.T.) time-series long-short portfolio strategies trade on uncertainty-adjusted (transformed) characteristic-based signals \( z_{i,t_{-t_{-t_{-t}}}} \) and scaled by target signal volatilities. Cyclic carry is essentially normalized dynamic carry. This type of portfolio strategies has dynamic (cross-sectional long-short) and market-timing trade implications.

\[
\sum_{i,t} \left\{ T_i,t+2 \left[ z_i,t_{-t_{-t_{-t}}} \right] \right\} = \sum_{i,t} \left\{ T_i,t+2 \left[ \left( z_i,t_{-t_{-t_{-t}}} - \bar{z}_t \right) - \left( \bar{z}_t - \bar{z}_t \right) \right] \right\} + \sum_{i,t} \left\{ T_i,t+2 \left( z_t \right) \right\} \tag{12}
\]

\(^9\)Brandt, Santa-Clara, and Valkanov (2009) propose a parametric portfolio policy that optimal portfolio weights depend on certain state variable(s). They argue that volatility is an ideal candidate given its pivotal role in alpha generation (Fleming, Kirby, and Ostdiek, 2001, 2003; Moreira and Muir, 2017).
The cross-sectional long-short portfolio strategies with \( z_{i,t} \) can also be decomposed into expected dynamic cyclic trade (EDCT) and unexpected dynamic cyclic trade (UDCT).

\[
\sum_{i,t} [r_{i,t+2}(z_{i,t}\bar{z}_t - \bar{z}_{i,t})] = \sum_{i,t} [r_{i,t+2}(z_{i,t}\bar{z}_t - \bar{z}_{i,t})] + \sum_{i,t} [r_{i,t+2}(v_{i,t}\bar{v}_t - \bar{v}_{i,t})] \tag{13}
\]

where \( z_{i,t}\bar{z}_t = \delta_i z_{i,t-1} \), \( \bar{z}_{i,t} = \frac{1}{N} \sum_{i=1}^N z_{i,t} \), \( \bar{z}_{i,t} = \bar{z}_{i,t} + \bar{v}_t \), \( \bar{v}_t = \frac{1}{N} \sum_{i=1}^N v_{i,t} \), and \( v_{i,t} = \frac{\mu_{i,t}}{\sigma_i} \).

The market-timing trade of \( z_{i,t}\bar{z}_t \) can also be decomposed into expected market-timing cyclic trade (EMCT), and unexpected (UMCT) market-timing cyclic trade with portfolio weights proportional to \( \bar{z}_{i,t} \) and \( \bar{v}_t \), respectively. We find that market-timing carry trades, regardless of level or cyclic, expected or unexpected component, do not perform well across asset classes. We do not explore it further, and henceforth, the portfolio strategies based on unexpected or unexpected cyclic carry refer to dynamic trades rather than market-timing trade.

The traditional cross-sectional long-short portfolio strategies, or characteristic-based factors, focus on the level of the characteristics (as trading signals), since they only care about the absolute magnitude rather than their relative strength compared to its own history. The signal-based transformation of the volatility-managed time-series long-short portfolio strategies provides a new angle to measure characteristic-based risk premia. The resulting signals are economically meaningful: it is the signal dynamic component (or equivalently, the conditional cross-sectional dispersion) adjusted by the instability of the signal. This measurement should correspond to the economic cycles, e.g. policy cycles for currencies, dividend cycles for equities, and inventory cycles for commodities.

We show that the cyclic carry captures risk premium associated with the cyclic component other than the dynamic trade component and has low correlations with the levels of carry.\(^{10}\) We also isolate the level effect from the unexpected component, because

\(^{10}\)It also possesses several favorable features relative to regression based method for extracting cycle components. First, it is computationally light and less subject to estimation error. Second, it captures cycles directly from detrended series rather than specifying the trend component in regression. Third, it normalizes cycles so that the level effect of original signals is eliminated. We demonstrate benefits of
high level of the original signal tends to have high level of unexpected component, which renders the portfolio sorting less effective. To capture an uncorrelated risk premium of carry trades, we separate not only the cyclic carry from the level of carry but also the unexpected carry from the expected carry. The *unexpected cyclic carry* is thereby measured as the shock to cyclic carry.

To summarize, static carry (dynamic carry) captures the alpha persistence (alpha decay). Unexpected carry as a shock to carry is the main force that drive dynamic carry. Cyclic carry (unexpected cyclic carry) eliminates the persistent cross-sectional differences in the levels of carry (unexpected carry). As a result, both level and cyclic effects are removed from unexpected cyclic carry. Again, we are aware that functional form from signals to returns, \( r_{i,t+1} = f(x_{i,t}) \) is agnostic. Constructing constituent portfolio strategies using the signal decomposition and transformation procedures and combining them either using naive diversification or optimally relaxes the assumption that each component of the trading signals contributes to risk premia homogeneously, which, to some extent, alleviates the parameter and model uncertainty problems.

4 Trading Instruments and Exercises

The trading instruments in this paper include 31 currency futures/forwards, 27 equity index futures\(^{11}\), and 30 commodity futures. The tickers for the trading instruments and relevant total return indices are reported in Table C.1 in Appendix C, and the data set is available from Bloomberg and Reuters.\(^{12}\)

\(^{11}\)We exclude some equity index futures, e.g., DJIA Mini (DMU), NASDAQ 100 E-Mini (NQ), RUSSELL 2000 (RTAU), TOPIX (TP), FTSE China A50 (XU), etc., also volatility index futures such as CBOE VIX (UX), to avoid regional concentration of risk.

\(^{12}\)We do not perform tests on bond futures because the limited country coverage of trading instruments leads to under-diversified or over-concentrated portfolio strategies while currency, equity index, and commodity futures have broader samples.
4.1 Signal Measurements and Measurement Errors

The measurements of carry take a general form as below:

\[
x_{i,t}^{c\psi} = \frac{P_{i,t}}{F_{i,t}^{\psi}} - 1 \left( \frac{T_{a\psi}}{T_{i,t}^{(F\psi)} - T_{i,t}^{(P\psi)}} \right)
\]

(14)

where \(P_{i,t}\) denotes the baseline prices, which can be spot prices for exchange rates and equity indices, or futures price for commodity curves (front or neighbour contracts); \(F_{i,t}\) represents the forward or futures prices (trading instrument) of active contracts being traded in the markets; \(T_{a\psi}\) is the annualization factor, and \(T_{i,t}^{(P\psi)}\), and \(T_{i,t}^{(F\psi)}\) is the corresponding time to expiry of two prices used for calculating carry. Implementing carry trades via futures markets are different from via spot markets in a sense that we need to consider the prospective carry besides contemporaneous carry. Taking signal dynamics into account helps investors to evaluate prospective carry. Trading \(F_{i,t}\) on carry \(x_{i,t}^{c\psi}\) assumes the movement of \(F_{i,t}\) toward \(P_{i,t}\) in future.

In our trading exercise, the portfolios are rebalanced daily so that the alpha decay can be detected at a granular level. By doing so, we are inevitably encountered with a serious non-synchronicity issue between spot and futures markets in measuring currency, equity, and commodity carry signals.\(^{13}\) We present a direct test of alpha decay by examining how average daily excess returns of the portfolio strategies reacts to the lagged signals.\(^{14}\) Besides the non-synchronicity issues, there are strong seasonal variations in commodity inventories and consumptions. We find that these seasonalities are considerably reflected in the commodity carry while it is negligible in equity and currency markets. Therefore, we deseaseasonalize the commodity carry in our empirical analysis.

\(^{13}\)This issue arises from differences in trading hours of exchanges across countries, extra trading hours of futures market after spot market, and market segmentation and illiquidity. To alleviate this issue, we employ historical intraday data.

\(^{14}\)We also report the effects of rebalancing frequency and signal half-life in Figure C.1 and C.2 in Appendix C.
4.2 Portfolio Construction and Transaction Costs

The initial portfolio weights are already specified in our signal-based framework for constructing portfolio strategies, e.g., cross-sectional dispersion weighting scheme where
\[ x_{i,t}^d = x_{i,t} - \bar{x}_t \]
as in Asness, Moskowitz, and Pedersen (2013) for cross-sectional long-short carry trades, and the time-series deviation weighting scheme where
\[ x_{i,t}^{d\psi} = x_{i,t} - \bar{x}_{i,t}^\psi \]
for time-series long-short carry trades. The final portfolio weights are then computed as
\[ w_{i,t}^+ = \frac{x_{i,t}^d}{\sum x_{i,t}^d} \text{ for long positions, and } w_{i,t}^- = \frac{x_{i,t}^{d\psi}}{\sum x_{i,t}^{d\psi}} \text{ for short positions.} \]

We take (i) commission fee per contract \( CF_{i,t+1} \), (ii) half bid-ask spread \( BAS_{i,t+1}/2 \), and (iii) market impact estimates from a nonlinear function\(^1\) that
\[ \Delta Q_{i,t+1} \cdot \frac{\text{volatility of the trading instrument}}{\text{in terms of generic contract}} \]
\[ \Delta Q_{i,t+1} \cdot \frac{\text{order size}}{\text{in terms of percentage of total volume}} \]
where \( Q_{i,t+1} \) denotes contract price level denominated in local currency, \( CS_{i,t+1} \) represents the contract size, and \( ER_{i,t+1} \) is the exchange rate conversion factor (to USD).\(^2\)

\[ TC_{i,t+1} = \Delta Q_{i,t+1} \cdot CS_{i,t+1} \cdot P_{i,t+1} \cdot \left( \frac{CF_{i,t+1}}{CS_{i,t+1} \cdot P_{i,t+1}} + \frac{BAS_{i,t+1}}{2P_{i,t+1}} + MT_{i,t+1} \right) \cdot \frac{1}{ER_{i,t+1}} \quad (15) \]

where \( P_{i,t+1} \) denotes contract price level denominated in local currency, \( CS_{i,t+1} \) represents the contract size, and \( ER_{i,t+1} \) is the exchange rate conversion factor (to USD).\(^2\)

\[ Q_{i,t+1} = \left( \frac{\frac{P_{i,t+1} \cdot w_{i,t+1} \cdot ER_{i,t}}{CS_{i,t+1} \cdot P_{i,t+1}}}{\left( \frac{1}{CS_{i,t+1} \cdot P_{i,t+1}} \right) \cdot \frac{1}{ER_{i,t+1}} \cdot \gamma_{i,t+1}} \right) \quad (16) \]

\[ P_{i,t+2} = \frac{Q_{i,t+1} \cdot CS_{i,t+1} \cdot P_{i,t+1}}{\frac{1}{ER_{i,t+1}} \cdot \gamma_{i,t+1}} \quad (17) \]

where \( Q_{i,t+1} \) is the number of contracts to hold at time \( t \), and \( w_{i,t+1} \) is the portfolio weight.

