Currency Portfolio Selection with Factors: Additive Gradients and Model Sparsity in a Data-Rich Environment*

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Abstract

In this paper, we propose a novel portfolio selection procedure for optimal factor investing that treats expected returns as a sum of additive gradients meanwhile tackling both parameter and model uncertainty in large cross sections. This macro-financial dynamic asset pricing approach embraces strategic and tactical portfolio allocation among multiple risk premia. We show that, when applied to FX markets, our factor-based strategic portfolio policy statistically significantly outperforms other 16 allocation rules, including naive diversification and well-known portfolio optimizers, and generates substantial economic values. We then extend it to solve a tactical allocation problem — factor timing conditional on high dimensional macro and financial data, but find little evidence of improvement in investment performance beyond the strategic allocation framework. The analyses suggest that (i) model sparsity is crucial, (ii) short-run deviations from long-run expected returns are difficult to capture, and (iii) focusing on the long-run expected returns is already mean-variance efficient and not sub-optimal. The results are robust to choices of a wide range of parameter settings and advanced statistical and machine learning forecasting methods.

Keywords: Portfolio Optimization, Factor Investing, Factor Timing, Strategic and

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1 Introduction

Nowadays, factor investing, such as rule-based equity smart-beta products and other systematic trading strategies based on alternative risk premia, is becoming more and more popular in industry. The alternative risk premia, e.g., carry, momentum, and value in global macro space, are less exploited. Ample literature explores additional anomalies that far exceed the number of principal components (PC) required to explain the cross section of stock returns (see Cochrane, 2011; Harvey, Liu, and Zhu, 2016, for example). Kozak, Nagel, and Santosh (2018, 2019) show that PC-sparse model outperforms characteristic-sparse model. Identifying the characteristics or anomalies that provide unique (orthogonal) predictive information for stock returns in a cross-sectional setting is an important question for scholars to answer (see Green, Hand, and Zhang, 2017; Light, Maslov, and Rytchkov, 2017; Freyberger, Neuhierl, and Weber, 2017; Cattaneo, Crump, Farrell, and Schaumburg, 2019, among others). It is closely related to how to allocate weights to various anomalies in forming an optimal portfolio for the factor investing in reality. DeMiguel, Martin-Utrera, Nogales, and Uppal (2018) emphasize that optimal portfolio allocation to anomalies or characteristics is very different from examining independent factors that explain the cross-sectional return variations. Our paper provides a novel strategic and tactical portfolio allocation framework for factor investing and the analysis focuses on foreign exchange (FX) markets, where carry, momentum, and value are three best-known risk premia.

Barroso and Santa-Clara (2015) employ a parametric portfolio policy framework proposed by Brandt, Santa-Clara, and Valkanov (2009) to study the diversification benefit from incorporating currency characteristics in constructing an optimal currency portfolio. They find that carry, momentum, and value are attributable to superior portfolio performance of an optimized currency portfolio in terms of largely increased Sharpe ratio and reduced downside risk. Similarly, Ackermann, Pohl, and Schmedders (2016) reveal that return forecasting using interest rates is less subject to estimation errors and thereby the expected returns predicted by yields renders Markowitz mean-variance portfolio optimization a better performing portfolio strategy than naive diversification, in contrast to the empirical findings of Garlappi, Uppal, and Wang (2007), DeMiguel, Garlappi, and Uppal (2009) that, due to considerably parameter and model uncertainty, Markowitz portfolio rule performs poorly in applications.

Instead, we argue that the factor structure embedded in currency carry, momentum, and value risk premia[1] can be utilized in the portfolio optimization process to overcome the uncertainty in estimations and beat the naive diversification (equally-weight basket) in the standard Markowitz mean-variance setting. We show that factor investing in FX markets that explores the risk factor that explains the cross section of currency anomalies generates superior performance in portfolio optimization with multiple risk premia. Our proposed approach is a concept of strategic allocation, as it focuses on the long-run relations of the currency anomalies with the risk factor. We show that the performance improvements beyond conventional methods are robust to different measures (with an out-of-sample Sharpe ratio up to 1.10 after transaction costs). Specifically, we compare it with 16 existing portfolio rules, such as naive diversification, standard Markowitz mean-variance, minimum-variance, maximum-diversification, risk-parity, and volatility-timing/targeting optimizers, and other well-known portfolio policies (see Appendix E). Particularly, the $1/N$ rule is shown to be very difficult to beat in the existing literature on portfolio choice due to the inevitable estimation errors involved in the parametric methods (Garlappi, Uppal, and Wang, 2007; DeMiguel, Garlappi, and Uppal, 2009). It is evident that our proposed strategic allocation framework of factor-based portfolio optimization is mean-variance efficient.

[1] It is worth mentioning that our research fundamentally is different from Maurer, To, and Tran (2017). They suggest an optimal factor strategy for trading currencies by constructing a tangency portfolio that is perfectly negatively correlated with the Stochastic Discount Factor (SDF) of the country of the denominated currency. By theory, it should give a maximum attainable Sharpe ratio, although relevant shrinkage methods should be applied when dealing with the covariance matrix due to the facts of market friction and estimation error, even all risks are supposed to be priced in currency markets. Their method is not to optimally combine multiple risk premia with zero-investment long/short strategies, rather, their portfolio is leveraged.

As far as we know, we are the first to suggest the use of factor structure in multiple risk premia as a solution for the optimal factor investing problem on a theoretical ground that the principal-component space should be spanned by characteristic space (see Giglio and Xiu, 2017, for the rotation-invariant argument). Even though we apply it to three well-known risk premia in currency markets, it should be stressed that our proposed approach can be applied to any other asset classes and corresponding anomalies. The well-established anomalies in FX markets studied in this paper are treated as distinguished risk premia in the literature. While it is difficult to explain the sizeable excess returns to carry, momentum, and value trades over the past 40 years — in a pure time-series setting, recent literature resorts to cross-sectional asset pricing test using portfolio approach and shifts the focus from a particular anomaly to cross-anomaly investigation. Although there is a growing number of literature on FX markets, most of the studies concentrate on currency carry trade. Notwithstanding, the risk factors proposed to explain risk compensations to carry trade, such as global FX volatility risk (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a), global skewness (crash) risk (Brunnermeier, Nagel, and Pedersen, 2009; Rafferty, 2012), global illiquidity risk (Banti, Phylaktis, and Sarno, 2012), or global imbalances risk in terms of net foreign assets (Della Corte, Riddiough, and Sarno, 2016), fail to price the cross section of currency momentum and value risk premia. Their risk sources also remain unclear (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a, 2017). We propose a novel macro-financial dynamic asset pricing approach for optimal currency factor investing in a data-rich environment. We take the advantage of reverse engineering by employing factor models that demonstrate the existence of a common factor priced not only in the cross section of each of the currency carry, momentum, and value risk premia, respectively, but also in their joint cross section. Then, we explore the economic value of this risk factor in the construction of an optimal currency portfolio investing in multiple risk premia. We also differentiate tactical from strategic portfolio allocation and use a large data set of macro and financial variables to extract predictive information.

Following the recent literature (Lustig, Roussanov, and Verdelhan, 2011; Burnside, Eichenbaum, and Rebelo, 2011; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a,b, 2017), we sort currencies by lagged carry, momentum, and value signals (see Asness, Moskowitz, and Pedersen, 2013; Kroencke, Schindler, and Schrimpf, 2014) in order to construct cross-sectional portfolios. We then extract the principal components from the currency portfolios of carry, momentum, and value trades. These principal components can help us to recover the factor space (see Giglio and Xiu, 2017, for details) and hence to optimally select or assign weights to multiple characteristics or anomalies in handling the factor zoo problem (Cochrane, 2011; Harvey, Liu, and Zhu, 2016). The first two principal components explain up to about 80% of the cross-sectional variation, the first principal component is essentially the FX market portfolio, as known as "dollar risk" (DOL). It is a trading strategy that borrows in (domestic) USD and invests in global (foreign) currencies. The factor loadings of these portfolios on the first principal component are almost at same level, while the factor loadings on the second principal component (PCS) are almost strictly monotonic from negative to positive within each type of currency portfolios. Therefore, PCS is identified as a slope factor. As a result, if PCS is priced in the cross section with a statistically significant premium, we expect the factor price is positive, and vice versa. Empirical asset pricing test is employed to explore the factor structure in the cross section currency carry, momentum, and value portfolios. We show that PCS can price the cross section of portfolio excess returns of all three types of currency premia, both individually and jointly with statistically factor price, implying that PCS is a common risk source for carry, momentum, and value. We then analyze the economic value of this factor structure PCS in modern currency investment management — factor investing of alternative risk premia.

PCA does not offer an explicit way to construct portfolio strategies but characteristics such as carry, momentum, and value do. Trading strategies based on characteristic-based factors provide a not only systematic but also economically meaningful approach to invest in risk premia. While PC-sparse model dominates characteristic-sparse model (see Kozak, Nagel, and Santosh, 2018, 2019), which implies that PCA on the cross sections of characteristic-sorted portfolios across anomalies offers a way on how to optimally allocate capital among these characteristic-based factors. Using the expected returns and covariance matrix estimated from the PC-based asset pricing tests in the standard Markowitz mean-variance portfolio optimizer to combine characteristic-based factors (strategies trading on risk premia), we are able to turn the statistical significance of empirical asset pricing into economic values in real-world investment practice.

We further extend our strategic allocation framework, namely factor-based portfolio optimization, to a macro-financial data-rich environment. We test whether or not the short-run return deviations of portfolio strategies (characteristic-based factor) from their long-run means (expected returns) can be captured by adjusting the portfolio weights away from the long-run strategic weights. The active tactical weights may be driven by the short-run deviations of state variables from their long-run equilibrium levels. Hence, we utilize a wide range of advanced statistical and machine learning forecasting methods (see Appendix F) designed in particular for the characteristics selection problem in predictive regressions with high-dimensional macroeconomic fundamental and financial data. It is similar to the concepts of additive models in statistical science and gradient boosting in machine learning in the sense that the expected returns are modeled by an empirical asset pricing (linear factor) model (extracting long-run expected returns) plus residual predictive models with high-dimensional data (capturing short-run deviations from expected returns — a factor-timing function). We call these two parts "additive gradients" and do the "model boosting". Notwithstanding, we fail to find supportive empirical results for the tactical portfolio allocation, which is a conditional factor timing model based on a large and readily available macro and financial data. It does not economically or statistically improve the investment performance upon our strategic portfolio allocation framework. This suggests that (i) short-run deviations from expected returns are difficult to capture (conditional factor timing seems to be impossible), and (ii) focusing on the long-run expected returns is already mean-variance efficient and not sub-optimal. To summarize, we contribute to the literature by proposing an integrated framework of combining characteristic-based portfolio strategies, factor sparsity of empirical asset pricing, and robust portfolio optimization, for strategic and tactical portfolio allocation in factor investing practice.

The structure of the paper is organized as follows: Section 2 gives a brief summary of related literature. Section 3 presents the data sources, construction of currency portfolios and strategies, and empirical asset pricing and portfolio choice methodologies we used in this paper. We provide empirical findings and discussions in Section 4, further robustness checks in Section 5 and draw a conclusion in Section 6. Some of the econometric techniques and additional results are included in the complementary appendix.

2 Related Literature of Currency Risk Premia

Carry, momentum and value trades are three well-recognized trading strategies in FX markets. Currency carry trade has become a heated topic in the recent decade, while, in comparison, currency momentum and value strategies are not well explored yet. The deviation from UIP and PPP of currencies has drawn many researchers' attention as they struggle to explain the excess returns profits associated with these currency trading strategies. Recent years has witness a shift of research focus from time-series investigation to cross-sectional asset pricing tests on these puzzles with an emphasis on the risk compensation explanation, starting from Bansal and Dahlquist (2000) and flourishing from Lustig, Roussanov, and Verdelhan (2011) that apply the characteristic-sorting portfolio approach stemming from the studies on stock market. As highlight by Cochrane (2005), the prices of individual assets are highly volatile and thereby their expected returns, covariances, and corresponding betas are always estimated inaccurately, while the portfolio approach reduces the volatilities in the grouped asset returns by diversification that, to some extent, eliminates the time-vary idiosyncratic components, and instead focuses on the common characteristics across assets.

According to Burnside (2011), the conventional, traditional risk factors, such as consumption growth (Lustig and Verdelhan, 2007) measured by durable Consumption-based CAPM (CCAPM) setting of Yogo (2006), Chicago Board Options Exchange's (CBOE) VIX index as the measure of volatility risk, T-Bill Eurodollar (TED) Spreads as the illiquidity risk indicator, Pástor and Stambaugh's (2003) liquidity measure, and Fama and French (1993) factors, do not covary enough to explain the excess returns of carry trade. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) propose a global volatility (innovation) risk factor based on Merton's (1973) Intertemporal CAPM (ICAPM), and it successfully captures the cross sectional excess returns of currency carry trades with a high R^2. They show that high interest-rate currencies deliver negative returns in the times of high unexpected volatility while low interest-rate currencies offer a hedge against the volatility risk by yielding positive returns. Farhi and Gabaix (2016) build a novel tractable model of exchange rates that representative agents attach a substantial weight, in their consumption and investment decisions, to the possibility of rare but extreme events, which are the major sources of currency risk premia. It is also stressed by Jurek (2014), Brunnermeier, Nagel, and Pedersen (2009), Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015), and Chernov, Graveline, and Zviadadze (2018) that currency premia reflect the compensations to investors for crash risk. Given that the comovements of high interest-rate currencies with the aggregate market conditional on high volatility regime is stronger than it is conditional on low volatility regime, and this phenomenon also exists in other asset classes, Lettau, Maggiori, and Weber (2014) utilize a Downside Risk CAPM (DR-CAPM) that is able to jointly price the cross section of currencies, equities, sovereign bonds, and commodities.

Gabaix and Maggiori (2015) put forward a theoretical framework which bridges the valuation channel (Gourinchas and Rey, 2007, 2013) to the international capital flows. In their framework, currency of a debtor country must offer a risk premium for the financial intermediary to absorb the exchange rate risk associated with the global imbalances arising from international capital flows. Currencies are exposed to large depreciation risk when their risk-bearing capacity declines, e.g., high market risk sentiment and funding liquidity constraint (Brunnermeier and Pedersen, 2009; Ferreira Filipe and Suominen, 2013). Scholars also relate the currency premia to the equilibrium exchange rate misalignment (MacDonald, 2005; Clarida, Galí, and Gertler, 2002; Engel, 2011; Jordà and Taylor, 2012; Huang and MacDonald, 2013b), sovereign credit risk (Huang and MacDonald, 2013a; Augustin, 2018) and speculative activities in FX markets (Abreu and Brunnermeier, 2003; Brunnermeier, Nagel, and Pedersen, 2009; Plantin and Shin, 2011). Verdelhan (2010) set forth a consumption habit model in which agents with preference settings as in Campbell and Cochrane (1999) can generate notable deviation from UIP. Infrequent currency portfolio decision (rational inattention) is another possible solution that also accounts for "delayed overshooting" (Bacchetta and Van Wincoop, 2010). Burnside, Eichenbaum, and Rebelo (2009) argue from the perspective of market microstructure that it is the adverse selection from which the forward premium puzzle arises. Burnside, Han, Hirshleifer, and Wang (2011), and Ilut (2012) further suggest behaviorial explanations of investors' overconfidence, and of slow reaction to news announcements induced by ambiguity aversion, respectively, for the existence of forward bias.

Momentum strategies can be simply identified as longing (shorting) assets with positive (negative) lagged returns, betting the past performance will continue in different horizons. Burnside, Eichenbaum, and Rebelo (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) study currency momentum portfolios and find that it is hard for traditional risk factors to explain the cross section of currency momentum excess returns, which are partially explained by transaction costs as the proxy for the limit-to-arbitrage of investors. Valuation is perhaps one of the most challenging but important tasks in the field of asset pricing. Value strategies invest in undervalued assets funded by overvalued assets, and are found quite profitable across asset classes (Asness, Moskowitz, and Pedersen, 2013). There is ample existing literature in equity and fixed income valuation while less work is found in currency and commodity valuation. The 5-year changes in real exchange rate (RER) (Asness, Moskowitz, and Pedersen, 2013) may be a better benchmark as the valuation signal for currencies than PPP (Taylor, Peel, and Sarno, 2001) from the angle of implementation as a trading strategy, as the mean reversion is found to be nonlinear (Taylor, 2002), the signal extraction process involves parameter and model uncertainty in estimations (Rossi, 2005), and macroeconomic variables are subject to revision bias. RER level imply by PPP fails to capture currency values as undervalued (overvalued) currencies are predicted to appreciate (depreciate), while the 5-year changes RER enhance the prediction power (Asness, Moskowitz, and Pedersen, 2013; Kroencke, Schindler, and Schrimpf, 2014; Barroso and Santa-Clara, 2015). Menkhoff, Sarno, Schmeling, and Schrimpf (2017) investigate the relation between RER, spot exchange rate changes, and risk premia in a multi-currency portfolio setting. They reveal that it is necessary to adjust the RER for Harrod-Balassa-Samuelson (HBS) effects, net foreign asset (NFA), output gap, and the quality of a country's exports to better measure the currency fair value. Dahlquist and Hasseltoft (2019) propose to instead invest in currencies by the momentum signals of macroeconomic fundamentals and the trading strategy generates notable alpha after controlling for currency carry, momentum, and value trades. Their research suggest that investors' expectations on macroeconomic fundamentals, including interest-rate differentials, are positively related to their past trends. Dahlquist and Penasse (2017) demonstrate that it is the RER, not the interest rate differential, that acts as the main predictor of currency returns at longer horizons, which is linked to other puzzling behavior of currencies — (i) the RER contemporaneously appreciates with the increase in interest rate differential; and (ii) the relationship between currency risk premia and the interest rate differential reverses from positive to negative over longer horizons. There is a type of missing risk premium that captures deviations from the PPP to rationalize these empirical findings.