To avoid look-ahead bias, we adopt the exchange rate at time \( t \) end of day to determine

\(^1\)It may follow the square-root law, e.g., \( = 1/2 \), among many other power-law settings. It ignores the influence from the duration of order execution.

\(^2\)For commodity futures, there could be multiple tradable contracts available on curve \( i \) at time \( t+1 \). Transaction costs across the curve for a certain commodity futures could vary significantly since different points of the curve do not share similar degrees of liquidity.
the number of contracts to hold at time $t + 1$ end of day. We divide the profit and loss $P\&L_{i,t+2}^{(j)}$ by the portfolio notional value $PNV$ to convert it into returns (realized at time $t + 2$) before transaction costs. Given that the constituent carry strategies are highly scalable, the impact of $PNV$ on the calculation of returns is negligible. To alleviate the entry bias of strategies, we report returns without reinvestment.

5 A Systematic View of Carry

In this section, we present the empirical results of multi-asset systematic carry strategies trading on the decomposed and transformed carry signals. We show that understanding the properties of distinctive components of carry is crucial in constructing an enhanced portfolio strategy of carry. The sources of carry trade risk premia are different — the excess returns may stem from static trade (currency market), dynamic trade (equity market), or both (commodity market). The dynamic trades across asset classes are commonly driven by the unexpected carry. Cyclic carry is a hidden risk premium that offers considerable excess returns with low correlations with other constituent carry strategies. The unexpected cyclic component further provides additional diversification benefits in the comprehensive carry trades that combines the risk premia associated with not only the level and cycle of carry but also the shocks to carry. The market-timing portfolio strategies do not perform well across asset classes. Hence, we do not explore it further in terms of expected and unexpected components.

5.1 Rebalancing Frequency and Alpha Decay

Figure 1 below shows the alpha decay in multi-asset cross-sectional and time-series carry trades. The alpha decay represents the sensitivity of investment performance to the speed in arrival of information or trading signals. We find that there is negligible alpha decay in cross-sectional currency carry trades, while the alpha decay rates in both cross-sectional and time-series equity carry trades are quite fast especially in the first 10
trading days. The alpha decay in both cross-sectional and time-series commodity carry trades is similar to that of equity carry trades but with slower rates. These empirical findings indicate that the static component of an alpha signal plays a pivotal role in determining the speed of alpha decay of a trading strategy. More specifically, the alpha decay rate decreases as the contribution of the static component increases. Thus, we can rationalize the empirical evidence that the alpha decay rate is slower in the currency carry trades because the static carry of currencies accounts for much higher proportion of the total returns than that of equity indices and commodities in the cross-sectional long-short strategies. As demonstrated in the figures, alpha decay is very important for measuring risk premia, and higher-frequency implementation is an effective way to discover it.\textsuperscript{17}

5.2 Static Carry vs. Dynamic Carry

As shown in Table 1, static carry consistently contributes over 75\% of total returns in cross-sectional currency carry trades, about 4.5\% per annum (p.a.).\textsuperscript{18} Since the market-timing trades fail to offer positive excess returns, the time-series carry trades in currency market produce minimal positive excess returns and Sharpe ratios. The yield component is the main contributor to the cross-sectional carry trades while the exchange return component negatively contributes to the total returns, reflecting the violation of the UIP. The cross-sectional currency carry trades offer excess returns of approximately 8.2\% p.a. and high Sharpe ratios of over 0.9 after transaction costs. However, the high performance is accompanied with negative skew and excess kurtosis.

\textsuperscript{17}As expected from Figure C.1 and C.2 in Appendix A that reveal notable alpha decay with respect to signal half-life and rebalancing frequency. Faster reaction to new information (shorter half-life) would produce higher excess returns but is also accompanied by higher transaction costs, which also manifests itself in terms of rebalancing frequency. Therefore, higher excess returns do not necessarily justify faster reaction to new information of carry signals because of the disproportionate increases in transaction costs.

\textsuperscript{18}Note that gross mean excess returns consist of excess returns from dynamic trades, static trades (for cross-sectional long-short strategies) or market-timing trades (for time-series long-short strategies), and a residual component in the portfolio construction. It is also worth to emphasize that the payoffs to dynamic trade and static trade (market-timing trade) do not necessarily sum up to that of the cross-sectional (time-series) long-short strategy, owing to an additional “residual” component.
In contrast to currencies, Table 1 reveals that dynamic carry in equity and commodity markets is the key driver of both cross-sectional and time-series carry trades. It contributes overwhelmingly 85% of the total returns to equity carry trades, up to about 14.4% per annum. Static and market-timing trades generate only about one fifth of the excess returns relative to dynamic carry. As a result, both cross-sectional and time-series equity carry trades perform very well, yielding excess returns after transaction costs about 16.3% and 15.7% per annum (with Sharpe ratios approximately 1.4, and 1.2), respectively.

Although equity and commodity carry trades share similar risk and return profiles, the sources of risk premia between cross-sectional and time-series are different. For the cross-sectional trades, almost all the excess returns can be attributable to the yield component. For the time-series trades, however, it is the stock return component that accounts for over 60% of the excess returns. Intriguingly, equity indices with high carry do not experience declines in prices relative to low carry equity indices.

Table 1 above also reports the descriptive statistics of commodity carry trades where carry is computed either relatively to the front contracts or neighbour contracts. Overall, the performance of commodity carry strategies using front contracts is close to that using neighbour contracts. The drops in prices of high carry (convenience yield in excess of cost of carry) commodities relative to that of low carry commodities do not offset the carry yield, similarly to currency market. Static carry (dynamic carry) contribute approximately 35% (65%) to the total returns of cross-sectional carry trades while the market-timing trades do not have any significant marginal contribution to the time-series carry trades. The cross-sectional and time-series carry trades offer excess returns about 16.1% and 12.9% per annum after transaction costs with the corresponding Sharpe ratios of 1.2 and 1.0 respectively.
5.3 Unexpected Dynamic Carry

We next examine whether it is the expected or unexpected component of carry that drives the risk premia associated with the dynamic trades.\textsuperscript{19} We find supportive evidence in Table 2 below that the unexpected carry is the main force.

[Insert Table 2 about here]

The excess returns, and the Sharpe ratio of unexpected carry trades in equity market are around 12.9\%, and 1.1, respectively, and the yield and stock return components equally contribute to the total returns. Commodity market is a special in as sense that it doubles the excess returns (over 14.4\%) and the Sharpe ratios (up to 1.0) of cross-sectional carry strategies trading on the unexpected carry. This result is not driven by the seasonality of commodities, since we already deseasonalize the commodity carry. As expected, the performance of unexpected carry trade in currency market is not as good as those in equity and commodity markets, owing to the fact that interest rates are highly persistent and currency carry trades are predominately driven by the static component.

5.4 Cyclic Carry and Unexpected Cyclic Carry

In this section, we raise a question: whether cyclic component is a hidden risk premium of carry trades or not. We reveal that cyclic carry provides a new angle of carry trade by differentiating the relative strength from the absolute strength of the carry signals. It, by construction, aims to capture the cyclic component of carry signals, which can potentially be associated with economic cycles, such as the monetary policy cycles (currency market), dividend cycles (equity market), and inventory cycles (commodity market).

[Insert Table 3 about here]

Table 3 reports the cross-sectional carry strategies trading on cyclic carry measured

\textsuperscript{19}While we use a 12-month formation period for the dynamic trades, our results (in terms of excess returns and Sharpe ratios) are robust to other formation periods from 3-month, 6-month, etc. across asset classes.
using expanding windows.\textsuperscript{20} The dividend cycle of equity carry has similar length to the inventory cycle of commodity carry, while the interest-rate cycle is typically longer. As a consequence, there is not much risk premium associated with the slow mean-reverting cyclic carry in currency market, offering about 3.1\% p.a. excess return and 0.4 Sharpe ratio. The cyclic carry trades generate excess returns (Sharpe ratios) over 13.7\% (1.3) in equity market, and up to 14.3\% (1.1) in commodity market.

\[\text{Insert Table 4 about here}\]

The results in Table 4 on the unexpected cyclic carry are not qualitatively similar to those of the unexpected carry. The unexpected cyclic carry cross-sectional trade in currency market almost doubles the excess returns, and Sharpe ratio of unexpected and cyclic currency carry trade, i.e., over 6\% p.a. and 0.8, respectively, after transaction costs. The performance metrics of these constituent carry strategies in equity and commodity markets are also impressive, yielding excess returns after transaction costs of approximately 9.4\% (14.9\%) excess return and 0.8 (1.2) Sharpe ratio trading equity index futures (commodity futures). The corresponding time-series trade has similar strong performance, while that of the unexpected carry trade without eliminating the level effect does not work across asset classes. This empirical evidence suggests that the cyclic effect of carry shocks is important to understand carry trade risk premia and it is missing in existing literature. It is noticeable that the yield and underlying return components of both cyclic and unexpected cyclic again equally contribute to the total returns for both currency and equity carry trades. Together with the consistent results from strategies trading on the level of carry and unexpected carry, it is convincing that equity carry does possess a market-timing power.

\textsuperscript{20}Our results are robust to various rolling-window settings from minimum 3-year to maximum 10-year.
5.5 Cross-Sectional Long-Short vs. Time-Series Long-Short

So far, we have covered both cross-sectional and time-series strategies trading on original carry, and previous analyses on unexpected carry, cyclic carry, and unexpected cyclic carry focus on cross-sectional strategies. Time-series carry trades perform very well in equity and commodity markets but not in currency market. In this section, we compare and contrast cross-sectional with time-series strategies trading on different carry components.

The unconditional dispersion \( \bar{\bar{x}}_t - \bar{x} \) equals to zero by construction. Hence, there is no static trade component across unexpected, cyclic, and unexpected cyclic carry trades. They essentially trade on conditional dispersion \( x_{i,t} - \bar{x}_t \) only, as a part of dynamic trade. As a result, the corresponding time-series strategies become cross-sectional strategies with market-timing overlays \( \bar{x} - \bar{\bar{x}} \), or equivalently trading on \( x_{i,t} \) without cross-sectional or time-series comparisons.

As shown from Table 1 to Table 4, we find that time-series unexpected carry trades do not perform well across asset classes, implying that the market-timing overlays of unexpected carry are risk-reversal trades. The market-timing overlays of both cyclic carry and unexpected cyclic carry also do not contribute to the corresponding time-series trades. Although they offer substantial excess returns (approximately 6% from currencies, 13.4% from equity indices, and 14.3% from commodities), almost all the performance are generated by the conditional dispersion trades of cross-sectional strategies.

5.6 Comprehensive Carry Trades

Can we improve plain vanilla carry trades by incorporating relevant hidden risk premia and constructing comprehensive cross-sectional and time-series long-short carry trades? In this section, we answer this question by examining the investment performance from a simple combination of constituent carry strategies.
Table 5 reports the correlation matrix of both cross-sectional and time-series long-short constituent carry strategies. Consistent with previous results, static trades dominate the cross-sectional currency carry trades while dynamic trades are the key driver of the time-series carry trades across asset classes. Given that cyclic carry is naturally related to dynamic carry, we expect that the cross-sectional long-short portfolio strategies of cyclic carry are intimately associated with the time-series ones, and that the time-series long-short, both level and cyclic (unexpected cyclic), carry trades are predominately driven by dynamic (unexpected) carry component. Cross-sectional cyclic and unexpected cyclic currency carry trades are highly correlated with the corresponding time-series trades. Interestingly, high correlation between level (unexpected) and cyclic (unexpected cyclic) commodity carry trades suggests that cyclic effect dominates level effect in commodity market, even though seasonality has already been removed from the original signals. Overall, the correlations across different components of carry are low. Together with the statistically significant risk premia, it is evident that constituent carry strategies offer substantial diversification benefits to the conventional carry trades.

[Insert Figure 2 about here]

[Insert Figure 3 about here]

Next step, we obtain optimal out-of-sample portfolio weights of different constituent carry strategies using a standard bootstrapping procedure that maximize the Sharpe ratios of comprehensive cross-sectional and time-series carry trade portfolios. The optimization procedure naturally takes the covariance matrix into account and makes a trade-off between marginal risk contribution and return of each constituent carry strategy. We expect the portfolio weights to become more stable with more data available. We report the portfolio allocation results where portfolios are rebalanced semi-annually, and we find that the relative importance of each portfolio component remains qualitatively unchanged when portfolios are rebalanced at quarterly or annual frequency.

Figure 2 shows the portfolio allocations among three components: static (or market-
timing), dynamic, and cyclic trades. All three components receive stable and significant portfolio weights across asset classes in the cross-sectional trades. The static (dynamic) and cyclic components are almost equally important in commodity market (equity market). The importance of static and dynamic components is declining while that of the cyclic component is rising in currency market. The market-timing component receives the least portfolio weights in the time-series trades across asset classes, but it is becoming more important in equity market over time. In time-series trades, the cyclic component is assigned the highest portfolio weights in currency market, while it is the dynamic component that receives the most significant portfolio weights in commodity market. The dynamic and cyclic components in time-series trades are almost equally important in equity market.

Figure 2 further shows the portfolio allocations among five components: static (or market-timing), expected and unexpected dynamic, and expected and unexpected cyclic trades. The unexpected cyclic component is allocated with dominant portfolio weights in time-series trades across asset classes. It is also a very important component in the cross-sectional trades in currency and commodity markets. The static and unexpected dynamic components are almost equally important in the cross-sectional trades of commodity market, while the unexpected dynamic component receives the highest portfolio weights in the cross-sectional trades of equity market. As expected, the expected components in dynamic and cyclic carry are almost the least important in maximizing the risk-adjusted returns of the comprehensive carry trade portfolios.

[Insert Figure 4 about here]

[Insert Figure 5 about here]

Figure 4 (Figure 5) presents the cumulative performance of excess returns of comprehensive cross-sectional (time-series) carry trade and the constituent portfolio strategies across asset classes. The comprehensive carry trades that optimally combine the constituent strategies constructed using different carry components provide substantial
improvements upon the benchmark plain vanilla carry trades, yielding about 7%, 13.9%, and 15.5% per annum (5%, 14.4%, and 13.8%) excess returns after transaction costs, from cross-sectional (time-series) trading in currency, equity, and commodity market, respectively (see Table 6 below).\textsuperscript{21} Compared with benchmark carry trades, the alpha is consistently above 3% and up to more than 6% with statistically significance. The active returns are also positive from over 1.5% and up to 7% with an information ratio ranging from 20% to 100%.

\[\text{Insert Table 6 about here}\]

\section*{5.7 Robustness to Parameter and Model Uncertainty}

We employ robust Sharpe ratio tests proposed by Ledoit and Wolf (2008) and find supportive evidence of the superior performance of comprehensive carry trades over benchmark carry trades. The improvements in Sharpe ratios are robust to different combinations of parameters and models, including signal half-lives from 1-month to intraday, normalization periods from rolling windows (minimum 3-year and maximum 10-year) to expanding window, formation periods from 1-quarter to 1-year, and randomly drop up to 15% of the tradable assets. As shown in Figure 6 below, the improvements in Sharpe ratios are consistently above zero in over 5000 simulations for each asset class except for only a few extreme cases of parameter and model combinations for cross-sectional commodity carry (vs. front contract) trades. Furthermore, the combined carry trades across asset classes do not tend to experience simultaneous drawdowns during the financial crises, in contrast to the findings of Kojien, Moskowitz, Pedersen, and Vrugt (2017). All these can be attributable to: (i) relaxing the parameter restrictions imposed in conventional approaches when we treat the characteristic as a signal process (handling parameter uncertainty), (ii) acknowledging that different signal components contribute to the characteristic-related risk premia distinctively (dealing with model uncertainty), (iii) identifying a combination of useful characteristic component for factor investing,

\textsuperscript{21}The corresponding Sharpe ratios are 1.2, 1.5, and 1.4 (0.9, 1.6, and 1.2), respectively.
and (iv) the diversification benefits from constituent trading strategies with low pairwise correlations.

[Insert Figure 6 about here]

6 Risk Premia or Limits to Arbitrage

We should be able to observe a corresponding increasing or decreasing pattern in the average cross-sectional returns of portfolios sorted by the predictor in order to establish the cross-sectional signal-return predictive relation. Therefore, we examine the performance of cross-sectional portfolios sorted according to carry, static carry, dynamic carry, unexpected carry, cyclic carry, and unexpected cyclic carry across asset classes. We then implement asset pricing tests on these portfolios to better understand their risk compensations. Figure 7 below presents the cross-sectional returns and Sharpe ratios that consistently exhibit monotonically increasing patterns from portfolio 1 (assets in the bottom quintile) to portfolio 5 (assets in the top quintile).

[Insert Figure 7 about here]

We employ standard procedures of empirical asset pricing tests, Generalized Method of Moments (GMM) of Hansen (1982) and Fama-MacBeth (FMB) two-step OLS approach (Fama and MacBeth (1973)), to estimate risk exposures and prices of risk factors as in Cochrane (2005). In addition, we reply on two other statistical metrics to evaluate the performance of a linear factor model, i.e., a $\chi^2$ test of zero joint cross-sectional pricing error based on Shanken (1992) adjustment for standard error estimates$^{22}$, and a simulation-based Hansen and Jagannathan (1997) test of zero Hansen-Jagannathan distance ($HJD$)$^{23}$. For a model to be accepted as a valid risk-based explanation, it

$^{22}$We also perform a $\chi^2$ test of zero pricing error based on the Newey and West (1987) HAC estimator. As the results are consistent with those estimated by the Shanken (1992) estimator, we don’t report in this paper.

$^{23}$Please refer to Appendix B for details.
should satisfy the aforementioned conditions with the statistically significant price of risk as well as beta spread, and trending beta exposures across portfolios.

We construct the equally-weighted basket of the whole sample as a global market portfolio for each asset class and use this market portfolio as a level factor. Given a clear factor structure in the cross section of systematic carry, we select a wide range of 35 risk factors as candidates (slope factors) for potential risk-based explanations of the abnormal carry trades. We categorize them into 4 groups (see Appendix C): (i) 7 risk factors in a market-state group; (ii) 14 risk factors in a market-uncertainty group; (iii) 3 risk factors in a financial-intermediary group; and (iv) 11 risk factors in a equity (risk-premia and mispricing) factor group. We use the innovations to AR(1) processes of some of the original series as risk factors.

We implement asset pricing tests on all 7 (carry components) × 5 (portfolio quintiles) × 4 (asset classes) aforementioned cross-sectional portfolios and find that only a few out of 35 risk factors possess statistically significant pricing power by strictly satisfying all criteria postulated above. The market-state group, market-uncertainty group, and intermediary and mispricing group of risk factors is reported in Figure 8 below.

[Insert Figure 8 about here]

The asset-specific volatility risk factor ($VOL$) as in Menkhoff, Sarno, Schmeling, and Schrimpf (2012), Pástor and Stambaugh’s (2003) liquidity risk measure ($LIQ$), and Japan economic policy uncertainty index ($EPU_{JP}$) as in Baker, Bloom, and Davis (2016) succeed in explaining the cross section of our daily-rebalanced currency carry trade portfolios with statistically significant beta spreads and risk prices with correct signs, high cross-sectional adjusted $R^2$, and low model mis-specification risk. These results conform with the funding liquidity story of Brunnermeier and Pedersen (2009); Ferreira Filipe and Suominen (2013).

\footnote{There should be no statistically significant difference in the cross-sectional loadings of carry trade portfolios on the market portfolio.}

\footnote{Given the number of model specifications, we only report groupwise asset pricing results. Please refer to Table C.2, C.3, and C.4 in Appendix C for details.}
The risk premium associated with currency cyclic carry trade seem to be related to the financial intermediary ($IAP_{IR}$) proposed by He and Krishnamurthy (2013) and He, Kelly, and Manela (2017) and Daniel, Hirshleifer, and Sun’s (2017) behavioral mispricing ($MPF_B$) risks.

No candidate risk factor is able to price the cross sections of equity carry or the constituent carry trades. One exception is that the excess return to equity dynamic carry trade can be rationalized by its exposure to mispricing factor — the underreaction to earnings surprises in stock markets measured by Daniel, Hirshleifer, and Sun’s (2017) limited-attention behavioral factor ($BMF_I$). The U.S. economic policy uncertainty ($EPU_{US}$) as in Baker, Bloom, and Davis (2016), and crash risk ($CSK$) as in Rafferty (2012) is priced in the cross section of commodity carry, and static carry (vs. front contract) portfolios, respectively. The commodity cyclic carry (vs. neighbour contract) trade is rewarded for asset-specific volatility risk ($VOL$) while the cross section of commodity unexpected cyclic carry (vs. neighbour contract) is explained by macro fundamentals-related business cycle uncertainty ($BCU_{M1}$) as in Jurado, Ludvigson, and Ng (2015). These findings are consistent with Casassus, Liu, and Tang (2013); Gospodinov and Ng (2013) that establish a predictive relation between commodity convenience yields and economic conditions.

Koijen, Moskowitz, Pedersen, and Vrugt (2017) claim that carry trades are exposed to volatility, liquidity, and financial distress risks, we find similar but limited evidence in the cross section. The broad risk factors considered in this paper fail to consistently price the cross sections of constituent carry portfolios, suggesting the existence of hidden carry trade risk premia with low correlations. These findings further raise the concerns about the estimates of risk premia and new challenges on classical asset pricing models and provide omitted perspectives in defining factors, which, in turn, introduces measurement errors in risk premia.