To summarize, although the existing literature does not identify an economically meaningful risk factor that offers a unified explanation for the excess returns to currency carry, momentum, and value trades, we uncover a common risk factor that is able to price their joint cross sections simply using PCA. Provided that there is no existing economic theory trying to rationalize these three types of currency risk premia simultaneously, this paper examines the economic values of this common risk factor instead of its economic context. One of the potential economic values is the nowadays fashionable factor investing that performs optimal portfolio allocation among multiple risk premia.

3 Data and Methodologies

In this section, we provide the data sources and processing procedures, introduce currency portfolio construction and the factor models employed to investigate the common risk factors of FX trading strategies, and propose a factor-based portfolio optimization approach for strategic factor allocation and extend it to tactical factor allocation in a macro and financial data-rich environment.

3.1 Data Sets and Sources

Spot Rates, Forward Rates, and Price Levels: The data set is collected from WM/Reuters (WMR) and Barclays Bank International (BBI) via Datastream **from January 1976 to March 2016** and contains 56 currencies' (29 developed economies and 27 emerging markets) spot and 3-month forward rates against USD[2] (the developed countries are highlighted in italics): *Germany* (DEM), *France* (FRF), *Italy* (ITL), *Spain* (ESP), *Portugal* (PTE), *Netherlands* (NLG), *Belgium* (BEF), *Austria* (ATS), *Greece* (GRD), *Ireland* (IEP), *Finland* (FIM), *Euro Area* (EUR), *United States* (USD), *United Kingdom* (GBP), *Canada* (CAD), *Australia* (AUD), *New Zealand* (NZD), *Switzerland* (CHF), *Norway* (NOK), *Sweden* (SEK), *Denmark* (DKK), *Slovenia* (SIT), *Israel* (ILS), Russia (RUB), *Japan* (JPY), *South Korea* (KRW), *Singapore* (SGD), *Taiwan* (TWD), *Hong Kong* (HKD), Slovakia (SKK), Lithuania (LTL), Latvia (LVL), Estonia (EEK), Cyprus (CYP), Malta (MTL), Hungary (HUF), Czech Republic (CZK), Croatia (HRK),

[2]See Appendix A for data screening. 1-month forward rates are more affected by monetary policy and market liquidity. As a result, we choose 3-month forward rates.

Poland (PLN), Romania (RON), Ukraine (UAH), Bulgaria (BGN), Turkey (TRY), India (INR), Malaysia (MYR), Thailand (THB), Philippines (PHP), Indonesia (IDR), South Africa (ZAR), Egypt (EGP), Mexico (MXN), Brazil (BRL), Argentina (ARS), Chile (CLP), Colombia (COP), Peru (PEN). The corresponding price levels from OECD with cross validations by data from IMF and World Bank.

Macroeconomic and Financial Time Series: The macroeconomic data set, as known as "FRED MD", is readily available from the website of Federal Reserve Bank of St. Louis (`http://research.stlouisfed.org/econ/mccracken/sel/`). It contains 135 U.S. macroeconomic time series, which are categorized into 8 groups (1) output and income, (2) labor market, (3) housing, (4) consumption, orders and inventories, (5) money and credit, (6) bond and exchange rates, (7) prices, and (8) stock market, as in McCracken and Ng (2016). The financial data set, containing 39 global financial time series, is collected from AQR's data library (`https://www.aqr.com/library/data-sets`). It consists of the multi-asset market portfolios, and risk premia — (1) cross-sectional carry, (2) time-series carry, (3) value, (4) cross-sectional momentum, (5) time-series momentum (trend-following) in global equity, fixed income, commodity, FX, and credit markets. As for global equity market, we further download the market capitalization (SMB) factor, alternative value (HML) factor as in Asness and Frazzini (2013), betting-against-beta (BAB) factor, and quality (QMJ) factor. The credit risk premia after proper adjustment for term premia (see Asvanunt and Richardson, 2016) are also included. In sum, we have 174 predictors in total.

3.2 Portfolio Construction

Following Lustig, Roussanov, and Verdelhan (2011), Burnside, Eichenbaum, and Rebelo (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), Menkhoff, Sarno, Schmeling, and Schrimpf (2012b), Menkhoff, Sarno, Schmeling, and Schrimpf (2017), at the end of each period t, we obtain 5 portfolios (P_1, ..., P_5) for each trading strategy by sorting currencies of developed economies and whole sample (including emerging markets) into portfolios according to lagged 1-month forward premia (for carry trade), lagged 3-month exchange rate returns (for momentum trade), and lagged 5-year changes in real exchange rate (for value trade), respectively. Currencies are ranked from low to high by signal values, i.e., P_1 contains currencies with the lowest 20% signal values, and P_5 contains currencies with the highest 20% signal values. $x^k_{i,t}$ represents the baseline signal of currency i at time t, where the signal $k = \{C, M, V\}$. The sorting bases for carry trade $x^C_{i,t}$, momentum trade $x^M_{i,t}$, and value trade $x^V_{i,t}$ are shown as follows, respectively (see also Asness, Moskowitz, and Pedersen, 2013; Menkhoff, Sarno, Schmeling, and Schrimpf, 2017; Kroencke, Schindler, and Schrimpf, 2014):

$$x^C_{i,t} = \frac{F_{i,t}}{S_{i,t}} - 1 \tag{1}$$

$$x^M_{i,t} = \prod_{\tau=0}^{2}(1 + r^{\mathrm{e}}_{i,t-\tau}) - 1 \tag{2}$$

$$x^V_{i,t} = \frac{Q_{i,t-60}}{Q_{i,t-3}} - 1 \tag{3}$$

where $r^{\mathrm{e}}_{i,t-\tau}$ represents excess returns of currency i in period $t-\tau$. $Q_{i,t}$ denotes the real exchange rate and $Q_{i,t} = S_{i,t}P_{i,t}/P^*_{i,t}$. $P_{i,t}$ and $P^*_{i,t}$ are the domestic, and foreign price level of consumer goods, respectively. Currencies are equally weighted within each of 3×5 portfolios. Moreover, the past 1-month excess returns and past 3-month changes in real exchange rate are skipped to avoid the correlation between carry and momentum trades, and that between momentum and value trades. Thus, non-overlapping information is used to construct currency portfolios (see also Fama and French, 1996). After these adjustments, the sample period is from February 1981 to March 2016.

The monthly excess return without transaction cost for holding a currency against USD at time $t+1$ is given by:

$$r^{\mathrm{e}}_{i,t+1} = \frac{F_{i,t} - S_{i,t+1}}{S_{i,t}} \tag{4}$$

which is equivalent to the forward premium $(F_{i,t} - S_{i,t})/S_{i,t}$ subtracted by the change in spot rate $(S_{i,t+1} - S_{i,t})/S_{i,t}$. The data screening procedure is shown in Appendix A, and the adjustments of excess returns for transaction costs are reported in Appendix B.

We report results for high-minus-low portfolios denoted by HML, which is the difference in payoffs between P_5 and P_1. In addition to the benchmark, we also build currency portfolios using different weighting schemes as robustness checks. Following Hassan and Mano (2019), Menkhoff, Sarno, Schmeling, and Schrimpf (2017), the signal-dispersion weights are computed as:

$$w_{i,t:t+1} = c_t \left[x_{i,t}^k - K_{t:t+1}^{-1} \sum_{i=1}^{K_{t:t+1}} x_{i,t}^k \right] \tag{5}$$

where $K_{t:t+1}$ denotes the total number of currencies available at time t and $t+1$, and $K_{t:t+1}^{-1} \sum_{i=1}^{K_{t:t+1}} x_{i,t}^k$ represents the cross-sectional mean of the signal. c_t is a scaling factor such that the absolute values of the currency weights sum up to one. We assign positive portfolio weights to currencies with a value above the cross-sectional average, while negative portfolio weights to currencies with a below-average value. The signal-rank weighted HML portfolio are reported as well and are calculated as:

$$w_{i,t:t+1} = c_t \left[rank(x_{i,t}^k) - K_{t:t+1}^{-1} \sum_{i=1}^{K_{t:t+1}} rank(x_{i,t}^k) \right] \tag{6}$$

where the rank of signal $x_{i,t}^k$ is used instead of the value of $x_{i,t}^k$. This weighting approach is widely practiced in the financial industry when some assets have extreme signals and the outliers will receive smaller weights, but this procedure has a disadvantage that it does not permit precise decompositions. The overall results of the portfolio and strategy performance are similar to existing literature.

3.3 Factor Models for Asset Pricing and Portfolio Choice

The linear factor model implies a beta pricing model where the expected excess return of portfolio j depend on its risk exposures β_j to common factors and the corresponding factor prices λ:

$$\mathbb{E}[r^{\mathrm{e}}_{j,t+1}] = \sum_{n=1}^{N} \beta_{j,n} \cdot \lambda_n \tag{7}$$

where the subscripts n denote the corresponding risk factors, N in total. Two different procedures are employed to estimate the risk exposures β and factor prices λ: Generalized Method of Moments (Hansen, 1982), as known as "GMM",[3] and Fama-MacBeth (FMB) two-step OLS approach (Fama and MacBeth, 1973). The estimation methodologies and procedures are delegated to Appendix C and D.

Garlappi, Uppal, and Wang (2007), DeMiguel, Garlappi, and Uppal (2009) among others reveal that parameter and model uncertainty is the key issue for portfolio optimizers such as Markowitz mean-variance problem, especially, the estimates of expected returns are severely subject to estimation errors. Here, we propose a macro-financial dynamic asset pricing approach for strategic and tactical allocations for factor investing problem. The strategic allocation solution in between risk premia is the factor-based portfolio optimization approach exploring the factor structure of currency risk premia. We demonstrate how the empirical asset pricing test can be factor investing in currency markets by applying the estimated risk exposures and prices to Markowitz mean-variance problem with multiple risk premia. The optimal portfolio weights of Markowitz mean-variance portfolio optimizer are given by:

$$\omega_t \propto \mathbb{E}[\Sigma_{r^{\mathrm{e}},r^{\mathrm{e}},t+1}]^{-1} \cdot \mathbb{E}[r^{\mathrm{e}}_{t+1}] \tag{8}$$

where ω_{t+1} is scaled by risk aversion coefficient γ, normally ranging from 2 to 6. The portfolio weights on the risky assets or risk premia must sum up to one, we obtain the tangency portfolio:

$$\omega_t = \frac{\mathbb{E}[\Sigma_{r^{\mathrm{e}},r^{\mathrm{e}},t+1}]^{-1} \cdot \mathbb{E}[r^{\mathrm{e}}_{t+1}]}{1_N \mathbb{E}[\Sigma_{r^{\mathrm{e}},r^{\mathrm{e}},t+1}]^{-1} \cdot \mathbb{E}[r^{\mathrm{e}}_{t+1}]} \tag{9}$$

[3]Following Burnside (2011), we impose additional moment restrictions. Please see Appendix D for details.

where the expected returns and covariance matrix in Equation (9) are generally obtained via calculating the sample mean and covariance of r^{e} up to time t. Alternative, we propose to estimate them via a factor-based approach. In general, let's consider a linear factor model as in the empirical asset pricing tests:

$$r^{\mathrm{e}}_{j,t} = \alpha_j + \beta_j f_t + \zeta_{j,t} \tag{10}$$

The expected returns and covariance matrix can then be computed as:

$$\begin{aligned} \mathbb{E}[r^{\mathrm{e}}_{t+1}] &= \beta_t \lambda_t \\ \mathbb{E}[\Sigma_{r^{\mathrm{e}},r^{\mathrm{e}},t+1}] &= \beta_t \Sigma_{f,f,t} \beta_t^{\top} + \Sigma_{\zeta,\zeta,t} \end{aligned} \tag{11}$$

where $\Sigma_{\zeta,\zeta,t}$ are the covariance matrix of the pricing errors ζ. The assets in combination are risk premia, essentially zero-investment strategies of high-minus-low (sorted) portfolios, where the expected returns to such portfolio strategies $\mathbb{E}[r^{\mathrm{e}}_{t+1}] = (\beta_{H,t} - \beta_{L,t})\lambda_t$ where $\beta_{H,t}$ ($\beta_{L,t}$) is the risk exposure of the portfolio containing, e.g., the highest (lowest) yielding, strongest (weakest) trending, or most undervalued (overvalued) currencies, respectively, in our case. The expected covariance matrix among currency carry, momentum, and value risk premia can be computed accordingly as well. An important benefit of using factor-based portfolio optimization from empirical asset pricing tests is that the parameter estimates are less subject to estimation errors, for a simple reason that idiosyncratic components of individual assets are largely reduced when put into a basket, and hence risk premia, or equivalently, the payoffs to long/short strategies are more predictable (see also Bakshi and Panayotov, 2013, for time-series forecasting exercise).

3.4 Factor-Based Portfolio Optimization in a Macro-Financial Data-Rich Environment

The parameters of the factor-based strategic allocation for currency factor investing, i.e., risk exposures β_t and factor prices λ_t, are estimated using a rolling window up to time t in order to assess the out-of-sample performance. And the rolling-window length is not optimally chosen so as to reflect the robustness of our proposed approach under parameter uncertainty. Rather, we test a wide range of rolling-window lengths. To reduce the estimation errors and maintain the robustness parameter estimates, capturing the business cycle risk in the asset pricing estimation for β_t and λ_t is crucial. We refer to the National Bureau of Economic Research (NBER),[4] there are 11 business cycles from 1945 to 2009, with an average length of about 70 months. Thus, a rolling-window length should span at least 2 business cycles for robust asset pricing estimates. We show that the empirical results remain qualitatively similar using a wide range of different rolling-window lengths. Furthermore, we demonstrate the economic value of exploring our proposed principal component slope factor in combining multiple currency risk premia, and we compare the performance of the currency portfolios generated by our factor-based version of mean-variance optimizer with various types of portfolio optimizers, including **a group of portfolio optimizers with different objectives and optimality assumptions**: (1) naive diversification ($1/N$), (2) standard Markowitz mean-variance approach, (3) minimum variance, (4) maximum diversification, (5) maximum decorrelation, (6) risk parity, (7) equal risk contribution (Maillard, Roncalli, and Teïletche, 2008), and (8) volatility timing/targeting; and **another group of portfolio optimizers where inputs are estimated by various shrinkage methods**: (9) Bayesian-Stein shrinkage method (Jorion, 1986), (10) MacKinlay and Pástor (2000) tangency portfolio, (11) Bayesian data-and-model method (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005), (12) Kan and Zhou (2007) three-fund rule, (13) Garlappi, Uppal, and Wang (2007) multi-prior max-min approach,

[4]Please see the link `http://www.nber.org/cycles.html`.

(14) DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$, (15) Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$, and (16) Tu and Zhou (2011) combination of three-fund rule with $1/N$, 16 in total for comparison (see Appendix E for technical details). The $1/N$ is shown in the literature to be seemingly unbeatable owing to the inevitable byproduct of estimation errors in parametric methods (see Garlappi, Uppal, and Wang, 2007; DeMiguel, Garlappi, and Uppal, 2009, among others). Nevertheless, our proposed factor-based approach utilizing the second principal component (PCS) is less subject to estimation errors in the portfolio optimization process, in particular, on the expected returns estimates.

Beside the strategic allocation of risk premia in currency factor investing discussed above, we further extend our factor-based portfolio optimization approach to tactical allocation, or equivalently, conditional factor timing based on high dimensional macro and financial data. It essentially tests whether or not short-run deviations of portfolio strategies' payoffs from expected returns, or equivalently, short-run deviations of pricing factors (risk premia) from their long-run means (risk prices), are driven by short-run deviations of state variables from their long-run equilibria, for which we use proxies from a large set of macro and financial data described before. In this case, the expected returns are modeled by an empirical asset pricing (linear factor) model (extracting long-run expected returns) plus residual predictive models with high-dimensional data (capturing short-run deviations from expected returns — a factor-timing function). This approach shares similarities to the concepts of additive models in statistical science and gradient boosting in machine learning. So, we call these two parts "additive gradients" and do the "model boosting" as follows:

$$r^{\mathrm{e}}_{t+1} - \mathbb{E}_t[r^{\mathrm{e}}_{t+1}] \equiv (\hat{\beta}_{H,t} - \hat{\beta}_{L,t})(f_{t+1} - \hat{\lambda}_t) + \varepsilon_{t+1} = \beta_y y_t + \beta_z z_t + \upsilon_{t+1} \qquad (12)$$

where y_t, and z_t denote macroeconomic fundamental movements and financial asset fluctuations, respectively; the corresponding coefficients β_y and β_z can be estimated by various regularization and other statistical methods; and note that we do not need a constant on the RHS of Equation (12), as $\mathbb{E}_t[r^{\mathrm{e}}_{t+1}] = \beta_t\lambda_t$ plays the role of a constant. Estimating Equation (12) works as a conditional factor-timing overlay. Due to the high dimensionality of the macro and financial data, we employ a wide range of advanced statistical and machine learning forecasting methods, including **regularization methods with various penalty settings**: (1) elastic net (EN) proposed by Zou and Hastie (2005), (2) adaptive LASSO ($LASSO_A$) introduced by Zou (2006), and (3) group LASSO ($LASSO_G$) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples);[5] **model selection and averaging methods**: (4) Bayesian model averaging (BMA) proposed by Raftery, Madigan, and Hoeting (1997) and (5) complete subset regression (CSR) introduced by Elliott, Gargano, and Timmermann (2013); and **latent variable approaches**: (6) partial least squares (PLS) which is adopted by Light, Maslov, and Rytchkov (2017) to explain the cross section of stock returns via aggregating information from characteristics, and (7) three-pass regression filter (TPF) proposed by Kelly and Pruitt (2015) where PLS is shown to be a special case of TPF, to tackle the curse of high dimensionality in the predictive regression for tactical allocation among multiple risk premia of currency factor investing (see Appendix F for technical details).