Since most of the risk factors that are capable of explaining the cross sections of
certain constituent carry portfolios can be regarded as state variables in the ICAPM, such as volatility and liquidity risks (see Della Corte, Ramadorai, and Sarno, 2016). They may serve as the proxies for time-varying arbitrage risk and should be negatively correlated with future investment opportunities. Thus, we employ predictive regressions to investigate whether their pricing power stems from limits to arbitrage or not. We adopt the interaction between the proxy for risk-bearing capacity of financial intermediary $IAP_{IR}$ and data-based financial distress index ($FSI_D$) of Federal Reserve Bank of St. Louis as an additional state variable according to He and Krishnamurthy (2013); Adrian, Etula, and Muir (2014); Gabaix and Maggiori (2015); He, Kelly, and Manela (2017).

[Insert Table 7 about here]

Table 7 above presents their predictive power on the next-period (1-month ahead) payoffs to high-minus-low constituent carry trades. Statistically significant and positive predictive coefficients along with consistent signs in the cross-sectional asset pricing tests are supportive evidence for the limits-to-arbitrage story. The pricing power of macro fundamentals-related business cycle uncertainty ($BCU_{M1}$) on the excess returns to unexpected cyclic carry (vs. neighbour contract) strategy in commodity market seems to be driven by limits to arbitrage. The statistically significant predictive coefficient of asset-specific volatility risk, and crash risk is inconsistent with respective signs in the cross-sectional asset pricing test on cyclic commodity carry (vs. neighbour contract), and static commodity carry (vs. front contract). This empirical evidence implies investor overreaction and delayed correction behavior during the market turmoils in commodity market. The consistent sign of the predictive coefficient of financial intermediary risk-bearing capacity suggests a risk-based explanation for the excess returns to cyclic currency carry trade. It is worth mentioning that the sign of coefficient of the interaction term $IAP_{IR} \times FSI_{D}$ on static currency carry strategy are statistically significant but differs from those (also statistically significant) on other currency carry components. This reveals that investors are rewarded by currency carry trade via different mechanisms.
7 Conclusion

In this paper, we focus on one of the uncharted fields in the uncertainty domain of characteristic-return relations: Do we manage to capture the risk premia associated with certain characteristics properly using the standard mapping methods between characteristics and returns? To answer this question, we propose a simple econometric framework that treats characteristics as signal processes and extract differentiated components of the characteristic through signal decomposition and transformation. We then apply it to carry trades in multiple asset classes and investigate its capacity of alpha capture. We show that the extracted signal components, static carry, expected dynamic carry, unexpected dynamic carry, cyclic carry, and unexpected cyclic carry, provide a more complete assessment of the risk premia associated with the characteristic, carry.

We reveal that these extracted signal components offer a better overall assessment of the characteristic carry and provide distinctive aspects of factor investing in carry trade risk premia. We find that each of the signal components carries a statistically significant risk premium with relatively low correlations with each other, implying that these components contribute to risk premia in heterogeneous ways. Comprehensive multi-asset cross-sectional and time-series carry trades that optimally combine the constituent strategies constructed using different carry components substantially improve the investment performance upon traditional factor investing. Therefore, it is important for investors to incorporate various dimensions of a characteristic in their decision-making process of factor investing.

We reconcile the superior performance of comprehensive carry trades with our proposed factor investment approach from three aspects. First, we show that constituent carry strategies offer diversification opportunities through low correlations. Static carry accounts for a major proportion of the excess returns in currency market while dynamic carry predominantly drives the risk premia in equity and commodity markets and the unexpected dynamic carry component is the driving force. For the cross-sectional
trades, the key driver of excess returns is the carry component, while it is the return component for the time-series trades. Hence, understanding the properties of distinctive components of carry helps us to handle the parameter and model uncertainty (alpha uncertainty) problems and to build an enhanced portfolio strategy of carry. Second, unexpected dynamic component, the cyclical component, and especially unexpected cyclic component, also contains a hidden risk premium that provides considerable excess returns with low correlations with other constituent carry strategies. The (unexpected) cyclic carry captures the risk premium unrelated to the level of carry but closely associated with the (shocks to) economic cycles. Third, we further reveal additional alpha generated from higher rebalancing frequency, which is related to the contribution of the static component to the risk premia or the signal nature of a characteristic. We find that capturing the variation of alpha decay across asset classes is non-trivial for measuring risk premia even after taking transaction costs into account, and thus higher-frequency implementation is an effective way to discover them.

We implement extensive empirical asset pricing tests on the cross-sectional portfolios of the signal components derived from the characteristic carry, but fail to identify a risk factor that consistently explain the cross-sectional risk premia associated with constituent carry trades. This implies the existence of hidden carry trade risk premia with low correlations. Investors are able to harvest the unexploited risk premia associated with a characteristic using our approach. These findings also raise the concerns about the measurement errors in risk premia or omitted risk premia, as well as new challenges on classical asset pricing models.
References


This figure shows the alpha decay of the daily-rebalanced cross-sectional and time-series long-short carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The alpha decay is measured in terms of the response of return and Sharpe ratio to the delay in reaction to the carry signals with updated information. Up to 1-month (21 trading days) delay is reported. 0 means no delay, which is to update signal information at the end of day $t$, trade at the end of day $t+1$, and get the performance at the end of day $t+2$. The carry signals are measured using intraday data. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.).
Table 1: Descriptive Statistics of Cross-Asset Carry Portfolio Strategies

<table>
<thead>
<tr>
<th></th>
<th>Cross-Sectional Long-Short</th>
<th>Time-Series Long-Short</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross Mean (%)</td>
<td>8.49</td>
<td>17.67</td>
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<tr>
<td>· Static (%)</td>
<td>4.54</td>
<td>3.16</td>
</tr>
<tr>
<td>· Dynamic (%)</td>
<td>1.76</td>
<td>14.43</td>
</tr>
<tr>
<td>· Market-Timing (%)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>· Transaction Cost (%)</td>
<td>0.25</td>
<td>1.42</td>
</tr>
<tr>
<td>· Net Mean (%)</td>
<td>8.24</td>
<td>16.25</td>
</tr>
<tr>
<td>· Carry (%)</td>
<td>10.82</td>
<td>14.65</td>
</tr>
<tr>
<td>· Underlying Return (%)</td>
<td>-2.58</td>
<td>1.60</td>
</tr>
<tr>
<td>Volatility (%)</td>
<td>8.87</td>
<td>11.65</td>
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<tr>
<td>Sharpe Ratio</td>
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<td>1.39</td>
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<td>Skew</td>
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<td>Kurtosis</td>
<td>0.66</td>
<td>1.20</td>
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<tr>
<td>Maximum Drawdown (%)</td>
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<td>-12.82</td>
</tr>
<tr>
<td>Calmar Ratio</td>
<td>-3.00</td>
<td>-0.79</td>
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This table reports the descriptive statistics of daily-rebalanced cross-sectional and time-series long-short carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The carry signals are measured using intraday data. Note that the residual component as a result of portfolio construction is not reported. Thereby the sum of dynamic component with static or market-timing component does not necessarily equal to the gross mean return. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.). Figures are annualized except for maximum drawdown, skew and kurtosis. The latter two are calculated based on monthly series, which are converted from daily series. Calmar ratio with negative net mean return is not reported.
Table 2: Descriptive Statistics of Cross-Asset Unexpected Dynamic Carry Portfolio Strategies

<table>
<thead>
<tr>
<th></th>
<th>Cross-Sectional Long-Short</th>
<th>Time-Series Long-Short</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Currency (vs. F.C.)</td>
<td>Equity Index (vs. N.C.)</td>
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<td>Gross Mean (%)</td>
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<td>· Net Mean (%)</td>
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<td>··· Carry (%)</td>
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<td>6.53</td>
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<tr>
<td>··· Underlying Return (%)</td>
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<td>6.37</td>
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<td>Sharpe Ratio</td>
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<td>1.11</td>
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<td>1.16</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.87</td>
<td>5.07</td>
</tr>
<tr>
<td>Maximum Drawdown (%)</td>
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<td>-15.55</td>
</tr>
<tr>
<td>Calmar Ratio</td>
<td>-6.89</td>
<td>-1.21</td>
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</table>

This table reports the descriptive statistics of daily-rebalanced cross-sectional and time-series long-short carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The unexpected dynamic carry signals are constructed using 1-year formation period. Note that the residual component as a result of portfolio construction is not reported. Thereby the sum of dynamic component with static or market-timing component does not necessarily equal to the gross mean return. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.). Figures are annualized except for maximum drawdown, skew and kurtosis. The latter two are calculated based on monthly series, which are converted from daily series. Calmar ratio with negative net mean return is not reported.
Table 3: Descriptive Statistics of Cross-Asset Cyclic Carry Portfolio Strategies

<table>
<thead>
<tr>
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<th>Cross-Sectional Long-Short</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Currency Equity Index (vs. F.C.) (vs. N.C.) Commodity Carry (%)</td>
<td>Currency Equity Index (vs. F.C.) (vs. N.C.) Commodity Carry (%)</td>
</tr>
<tr>
<td>Gross Mean (%)</td>
<td>3.46 15.36 12.32 15.10</td>
<td>2.92 15.08 10.40 12.42</td>
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<tr>
<td>· Transaction Cost (%)</td>
<td>0.30 1.62 0.77 0.80</td>
<td>0.31 1.71 0.67 0.71</td>
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<tr>
<td>· Net Mean (%)</td>
<td>3.16 13.74 11.55 14.30</td>
<td>2.61 13.37 9.73 11.71</td>
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<tr>
<td>· Carry (%)</td>
<td>1.13 6.27 15.18 15.52</td>
<td>1.11 5.81 18.19 18.25</td>
</tr>
<tr>
<td>· Underlying Return (%)</td>
<td>2.03 7.47 -3.63 -1.22</td>
<td>1.50 7.56 -8.46 -6.54</td>
</tr>
<tr>
<td>Volatility (%)</td>
<td>7.34 10.56 12.96 12.90</td>
<td>7.36 12.29 13.27 13.25</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.43 1.30 0.89 1.11</td>
<td>0.35 1.09 0.73 0.88</td>
</tr>
<tr>
<td>Skew</td>
<td>-0.09 0.07 -0.22 -0.08</td>
<td>-0.13 0.11 -0.04 -0.03</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.13 0.50 0.67 0.74</td>
<td>0.14 -0.02 -0.15 -0.06</td>
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<td>Calmar Ratio</td>
<td>-5.04 -0.98 -4.41 -2.00</td>
<td>-6.07 -1.23 -4.54 -2.85</td>
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</table>

This table reports the descriptive statistics of daily-rebalanced cross-sectional and time-series long-short carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The cyclic carry signals are constructed using expanding window. Note that the residual component as a result of portfolio construction is not reported. Thereby the sum of dynamic component with static or market-timing component does not necessarily equal to the gross mean return. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.). Figures are annualized except for maximum drawdown, skew and kurtosis. The latter two are calculated based on monthly series, which are converted from daily series. Calmar ratio with negative net mean return is not reported.
Table 4: Descriptive Statistics of Cross-Asset Unexpected Cyclic Carry Portfolio Strategies