We assign a prior weight $w_\zeta \in [0, 1)$ to the assumption of zero long-run deviations from expected returns given the empirical implications of the asset pricing model while a prior weight of $1 - w_\zeta$ to the predicted short-run deviations by aforementioned large set of macro and financial variables in order to form the short-run return forecasts in the tactical allocation framework as follows:

$$\mathbb{E}_t[r^{\mathrm{e}}_{t+1}] = (\hat{\beta}_{H,t} - \hat{\beta}_{L,t})\hat{\lambda}_t + (1 - w_\zeta)(\hat{\beta}_y y_t + \hat{\beta}_z z_t) \tag{13}$$

Although predictive regressions could possibly add the economic value of factor timing,

[5] Freyberger, Neuhierl, and Weber (2017) apply adaptive group LASSO to select a sparse set of characteristic-based factors from competing empirical asset pricing models.

they may also introduce noise into the expected returns and contaminate the strategic allocation framework. We can test the economic value added via the tactical allocation to the strategic allocation by varying the prior belief w_ζ.

4 Empirical Results

In this section, we provide the preliminary analysis on the cross section of currency portfolios of three types of risk premia in FX markets and the corresponding trading strategies. We then explore the factor structure of these FX anomalies and perform asset pricing tests to solve the portfolio choice problem of optimal currency factor investing, for which we propose a novel integrated strategic and tactical allocation framework, namely factor-based portfolio optimization in a macro-financial data-rich environment.

4.1 Preliminary Analysis of Portfolio Strategies

Table 1-3 show the descriptive statistics of the equally weighted currency carry, momentum, and value portfolios sorted by lagged 1-month forward premia, lagged 3-month exchange rate excess returns, and lagged 5-year changes in real exchange rate respectively. The High-Minus-Low (HML) portfolios that long portfolio 5 and short portfolio 1 are also reported in Table 1-3 with different weighting schemes, i.e., equally-weighted (E), dispersion-weighted (D), and rank-weighted (R). The all countries (upper panel) and developed economies (lower panel) are exhibited separately in the tables. As shown in Table 1-3, the average excess returns and Sharpe ratios of carry, momentum, and value trades increase monotonically from negative to positive for both developed economies and whole sample including emerging markets. The Sharpe ratios of currency carry, momentum, and value trading strategy can reach up to about 0.65, 0.60, and 0.40, respectively, over a 40-year history. This indicates that incorporating FX investment styles into portfolio and risk management process is very important.

Table 1 about here

Table 2 about here

Table 3 about here

Let's start from currency carry trade portfolios. The exchange rate components (FX) exhibit a decreasing pattern but not strictly monotonic, there is still a large spread in the excess returns (after taking the yield component (IR) into account) between low-yield and high-yield currency portfolios, indicating that the interest rate differentials are biased predictors of future exchange rate movements — the violation of the UIP. Consistent with the empirical findings of Brunnermeier, Nagel, and Pedersen (2009), Rafferty (2012), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), there are also an increasing trend in volatility and a decreasing trend in skewness across the currency carry trade portfolios, while those of the currency momentum and value portfolios do not exhibit similar patterns. This may also help to explain why the global volatility risk factor of Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) and the global skewness (crash) risk factor of Rafferty (2012) fail to price the cross section of currency momentum and value premia. It is also worth to point out that the turnover ratio of momentum trade is very high, implying the transaction costs may consume a substantial part of the returns. The carry and value trade both have similar low level of turn over ratios. All above statements hold for both developed economies and whole sample including emerging markets.

4.2 Factor Structure of FX Anomalies

Given the strong factor structure but seemingly distinctive risk profile of each of the three types of currency premia, some questions naturally arise: Does the common slope risk factor for the carry, momentum, and value really exist? If yes, is it latent or observable? And if it is unobservable, can macroeconomic fundamentals and financial variables capture its fluctuations? And can they provide additional predictive information about expected returns beyond the common latent factor? To answer these questions, we first employ Principal Component Analysis (PCA) to explore the factor structure across all three types of currency premia, and we find that the first two principal components surprisingly explain 60% - 80% of the cross-sectional variations of these currency portfolios. The first principal component is essentially the dollar risk factor (DOL) of Lustig, Roussanov, and Verdelhan (2011), which can be regarded as a proxy for the FX market portfolio. The second principal component (PCS) is the focus of this paper. If PCS is a potential common risk factor, it is expected to be a slope factor that the risk exposures of the currency portfolios of carry, momentum, and value should be increasing from negative to positive if the factor price is statistically significant and positive, and vice versa for negative factor price. We then perform asset pricing tests of PCS on all three types of currency risk premia, both individually and jointly. The details of estimation methodologies are described in Appendix D.

Table 4 about here

Table 4 presents cross-sectional asset pricing results of five currency carry portfolios with two risk factors DOL and PCS. DOL works as an intercept factor because the risk exposures to DOL are almost at the same level so that it does not contribute the cross-sectional variations in expected returns. While the exposures to PCS are monotonically increasing from low-yield currency portfolio to high-yield currency portfolio. Thus, PCS works as the slope factor and is the parameters of interests. The coefficients of risk exposure β_{PCS}, factor loading b_{PCS}, and factor price λ_{PCS} are all statistically significant. The estimated factor price is 11.87% p.a. for the whole sample including emerging markets and 7.82% p.a. for the developed economies sample. The factor model generates high cross-sectional R^2 of about 90% for both sample coverages. The Mean Absolute Pricing Errors ($MAPE$) are relatively low, about 0.40 - 0.50. We also accept that the model is not mis-specified as it passes both zero-pricing error χ^2 test and zero HJ-distance test of Hansen and Jagannathan (1997). These results confirm that the slope principal component (PCS) has explanatory power for the excess returns of currency carry trade.

Table 5 about here

Table 6 about here

We implement the same empirical tests on currency momentum and value portfolios using DOL and PCS as risk factors, and the results are reported in Table 5 and Table 6, respectively. The findings are very close to what we obtain using currency carry trade portfolios. The risk exposures to PCS are monotonic and increasing from negative to positive, i.e., the loser or low-value currencies provide a hedge for the winner or high-value currencies against some certain risk sources, and it is common to all three types of currency premia. Again, b_{PCS} and λ_{PCS} are statistically significant. The factor price of PCS to momentum trade is 3.91% p.a. for all countries sample and 3.22% p.a. for developed economies sample, while, to value trade, it is priced at 3.58% p.a. for whole sample including emerging markets and 4.34% p.a. for developed economies sample. The cross-sectional R^2 for momentum trade is as high as 0.98 of all countries and 0.81 for developed economies while about 0.75 for value trade on both samples. We also cannot reject the null hypothesis of zero pricing error of χ^2 test and zero HJ-distance of Hansen and Jagannathan (1997) test. $MAPE$ are very low. These results confirm that PCS works well on individual currency risk premia. The next step is to test it on their joint cross section.

Table 7 about here

Given that the risk exposures of currency portfolios to DOL and PCS remain the same, we only report factor loadings b_{PCS} and factor prices λ_{PCS}. As shown in Table 7, both of them are statistically significant. λ_{PCS} is priced at 4.89% p.a. for the whole sample with emerging markets and 4.64% p.a. for the sample of developed economies. The cross-sectional R^2 are approximately 0.70 for both samples. The $p-value$ of χ^2 test and of HJ-distance test both confirm that the model is correctly specified. The empirical findings are robust to adding additional tested assets that may have a different factor structure (see Lewellen, Nagel, and Shanken, 2010, for details), and thereby, the joint cross-section asset pricing tests verify that PCS performs well in explaining the cross-sectional variations in excess returns of currency carry, momentum, and value portfolios. PCS can price excess returns of the cross-sectional portfolios of all three types of currency risk premia, both individually and jointly. We further investigate how to utilize the factor structure PCS for currency investment.

[Insert Figure 1 about here]

Figure 1 above visualizes the cross-sectional goodness of fit of the pricing model with the common risk factor PCS for three well-recognized currency risk premia. We can see that PCS well captures the cross-sectional variations of currency carry, momentum, and value portfolios.

4.3 Strategic Factor Allocation: Factor-Based Portfolio Optimization

The empirical analysis above suggests the existence of a common factor of currency carry, momentum, and value risk premia. In this section, we further test the performance of the currency portfolios generated by exploiting the factor structure of currency risk premia. If the factor structure is real, we expect the improvement in currency investment performance that combines multiple risk premia. Specifically, we apply the second principal component (PCS) to standard Markowitz mean-variance portfolio optimization where the expected returns are formed by the product of the risk exposures and risk price and the covariance matrix is computed accordingly. We compare it with other 16 types of well-known portfolio optimizers listed in Section 3.[6]

[Insert Figure 2 about here]

Figure 2 shows the investment performance of currency factor-investing portfolios in terms of cumulative excess returns after transaction costs. We compare our factor-based Markowitz portfolios with other 16 types of portfolio optimizers where the risk-

[6]Technical details are reported in Appendix E.

aversion coefficient γ is set to 6.[7] The average (from 140-month to 210-month rolling window lengths) transaction-cost adjusted cumulative excess returns generated by our PCS factor-based version of Markowitz mean-variance optimizer is both economically and statistically greater than those produced by 16 alternative portfolio optimizers while the differences in investment performance among other 16 competing portfolio optimizers are relatively small. We further report its outperformance via not only various statistical measures but also economic values of switching from 16 competing portfolio optimizers to our proposed factor-based approach.

[**Insert Table 8 about here**]

[**Insert Table 9 about here**]

[**Insert Table 10 about here**]

[**Insert Table 11 about here**]

Table 8 to 11 report the performance metrics of our factor-based currency portfolio optimization with multiple risk premia that exploits the cross-anomaly factor structure by applying its principal component slope factor to standard Markowitz mean-variance framework. It is reported in comparison with other well-recognized asset allocation rules with a risk-aversion coefficient of 6. The performance of our factor-based Markowitz mean-variance portfolio optimizer that explores the principal component slope factor steadily ranks the first among all other popular portfolio optimizers, across Sharpe ratio (ranging from 0.89 to 1.10, and much higher than those of other competing portfolio optimizers by over 0.1 and up to 0.3), Sortino ratio that penalizes the downside risk (from 1.26 to 1.56, and again much greater than those of other competing portfolio optimizers by about 0.2 and up to 0.5), certainty equivalent returns (CEQ) that assumes investors are averse to uncertainty (from 3.61 to 4.58, which is up to 1.5% higher than those of other alternative portfolio optimizers), and Calmar ratio that calculates the mean divided by the (absolute value of) maximum drawdown of the return series (up to 69% of the

[7]The degree of relative risk aversion γ follows a standard setting from 2 to 6.

maximum drawdown is covered by annual return, which is approximately 50% and up to almost 100% more than those of other alternative portfolio optimizers), suggesting our factor-based approach that utilize the cross-anomaly factor structure outperforms other alternative portfolio optimizers by yielding better risk-adjusted returns with less drawdowns.

It is worth noticing that the expected returns formed by the factor-based approach are designed to reflect the long-run returns based on risk exposures, where the rolling window lengths are chosen to be compatible with the business-cycle durations. Therefore, they should be robust to a variety of market scenarios instead of being sensitive to short-term volatility risks. In the other words, it may not perform as well as, e.g., the volatility-timing portfolio, in a distressed market. Nevertheless, the factor-based approach still ranks the first in terms of Sortino ratio and Calmar ratio, suggesting its overall accuracy in estimating the expected returns across different market conditions, in particular, in the upside of the investment performance. Even though it does not rank the first in Omega ratio,[8] being the best in several risk-adjusted return measures implies that the revenues produced in the upside are quite persistent, or in the other words, less volatile.

$\mathcal{F}$, and $\mathcal{P}$ are performance fees proposed by Fleming, Kirby, and Ostdiek (2001, 2003), and Goetzmann, Ingersoll, Spiegel, and Welch (2007), respectively (see in Appendix G for details). We use these approaches to evaluate how much that risk-averse investors are willing to pay for switching from the competing portfolio optimizers to our factor-based Markowitz mean-variance approach. Notwithstanding that they are meant to be manipulation-proof, these approaches do not take the portfolio volatility into account — they only work for comparing portfolio strategies with similar levels of volatilities. We need to re-scale the portfolio strategies to the same risk profile in terms of volatility in order to employ their approaches. The performance fees are ranging from 0.50% to 1.44%, which are considerably high fees for investment management industry nowadays.

[8] $\Omega = \int_0^{+\infty}[1-F(r^{\mathrm{e}})]dr^{\mathrm{e}} \Big/ \int_{-\infty}^{0} F(r^{\mathrm{e}})dr^{\mathrm{e}}$, which considers the entire return distribution, especially for non-normal investments.

Moreover, the Sharpe ratios generated by the PCS factor-based approach are statistically higher than other alternative methods according to the robust Sharpe ratio difference test suggested by Ledoit and Wolf (2008).

We attribute the outperformance of our factor-based approach to the fact that it is less subject to estimation errors, especially in forming the expected returns for portfolio construction, on the theoretical ground that the principal-component space should be spanned by characteristic space and hence the principal components can help us to recover the factor space (see Giglio and Xiu, 2017, for the rotation-invariant argument). This further validates the pricing power of the asset pricing tests using PCS, as pointed out by Kozak, Nagel, and Santosh (2018, 2019) that the PC-sparse model should outperform the characteristic-sparse model. However, PCA does not offer an explicit way to construct portfolio strategies but characteristics do. Trading strategies based on characteristic-based factors provide a systematic and economically meaningful way for investment in risk premia, while PCA on the cross sections of characteristic-sorted portfolios sheds light on how to optimally allocate capital among these trading strategies for factor investing. In this way, we turn the statistical significance of empirical asset pricing into economic values in real-world investment practice. It is worth mentioning that inputs estimated by various shrinkage methods do not have statistically significant impacts on the investment performance across different groups of portfolio optimizers with different objectives and optimality assumptions.

Given that our proposed strategic allocation framework of factor-based portfolio optimization beats standard Markowitz mean-variance method (mean-variance efficiency property), several questions naturally raise: (i) can it be sub-optimal? and (ii) can we improve its performance by conditioning the portfolio weights on other investment-related information given the availability of huge macro and financial data? The next step is to investigate whether or not high-dimensional macro-financial data can help to forecast the short-run deviations from expected returns in a tactical allocation framework, which adds an active-weight overlay upon the strategic allocation benchmark.

4.4 Tactical Factor Allocation: Extension to a Macro-Financial Data-Rich Environment

The predicted short-run deviations from expected returns can be considerably large and unstable compared to the expected returns per se, which are turned into extreme and volatile weights constructed via the standard Markowitz mean-variance framework. The final portfolio weights can be driven predominantly by the tactical weights rather than the strategic weights. Therefore, it is reasonable to impose a restriction to constrain the forecasts short-run return deviations by attaching a prior weight w_ζ to the hypothesis that long-run deviations from expected returns are zero. By doing so, we not only generate more stable weights to avoid both the noise introduced via forecasts of short-run return deviations and unnecessary transaction costs, but also provide a framework that nests both pure strategic allocation and the mixture of strategic and tactical allocation via varying the prior weight. Moreover, we expect that regularized regression methods designed to tackle parameter uncertainty produce portfolio weights (tactical/active weights) more close to the strategic weights (zeros) than other predictive methods, such as the estimators aiming to deal with model uncertainty or relying on latent factors. Since we have a strong prior belief in the hypothesis, we discuss the empirical results of $w_\zeta = 0.95$ in this section below and also report those of $w_\zeta = 0.50$ in next section of further robustness check, where we reveal that attaching more prior weights to the short-run return deviation forecasts produces overall worse investment performance than strategic allocation, suggesting the short-run return deviation forecasts are actually very noisy across a wide range of estimators.

[Insert Figure 3 about here]

As shown in Figure 3 above and as expected, regularized regression methods, elastic net and adaptive LASSO, which penalize model overfitting via the trade-off between bias and variance of forecasting errors, are not sensitive to the prior weight.[9] Hence

[9] Please refer to the comparison in next section of further robustness check.

the corresponding investment performance in terms of cumulative excess return after transaction costs closely tracks that of strategic allocation via factor-based portfolio optimization. The overlay of short-run deviations from expected returns predicted by other forecasting methods adopted in this paper, such as those dealing with model uncertainty and latent variable approaches, notably deteriorate the investment performance of strategic allocation framework. Group LASSO that encourages sparsity at group level has comparable investment performance to Bayesian model averaging and complete subset regression that are proposed to handle model uncertainty or variable selection, while there is no statistically significant difference between the investment performance of the partial least squares (PLS) and that of three-pass regression filter (TPF). PLS is actually a special case of TPF (see Kelly and Pruitt, 2015), and both belong to the category of latent factor approaches.

[Insert Table 12 about here]

[Insert Table 13 about here]

Table 12 and Table 13 report a comprehensive evaluation of the investment performance of the tactical overlay where active weights (over strategic allocation weights) are produced by predictive regressions. Again, we adopt a rolling window spanning 2-3 business cycles according to the NBER average business cycle length. Overall, the penalized regression methods such as EN and $LASSO_A$ generate the best investment performance in multiple performance measures across Sharpe ratio, Sortino ratio, CEQ, Omega ratio, Calmar ratio, and performance fees. Nevertheless, the results are mixed and the outperformance is not statistically significant judged by the criterion of Ledoit and Wolf (2008) robust Sharpe ratio difference test. It is worth noticing that model averaging and combination methods such as BMA and CSR, in particular the latter, in some cases yields the best investment performance as indicated by several performance metrics. $LASSO_G$ and latent factor approaches such as PLS and TPF that push the portfolio weights to deviate largely from strategic weights via the tactical overlay of active weights overall give the worst investment performance. All these empirical findings suggest that the strategic allocation is not sub-optimal and already mean-variance efficient as it beats standard Markowitz mean-variance method. Variety of advanced forecasting methods fail to capture short-run deviations from expected returns conditioning on a large set of macro and financial data, and as a result, the active weight adjustments via tactical overlay only introduce noise in the expected return formulation process, which points to a conclusion that factor timing via a large and readily available macro and financial data seems to be impossible.

5 Further Robustness Checks

Besides (i) comparing our proposed approach with various portfolio optimizers, (ii) estimating the model with a wide span of rolling-window length, (iii) adopting a broad range of forecasting methods, and (iv) judging investment performance with different measures, we implement further robustness checks on three aspects: (v) degree of relative risk aversion, (vi) prior weight attached to the zero long-run deviations from the expected returns implied by the empirical asset pricing models, and (vii) differentiating investment leg from funding leg in the forecasting exercises.

5.1 Degree of Relative Risk Aversion

A standard setting for the degree of relative risk aversion γ ranges from 2 to 6. We further test our framework with $\gamma = 2$. The empirical results remain qualitatively the same across different rolling-window lengths (2-3 business-cycle durations). We also report investment performance comparison among portfolio optimizers with a risk-aversion coefficient of 2 (see Figure H.1. and Table H.1. to H.4. in Appendix H), showing that our empirical findings are robust to changes of risk coefficient. It is worth mentioning that being less risk averse encourages taking more risky positions and thus produces worse investment performance for several risk-aversion dependent portfolio optimizers.

5.2 Prior Weight on Zero Long-Run Deviations from Expected Returns

As discussed before, the predicted short-run deviations from expected returns can be considerably large and unstable relative to the expected returns per se, which may be turned into extreme and volatile weights constructed by the standard Markowitz mean-variance optimal rule. Attaching a prior weight to the hypothesis of zero long-run deviations from expected returns is a solution to alleviate this problem. We vary the prior weights from 0.95 to 0.50 in order to understand how it affects the forecasting accuracy of short-run deviations. Thereby, we expect that regularized regression methods designed to handle parameter uncertainty produce more stable weights than other predictive methods, such as the estimators aiming to deal with model uncertainty and relying on latent factors. The Figure H.2. and Table H.5. to H.6. in Appendix H provide supportive evidence that the signal-to-noise ratios in the point predictions of short-run deviations from expected returns are low across a broad range of forecasting methods.

5.3 Differentiating Investment Leg from Funding Leg

Inspired by Lu and Jacobsen (2016) where they reveal directional cross-asset return predictability that equity returns predict the funding leg of carry trade (low interest-rate currencies) while commodity returns forecasts the investment leg (high yield currencies), we perform separate forecasting exercises on the investment leg and funding leg of currency trading strategies and then aggregate the predictions from both long and short legs. This implementation relaxes the restrictions on the parameters that assume both long and short legs share the same degree of sensitivity to the predictors, and therefore, may improve the forecasting performance. As shown in Figure H.3. and Table H.7. to H.8. in Appendix H, we find little evidence that differentiating investment leg from funding leg helps much in forecasting the short-run deviations from expected returns for tactical currency allocation in a high-dimensional environment.

6 Conclusion

In a pure time-series setting, scholars find it hard to explain the well-established anomalies in FX markets — a long history of sizeable excess returns to carry, momentum, and value trades. In some more recent literature, scholars resort to cross-sectional asset pricing test using portfolio approach and also shift the focus from a particular anomaly to cross-anomaly investigation. Still, the existing literature finds that risk factors which are helpful in explaining currency carry trades can hardly rationalize the momentum and value premia simultaneously. In this paper, we find the existence of a principal-component based common factor that is priced in the cross section of currency carry, momentum, and value risk premia, both individually and jointly.

The question is: how can we turn the statistical significance of empirical asset pricing test into economic values in real-world investment practice? Inspired by the studies of Giglio and Xiu (2017), Kozak, Nagel, and Santosh (2018), Kozak, Nagel, and Santosh (2019), we suggest to utilize the rotation-invariant feature of the factor space to optimally combine characteristic-based factors to solve the risk premia investing problem. Characteristic-based factors provide an explicit way to construct portfolio strategies to harvest risk premia, but PCA does not. However, given the factor structure revealed by PCA in the joint cross section of currency carry, momentum, value portfolios, we propose a factor-based approach to construct the optimal factor investing portfolio of multiple currency risk premia. It is achieved by the combination of standard Markowitz mean-variance portfolio optimization with asset pricing tests. The factor-based version of Markowitz mean-variance portfolio offers superior and robust investment performance beyond 16 well-known competing portfolio optimizers widely used or practiced in academia and industry, implying that our proposed strategic allocation framework is already mean-variance efficient. We attribute the outperformance of our factor-based approach to the fact that it is less subject to estimation errors, especially in forming the expected returns for portfolio construction, as the principal-component space should be spanned by characteristic space. This further validates the pricing power of the asset pricing tests using the second (slope) principal component (PCS).

We further extend our strategic asset allocation framework to incorporate tactical asset allocation, or equivalently, factor timing feature in a macro-financial data-rich environment. We test whether or not the short-run return deviations of characteristic-based factors from expected returns can be captured by adjusting the portfolio weights away from the long-run strategic weights. The active tactical weights may be driven by the short-run deviations of state variables from their long-run equilibrium levels. Similar to the concepts of additive models in statistical science and gradient boosting in machine learning, the expected returns of portfolio strategies are modeled by an empirical asset pricing (linear factor) model (extracting long-run expected returns) plus residual predictive models with high-dimensional data (capturing short-run deviations from expected returns — a factor-timing function). We call these two parts "additive gradients'. Thus, to do the "model boosting", we employ a wide range of advanced statistical and machine learning forecasting methods designed in particular for the characteristics selection problem in predictive regressions with high-dimensional data. We cannot find supportive empirical results for our tactical portfolio allocation model in the sense that it does not economically or statistically improve the investment performance upon our strategic portfolio allocation framework. This suggests that short-run deviations from expected returns are difficult to capture, or equivalently, the conditional factor timing based on a large and readily available macro and financial data seems to be impossible, and that focusing on the long-run expected returns is already mean-variance efficient and not sub-optimal. In summary, we contribute to the literature by proposing an integrated framework that combines characteristic-based portfolio strategies, factor sparsity of empirical asset pricing, and robust portfolio optimization for strategic and tactical portfolio allocation in factor investing practice.

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Table 1: Descriptive Statistics of Currency Carry Portfolio (1981.2-2016.3)

All Countries with Transaction Costs									
Portfolios	C_1	C_2	C_3	C_4	C_5	Avg.	HML^E	HML^D	HML^R
Mean (%)	-3.83	-0.76	-0.37	0.73	1.26	-0.59	5.09	6.59	3.49
FX (%)	-1.06	-0.26	-1.61	-2.58	-7.03	-2.51	-5.97	-7.42	-5.13
IR (%)	-2.77	-0.50	1.24	3.31	8.29	1.91	11.06	14.01	8.61
Std.Dev. (%)	8.85	8.92	8.74	9.08	9.83	8.26	8.10	10.15	6.25
Skewness	-0.01	-0.09	-0.14	-0.21	-0.19	-0.12	-0.17	0.76	-0.20
Kurtosis	0.30	0.31	0.37	0.46	0.43	0.33	0.37	2.03	0.37
Sharpe Ratio	-0.43	-0.09	-0.04	0.08	0.13	-0.07	0.63	0.65	0.56
MDD (%)	-21.87	-18.14	-20.39	-23.60	-25.03	-20.04	-14.83	-15.36	-13.51
AC(1)	0.05	0.07	0.08	0.10	0.16	0.11	0.06	0.37	0.11
TOR	0.17	0.28	0.29	0.26	0.17				
Developed Countries with Transaction Costs									
Portfolios	C_1	C_2	C_3	C_4	C_5	Avg.	HML^E	HML^D	HML^R
Mean (%)	-3.40	-1.83	0.25	0.42	1.63	-0.59	5.03	3.98	3.56
FX (%)	-0.70	-1.02	-0.48	-1.90	-4.09	-1.64	-3.39	-4.27	-2.98
IR (%)	-2.70	-0.81	0.72	2.32	5.72	1.05	8.42	8.25	6.54
Std.Dev. (%)	9.03	8.55	8.65	8.62	10.74	8.18	8.68	7.52	6.50
Skewness	0.02	-0.08	-0.10	-0.10	-0.22	-0.09	-0.21	-0.26	-0.21
Kurtosis	0.32	0.33	0.36	0.30	0.50	0.31	0.41	0.42	0.36
Sharpe Ratio	-0.38	-0.21	0.03	0.05	0.15	-0.07	0.58	0.53	0.55
MDD (%)	-21.87	-24.15	-17.14	-21.55	-30.90	-19.42	-22.95	-15.70	-14.78
AC(1)	0.02	0.11	0.07	0.07	0.12	0.09	0.05	0.02	0.05
TOR	0.18	0.29	0.29	0.25	0.14				

This table reports statistics of the annualized monthly excess returns in USD of currency carry portfolios sorted by lagged 1-month forward premia. All excess returns are adjusted for transaction costs (bid-ask spreads). The portfolios are rebalanced according to the new arrival signals at the end of each month. Mean, exchange rate returns (FX), interest rate differentials (IR) and standard deviation are annualized and reported in percentage. Skewness, kurtosis and Sharpe ratio are also reported in annualization. 'MDD' and 'AC(1)' denote the maximum drawdown and the first order autocorrelation coefficient, respectively. 'TOR' represents the turnover ratio of a portfolio. 'Avg.' is the average excess returns of all portfolios in long positions. 'HML' is the excess return to a strategy investing in Portfolio C_5 and funded by Portfolio C_1. And the superscripts E, D, and R of 'HML' represent the different weighting schemes: equally-weighted (within a range of extreme signals), signal-dispersion weighted, and signal-rank weighted, respectively. The latter two weighting schemes use a complete set of signals. The sample period is from February 1981 to March 2016.

Table 2: Descriptive Statistics of Currency Momentum Portfolio (1981.2-2016.3)

All Countries with Transaction Costs									
Portfolios	M_1	M_2	M_3	M_4	M_5	Avg.	HML^E	HML^D	HML^R
Mean (%)	-3.15	-1.88	-1.21	0.11	1.78	-0.87	4.93	4.43	3.28
FX (%)	-5.18	-4.14	-2.24	-1.37	-0.61	-2.71	4.57	3.41	3.04
IR (%)	2.03	2.25	1.03	1.48	2.39	1.84	0.36	1.01	0.24
Std.Dev. (%)	9.67	9.28	9.04	9.03	8.73	8.21	8.60	9.07	6.48
Skewness	-0.10	-0.18	-0.05	-0.08	-0.15	-0.12	0.01	0.12	-0.02
Kurtosis	0.35	0.37	0.30	0.34	0.44	0.33	0.34	0.56	0.31
Sharpe Ratio	-0.33	-0.20	-0.13	0.01	0.20	-0.11	0.57	0.49	0.51
MDD (%)	-26.05	-27.31	-18.63	-19.44	-16.72	-20.11	-15.08	-16.81	-9.90
AC(1)	0.08	0.06	0.04	0.10	0.09	0.11	-0.13	-0.07	-0.10
TOR	0.43	0.59	0.67	0.61	0.44				
Developed Countries with Transaction Costs									
Portfolios	M_1	M_2	M_3	M_4	M_5	Avg.	HML^E	HML^D	HML^R
Mean (%)	-2.55	-1.53	-0.74	-0.27	0.79	-0.86	3.34	2.75	2.04
FX (%)	-2.71	-1.83	-1.42	-1.55	-1.48	-1.80	1.23	0.80	0.28
IR (%)	0.16	0.30	0.68	1.28	2.28	0.94	2.11	1.94	1.76
Std.Dev. (%)	9.45	9.21	9.17	9.16	8.88	8.13	8.79	8.00	6.55
Skewness	-0.06	-0.17	-0.06	-0.06	-0.13	-0.09	0.04	0.05	0.07
Kurtosis	0.40	0.43	0.31	0.32	0.42	0.31	0.44	0.43	0.44
Sharpe Ratio	-0.27	-0.17	-0.08	-0.03	0.09	-0.11	0.38	0.34	0.31
MDD (%)	-22.52	-25.83	-21.77	-17.43	-16.72	-19.46	-15.08	-15.35	-12.74
AC(1)	0.05	0.11	0.03	0.08	0.09	0.09	-0.09	-0.07	-0.06
TOR	0.43	0.58	0.68	0.60	0.46				

This table reports statistics of the annualized monthly excess returns in USD of currency momentum portfolios sorted by lagged 3-month exchange rate returns. All excess returns are adjusted for transaction costs (bid-ask spreads). The portfolios are rebalanced according to the new arrival signals at the end of each month. Mean, exchange rate returns (FX), interest rate differentials (IR) and standard deviation are annualized and reported in percentage. Skewness, kurtosis and Sharpe ratio are also reported in annualization. 'MDD' and 'AC(1)' denote the maximum drawdown and the first order autocorrelation coefficient, respectively. 'TOR' represents the turnover ratio of a portfolio. 'Avg.' is the average excess returns of all portfolios in long positions. 'HML' is the excess return to a strategy investing in Portfolio M_5 and funded by Portfolio M_1. And the superscripts E, D, and R of 'HML' represent the different weighting schemes: equally-weighted (within a range of extreme signals), signal-dispersion weighted, and signal-rank weighted, respectively. The latter two weighting schemes use a complete set of signals. The sample period is from February 1981 to March 2016.

Table 3: Descriptive Statistics of Currency Value Portfolios (1981.2-2016.3)

All Countries with Transaction Costs									
Portfolios	V_1	V_2	V_3	V_4	V_5	Avg.	HML^E	HML^D	HML^R
Mean (%)	-1.52	-1.22	-0.65	0.64	0.66	-0.42	2.19	2.03	1.29
FX (%)	-3.66	-3.09	-2.01	-1.29	-1.35	-2.28	2.30	1.79	1.36
IR (%)	2.13	1.87	1.36	1.93	2.01	1.86	-0.12	0.24	-0.07
Std.Dev. (%)	9.24	9.21	9.50	9.01	8.34	8.21	8.20	7.47	6.15
Skewness	-0.15	-0.15	-0.12	-0.08	-0.07	-0.12	-0.09	-0.16	-0.09
Kurtosis	0.38	0.36	0.38	0.30	0.35	0.34	0.40	0.53	0.40
Sharpe Ratio	-0.16	-0.13	-0.07	0.07	0.08	-0.05	0.27	0.27	0.21
MDD (%)	-25.92	-20.42	-22.11	-17.88	-15.28	-20.01	-14.75	-15.10	-12.98
AC(1)	0.14	0.11	0.09	0.04	0.07	0.10	0.07	0.03	0.10
TOR	0.12	0.25	0.30	0.25	0.14				
Developed Countries with Transaction Costs									
Portfolios	V_1	V_2	V_3	V_4	V_5	Avg.	HML^E	HML^D	HML^R
Mean (%)	-2.09	-1.57	-0.23	0.39	1.11	-0.48	3.20	2.98	2.21
FX (%)	-3.50	-2.61	-1.03	-0.47	0.19	-1.48	3.69	3.22	2.58
IR (%)	1.41	1.04	0.80	0.86	0.92	1.00	-0.49	-0.24	-0.37
Std.Dev. (%)	9.60	9.60	9.25	9.53	9.21	7.93	8.12	8.76	7.45
Skewness	-0.19	-0.19	-0.16	-0.07	-0.07	0.03	-0.09	0.15	0.12
Kurtosis	0.47	0.47	0.40	0.37	0.30	0.34	0.31	0.60	0.67
Sharpe Ratio	-0.22	-0.17	-0.02	0.04	0.12	-0.06	0.39	0.34	0.30
MDD (%)	-27.87	-27.87	-25.06	-20.05	-24.56	-21.04	-19.39	-14.63	-15.10
AC(1)	0.10	0.10	0.09	0.05	0.08	0.07	0.09	0.09	0.10
TOR	0.13	0.26	0.32	0.28	0.16				

This table reports statistics of the annualized monthly excess returns in USD of currency value portfolios sorted by lagged 5-year changes in real exchange rate. All excess returns are adjusted for transaction costs (bid-ask spreads). The portfolios are rebalanced according to the new arrival signals at the end of each month. Mean, exchange rate returns (FX), interest rate differentials (IR) and standard deviation are annualized and reported in percentage. Skewness, kurtosis and Sharpe ratio are also reported in annualization. 'MDD' and 'AC(1)' denote the maximum drawdown and the first order autocorrelation coefficient, respectively. 'TOR' represents the turnover ratio of a portfolio. 'Avg.' is the average excess returns of all portfolios in long positions. 'HML' is the excess return to a strategy investing in Portfolio V_5 and funded by Portfolio V_1. And the superscripts E, D, and R of 'HML' represent the different weighting schemes: equally-weighted (within a range of extreme signals), signal-dispersion weighted, and signal-rank weighted, respectively. The latter two weighting schemes use a complete set of signals. The sample period is from February 1981 to March 2016.