<table>
<thead>
<tr>
<th></th>
<th>Cross-Sectional Long-Short</th>
<th>Time-Series Long-Short</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross Mean (%)</td>
<td>6.54</td>
<td>11.17</td>
</tr>
<tr>
<td>· Transaction Cost (%)</td>
<td>0.47</td>
<td>1.77</td>
</tr>
<tr>
<td>· Net Mean (%)</td>
<td>6.07</td>
<td>9.40</td>
</tr>
<tr>
<td>· · Carry (%)</td>
<td>2.38</td>
<td>5.35</td>
</tr>
<tr>
<td>· · · Underlying Return (%)</td>
<td>3.69</td>
<td>4.05</td>
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<tr>
<td>Volatility (%)</td>
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<td>11.84</td>
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<tr>
<td>Sharpe Ratio</td>
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<td>0.79</td>
</tr>
<tr>
<td>Skew</td>
<td>-0.14</td>
<td>-0.23</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.37</td>
<td>2.48</td>
</tr>
<tr>
<td>Calmar Ratio</td>
<td>-1.79</td>
<td>-1.94</td>
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</table>

This table reports the descriptive statistics of daily-rebalanced cross-sectional and time-series long-short carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The unexpected cyclic carry signals are constructed using 1-year formation period. Note that the residual component as a result of portfolio construction is not reported. Thereby the sum of dynamic component with static or market-timing component does not necessarily equal to the gross mean return. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.). Figures are annualized except for maximum drawdown, skew and kurtosis. The latter two are calculated based on monthly series, which are converted from daily series. Calmar ratio with negative net mean return is not reported.
Table 5: Correlation Matrix of Cross-Asset Cross-Sectional and Time-Series Long-Short Constituent Carry Portfolio Strategies

This table reports correlation matrix of daily-rebalanced cross-sectional and time-series long-short carry, static carry, dynamic carry, unexpected dynamic carry, cyclic carry, and unexpected cyclic carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The carry signals are measured using intraday data. The cyclic carry signals are constructed using expanding window, and the unexpected carry and unexpected cyclic carry use consistent 1-year formation periods. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.).
Figure 2: Optimal Portfolio Weights of Cross-Asset Cross-Sectional and Time-Series Long-Short 3 Constituent Carry Strategies

This figure shows the bootstrapped optimal portfolio weights to maximize Sharpe ratio in combination of daily-rebalanced cross-sectional (static STA, dynamic DYN, and cyclic CYC) and time-series (dynamic, market-timing MKT and cyclic) long-short constituent carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The carry signals are measured using intraday data. The cyclic carry signals are constructed using expanding window, and the unexpected carry and unexpected cyclic carry use consistent 1-year formation periods. The comprehensive carry trade incorporates all decomposed carry strategies. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.).
This figure shows the bootstrapped optimal portfolio weights to maximize Sharpe ratio in combination of daily-rebalanced cross-sectional (static STA, expected dynamic EDC, unexpected dynamic UEC, expected cyclic ECC, and unexpected cyclic UCC) and time-series (expected dynamic, unexpected dynamic, market-timing MKT, expected cyclic, and unexpected cyclic) long-short constituent carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The carry signals are measured using intraday data. The cyclic carry signals are constructed using expanding window, and the unexpected carry and unexpected cyclic carry use consistent 1-year formation periods. The comprehensive carry trade incorporates all decomposed carry strategies. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.).
Figure 4: Cumulative Excess Returns of Cross-Asset Cross-Sectional Long-Short Constituent Carry Strategies

This figure shows the cumulative performance (no reinvestment) of daily-rebalanced cross-sectional long-short carry, static carry, dynamic carry, unexpected dynamic carry, cyclic carry, unexpected cyclic carry, and comprehensive carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The carry signals are measured using intraday data. The cyclic carry signals are constructed using expanding window, and the unexpected carry and unexpected cyclic carry use consistent 1-year formation periods. The comprehensive carry trade incorporates all decomposed carry strategies. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.).
Figure 5: Cumulative Excess Returns of Cross-Asset Time-Series Long-Short Constituent Carry Strategies

This figure shows the cumulative performance (no reinvestment) of daily-rebalanced time-series long-short carry, static carry, dynamic carry, unexpected dynamic carry, cyclic carry, unexpected cyclic carry, and comprehensive carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The carry signals are measured using intraday data. The cyclic carry signals are constructed using expanding window, and the unexpected carry and unexpected cyclic carry use consistent 1-year formation periods. The comprehensive carry trade incorporates all decomposed carry strategies. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.).
Table 6: Descriptive Statistics of Cross-Asset Comprehensive Carry Portfolio Strategies

<table>
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<tr>
<th>Cross-Sectional Long-Short</th>
<th>Currency</th>
<th>Equity Index (vs. F.C.)</th>
<th>Commodity (vs. N.C.)</th>
<th>Time-Series Long-Short</th>
<th>Currency</th>
<th>Equity Index (vs. F.C.)</th>
<th>Commodity (vs. N.C.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross Mean (%)</td>
<td>7.57</td>
<td>15.33</td>
<td>14.72</td>
<td>16.38</td>
<td>5.59</td>
<td>16.05</td>
<td>12.93</td>
</tr>
<tr>
<td>· Transaction Cost (%)</td>
<td>0.55</td>
<td>1.47</td>
<td>0.83</td>
<td>0.88</td>
<td>0.56</td>
<td>1.63</td>
<td>0.79</td>
</tr>
<tr>
<td>· Net Mean (%)</td>
<td>7.02</td>
<td>13.86</td>
<td>13.89</td>
<td>15.50</td>
<td>5.03</td>
<td>14.42</td>
<td>12.14</td>
</tr>
<tr>
<td>· Carry (%)</td>
<td>7.59</td>
<td>10.33</td>
<td>19.19</td>
<td>19.31</td>
<td>4.16</td>
<td>7.71</td>
<td>20.18</td>
</tr>
<tr>
<td>· Underlying Return (%)</td>
<td>-0.57</td>
<td>3.53</td>
<td>-5.30</td>
<td>-3.81</td>
<td>0.87</td>
<td>6.71</td>
<td>-8.04</td>
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<tr>
<td>Volatility (%)</td>
<td>5.71</td>
<td>8.97</td>
<td>11.29</td>
<td>11.28</td>
<td>5.47</td>
<td>9.00</td>
<td>11.66</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>1.23</td>
<td>1.54</td>
<td>1.23</td>
<td>1.37</td>
<td>0.92</td>
<td>1.60</td>
<td>1.04</td>
</tr>
<tr>
<td>Skew</td>
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<td>0.43</td>
<td>-0.13</td>
<td>-0.08</td>
<td>-0.20</td>
<td>0.32</td>
<td>-0.07</td>
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<tr>
<td>Kurtosis</td>
<td>0.87</td>
<td>1.27</td>
<td>0.34</td>
<td>0.40</td>
<td>0.30</td>
<td>1.03</td>
<td>0.13</td>
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<tr>
<td>Maximum Drawdown (%)</td>
<td>-12.09</td>
<td>-8.60</td>
<td>-34.00</td>
<td>-24.22</td>
<td>-11.55</td>
<td>-8.24</td>
<td>-36.00</td>
</tr>
<tr>
<td>Calmar Ratio</td>
<td>-1.72</td>
<td>-0.62</td>
<td>-2.45</td>
<td>-1.56</td>
<td>-2.30</td>
<td>-0.57</td>
<td>-2.97</td>
</tr>
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</table>

This table reports the descriptive statistics of daily-rebalanced cross-sectional time-series long-short comprehensive carry portfolio strategies trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.) , , and corresponding \( t_{\psi} \)-stats are estimated in a model of \( y_{i,t} = \beta + \psi_{\psi} x_{i,t} + \epsilon_{i,t} \), where \( y_{i,t} \) is the return series of comprehensive carry and \( x_{i,t} \) is the return series of plain vanilla carry trade. The active return \( \Delta R \), tracking error \( \Delta \mathcal{E} \), and information ratio \( \Delta \mathcal{R} \) are computed using the difference in performance between comprehensive carry trade and plain vanilla carry trades scaled to the same risk profile in terms of volatility. Both Newey and West (1987) (HAC) and bootstrapped (BS) \( \psi_{\psi} \)-values of robust Sharpe ratio test of Ledoit and Wolf (2008) are reported.
Figure 6: Robust Improvements in Sharpe Ratios under Parameter and Model Uncertainty

This figure shows the box plots of the differences in Sharpe ratios between comprehensive carry trades and benchmark plain vanilla carry trades using different combinations of parameters and models (signal half-life, normalization approach, formation period, and randomly drop of the tradable assets). The strategies are daily-rebalanced cross-sectional and time-series long-short trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.).
This figure shows the return and Sharpe ratio of the cross section of the daily-rebalanced cross-sectional long-short carry, static carry, dynamic carry, unexpected dynamic carry, cyclic carry, and unexpected cyclic carry portfolio strategies trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures (CM). Futures are sorted by different carry signals into 5 portfolios (quintile), equally-weighted, and compute the performance respectively. The carry signals are measured using intraday data. The cyclic carry signals are constructed using expanding window, and the unexpected carry and unexpected cyclic carry use consistent 1-year formation periods. ‘CAR’ stands for carry, ‘STA’ for static carry, ‘DYN’ for dynamic carry, ‘UEC’ for unexpected dynamic carry, ‘CYC’ for cyclic carry, and ‘UCC’ for unexpected cyclic carry. Commodity carry are computed against front contract (vs. F.C.) with a subscript ‘F’ and also against neighbour contract (vs. N.C.) with a subscript ‘N’.

Figure 7: Cross-Sectional Performance of Cross-Asset Constituent Carry Portfolios
Figure 8: Asset Pricing Tests on the Cross Sections of Cross-Asset Constituent Carry Portfolios

This figure shows the t-statistics of the risk prices ($\lambda$) of linear factor models (LFM) with asset-specific market portfolio as the level factor and those proxies for market states or uncertainty, financial intermediary or equity (risk premia or mispricing) factors, as the slope factor. The test assets are the transaction-cost adjusted excess returns of 5 daily-rebalanced (converted into monthly excess returns) and equally-weighted portfolios across 6 constituent carry strategies across currency, equity index, and commodity futures markets. The reported results are estimated by Fama-MacBeth (FMB) without a constant in the second-stage regressions (Fama and MacBeth, 1973), and by the first-stage Generalized Method of Moments procedures. The $p$-values for $\chi^2$ statistics based on Shanken-adjusted standard errors (Shanken, 1992) (for testing the null hypothesis that the cross-sectional pricing errors jointly equal to zero) and for simulation-based Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) (for testing whether the HJD equals to zero) are reported. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) are estimated for risk prices. Adj-$R^2$ is adjusted $R$-squared. ‘CAR’ stands for carry (denoted by asterisk), ‘STA’ for static carry (denoted by circle), ‘DYN’ for dynamic carry (denoted by square), ‘UEC’ for unexpected dynamic carry (denoted by diamond), ‘CYC’ for cyclic carry (denoted by triangle), and ‘UCC’ for unexpected cyclic carry (denoted by pentagram). Factors and models accepted by the above statistical criteria and with statistically significant estimates in terms of risk exposures and risk prices as well as trending (either up or down) but not necessarily strictly monotonc cross-sectional beta are printed in bold. Color blue represents for currency, orange for equity index, green for commodity (vs. F.C.), and purple for commodity (vs. N.C.).
Table 7: Limits to Arbitrage Tests on the Cross-Asset High-Minus-Low (HML) Constituent Carry Strategies

<table>
<thead>
<tr>
<th>Currency</th>
<th>Equity Index</th>
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<th>Commodity (vs. N.C.)</th>
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<tbody>
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<td></td>
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</tr>
<tr>
<td>vVOt</td>
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<td>0.02</td>
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<td>0.19</td>
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<td>tu/stat</td>
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<td>-0.03</td>
<td>-0.03</td>
</tr>
<tr>
<td>vVOLt</td>
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<td>-0.11</td>
</tr>
<tr>
<td>tu/stat</td>
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<td>0.03</td>
<td>0.02</td>
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<tr>
<td>vCSKt</td>
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<td>1.17</td>
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<tr>
<td>tu/stat</td>
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<td>-0.44</td>
<td>-1.14</td>
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<tr>
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<td>-0.87</td>
<td>0.19</td>
</tr>
<tr>
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<td>-1.86</td>
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</table>

This table reports the results from limited-arbitrage tests using predictive regressions. The test assets are the transnational-adjusted cross-asset returns of daily-balanced portfolios of currency and commodity futures. For each test, the null hypothesis is that the test assets are not arbitrage. The critical values for the statistic are calculated using the Newey-West variable (Newey and West, 1987) with optimal lag selection (Andrews, 1991). The critical values are adjusted for serial correlation and heteroscedasticity. The table highlights the results for Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection. The critical values are adjusted for serial correlation and heteroscedasticity. The table highlights the results for Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection.
Appendix

to

“Characteristics as Signal Processes:
Asset Prices, Carry, and Risk Premia”

A Level versus Cycle

We demonstrate the difference between the risk premium associated with the level of carry and that with the cycles of carry in the graph below.

Without the loss of generality, we assume that Asset 1 and Asset 2 have two distinctive signal processes of a characteristic (such as carry), in terms of mean, variance, and cycle length; and that two assets share the same level of risk in terms of volatility. $P_1$, and $P_2$ is the cycle peak for Asset 1 and Asset 2, respectively; $T_1$, and $T_2$ is the cycle trough for Asset 1 and Asset 2, respectively. Here are two cases that help us to understand how cyclic carry captures a different angle of carry trade risk premia. Case 1: At a certain point of time, two signal processes intersect at the cycle peak of Asset 2, $P_2$, implying that two assets share the same level of carry and rank. As a result, two asset are allocated the same weight in portfolio construction. The cyclic (normalized) carry of Asset 2 is higher than that of Asset 1, because the carry signal of Asset 2 is at its peak. Then Asset 2 will be assigned a higher weight than Asset 1. Case 2: At another point of time, the carry signal of Asset 2 slides to its trough $T_2$ while that of Asset 1 just moves out of
its trough \( T_1 \). Given that the carry signal of Asset 2 is positive and that of Asset 1 is negative, the standard cross-sectional long-short carry trade will long Asset 1 and short Asset 2. While if we look at the cyclic measure of carry, Asset 1 has stronger business-cycle related carry than Asset 2. We will short both of them, and have a larger short position in Asset 2, according to the rules of a cross-sectional long-short strategy. This is a dramatic change in positioning from conventional carry trade to a strategy that trades on its cyclic measure.

**B Empirical Asset Pricing Models and Estimations**

The benchmark asset pricing Euler equation with a stochastic discount factor (SDF) implies the excess returns must satisfy the no-arbitrage condition (Cochrane, 2005):

\[
\mathbb{E}_t[M_{t+1} \cdot r_{j,t+1}^e] = 0
\]  

(18)

where \( \mathbb{E}_t[\cdot] \) is the expectation operator with the information available at time \( t \). The unconditional moment restrictions is given by applying the law of iterated expectations to Equation (18):

\[
\mathbb{E}[M_{t \psi} r_{j,t\psi}^e] = 0
\]  

(19)

The SDF takes a linear form of:

\[
M_{t \psi} = \xi \cdot \left( 1 - (f_{t \psi} - \mu_{f_t})^\top b \right)
\]  

(20)

where \( \xi \) is a scalar, \( f_{t \psi} \) is an \( n \times 1 \) vector of risk factors, \( \mu_{f_t} = \mathbb{E}[f_t] \), and \( b \) is a conformable vector of factor loadings. Since \( \xi \) is not identified by Equation (20), we set it equal to 1, implying \( \mathbb{E}[M_t] = 1 \). Rearranging Equation (19) with Equation (20) gives:

\[
\mathbb{E}[r_{t \psi}^e] = \text{cov}[r_{t \psi}^e, f_{t \psi}] \cdot b
\]  

(21)
or equivalently

\[
\mathbb{E}\left[r_{j,t}^e\right] = \text{cov}\left[r_{j,t}^e, f_t^\top\right] \Sigma_{f,j}^{-1} \Sigma_{f,k} \hat{\beta}
\]  
(22)

where \(\Sigma_{f,k} = \mathbb{E}\left[(f_t - \mu_f)(f_t - \mu_f)^\top\right]\). Equation (22) is the beta representation of the asset pricing model. \(j\) is the vector of exposures of portfolio \(j\) to the \(k\)-th risk factors, it varies across portfolios. \(\lambda\) is a \(n \times 1\) vector of factor prices associated with the tested risk factors.

The beta representation of the expected excess returns by a \(n\)-factor linear model can be written as:

\[
\mathbb{E}\left[r_{j,t}^e\right] = \sum_{k=1}^{n} j_{k} \lambda_{k}\n\]  
(23)

where the subscripts denote the corresponding risk factors. We rely on two procedures for the parameter estimates of the linear factor model: Generalized Method of Moments (Hansen, 1982), as known as GMM, and Fama-MacBeth (FMB) two-step OLS approach (Fama and MacBeth, 1973).

B.1 Generalized Method of Moments

In the first procedure, we estimate the parameters of the SDF — \(b\) and \(\mu_f\) — using the GMM and the moment restrictions in Equation (21) which can be rewritten as:

\[
\mathbb{E}\left\{r_{t}^e; [1 - (f_t - \mu_f)^\top b]\right\} = 0
\]  
(24)

The GMM estimators of \(\mu_f\) is set to be equal to a vector of the sample mean of risk factors, \(\bar{f}\). While \(b\) is given by:

\[
\hat{b} = \left(\Sigma_{f,e} W_{Tf} \Sigma_{f,e}^\top\right)^{-1} \Sigma_{f,e} W_{Tf} \bar{e}
\]  
(25)

53
where $\hat{\Sigma}_{r,r}$ is the sample covariance matrix between $r^e_t$ and $f_t$, $W_{\psi}$ is a weighting matrix, $\bar{r}$ is the sample mean of excess returns. Then the estimates of factor prices $\hat{\lambda} = \hat{\Sigma}_{f,f} \hat{\delta}$, where $\hat{\Sigma}_{f,f}$ is the sample covariance matrix of $f_t$. Following Burnside (2016), we impose an additional set of corresponding moment restrictions on the factor mean vector and factor covariance matrix:

$$g(\phi_t, \theta) = \left[ \begin{array}{c} r^e_{t\psi} \left[ 1 - (f^e + \mu_f)^T b \right] \\ f_{t\psi} - \mu_{f\psi} \\ \sum_{\psi} (f^e_{t\psi} - \mu_{f\psi}) (f^e_{t\psi} - \mu_{f\psi})^T - \hat{\Sigma}_{f,f} \end{array} \right] = 0 \quad (26)$$

where $\theta$ is a parameter vector containing $(b, \mu_{f\psi}, \Sigma_{f,f})$, $\phi_{t\psi}$ represents the data $(r^e_{t\psi}, f_t)$. By exploiting the moment restrictions $E[g(\phi_t, \theta)] = 0$ defined by Equation (26), the estimation uncertainty is thus incorporated in the standard errors of $\lambda$, and this method of point estimates is identical to that of Fama-MacBeth two-pass OLS approach (see Burnside, 2016). The standard errors are computed based on VARHAC procedure of Newey and West (1987) and the data-driven approach of optimal lag selection with a Bartlett kernel as in Andrews (1991). In the first stage of GMM estimator, $W_{\psi} = I_t$; In the subsequent stages of GMM estimator, $W_{\psi}$ is chosen optimally based on a Heteroskedasticity and Autocorrelation Consistent (HAC) estimate of the long-run variance-covariance matrix of the moment conditions, and then iterate to convergence. Given that the portfolio return series are correlated and different in variances, more weights will be attached to the linear combinations of moments that are more informative using an optimal weighting matrix.

$^{26}$It is owing to the fact that factor mean vector and covariance matrix have to be estimated.
B.2 Fama-MacBeth Approach

Additionally, we report the empirical results from the second procedure, FMB estimates. The first step is a time-series regression of each of portfolio’s excess returns on proposed risk factors to obtain corresponding risk exposures:

$$r_{j,t}^e = \beta_j \cdot \sum_{k=1}^{n} \beta_{j,k} \cdot F_{t,k} + \epsilon_{j,t}$$  \hspace{1cm} (27)

where $\epsilon_{j,t}$ is i.i.d. $N(0, \sigma_j^2)$, $j = 1, \cdots, N$ portfolios. The second step is a cross-sectional regression of each portfolio’s average excess returns on the estimated betas from the first step to acquire the risk prices:

$$\bar{r}_{j}^e = \sum_{k=1}^{n} \hat{\beta}_{j,k} \cdot \hat{\lambda}_{k}$$  \hspace{1cm} (28)

If market portfolio serves as a constant that allows for a common mispricing term, we do not include a constant in the second step of FMB. The estimates of the risk prices from FMB is numerically identical to those from GMM. The standard errors adjusted for measurement errors by Shanken (1992) approach are also reported besides Newey and West (1987) HAC standard errors with automatic lag length selection (Andrews, 1991).