Table 4: Asset Pricing of Currency Carry Portfolios: $DOL + PCS$

Factor Exposures			Factor Prices							
All Countries with Transaction Costs										
	β_{DOL}	β_{PCS}		b_{DOL}	b_{PCS}	λ_{DOL}	λ_{PCS}	R^2	$p-value$	$MAPE$
C_1	0.95	-0.23							χ^2	
	(0.04)	(0.04)	FMB			-0.57	11.87	0.91		0.40
C_2	1.03	-0.10				(1.45)	(3.80)		(0.28)	
	(0.03)	(0.03)				[1.39]	[3.43]		[0.19]	
C_3	1.02	0.05								
	(0.02)	(0.03)							$HJ-dist$	
C_4	1.01	0.16	GMM_1	-0.08	2.44	-0.57	11.87	0.91	0.55	0.40
	(0.04)	(0.03)		(0.21)	(0.84)	(1.40)	(3.61)			
C_5	0.10	0.15	GMM_2	-0.05	2.16	-0.31	10.52	0.88		0.50
	(0.04)	(0.06)		(0.21)	(0.76)	(1.39)	(3.37)			
Developed Countries with Transaction Costs										
	β_{DOL}	β_{PCS}		b_{DOL}	b_{PCS}	λ_{DOL}	λ_{PCS}	R^2	$p-value$	$MAPE$
C_1	0.94	-0.28							χ^2	
	(0.05)	(0.05)	FMB			-0.61	7.82	0.89		0.49
C_2	0.95	-0.18				(1.37)	(2.30)		(0.25)	
	(0.03)	(0.03)				[1.38]	[2.16]		[0.23]	
C_3	0.99	-0.03								
	(0.02)	(0.03)							$HJ-dist$	
C_4	0.96	0.19	GMM_1	-0.08	1.36	-0.61	7.82	0.89	0.30	0.49
	(0.03)	(0.04)		(0.19)	(0.44)	(1.38)	(2.31)			
C_5	1.16	0.32	GMM_2	-0.04	1.27	-0.30	7.25	0.85		0.62
	(0.05)	(0.07)		(0.19)	(0.42)	(1.36)	(2.25)			

This table reports asset pricing results for a linear factor model (LFM) based on dollar risk (DOL) as the intercept (global) factor (Lustig, Roussanov, and Verdelhan, 2011) and the second principal component (PCS) as the slope (country-specific) factor. The test assets are the transaction-cost adjusted excess returns of 5 currency carry portfolios based on currencies from all countries or developed countries. β denotes time-series factor exposures. The coefficient estimates of Stochastic Discount Factor (SDF) parameters (b) (cross-sectional factor loadings) and factor price (λ) are obtained by Fama-MacBeth (FMB) excluding a constant in the second-stage procedure, and by first-stage (GMM_1) and iterated (GMM_2) Generalized Method of Moments procedures. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) and corresponding p-value of χ^2 statistic (for testing the null hypothesis that the cross-sectional pricing errors are jointly equal to zero) are in the parentheses. The Shanken-adjusted standard errors (Shanken, 1992) and corresponding p-value of χ^2 statistic are in the brackets. The cross-sectional R^2, the simulation-based p-value of Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) for testing whether it is equal to zero ($HJ-dist$), and Mean Absolute Pricing Error ($MAPE$) are also reported. The sample period is from February 1981 to March 2016.

Table 5: Asset Pricing of Currency Momentum Portfolios: $DOL + PCS$

Factor Exposures			Factor Prices							
All Countries with Transaction Costs										
	β_{DOL}	β_{PCS}		b_{DOL}	b_{PCS}	λ_{DOL}	λ_{PCS}	R^2	$p-value$	$MAPE$
M_1	0.97	-0.61							χ^2	
	(0.03)	(0.04)	FMB			-0.89	3.91	0.98		0.18
M_2	1.06	-0.27				(1.39)	(1.13)		(0.82)	
	(0.02)	(0.03)				[1.39]	[1.14]		[0.80]	
M_3	1.04	0.04								
	(0.02)	(0.03)							$HJ-dist$	
M_4	1.03	0.22	GMM_1	-0.11	0.80	-0.89	3.91	0.98	0.24	0.18
	(0.02)	(0.03)		(0.18)	(0.25)	(1.39)	(1.13)			
M_5	0.88	0.63	GMM_2	-0.11	0.81	-0.88	3.93	0.98		0.18
	(0.02)	(0.03)		(0.18)	(0.25)	(1.39)	(1.13)			
Developed Countries with Transaction Costs										
	β_{DOL}	β_{PCS}		b_{DOL}	b_{PCS}	λ_{DOL}	λ_{PCS}	R^2	$p-value$	$MAPE$
M_1	0.96	-0.26							χ^2	
	(0.04)	(0.06)	FMB			-0.88	3.22	0.81		0.44
M_2	1.04	-0.28				(1.38)	(1.52)		(0.67)	
	(0.02)	(0.03)				[1.38]	[1.52]		[0.67]	
M_3	1.05	-0.07								
	(0.03)	(0.03)							$HJ-dist$	
M_4	1.05	0.09	GMM_1	-0.11	0.56	-0.88	3.22	0.81	0.32	0.44
	(0.02)	(0.03)		(0.17)	(0.27)	(1.38)	(1.53)			
M_5	0.88	0.57	GMM_2	-0.10	0.52	-0.77	2.97	0.80		0.38
	(0.03)	(0.03)		(0.17)	(0.27)	(1.37)	(1.50)			

This table reports asset pricing results for a linear factor model (LFM) based on dollar risk (DOL) as the intercept (global) factor (Lustig, Roussanov, and Verdelhan, 2011) and the second principal component (PCS) as the slope (country-specific) factor. The test assets are the transaction-cost adjusted excess returns of 5 currency momentum portfolios based on currencies from all countries or developed countries. β denotes time-series factor exposures. The coefficient estimates of Stochastic Discount Factor (SDF) parameters (b) (cross-sectional factor loadings) and factor price (λ) are obtained by Fama-MacBeth (FMB) excluding a constant in the second-stage procedure, and by first-stage (GMM_1) and iterated (GMM_2) Generalized Method of Moments procedures. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) and corresponding p-value of χ^2 statistic (for testing the null hypothesis that the cross-sectional pricing errors are jointly equal to zero) are in the parentheses. The Shanken-adjusted standard errors (Shanken, 1992) and corresponding p-value of χ^2 statistic are in the brackets. The cross-sectional R^2, the simulation-based p-value of Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) for testing whether it is equal to zero ($HJ-dist$), and Mean Absolute Pricing Error ($MAPE$) are also reported. The sample period is from February 1981 to March 2016.

Table 6: Asset Pricing of Currency Value Portfolios: $DOL + PCS$

Factor Exposures			Factor Prices							
All Countries with Transaction Costs										
	β_{DOL}	β_{PCS}		b_{DOL}	b_{PCS}	λ_{DOL}	λ_{PCS}	R^2	$p-value$	$MAPE$
V_1	0.99	-0.27							χ^2	
	(0.04)	(0.04)	FMB			-0.39	3.58	0.75		0.39
V_2	1.04	-0.12				(1.43)	(1.56)		(0.28)	
	(0.03)	(0.04)				[1.40]	[1.89]		[0.34]	
V_3	1.12	-0.10								
	(0.02)	(0.03)							$HJ-dist$	
V_4	1.03	0.03	GMM_1	-0.06	0.82	-0.39	3.58	0.75	0.20	0.39
	(0.03)	(0.03)		(0.26)	(0.37)	(1.40)	(1.35)			
V_5	0.80	0.36	GMM_2	-0.04	0.66	-0.25	3.54	0.71		0.41
	(0.04)	(0.06)		(0.26)	(0.34)	(1.37)	(1.76)			
Developed Countries with Transaction Costs										
	β_{DOL}	β_{PCS}		b_{DOL}	b_{PCS}	λ_{DOL}	λ_{PCS}	R^2	$p-value$	$MAPE$
V_1	1.02	-0.25							χ^2	
	(0.04)	(0.04)	FMB			-0.46	4.34	0.77		0.57
V_2	1.04	-0.13				(1.37)	(1.98)		(0.36)	
	(0.03)	(0.04)				[1.38]	[1.99]		[0.36]	
V_3	1.11	-0.09								
	(0.03)	(0.03)							$HJ-dist$	
V_4	1.05	0.05	GMM_1	-0.06	0.76	-0.46	4.34	0.77	0.27	0.57
	(0.03)	(0.03)		(0.17)	(0.36)	(1.37)	(2.00)			
V_5	0.76	0.43	GMM_2	-0.04	0.65	-0.30	3.73	0.73		0.58
	(0.04)	(0.04)		(0.17)	(0.35)	(1.37)	(1.95)			

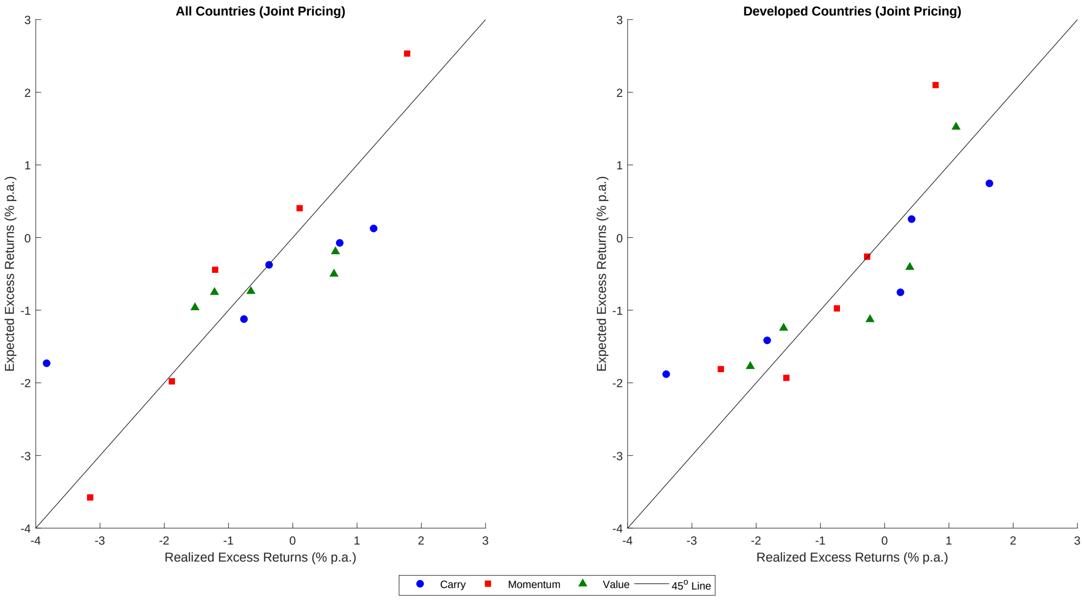
This table reports asset pricing results for a linear factor model (LFM) based on dollar risk (DOL) as the intercept (global) factor (Lustig, Roussanov, and Verdelhan, 2011) and the second principal component (PCS) as the slope (country-specific) factor. The test assets are the transaction-cost adjusted excess returns of 5 currency value portfolios based on currencies from all countries or developed countries. β denotes time-series factor exposures. The coefficient estimates of Stochastic Discount Factor (SDF) parameters (b) (cross-sectional factor loadings) and factor price (λ) are obtained by Fama-MacBeth (FMB) excluding a constant in the second-stage procedure, and by first-stage (GMM_1) and iterated (GMM_2) Generalized Method of Moments procedures. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) and corresponding p-value of χ^2 statistic (for testing the null hypothesis that the cross-sectional pricing errors are jointly equal to zero) are in the parentheses. The Shanken-adjusted standard errors (Shanken, 1992) and corresponding p-value of χ^2 statistic are in the brackets. The cross-sectional R^2, the simulation-based p-value of Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) for testing whether it is equal to zero ($HJ-dist$), and Mean Absolute Pricing Error ($MAPE$) are also reported. The sample period is from February 1981 to March 2016.

Table 7: Joint Asset Pricing of 3 FX Investment Styles across 15 Currency Portfolios: $DOL + PCS$

All Countries							
	b_{DOL}	b_{PCS}	λ_{DOL}	λ_{PCS}	R^2	$p - value$	$MAPE$
						χ^2	
FMB			-0.63	4.89	0.70		0.66
			(1.42)	(1.08)		(0.41)	
			[1.39]	[1.07]		[0.40]	
						$HJ - dist$	
GMM_1	-0.08	1.01	-0.63	4.89	0.70	0.25	0.66
	(0.18)	(0.25)	(1.39)	(1.08)			
GMM_2	-0.09	1.39	-0.69	6.77	0.60		0.82
	(0.18)	(0.24)	(1.41)	(1.08)			
Developed Countries							
	b_{DOL}	b_{PCS}	λ_{DOL}	λ_{PCS}	R^2	$p - value$	$MAPE$
						χ^2	
FMB			-0.63	4.64	0.71		0.63
			(1.37)	(1.17)		(0.58)	
			[1.38]	[1.17]		[0.58]	
						$HJ - dist$	
GMM_1	-0.08	0.81	-0.63	4.64	0.71	0.24	0.63
	(0.18)	(0.23)	(1.37)	(1.18)			
GMM_2	0.00	0.98	0.02	5.64	0.47		0.79
	(0.17)	(0.22)	(1.38)	(1.10)			

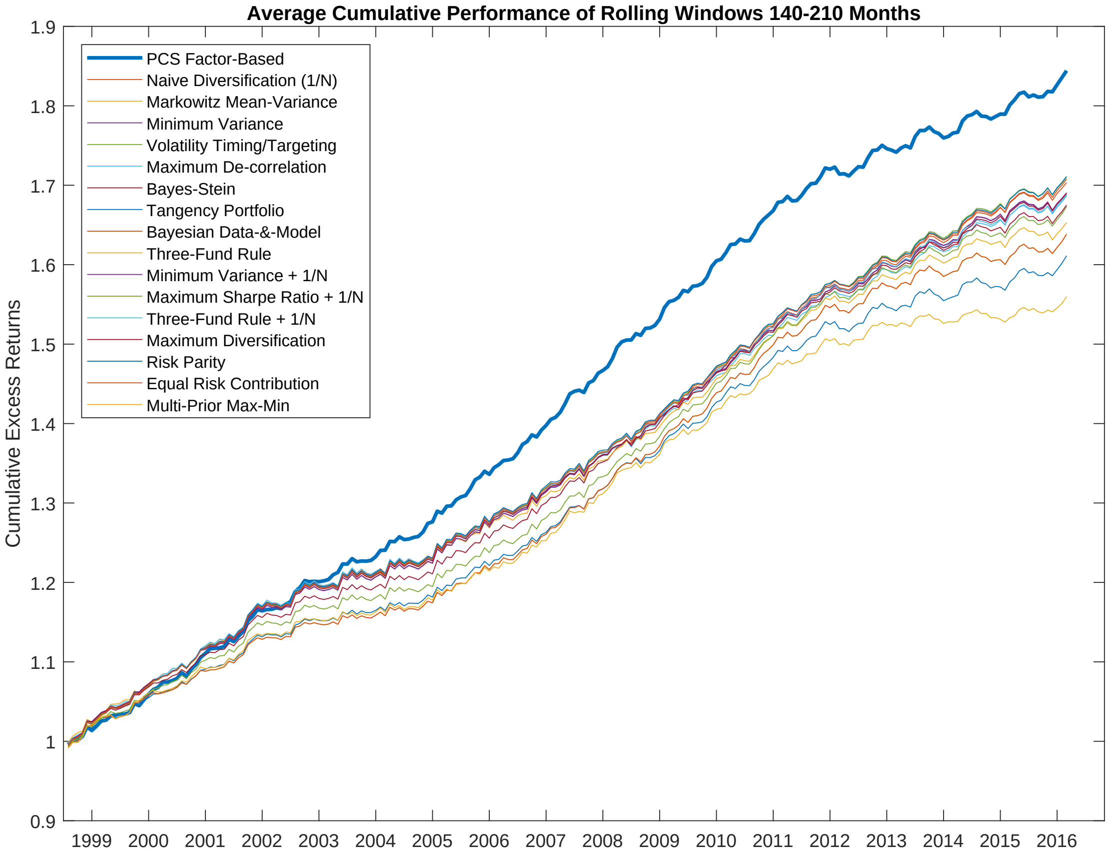
This table reports the results of joint asset pricing of 3 FX investment styles for a linear factor model (LFM) based on dollar risk (DOL) as the intercept (global) factor (Lustig, Roussanov, and Verdelhan, 2011) and the second principal component (PCS) as the slope (country-specific) factor. The test assets are the transaction-cost adjusted excess returns of 15 currency portfolios based on currencies from all countries and developed countries. β denotes time-series factor exposures. The coefficient estimates of Stochastic Discount Factor (SDF) parameters (b) (cross-sectional factor loadings) and factor price (λ) are obtained by Fama-MacBeth (FMB) excluding a constant in the second-stage procedure, and by first-stage (GMM_1) and iterated (GMM_2) Generalized Method of Moments procedures. Newey-West VARHAC standard errors (Newey and West, 1987) with optimal lag selection (Andrews, 1991) and corresponding p-value of χ^2 statistic (for testing the null hypothesis that the cross-sectional pricing errors are jointly equal to zero) are in the parentheses. The Shanken-adjusted standard errors (Shanken, 1992) and corresponding p-value of χ^2 statistic are in the brackets. The cross-sectional R^2, the simulation-based p-value of Hansen-Jagannathan distance (Hansen and Jagannathan, 1997) for testing whether it is equal to zero ($HJ - dist$), and Mean Absolute Pricing Error ($MAPE$) are also reported. The sample period is from 1981 to March 2016.