The predicted expected excess returns by the model is therefore $\hat{\Sigma}_{j,r} \hat{b}$, and the pricing errors are the model residuals $\hat{\epsilon} = \bar{r} - \hat{\Sigma}_{j,r} \hat{b}$. Then a statistic for over-identifying restrictions, $T \hat{\epsilon}^{T} \Sigma_{\hat{\epsilon},T}^{-1} \hat{\epsilon}$, can be constructed to test the null hypothesis that all pricing errors across portfolios are jointly zero, where $T$ is the sample size, $\Sigma_{\hat{\epsilon},T}$ is a consistent estimate of asymptotic covariance matrix of $\sqrt{T} \hat{\epsilon}$ and its inverse form is generalized. The test statistic is asymptotic distributed as $\chi^2$ with $\ell - n$ degrees of freedom. We report its $p$ – values based on both Shanken (1992) adjustment and Newey and West (1987) approach for FMB procedure, and the simulation-based $p$ – values for the test of whether the Hansen-Jagannathan (Hansen and Jagannathan, 1997) distance ($HJ-dist$) is equal

\footnote{See also Burnside (2016); Lustig, Roussanov, and Verdelhan (2011) on the issue of whether or not to include a constant.}
to zero\textsuperscript{28} for the GMM procedure. When factors are correlated, we should check the null hypothesis test $b = 0$ rather than $\lambda = 0$, in order to determine whether or not to include the factor given other factors. If $b$ is statistically significant, the corresponding factor helps to price the tested assets. $\lambda$ only answer the question of whether the corresponding factor is priced or not, whether its factor-mimicking portfolio carries a positive or negative risk premium (Cochrane, 2005).

\section*{C Data and Additional Results}

We categorize risk factors employed in this paper into 4 groups:

(i) 7 risk factors in a \textbf{market-state group}

- CBOE volatility index ($VXO$) as a proxy for market sentiment;

- asset-specific volatility risk ($VOL$) as in Menkhoff, Sarno, Schmeling, and Schrimpf (2012);\textsuperscript{29}

- asset-specific crash risk ($CSK$) as in Rafferty (2012);\textsuperscript{30}

- T-bill to Euro Dollar spread ($TED$) as a proxy for broad-market liquidity;

- liquidity risk measure ($LIQ$) as in Pástor and Stambaugh (2003);

- data-based financial stress index ($FSI_D$) of Federal Reserve Bank of St. Louis;


(ii) 14 risk factors in a \textbf{market-uncertainty group}

- geopolitical risk index ($GPR$) as in Püttmann (2018);

\textsuperscript{28}Hansen-Jagannathan distance gives a least-square distance between the tested pricing kernel and the closest pricing kernel among a set of pricing kernels that price the tested assets correctly (Hansen and Jagannathan, 1997). It is calculated by a weighted sum of random variables that follow a $\chi^2$ distribution.

\textsuperscript{29}It is computed by taking the average of volatility across trading instruments within an asset class.

\textsuperscript{30}It is measured by an aggregate-level of signed skewness as a product of skew and the sign of carry.
• economic policy uncertainty indices ($EPU$) as in Baker, Bloom, and Davis (2016);\(^{31}\)

• business cycle uncertainty measures ($BCU$) as in Jurado, Ludvigson, and Ng (2015).\(^{32}\)

(iii) 3 capital-risk-related risk factors ($IAP$) proposed by He and Krishnamurthy (2013) and He, Kelly, and Manela (2017) in a financial-intermediary group

• shocks to financial intermediary leverage ratio squared ($IAP_{LR^2}$);

• value-weighted investment returns to a portfolio of the primary dealers of the Federal Reserve Bank of New York ($IAP_{IR}$);

• growth rate shocks (in percentage) to financial intermediary capital ratio as a capital risk factor ($IAP_{CRF}$).

(iv) 11 risk factors in a equity (risk-premia and mispricing) factor group

• global size ($SMB$), value ($HML$), profitability ($RMW$), and investment ($CMA$) factors as in Fama and French (2015);

• global momentum factor ($WML$) as in Carhart (1997);

• global quality factor ($QMJ$) as in Asness, Frazzini, and Pedersen (2013);

• global betting-against-beta factor ($BAB$) as in Frazzini and Pedersen (2014);

• mispricing factors ($MPF$) as in Stambaugh and Yuan (2016);\(^{33}\)

• behavioral factors ($BMF$) as in Daniel, Hirshleifer, and Sun (2017).\(^{34}\)

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\(^{31}\)It includes global ($EPU$), U.S. ($EPU_{US}$), Europe ($EPU_{EU}$), China ($EPU_{CN}$), Japan ($EPU_{JP}$), U.K. ($EPU_{UK}$), and Australia ($EPU_{AU}$) indices.

\(^{32}\)It includes uncertainty measures in macro fundamentals ($BCU_M$) and financial markets ($BCU_F$), from 1-month ($1M$), 3-month ($3M$), to 12-month ($12M$), respectively.

\(^{33}\)It includes two clusters of risk factors: managerial ($MPF_M$) and behavior ($MPF_B$).

\(^{34}\)It also includes two clusters of risk factors: financing ($BMF_F$) and inattention ($BMF_I$).
### Table C.1: Symbology

#### Currency: Countries - Contract Tickers

- Australia - AUD/USD
- Brazil - USD/BRL
- Canada - USD/CAD
- Switzerland - USD/CHF
- Chile - USD/CLP
- Colombia - USD/COP
- Czech - USD/CZK
- Denmark - USD/DKK
- Euro Area - EUR/USD
- United Kingdom - GBP/USD
- Hungary - USD/HUF
- Indonesia - USD/IDR
- Israel - USD/ILS
- Japan - USD/JPY
- Korea - USD/KRW
- Mexico - USD/MXN
- Malaysia - USD/MYR
- New Zealand - NZD/USD
- Norway - USD/NOK
- Philippines - USD/PHP
- Peru - USD/PEN
- Poland - USD/PLN
- Portugal - USD/PT'
- Russia - USD/RUB
- Singapore - USD/SGD
- South Africa - USD/ZAR
- Spain - USD/ES
- Sweden - USD/SEK
- Thailand - USD/THB
- Turkey - USD/TRY
- United Kingdom - GBP/USD
- United States - USD/USD

#### Equity: Index Tickers - Contract Tickers

- AEX - EO
- AS51 - XP
- CAC - CF
- DAX - GX
- FBMKLCI - IK
- FTSEMID - ST
- HSCEI - HC
- OMX - QC
- IBEX - IB
- IBOV - BZ
- KOSPI2 - KM
- MEXBOL - IS
- NIFTY - IH
- NYSE - NY
- OMX - QC
- BX - IB
- BC - BZ
- HU - KM
- WIG20 - KM
- SPX - ES

#### Commodity: Underlying Assets - Contract Tickers

- Aluminium - LA
- Gold - GC
- Iron Ore - SCO
- Lead - LL
- Lean Hog - LH
- Cattle Feeder - FC
- Soybean Meal - SM
- Sugar #11 - SB
- Natural Gas - NG
- Palladium - PA
- Silver - SI
- Wheat - W
- Soybean Oil - BO
- Nickel - LN
- Platinum - PL
- Zinc - LX

This table reports the tickers of the trading instruments of 31 currency futures/forwards, 27 equity index futures, and 30 commodity futures. The ticker for WIG20 Index is ‘WIG’ until the mid of June 2014. The tickers of S&P GSCI total return indices on active contracts are in the parentheses: LA (SPGCCAPTR), CO (SPGCBRPTR), FC (SPGCCFCPTR), CC (SPGCCCPCTR), KC (SPGCCKCTR), LP (SPGCCLCTR), CT (SPGCCFTCTR), XB (SPGCCXFTCTR), GC (SPGCCGCTR), LL (SPGCCCLCTR), LH (SPGCCLLCTR), LS (SPGCCPPCTR), NG (SPGCCNCTR), LN (SPGCCKCTR), PA (SPGCCAPCTR), PL (SPGCCPLCTR), SI (SPGCCPCTR), S (SPGCCSCTR), SB (SPGCCSBCTR), W (SPGCCWHCTR), CL (SPGCCCLCTR), LX (SPGCCZCTR); not all listed commodity futures are included in S&P GSCI products.
This figure shows the alpha decay of the daily-rebalanced cross-sectional long-short carry portfolio strategies, trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The alpha decay is measured in terms of the response of Sharpe ratio to the signal half-life and rebalancing frequency (‘1M’ for 1-month, ‘2W’ for 2-week, ‘1W’ for 1-week, ‘3D’ for 3-day, and ‘1D’ for 1-day). Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.).
Figure C.2: Alpha Decay of Time-Series Long-Short Cross-Asset Carry Strategies: Signal Half-Life and Rebalancing Frequency

This figure shows the alpha decay of the daily-rebalanced time-series long-short carry portfolio strategies, trading 31 currency futures/forwards, 27 equity futures, and 30 commodity futures. The alpha decay is measured in terms of the response of Sharpe ratio to the signal half-life and rebalancing frequency (‘1M’ for 1-month, ‘2W’ for 2-week, ‘1W’ for 1-week, ‘3D’ for 3-day, and ‘1D’ for 1-day). Commodity carry are computed against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.).
<p>| Currency | STA  | DYN  | UEC  | CYC  | UCC | STA  | DYN  | UEC  | CYC  | UCC | STA  | DYN  | UEC  | CYC  | UCC | STA  | DYN  | UEC  | CYC  | UCC |
|----------|------|------|------|------|-----|------|------|------|------|-----|------|------|------|------|-----|------|------|------|-----|
| V XO     | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
| 2       | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
| Adj R²   | 0.76 | 0.82 | 0.93 | 0.83 | 0.93 | 0.76 | 0.82 | 0.93 | 0.83 | 0.93 | 0.76 | 0.82 | 0.93 | 0.83 | 0.93 | 0.76 | 0.82 | 0.93 | 0.83 |
| Adj R²   | 0.54 | 0.65 | 0.78 | 0.65 | 0.78 | 0.54 | 0.65 | 0.78 | 0.65 | 0.78 | 0.54 | 0.65 | 0.78 | 0.65 | 0.78 | 0.54 | 0.65 | 0.78 | 0.65 |
| p-value  | 0.08 | 0.04 | 0.01 | 0.04 | 0.01 | 0.08 | 0.04 | 0.01 | 0.04 | 0.01 | 0.08 | 0.04 | 0.01 | 0.04 | 0.01 | 0.08 | 0.04 | 0.01 | 0.04 |
| p-value  | 0.11 | 0.02 | 0.02 | 0.02 | 0.02 | 0.11 | 0.02 | 0.02 | 0.02 | 0.02 | 0.11 | 0.02 | 0.02 | 0.02 | 0.02 | 0.11 | 0.02 | 0.02 | 0.02 |
| p-value  | 0.05 | 0.03 | 0.01 | 0.04 | 0.01 | 0.05 | 0.03 | 0.01 | 0.04 | 0.01 | 0.05 | 0.03 | 0.01 | 0.04 | 0.01 | 0.05 | 0.03 | 0.01 | 0.04 |
| 3.72     | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 | 1.37 |
| p-value  | 0.11 | 0.02 | 0.02 | 0.02 | 0.02 | 0.11 | 0.02 | 0.02 | 0.02 | 0.02 | 0.11 | 0.02 | 0.02 | 0.02 | 0.02 | 0.11 | 0.02 | 0.02 | 0.02 |
| CSK      | 0.12 | 0.20 | 0.12 | 0.20 | 0.12 | 0.12 | 0.20 | 0.12 | 0.20 | 0.12 | 0.12 | 0.20 | 0.12 | 0.20 | 0.12 | 0.12 | 0.20 | 0.12 | 0.20 |
| s.e. (%) | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.02 | 0.01 | 0.02 | 0.01 |
| TED      | 0.45 | 0.77 | 0.11 | 0.06 | 0.45 | 0.02 | 0.77 | 0.11 | 0.06 | 0.45 | 0.02 | 0.77 | 0.11 | 0.06 | 0.45 | 0.02 | 0.77 | 0.11 | 0.06 |
| s.e. (%) | 0.07 | 0.04 | 0.07 | 0.04 | 0.07 | 0.07 | 0.04 | 0.07 | 0.04 | 0.07 | 0.07 | 0.04 | 0.07 | 0.04 | 0.07 | 0.07 | 0.04 | 0.07 | 0.04 |
| LIQ      | 0.28 | 0.18 | 0.39 | 0.29 | 0.39 | 0.28 | 0.18 | 0.39 | 0.29 | 0.39 | 0.28 | 0.18 | 0.39 | 0.29 | 0.39 | 0.28 | 0.18 | 0.39 | 0.29 |
| s.e. (%) | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.03 | 0.04 | 0.03 | 0.04 |
| F SI      | 0.71 | 0.77 | 0.11 | 0.06 | 0.71 | 0.02 | 0.77 | 0.11 | 0.06 | 0.71 | 0.02 | 0.77 | 0.11 | 0.06 | 0.71 | 0.02 | 0.77 | 0.11 | 0.06 |
| s.e. (%) | 0.07 | 0.04 | 0.07 | 0.04 | 0.07 | 0.07 | 0.04 | 0.07 | 0.04 | 0.07 | 0.07 | 0.04 | 0.07 | 0.04 | 0.07 | 0.07 | 0.04 | 0.07 | 0.04 |</p>
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</tbody>
</table>