Figure 1: The Pricing Power of Common Risk Factor PCS



This figure shows the expected excess returns of 15 currency portfolios of carry, momentum, and value trades priced by common risk factor PCS versus the realized excess returns of these currency portfolios. The sample involves 56 global currencies (29 of developed economies and 27 of emerging markets) from February 1981 to March 2016.

Figure 2: Strategic Asset Allocation: Out-of-Sample Performance of Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$)



This figure shows the cumulative average performance (excess returns after transaction costs) of factor-based currency factor-investing portfolio strategies across different rolling-window lengths spanning 2-3 business cycles (according to NBER), and using various optimizers, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). The out-of-sample period is from August 1998 to March 2016. All series are adjusted to the same risk profile as the factor-based portfolio strategy, in terms of portfolio volatility, for comparison.

Table 8: Strategic Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$)

Rolling Window: 140M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	4.37	3.30	3.51	3.32	3.30	3.32	3.41	3.48	3.51	3.50	3.32	3.36	3.40	3.32	3.35	3.31	2.97
Std.Dev. (%)	4.89	4.27	5.10	4.46	4.31	4.38	4.67	5.13	5.10	4.82	4.46	4.63	4.50	4.41	4.30	4.36	4.61
Sharpe Ratio	**0.89**	0.77	0.69	0.74	0.77	0.76	0.73	0.68	0.69	0.73	0.74	0.73	0.76	0.75	0.78	0.76	0.65
Sortino Ratio	**1.26**	1.09	0.90	0.99	1.06	1.05	0.97	0.91	0.90	0.99	0.99	1.01	1.05	1.02	1.09	1.05	0.91
CEQ	**3.65**	2.75	2.73	2.72	2.75	2.74	2.76	2.69	2.73	2.80	2.72	2.72	2.80	2.73	2.80	2.74	2.34
Omega Ratio	**1.07**	1.06	0.97	1.04	1.04	1.05	0.94	0.98	0.97	1.00	1.04	0.98	**1.07**	1.03	1.04	1.05	0.91
Calmar Ratio	**0.39**	0.30	0.30	0.32	0.30	0.32	0.33	0.26	0.30	0.38	0.32	0.30	0.34	0.32	0.31	0.31	0.26
$\mathcal{F}$ (%)	-	0.59	1.00	0.73	0.62	0.67	0.80	1.05	1.00	0.82	0.73	0.81	0.67	0.69	0.56	0.65	1.21
$\mathcal{P}$ (%)	-	0.59	1.01	0.73	0.62	0.66	0.80	1.05	1.01	0.82	0.73	0.81	0.67	0.69	0.56	0.65	1.21
LW Test	-	0.10	0.02	0.09	0.10	0.09	0.07	0.01	0.02	0.09	0.09	0.05	0.08	0.09	0.10	0.09	0.02
Rolling Window: 150M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	4.64	3.13	3.57	3.21	3.13	3.20	3.33	3.51	3.57	3.27	3.21	3.30	3.20	3.22	3.19	3.17	3.13
Std.Dev. (%)	4.86	4.27	5.15	4.44	4.31	4.35	4.65	5.06	5.15	4.63	4.43	4.61	4.41	4.37	4.31	4.34	4.76
Sharpe Ratio	**0.96**	0.73	0.69	0.72	0.73	0.74	0.72	0.69	0.69	0.71	0.72	0.72	0.73	0.74	0.74	0.73	0.66
Sortino Ratio	**1.37**	1.03	0.91	0.98	1.00	1.03	0.97	0.96	0.91	0.99	0.98	1.00	1.02	1.02	1.03	1.01	0.90
CEQ	**3.94**	2.58	2.77	2.62	2.57	2.64	2.68	2.74	2.77	2.63	2.62	2.66	2.62	2.65	2.63	2.60	2.46
Omega Ratio	1.07	1.05	0.94	1.00	1.03	1.04	0.95	1.02	0.94	1.03	1.02	0.92	**1.08**	1.04	1.04	1.04	0.94
Calmar Ratio	**0.59**	0.28	0.28	0.30	0.29	0.30	0.31	0.28	0.28	0.38	0.30	0.30	0.33	0.30	0.29	0.29	0.25
$\mathcal{F}$ (%)	-	1.08	1.28	1.13	1.12	1.06	1.16	1.27	1.28	1.21	1.12	1.17	1.11	1.06	1.05	1.10	1.44
$\mathcal{P}$ (%)	-	1.08	1.28	1.12	1.12	1.05	1.16	1.27	1.28	1.21	1.12	1.16	1.11	1.06	1.05	1.09	1.44
LW Test	-	0.04	0.00	0.04	0.04	0.04	0.01	0.00	0.00	0.01	0.04	0.01	0.02	0.05	0.05	0.04	0.01

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with other popular approaches in practice, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Table 9: Strategic Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$)

Rolling Window: 160M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	5.05	3.51	4.06	3.61	3.51	3.60	3.84	4.08	4.06	3.85	3.61	3.87	3.68	3.59	3.54	3.57	3.60
Std.Dev. (%)	4.80	4.21	5.06	4.39	4.26	4.28	4.58	4.88	5.06	4.50	4.38	4.53	4.31	4.32	4.26	4.28	4.78
Sharpe Ratio	**1.05**	0.83	0.80	0.82	0.82	0.84	0.84	0.83	0.80	0.86	0.82	0.85	0.85	0.83	0.83	0.83	0.75
Sortino Ratio	**1.53**	1.20	1.08	1.15	1.17	1.22	1.18	1.19	1.08	1.24	1.15	1.24	1.23	1.18	1.18	1.19	1.08
CEQ	**4.36**	2.98	3.29	3.04	2.96	3.05	3.22	3.36	3.29	3.24	3.04	3.26	3.13	3.03	3.00	3.02	2.92
Omega Ratio	1.06	1.12	1.01	1.09	1.11	1.10	1.02	1.11	1.01	1.14	1.09	1.03	**1.18**	1.10	1.09	1.11	1.02
Calmar Ratio	**0.65**	0.44	0.41	0.43	0.44	0.44	0.45	0.50	0.41	0.48	0.43	0.48	0.46	0.43	0.43	0.44	0.31
$\mathcal{F}$ (%)	-	1.06	1.21	1.10	1.10	1.02	1.03	1.05	1.21	0.95	1.10	0.96	0.96	1.07	1.07	1.06	1.44
$\mathcal{P}$ (%)	-	1.05	1.21	1.10	1.10	1.01	1.02	1.05	1.21	0.94	1.09	0.95	0.95	1.06	1.06	1.05	1.43
LW Test	-	0.04	0.00	0.04	0.04	0.04	0.02	0.00	0.00	0.03	0.04	0.01	0.04	0.04	0.04	0.04	0.00
Rolling Window: 170M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	5.28	3.92	4.56	4.18	3.94	4.13	4.25	4.36	4.56	4.01	4.17	4.18	3.97	4.15	4.00	4.05	4.10
Std.Dev. (%)	4.81	4.16	4.91	4.26	4.20	4.20	4.45	4.84	4.91	4.40	4.25	4.50	4.24	4.22	4.19	4.20	4.66
Sharpe Ratio	**1.10**	0.94	0.93	0.98	0.94	0.98	0.95	0.90	0.93	0.91	0.98	0.93	0.94	0.98	0.95	0.96	0.88
Sortino Ratio	**1.56**	1.36	1.36	1.44	1.34	1.47	1.40	1.31	1.37	1.32	1.44	1.36	1.36	1.45	1.38	1.41	1.44
CEQ	**4.58**	3.41	3.84	3.63	3.41	3.60	3.66	3.66	3.84	3.43	3.63	3.57	3.43	3.61	3.47	3.52	3.44
Omega Ratio	1.06	1.17	1.08	1.20	1.16	1.20	1.12	1.11	1.08	1.21	1.20	1.06	**1.26**	1.24	1.15	1.18	1.08
Calmar Ratio	**0.69**	0.49	0.51	0.51	0.49	0.52	0.52	0.52	0.51	0.54	0.51	0.52	0.52	0.52	0.49	0.51	0.35
$\mathcal{F}$ (%)	-	0.74	0.81	0.56	0.76	0.55	0.69	0.94	0.81	0.89	0.56	0.81	0.78	0.56	0.70	0.65	1.05
$\mathcal{P}$ (%)	-	0.74	0.80	0.55	0.76	0.54	0.68	0.94	0.80	0.89	0.56	0.81	0.77	0.55	0.69	0.64	1.04
LW Test	-	0.08	0.02	0.10	0.08	0.10	0.06	0.00	0.02	0.04	0.10	0.02	0.07	0.10	0.09	0.09	0.01

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with other popular approaches in practice, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Table 10: Strategic Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$)

	Rolling Window: 180M																
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	4.81	3.26	3.77	3.46	3.26	3.47	3.49	3.71	3.77	3.36	3.46	3.46	3.31	3.46	3.30	3.36	3.37
Std.Dev. (%)	4.75	4.02	4.72	4.10	4.06	4.04	4.28	4.69	4.72	4.26	4.10	4.34	4.10	4.07	4.06	4.05	4.52
Sharpe Ratio	**1.01**	0.81	0.80	0.84	0.80	0.86	0.82	0.79	0.80	0.79	0.84	0.80	0.81	0.85	0.81	0.83	0.75
Sortino Ratio	**1.44**	1.13	1.13	1.20	1.11	1.24	1.15	1.12	1.13	1.11	1.20	1.13	1.14	1.22	1.13	1.17	1.14
CEQ	**4.14**	2.78	3.10	2.96	2.76	2.98	2.94	3.04	3.10	2.81	2.95	2.90	2.81	2.96	2.80	2.87	2.76
Omega Ratio	1.09	1.12	1.00	1.14	1.09	1.18	1.02	1.08	1.00	**1.19**	1.14	1.04	1.17	1.17	1.09	1.13	1.08
Calmar Ratio	**0.62**	0.41	0.44	0.42	0.41	0.44	0.43	0.42	0.44	0.43	0.42	0.43	0.42	0.43	0.41	0.42	0.28
$\mathcal{F}$ (%)	-	0.96	1.02	0.80	1.00	0.73	0.94	1.06	1.02	1.07	0.80	1.02	0.98	0.78	0.96	0.87	1.27
$\mathcal{P}$ (%)	-	0.95	1.01	0.79	1.00	0.73	0.93	1.06	1.01	1.06	0.80	1.02	0.97	0.77	0.95	0.87	1.26
LW Test	-	0.07	0.00	0.09	0.06	0.10	0.02	0.00	0.01	0.02	0.09	0.01	0.04	0.10	0.06	0.08	0.01
	Rolling Window: 190M																
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	4.38	2.81	3.45	2.89	2.79	2.93	3.15	3.41	3.45	3.12	2.89	3.16	2.97	2.90	2.85	2.85	3.04
Std.Dev. (%)	4.72	3.94	4.55	4.01	3.99	3.94	4.13	4.53	4.55	4.09	4.01	4.19	3.99	3.97	3.98	3.97	4.34
Sharpe Ratio	**0.93**	0.71	0.76	0.72	0.70	0.74	0.76	0.75	0.76	0.76	0.72	0.75	0.74	0.73	0.71	0.72	0.70
Sortino Ratio	**1.30**	0.99	1.12	0.99	0.95	1.05	1.09	1.10	1.12	1.11	0.99	1.09	1.06	1.01	0.99	0.99	1.08
CEQ	**3.71**	2.35	2.83	2.41	2.31	2.47	2.64	2.80	2.83	2.62	2.40	2.63	2.49	2.43	2.37	2.38	2.48
Omega Ratio	1.15	1.09	1.00	1.10	1.06	1.14	1.11	1.03	1.00	**1.24**	1.10	1.06	1.18	1.09	1.07	1.12	1.09
Calmar Ratio	**0.58**	0.35	0.40	0.36	0.35	0.37	0.39	0.42	0.40	0.42	0.36	0.39	0.39	0.36	0.35	0.36	0.33
$\mathcal{F}$ (%)	-	1.01	0.80	0.98	1.08	0.87	0.78	0.82	0.80	0.78	0.98	0.82	0.86	0.93	1.01	0.99	1.07
$\mathcal{P}$ (%)	-	1.01	0.79	0.98	1.07	0.86	0.78	0.82	0.79	0.77	0.98	0.81	0.86	0.92	1.00	0.99	1.06
LW Test	-	0.06	0.02	0.05	0.05	0.07	0.05	0.02	0.02	0.07	0.05	0.03	0.07	0.06	0.06	0.06	0.01

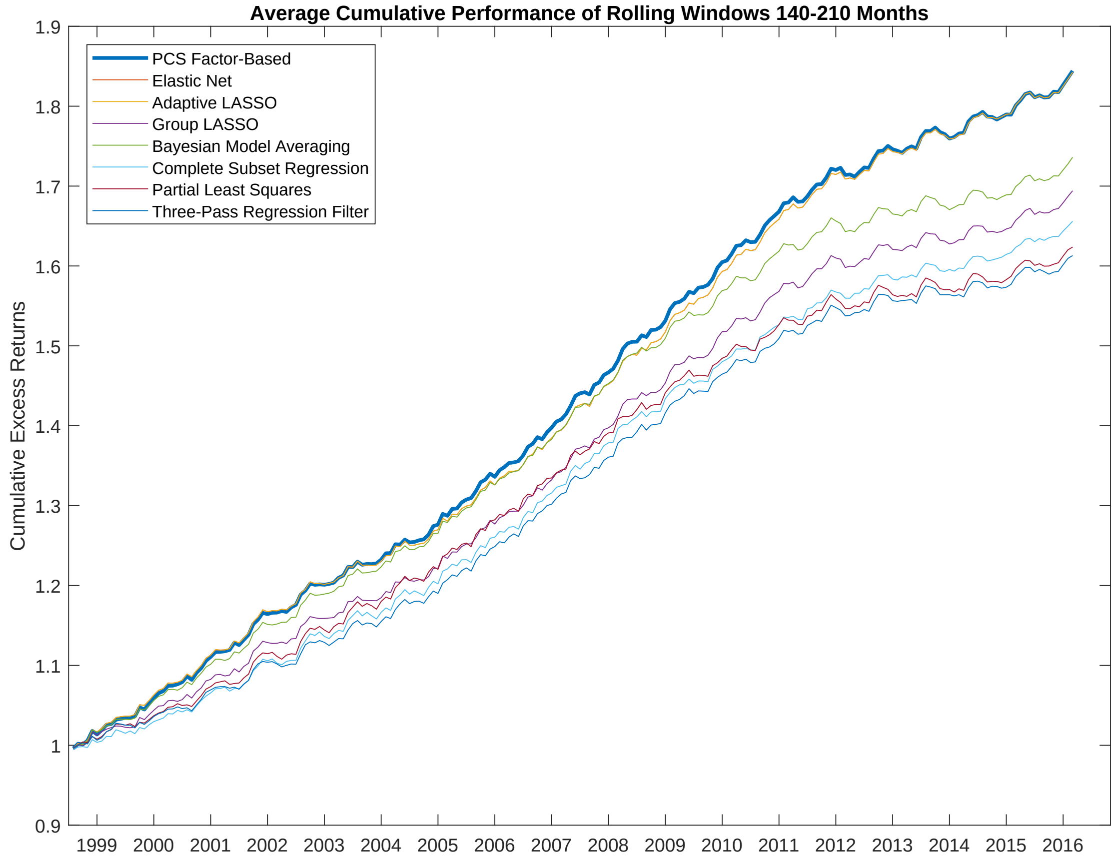
This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with other popular approaches in practice, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Table 11: Strategic Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$)

	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Rolling Window: 200M																	
Mean (%)	4.27	2.79	3.64	2.90	2.76	2.95	3.19	3.52	3.64	3.06	2.90	3.25	2.93	2.93	2.82	2.84	3.45
Std.Dev. (%)	4.70	3.99	4.53	4.03	4.03	3.97	4.14	4.53	4.53	4.09	4.03	4.21	4.01	4.00	4.03	4.01	4.40
Sharpe Ratio	**0.91**	0.70	0.80	0.72	0.69	0.74	0.77	0.78	0.80	0.75	0.72	0.77	0.73	0.73	0.70	0.71	0.78
Sortino Ratio	**1.26**	0.97	1.20	0.99	0.94	1.04	1.11	1.14	1.20	1.08	0.99	1.13	1.03	1.01	0.97	0.98	1.23
CEQ	**3.61**	2.31	3.02	2.41	2.28	2.48	2.68	2.90	3.02	2.56	2.41	2.72	2.44	2.45	2.33	2.36	2.87
Omega Ratio	1.11	1.10	0.97	1.07	1.07	1.11	1.03	1.03	0.97	**1.13**	1.07	1.06	1.10	1.08	1.06	1.11	1.09
Calmar Ratio	**0.58**	0.35	0.41	0.35	0.34	0.37	0.39	0.42	0.41	0.40	0.35	0.40	0.38	0.37	0.35	0.35	0.39
$\mathcal{F}$ (%)	-	0.98	0.50	0.89	1.05	0.78	0.64	0.62	0.50	0.75	0.89	0.63	0.84	0.82	0.98	0.94	0.58
$\mathcal{P}$ (%)	-	0.98	0.49	0.89	1.04	0.77	0.64	0.62	0.49	0.75	0.89	0.63	0.84	0.82	0.98	0.93	0.57
LW Test	-	0.07	0.08	0.07	0.06	0.10	0.09	0.04	0.08	0.08	0.07	0.07	0.08	0.09	0.07	0.07	0.09
Rolling Window: 210M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	4.38	2.79	3.59	2.87	2.76	2.92	3.12	3.54	3.59	2.96	2.87	3.18	2.87	2.90	2.81	2.82	3.57
Std.Dev. (%)	4.73	4.03	4.55	4.08	4.07	4.00	4.18	4.52	4.55	4.13	4.07	4.25	4.06	4.04	4.08	4.05	4.48
Sharpe Ratio	**0.93**	0.69	0.79	0.70	0.68	0.73	0.75	0.78	0.79	0.72	0.70	0.75	0.71	0.72	0.69	0.70	0.80
Sortino Ratio	**1.29**	0.96	1.17	0.96	0.92	1.02	1.07	1.17	1.17	1.04	0.96	1.08	1.00	0.99	0.95	0.96	1.25
CEQ	**3.71**	2.30	2.97	2.37	2.26	2.43	2.59	2.93	2.97	2.44	2.37	2.64	2.38	2.41	2.31	2.33	2.96
Omega Ratio	1.09	1.07	0.97	1.08	1.06	1.10	1.00	1.01	0.97	**1.12**	1.08	1.04	1.14	1.09	1.04	1.07	1.03
Calmar Ratio	**0.61**	0.35	0.41	0.35	0.34	0.36	0.38	0.43	0.41	0.38	0.35	0.39	0.36	0.36	0.35	0.35	0.41
$\mathcal{F}$ (%)	-	1.11	0.65	1.05	1.18	0.94	0.85	0.67	0.65	1.00	1.05	0.84	1.03	0.99	1.12	1.09	0.62
$\mathcal{P}$ (%)	-	1.11	0.65	1.05	1.18	0.93	0.85	0.67	0.65	0.99	1.05	0.84	1.03	0.99	1.12	1.08	0.61
LW Test	-	0.05	0.04	0.04	0.04	0.06	0.04	0.03	0.04	0.03	0.04	0.02	0.04	0.05	0.04	0.04	0.09

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with other popular approaches in practice, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p - value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Figure 3: Tactical Asset Allocation: Out-of-Sample Performance of Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$ and $w_\zeta = 0.95$)



This figure shows the cumulative average performance (excess returns after transaction costs) of currency factor-investing portfolio strategies across different rolling-window lengths spanning 2-3 business cycles (according to NBER), and using various forecasting methods on the residuals from the asset pricing tests, including Zou and Hastie (2005) elastic net (EN), Zou (2006) adaptive LASSO ($A - LASSO$), group LASSO ($G - LASSO$) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples), Raftery, Madigan, and Hoeting (1997) Bayesian model averaging (BMA), Elliott, Gargano, and Timmermann (2013) complete subset regression (CSR), partial least squares (PLS) (see Light, Maslov, and Rytchkov, 2017, for the application on stock markets), Kelly and Pruitt (2015) three-pass regression filter (TPF). The out-of-sample period is from August 1998 to March 2016. All series are adjusted to the same risk profile as the factor-based portfolio strategy, in terms of portfolio volatility, for comparison.

Table 12: Tactical Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$ and $w_\zeta = 0.95$)

	Rolling Window: 140M								Rolling Window: 150M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	4.37	4.45	4.45	4.04	4.44	4.59	4.95	4.85	4.64	4.79	4.78	4.43	4.63	4.45	4.38	3.87
Std.Dev. (%)	4.89	4.96	4.96	5.48	5.53	6.66	7.07	6.91	4.86	5.01	5.01	5.49	5.49	6.61	6.93	6.82
Sharpe Ratio	0.89	**0.90**	**0.90**	0.74	0.80	0.69	0.70	0.70	**0.96**	0.95	0.95	0.81	0.84	0.67	0.63	0.57
Sortino Ratio	**1.26**	1.25	1.25	0.99	1.08	0.98	1.00	1.01	**1.37**	**1.37**	**1.37**	1.06	1.14	0.98	0.91	0.81
CEQ	3.65	**3.71**	**3.71**	3.14	3.53	3.26	3.45	3.42	3.94	**4.03**	**4.03**	3.53	3.72	3.14	2.94	2.47
Omega Ratio	**1.07**	1.00	1.00	0.93	1.01	1.01	0.99	1.04	**1.07**	**1.07**	1.06	0.96	1.06	0.90	0.96	0.96
Calmar Ratio	0.39	**0.41**	**0.41**	0.23	0.31	0.25	0.30	0.32	**0.59**	0.52	0.52	0.34	0.31	0.26	0.26	0.26
$\mathcal{F}$ (%)	-	-0.02	-0.02	0.77	0.44	1.00	0.94	0.94	-	0.01	0.01	0.72	0.55	1.37	1.57	1.89
$\mathcal{P}$ (%)	-	-0.02	-0.02	0.77	0.44	0.99	0.94	0.93	-	0.01	0.01	0.72	0.55	1.36	1.56	1.87
LW Test	-	0.55	0.55	0.02	0.10	0.09	0.10	0.10	-	0.49	0.48	0.03	0.05	0.03	0.02	0.01
	Rolling Window: 160M								Rolling Window: 170M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	5.05	5.21	5.22	4.66	5.03	4.94	4.60	3.91	5.28	5.56	5.55	5.05	5.45	5.15	5.31	4.86
Std.Dev. (%)	4.80	5.03	5.03	5.55	5.53	6.70	6.88	6.80	4.81	5.00	5.00	5.35	5.31	6.47	6.66	6.65
Sharpe Ratio	**1.05**	1.03	1.04	0.84	0.91	0.74	0.67	0.58	1.10	**1.11**	**1.11**	0.95	1.03	0.80	0.80	0.73
Sortino Ratio	**1.53**	1.51	1.51	1.12	1.24	1.02	0.93	0.80	1.56	**1.58**	**1.58**	1.28	1.46	1.19	1.13	1.04
CEQ	4.36	**4.45**	**4.46**	3.74	4.12	3.60	3.18	2.52	4.58	**4.81**	4.80	4.20	4.61	3.89	3.98	3.54
Omega Ratio	1.06	**1.08**	**1.08**	0.93	1.07	0.97	0.99	0.97	1.06	1.05	1.05	1.00	**1.10**	1.04	1.03	1.03
Calmar Ratio	**0.65**	0.64	0.64	0.33	0.34	0.26	0.32	0.25	**0.69**	**0.69**	**0.69**	0.38	0.44	0.43	0.43	0.37
$\mathcal{F}$ (%)	-	0.09	0.08	1.02	0.68	1.52	1.85	2.30	-	-0.07	-0.06	0.73	0.34	1.45	1.45	1.76
$\mathcal{P}$ (%)	-	0.09	0.08	1.03	0.69	1.51	1.84	2.28	-	-0.07	-0.06	0.74	0.34	1.43	1.44	1.75
LW Test	-	0.29	0.31	0.01	0.03	0.02	0.01	0.00	-	0.72	0.70	0.01	0.10	0.02	0.03	0.01

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with an overlay of predicted regressions on the short-run deviations from expected returns using various forecasting methods on the residuals from the asset pricing tests, including Zou and Hastie (2005) elastic net (EN), Zou (2006) adaptive LASSO (AL), group LASSO (GL) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples), Raftery, Madigan, and Hoeting (1997) Bayesian model averaging (BMA), Elliott, Gargano, and Timmermann (2013) complete subset regression (CSR), partial least squares (PLS) (see Light, Maslov, and Rytchkov, 2017, for the application on stock markets), Kelly and Pruitt (2015) three-pass regression filter (TPF). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Table 13: Tactical Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$ and $w_\zeta = 0.95$)

	Rolling Window: 180M								Rolling Window: 190M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	4.81	5.04	5.04	4.28	4.63	4.96	4.45	4.38	4.38	4.68	4.67	3.86	4.24	4.56	4.18	4.25
Std.Dev. (%)	4.75	4.86	4.86	5.21	5.08	5.80	6.28	6.09	4.72	4.86	4.86	5.25	5.18	5.70	6.13	6.09
Sharpe Ratio	1.01	**1.04**	**1.04**	0.82	0.91	0.86	0.71	0.72	0.93	**0.96**	**0.96**	0.74	0.82	0.80	0.68	0.70
Sortino Ratio	1.44	**1.48**	**1.48**	1.14	1.31	1.30	1.08	1.10	1.30	**1.35**	**1.35**	0.99	1.13	1.21	0.97	1.03
CEQ	4.14	**4.33**	**4.33**	3.47	3.85	3.95	3.27	3.26	3.71	**3.97**	**3.97**	3.03	3.44	3.58	3.05	3.14
Omega Ratio	1.09	1.05	1.05	1.02	1.05	**1.13**	1.07	1.04	1.15	**1.18**	**1.18**	1.03	1.08	1.06	1.05	1.09
Calmar Ratio	0.62	**0.66**	**0.66**	0.34	0.40	0.46	0.47	0.36	0.58	**0.61**	**0.61**	0.29	0.33	0.41	0.40	0.35
$\mathcal{F}$ (%)	-	-0.11	-0.11	0.90	0.49	0.75	1.44	1.40	-	-0.16	-0.16	0.91	0.51	0.61	1.16	1.08
$\mathcal{P}$ (%)	-	-0.11	-0.11	0.90	0.48	0.74	1.43	1.38	-	-0.16	-0.16	0.91	0.51	0.60	1.15	1.07
LW Test	-	0.91	0.91	0.00	0.04	0.08	0.03	0.04	-	0.95	0.95	0.01	0.06	0.10	0.07	0.08
	Rolling Window: 200M								Rolling Window: 210M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	4.27	4.47	4.47	3.70	4.13	5.02	4.72	5.06	4.38	4.53	4.53	3.92	4.13	5.21	4.72	4.85
Std.Dev. (%)	4.70	4.82	4.82	5.21	5.09	5.57	5.97	5.98	4.73	4.86	4.86	5.26	5.17	5.52	5.89	5.88
Sharpe Ratio	0.91	**0.93**	**0.93**	0.71	0.81	0.90	0.79	0.85	0.93	0.93	0.93	0.74	0.80	**0.94**	0.80	0.82
Sortino Ratio	1.26	1.29	1.29	0.93	1.13	**1.36**	1.13	1.29	1.29	1.30	1.30	1.01	1.10	**1.41**	1.19	1.22
CEQ	3.61	3.77	3.77	2.89	3.35	**4.09**	3.65	3.98	3.71	3.83	3.83	3.09	3.33	**4.29**	3.68	3.81
Omega Ratio	1.11	**1.14**	**1.14**	1.01	1.03	1.06	1.06	1.13	1.09	**1.12**	**1.12**	0.98	1.04	1.11	1.08	1.01
Calmar Ratio	**0.58**	**0.58**	**0.58**	0.27	0.33	0.56	0.48	0.46	0.61	**0.62**	**0.62**	0.30	0.32	0.60	0.47	0.43
$\mathcal{F}$ (%)	-	-0.09	-0.09	0.93	0.46	0.03	0.55	0.30	-	-0.03	-0.03	0.86	0.60	-0.08	0.60	0.48
$\mathcal{P}$ (%)	-	-0.09	-0.09	0.93	0.46	0.03	0.55	0.28	-	-0.03	-0.03	0.86	0.60	-0.08	0.59	0.47
LW Test	-	0.83	0.84	0.01	0.09	0.48	0.09	0.10	-	0.65	0.65	0.02	0.06	0.55	0.09	0.10

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with an overlay of predicted regressions on the short-run deviations from expected returns using various forecasting methods on the residuals from the asset pricing tests, including Zou and Hastie (2005) elastic net (EN), Zou (2006) adaptive LASSO (AL), group LASSO (GL) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples), Raftery, Madigan, and Hoeting (1997) Bayesian model averaging (BMA), Elliott, Gargano, and Timmermann (2013) complete subset regression (CSR), partial least squares (PLS) (see Light, Maslov, and Rytchkov, 2017, for the application on stock markets), Kelly and Pruitt (2015) three-pass regression filter (TPF). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Appendix

to

"Currency Portfolio Selection with Factors: Additive Gradients and Model Sparsity in a Data-Rich Environment"

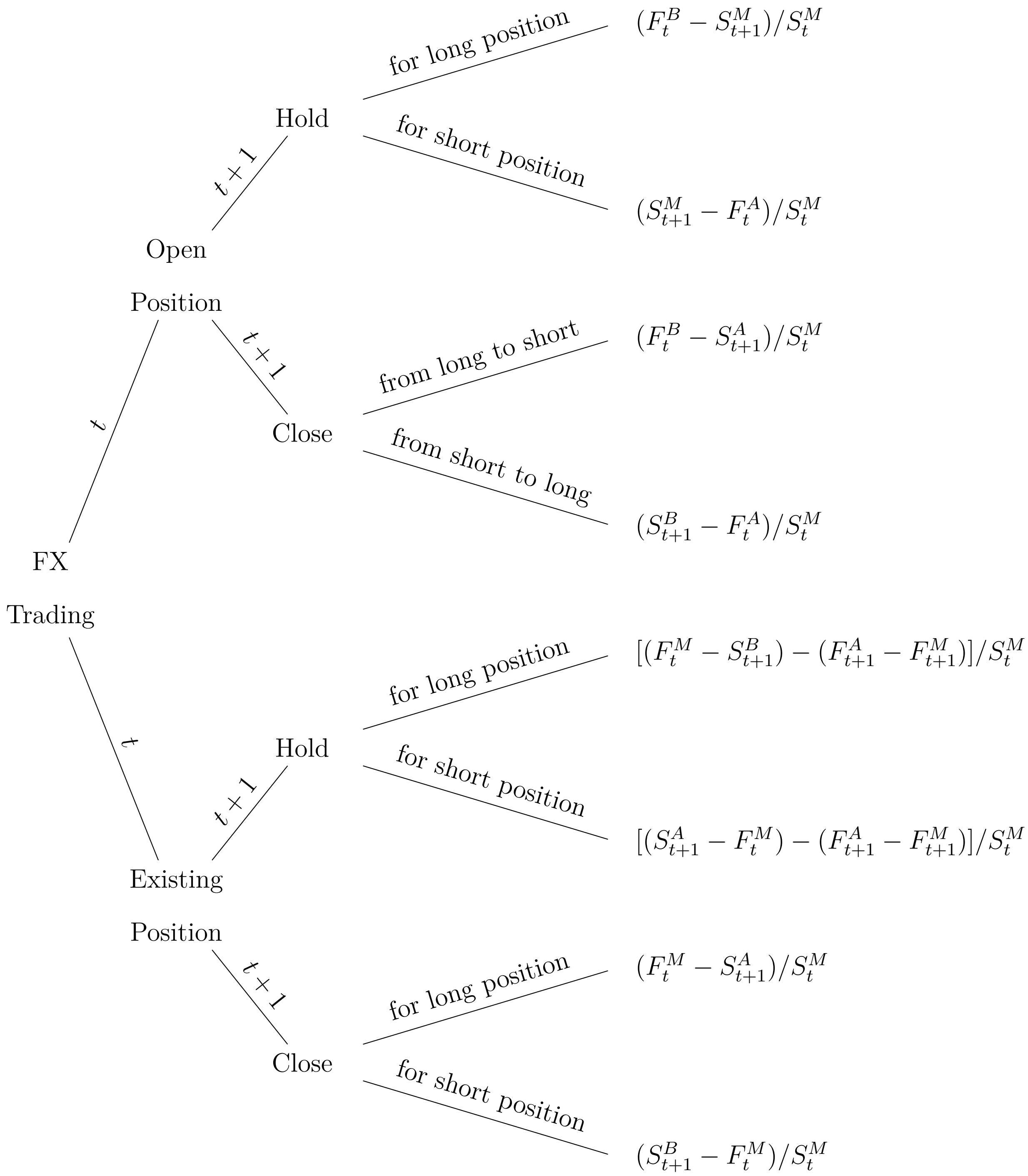
A Data Screening

Following Lustig, Roussanov, and Verdelhan (2011), Burnside, Eichenbaum, and Rebelo (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), Menkhoff, Sarno, Schmeling, and Schrimpf (2012b), Menkhoff, Sarno, Schmeling, and Schrimpf (2017), we compute the excess returns of holding a currency in USD on the last trading day of a month, i.e., the end-of-month data, not averaged over a month. Some countries are removed from our data sample as the reason of exchange rate regime, such as China (CNY), whose exchange rate is actively intervened as it has massive foreign reserves. We also exclude the currencies from the sample that largely deviate from CIP and/or have tradeability issues for the following periods: AED from July 2006 to November 2006; ARS from September 2008 to April 2009, and from May 2012 to June 2014; EGP from November 2011 to August 2013; IDR from August 1997 to May 2007; MYR from May 1998 to June 2005; RUB from December 2008 to January 2009; TRY from November 2000 to February 2004; and ZAR for August 1985, and from the January 2002 to May 2005. Since 1 January 1999, the Euro became the common currency of 11 member states (Austria, Belgium, France, Finland, Germany, Italy, Ireland, Luxembourg, Netherlands, Portugal, and Spain) of the European Union, and other EU states follow their steps to join the eurozone: Greece on 1 January 2001, Slovenia on 1 January 2007, Cyprus and Malta on 1 January 2008, Slovakia on 1 January 2009, Estonia on 1 January 2011, Latvia on 1 January 2014, and Lithuania on 1 January 2015.