This table reports the risk prices (λ) of factor models (FMB) with asset-specific market and country uncertainty factors as the risk asset factor and market uncertainty indices, and the market and country uncertainty indices. The market and country uncertainty indices are the Baker, Bloom, and Davis (2016) global EPU, EPU, and economic policy uncertainty indices, and Jurado, Ludvigson, and Ng (2017) US-Japan and financial markets (2016) 1-month horizon business cycle uncertainty indicators based on macro fundamentals. The parameter estimates are obtained by the first-stage Generalized Method of Moments procedures. The reported results are estimated by the RiskMetrics (Jorion, 1997) and by the BMA (Khan and Ritter, 2004) for simulating the null hypothesis that the cross-sectional pricing errors (jointly equal to zero) are zero. Newey-West VARHAC-standard errors (Newey and West, 1987) with optimal bandwidth selection (Andrews, 1991) are estimated for testing whether the β-declines to zero are reported. The two-sided test is based on the F statistic (Fama and MacBeth, 1973), and by the first-stage Generalized Method of Moments procedures. The parameter estimates are obtained by the RiskMetrics (Jorion, 1997) and by the BMA (Khan and Ritter, 2004) for simulating the null hypothesis that the cross-sectional pricing errors (jointly equal to zero) are zero. Newey-West VARHAC-standard errors (Newey and West, 1987) with optimal bandwidth selection (Andrews, 1991) are estimated for testing whether the β-declines to zero are reported. The two-sided test is based on the F statistic (Fama and MacBeth, 1973), and by the first-stage Generalized Method of Moments procedures. The parameter estimates are obtained by the RiskMetrics (Jorion, 1997) and by the BMA (Khan and Ritter, 2004) for simulating the null hypothesis that the cross-sectional pricing errors (jointly equal to zero) are zero. Newey-West VARHAC-standard errors (Newey and West, 1987) with optimal bandwidth selection (Andrews, 1991) are estimated for testing whether the β-declines to zero are reported. The two-sided test is based on the F statistic (Fama and MacBeth, 1973), and by the first-stage Generalized Method of Moments procedures. The parameter estimates are obtained by the RiskMetrics (Jorion, 1997) and by the BMA (Khan and Ritter, 2004) for simulating the null hypothesis that the cross-sectional pricing errors (jointly equal to zero) are zero. Newey-West VARHAC-standard errors (Newey and West, 1987) with optimal bandwidth selection (Andrews, 1991) are estimated for testing whether the β-declines to zero are reported. The two-sided test is based on the F statistic (Fama and MacBeth, 1973), and by the first-stage Generalized Method of Moments procedures.
This table reports the risk prices (A) of linear factor models (LFM) with asset-specific market portfolio as the level factor and intermediary and mispricing factors (shocks to financial intermediary capital ratio as a capital risk factor (see He and Krishnamurthy, 2013, for details) and He, Kelly, and Manela (2017), Frazzini and Pedersen (2014) global betting-against-beta factor, the behavioral cluster of Daniel, Hirshleifer, and Sun (2017) behavioral factors as the slope factor. The test assets are the transaction-cost adjusted excess returns of 5 daily-rebalanced (converted into monthly excess returns) and equally-weighted portfolios across 7 constituent carry strategies across currency, equity index, and commodity futures markets. The reported results are estimated by Fama-MacBeth (FMB) without a constant in the second-stage regressions (Fama and MacBeth, 1973), and by the first-stage Generalized Method of Moments (GMM) statistics based on Shanken-adjusted standard errors (Shanken, 1992) (for testing the null hypothesis that the cross-sectional pricing errors jointly equal to zero) and for simulation-based Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) (for testing whether the HJD equals to zero) are reported. Newey-West Adj $R^2$ is adjusted $R^2$. 'CAR' stands for carry, against front contract (vs. F.C.) and also against neighbour contract (vs. N.C.). Factors and models accepted by the above statistical criteria and with statistically significant estimates in terms of risk exposures and risk prices as well as trending (either up or down) but not necessarily strictly monotonic cross-sectional beta are highlighted in bold.
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract ($CM_F$) and also against neighbour contract ($CM_N$). Futures are sorted by different carry signals into 5 portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is CBOE volatility index $VXO$. 

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This figure shows the cross-sectional beta of cross-asset constituent carry portfolios: $VXO$. 

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Figure C.3: Cross-Sectional Beta of Cross-Asset Constituent Carry Portfolios: $VXO$
Figure C.4: Cross-Sectional Beta of Cross-Asset Constituent Carry Portfolios: \( VOL \)

This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CM\(_F\)) and also against neighbour contract (CM\(_N\)). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is asset-specific volatility risk \( VOL \).
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CM_F) and also against neighbour contract (CM_N). Futures are sorted by different carry signals into 5 portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is asset-specific crash (skew) risk CSK.
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CM_F) and also against neighbour contract (CM_N). Futures are sorted by different carry signals into 5 portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is T-bill to Euro Dollar spread TED.
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CMF) and also against neighbour contract (CMN). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Pástor and Stambaugh (2003) liquidity risk measure \( LIQ \).
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CMF) and also against neighbour contract (CMN). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is data-based financial stress index $FSI_{D_{\text{f}}}$. 

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This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CMF) and also against neighbour contract (CMN). Futures are sorted by different carry signals into 5-portfolio quintiles, daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Püttmann (2018) geopolitical risk index $GPR$. 
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CMF) and also against neighbour contract (CMN). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Baker, Bloom, and Davis (2016) global economic policy uncertainty index $EPU$. 

Figure C.10: Cross-Sectional Beta of Cross-Asset Constituent Carry Portfolios: $EPU$
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CMF) and also against neighbour contract (CMN). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Baker, Bloom, and Davis (2016) U.S. economic policy uncertainty index $EPU_{US}$. 

Figure C.11: Cross-Sectional Beta of Cross-Asset Constituent Carry Portfolios: $EPU_{US}$
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CMF) and also against neighbour contract (CMN). Futures are sorted by different carry signals into 5-portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Baker, Bloom, and Davis (2016) Japan economic policy uncertainty index $EPU_{JP}$. 

Figure C.12: Cross-Sectional Beta of Cross-Asset Constituent Carry Portfolios: $EPU_{JP}$
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CM_F) and also against neighbour contract (CM_N). Futures are sorted by different carry signals into 5 portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Jurado, Ludvigson, and Ng (2015) 1-month horizon business cycle uncertainty indicators based on macro fundamentals $BCU_{M1}$.
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CMF) and also against neighbour contract (CMN). Futures are sorted by different carry signals into 5 portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Jurado, Ludvigson, and Ng (2015) 1-month horizon business cycle uncertainty indicators based on financial markets BCUF1.
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CM_F) and also against neighbour contract (CM_N). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is shocks to He and Krishnamurthy (2013) and He, Kelly, and Manela (2017) financial intermediary leverage ratio squared $IAP_{LR^2}$. 
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CM₉) and also against neighbour contract (CM₈). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is He and Krishnamurthy (2013) and He, Kelly, and Manela (2017) value-weighted investment returns to a portfolio of the primary dealers of the Federal Reserve Bank of New York $IAP_{IR}$. 

$\text{Figure C.16: Cross-Sectional Beta of Cross-Asset Constituent Carry Portfolios: } IAP_{IR}$
Figure C.17: Cross-Sectional Beta of Cross-Asset Constituent Carry Portfolios: $IAP_{CRF}$

This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract ($CM_F$) and also against neighbour contract ($CM_N$). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is He and Krishnamurthy (2013) and He, Kelly, and Manela (2017) growth rate shocks (in percentage) to financial intermediary capital ratio as a capital risk factor $IAP_{CRF}$. 

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Figure C.18: Cross-Sectional Beta of Cross-Asset Constituent Carry Portfolios: BAB

This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CM_F) and also against neighbour contract (CM_N). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Frazzini and Pedersen (2014) global betting-against-beta BAB factor.
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CMF) and also against neighbour contract (CMN). Futures are sorted by different carry signals into 5-portfolio quintile, daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Stambaugh and Yuan (2016) behavioral-cluster mispricing factor $MPR_B$. 
This figure shows the cross-sectional beta of carry (CAR), static carry (STA), dynamic carry (DYN), unexpected dynamic carry (UEC), cyclic carry (CYC), and unexpected cyclic carry (UCC) portfolios trading 31 currency futures/forwards (FX), 27 equity futures (EQ), and 30 commodity futures. Commodity carry are computed against front contract (CMF) and also against neighbour contract (CMN). Futures are sorted by different carry signals into 5- portfolios (quintile), daily-rebalanced and equally-weighted, and compute the performance respectively. The risk factor is Daniel, Hirshleifer, and Sun (2017) inattention-cluster behavioral factor BMFI.
References