We download the BBI USD quotes from December 1983 to November 1996, and WMR USD quotes are adopted as soon as they are available from December 1996. Following Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), we convert the WMR GBP quotes from January 1976 to November 1983 into USD quotes using the WMR USD/GBP exchange rates. Forward rate and bid-ask spread quotes for AUD and NZD from January 1976 to November 1983, and for JPY from January 1976 to June 1978 are not available. We calculate synthetic forward rates implied by the interest rate differentials using Covered Interest Rate Parity (CIP) (Campbell, Serfaty-de Medeiros, and Viceira, 2010) and also the bid-ask spreads using the largest spreads in the remaining G10 currencies (see Kroencke, Schindler, and Schrimpf, 2014). After that, we obtain a complete sample of G10 currencies.

B Transaction Costs

Transaction costs vary across time and currency pairs, and those of new position are much bigger than thoes of a rolled over position in currency markets. Therefore, we distinguish opening a new position from rolling an existing position over in calculating the excess returns. Following the procedure of Darvas (2009), we adjust the position excess returns for transaction costs that the investors pay an entire spot market spread and a half swap point spread for opening and closing a position, while a half swap point spread for the rollover of a position. Then the position excess returns vary across the following four scenarios:



where superscripts B, M, and A denote bid price, middle price, and ask price, respectively. Any change in portfolio weight of a currency is taken into account for transaction costs.

C Linear Factor Model

Under no-arbitrage condition, currency excess (risk-adjusted) returns must have a zero price and satisfy the benchmark asset pricing Euler equation (Cochrane, 2005):

$$\mathbb{E}_t[M_{t+1} \cdot r^{\mathrm{e}}_{t+1}] = 0 \tag{14}$$

where M_{t+1} is a linear stochastic discount factor (SDF). r^{e}_{t+1} denotes excess returns of portfolios at time $t+1$. And $\mathbb{E}_t[\,\cdot\,]$ is the mathematical expectations operator with the information available at time t. Applying the law of iterated expectations to Equation (14), we obtain the corresponding version with the unconditional moment restriction:

$$\mathbb{E}[M_t \cdot r^{\mathrm{e}}_t] = 0 \tag{15}$$

The linear SDF takes a form of:

$$M_t = \xi \cdot \left[1 - (f_t - \mu)^\top b\right] \tag{16}$$

where ξ is a scalar, f_t is a $N \times 1$ vector of risk factors, $\mu = \mathbb{E}[f_t]$, and b is a $N \times 1$ vector of factor loadings. Because ξ is not identified by Equation (16), we set $\xi = 1$, implying $\mathbb{E}[m_t] = 1$. Given this assumption, we rearrange Equation (15) with Equation (16):

$$\mathbb{E}[r^{\mathrm{e}}_t] = \mathrm{cov}[r^{\mathrm{e}}_t \cdot {f_t}^\top] \cdot b \tag{17}$$

or equivalently

$$\mathbb{E}[r^{\mathrm{e}}_t] = \underbrace{\mathrm{cov}[r^{\mathrm{e}}_t, f^\top_t]\, \Sigma^{-1}_{f,f}}_{\beta} \cdot \underbrace{\Sigma_{f,f}\, b}_{\lambda} \tag{18}$$

where $\Sigma_{f,f} = \mathbb{E}[(f_t - \mu)(f_t - \mu)^\top]$. Equation (18) is the beta representation of the asset pricing model in Equation (17). β_j is the coefficient that regress r^{e}_t on f and it measures the exposures of payoff to N risk factors. λ is a $N \times 1$ vector of factor prices associated with the tested risk factors, and λ is not portfolio-specific.

D Estimations of Factor Model

We reply 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).

D.1 Generalized Method of Moments

The parameters of the SDF — b and μ are estimated by GMM. We rearrange Equation (15) with Equation (16):

$$\mathbb{E}\{r_t^{\mathrm{e}} \cdot [\,1 - (f_t - \mu)^\top\, b\,]\} = 0 \tag{19}$$

The GMM estimator of μ is essentially a vector of the sample mean of risk factors $\overline{f}$. While factor loading matrix b is calculated as:

$$\hat{b} = \left(\hat{\Sigma}_{f,r^{\mathrm{e}}}^\top\, W_T\, \hat{\Sigma}_{f,r^{\mathrm{e}}}\right)^{-1} \hat{\Sigma}_{f,r^{\mathrm{e}}}^\top\, W_T\, \overline{r^{\mathrm{e}}} \tag{20}$$

where $\overline{xr}$ is the sample mean of excess returns, $\hat{\Sigma}_{f,r^{\mathrm{e}}}$ is the sample covariance matrix between r_t^{e} and f_t, W_T is a weighting matrix. The vector of factor prices λ is given by $\hat{\lambda} = \hat{\Sigma}_{f,f}\, \hat{b}$, where $\hat{\Sigma}_{f,f} = \mathbb{E}[(f_t - \mu)(f_t - \mu)^\top]$ is the factor covariance matrix. We also include an additional set of corresponding moment restrictions on the factor mean vector and factor covariance matrix as in Burnside (2011):

$$g(\phi_t, \theta) = \begin{bmatrix} r_t^{\mathrm{e}} \cdot [\,1 - (f_t - \mu)^\top\, b\,] \\ \\ f_t - \mu \\ \\ (f_t - \mu)(f_t - \mu)^\top - \Sigma_{f,f} \end{bmatrix} = 0 \tag{21}$$

where the vector θ contains the parameters $(b, \mu, \Sigma_{f,f})$, ϕ_t denotes the data of (r^{e}_t, f_t). The estimation uncertainty[10] is thus incorporated in the standard errors of λ via exploiting the moment restrictions of $\mathbb{E}[g(\phi_t, \theta)] = 0$ as in Equation (21), and this point-estimation method is identical to that of Fama-MacBeth two-pass OLS approach (see Burnside, 2011, for details). Based on the VARHAC procedure as in Newey and West (1987) and the data-driven approach of optimal lag selection with a Bartlett kernel of Andrews (1991), we compute the standard errors. The weighting matrix is set to be identical matrix, i.e., $W_T = I_n$, in the first stage of GMM estimator, while W_T is chosen optimally in the next stage. We only report the empirical results from the first stage and the iterate-to-convergence GMM estimators.

D.2 Fama-MacBeth Approach

we further report the empirical results from the FMB two-step estimator. The first step is a time-series one, regressing the excess returns of each portfolios on proposed risk factors to acquire corresponding risk exposures:

$$r^{\mathrm{e}}_{j,t} = \alpha_j + \sum_{n=1}^{N} \beta_{j,n} \cdot f_{t,n} + \varepsilon_{j,t} \tag{22}$$

where $\varepsilon_{j,t}$ is $i.i.d.$ $\mathcal{N}(0, \sigma_j^2)$ for $j = 1, \cdots, J$ portfolios. The second step is a cross-sectional one, regressing the average excess returns across all portfolios on the estimated betas from the first step to obtain the risk prices:

$$\overline{r^{\mathrm{e}}_j} = \sum_{n=1}^{N} \hat{\beta}_{j,n} \cdot \hat{\lambda}_n \tag{23}$$

As pointed out by Burnside (2011), Lustig, Roussanov, and Verdelhan (2011), *DOL* should serve as a constant in order to allow for a common mispricing term. Thereby, we do not need to include a constant in the second step of the FMB. The estimates of the risk prices from FMB should be numerically identical to those estimated by the GMM.

[10] It is because the factor mean vector and covariance matrix have to be estimated.

Besides the HAC standard errors of Newey and West (1987) with automatic lag length selection using the procedure of Andrews (1991), we also report the standard errors that are adjusted for measurement errors as in Shanken (1992).

The predicted expected excess returns by the model is therefore given by $\hat{\Sigma}_{f,r^e}\,\hat{b}$, and accordingly, the pricing errors (or model residuals) $\hat{\varepsilon} = \overline{r^e} - \hat{\Sigma}_{f,r^e}\,\hat{b}$. $T\,\hat{\varepsilon}^\top\,V_T^{-1}\,\hat{\varepsilon}$ as a statistic for over-identifying restrictions can then be computed so as to test the null hypothesis of jointly zero pricing errors across all portfolios, where T is the sample size, V_T is a consistent estimate of asymptotic covariance matrix of $\sqrt{T}\,\hat{\varepsilon}$ with its generalized inverse form. The test statistic follows an asymptotic distribution of χ^2 with $n-k$ degrees of freedom. The corresponding $p-values$ based on both Shanken (1992) adjustment and Newey and West (1987) approach for the FMB procedure are reported, and we adopt simulation-based $p-values$ for the Hansen-Jagannathan (Hansen and Jagannathan, 1997) distance ($HJ-dist$) test[11] for the GMM procedure. The cross-sectional R^2 and Mean Absolute Pricing Errors (MAPE) are presented as well. To be cautious as stressed by Cochrane (2005), we should look at the null hypothesis test $b = 0$ rather than $\lambda = 0$ to determine whether or not to include the factor given other factors, in case that the factors in use could be highly correlated. A factor is said to be useful to price the tested assets if factor loading b is statistically different from zero, while statistical significance of factor price λ only tells whether the corresponding factor is priced or not, and whether its factor-mimicking portfolio carries a positive or negative risk premium.

[11] Hansen-Jagannathan (Hansen and Jagannathan, 1997) distance provides a least-square distance between the tested pricing kernel and the closest pricing kernel among a set of possible pricing kernels that price the tested assets without model mis-specification. It is calculated by a weighted sum of random variables that follow a χ^2 distribution. See Jagannathan and Wang (1996), Parker and Julliard (2005) for more details.

E Portfolio Optimizers

E.1 Naive Diversification ($1/N$)

Naive diversification is to equally allocate capital among assets $\omega_{\mathrm{nd}} = \vec{1}_N/N$, which is a portfolio strategy without parameter estimates or portfolio optimizations, and hence it is free of estimation errors. $\vec{1}_N$ is a $N \times 1$ vector of ones.

E.2 Standard Markowitz Mean-Variance

Markowitz mean-variance optimization maximizes a quadratic utility function:

$$\max_{\tilde{\omega}_{\mathrm{mkw}}} U(\tilde{\omega}_{\mathrm{mkw}}) = \tilde{\omega}_{\mathrm{mkw}}^{\top}\mu_r - \frac{\gamma}{2}\tilde{\omega}_{\mathrm{mkw}}^{\top}\Sigma_r\tilde{\omega} \qquad s.t.\ \ \vec{1}_N^{\top}\tilde{\omega}_{\mathrm{mkw}} = 1 \tag{24}$$

where γ denotes the risk-aversion coefficient, μ_r is the expected returns, Σ_r is the expected covariance matrix of asset returns. The closed-form solution of an optimal portfolio to the above problem can be easily computed as $\tilde{\omega}_{\mathrm{mkw}}^{\top} = \frac{\Sigma_r^{-1}\mu_r}{\gamma}$. The normalized optimal portfolio weights are:

$$\omega_{\mathrm{mkw}} = \frac{\hat{\Sigma}_r^{-1}\hat{\mu}_r}{\vec{1}_N^{\top}\hat{\Sigma}_r^{-1}\hat{\mu}_r} \tag{25}$$

E.3 Minimum Variance

A minimum-variance portfolio is characterized by a set of portfolio weights that find the ex-ante global minimum variance on the efficient frontier.

$$\min_{\tilde{\omega}_{\mathrm{mv}}} \tilde{\omega}_{\mathrm{mv}}^{\top}\Sigma_r\tilde{\omega}_{\mathrm{mv}} \qquad s.t.\ \ \vec{1}_N^{\top}\tilde{\omega}_{\mathrm{mv}} = 1 \tag{26}$$

The normalized portfolio weights of the closed-form solution to the above problem $\tilde{\omega}_{\mathrm{mv}} \propto \Sigma_r^{-1}\vec{1}_N$ are then given by:

$$\omega_{\mathrm{mv}} = \frac{\hat{\Sigma}_r^{-1}\vec{1}_N}{\vec{1}_N^{\top}\hat{\Sigma}_r^{-1}\vec{1}_N} \tag{27}$$

E.4 Volatility Timing/Targeting

A volatility-timing/targeting portfolio ignores the correlations among asset returns and thereby the portfolio weights are given by (see Dachraoui, 2018; Harvey, Hoyle, Korgaonkar, Rattray, Sargaison, and Van Hemert, 2018, for discussions):

$$\omega_{\text{vt}} = \frac{\hat{\sigma}_r^{-1}}{\vec{1}_N^\top \hat{\sigma}_r^{-1}} \tag{28}$$

where σ_r is the volatility vector of asset returns.

E.5 Maximum Decorrelation

A maximum-decorrelated portfolio is equivalent to the global minimum-variance portfolio under the assumptions of equal expected returns and volatilities across all assets:

$$\omega_{\text{mdc}} = \frac{\hat{\Omega}_r^{-1} \vec{1}_N}{\vec{1}_N^\top \hat{\Omega}_r^{-1} \vec{1}_N} \tag{29}$$

where Ω_r is the correlation matrix of asset returns.

E.6 Maximum Diversification

A maximum-diversified portfolio maximizes (see Choueifaty and Coignard, 2008; Clarke, De Silva, and Thorley, 2013, for details):

$$\max_{\omega_{\text{md}}} \frac{\omega_{\text{md}}^\top \sigma_r}{\omega_{\text{md}}^\top \Sigma_r \omega_{\text{md}}} \qquad s.t. \;\; \vec{1}_N^\top \omega_{\text{md}} = 1 \tag{30}$$

E.7 Risk Parity

A risk-parity portfolio equates the product of the portfolio weight and corresponding marginal risk contribution of each asset:

$$\omega_i^\top \odot \frac{\omega^\top \Sigma_r}{\omega^\top \Sigma_r \omega} \qquad \text{for} \;\; i = 1, 2, \cdots, N \tag{31}$$

which can be transform into the optimization problem below:

$$\max_{\omega_{\text{rp}}} \sum_{i=1}^{N} \log(|\omega_{i,\text{rp}}|) \qquad s.t. \ \sqrt{(\omega_{\text{rp}}^\top \Sigma_r \omega_{\text{rp}})} \leq \bar{\sigma}_p, \ \ \vec{1}_N^\top \omega_{\text{rp}} = 1 \ \text{ and } \ 0 \leq \omega_{\text{rp}} \leq 1 \tag{32}$$

where $\bar{\sigma}_p$ is the target portfolio volatility. Solving the Lagrangian of this portfolio optimisation problem achieves the aforementioned risk-parity objective.

E.8 Equal Risk Contribution

An equal risk-contribution portfolio equates the marginal risk contribution (ERC) which does not offer a closed-form solution. Maillard, Roncalli, and Teïletche (2008) provide a numerical solution to the ERC problem as follows:

$$\min_{\omega_{\text{erc}}} \sum_{i=1}^{N} \sum_{j=1}^{N} [\omega_{i,\text{erc}}(\Sigma_r \omega_{\text{erc}})_i - \omega_{j,\text{erc}}(\Sigma_r \omega_{\text{erc}})_j]^2 \qquad s.t. \ \vec{1}_N^\top \omega_{\text{erc}} = 1 \ \text{ and } \ 0 \leq \omega_{\text{erc}} \leq 1 \tag{33}$$

It basically minimizes the variance of re-scaled marginal risk contributions.

E.9 Bayes-Stein Shrinkage Method

This Bayes-Stein shrinkage method estimates the expected returns and covariance matrix as follows (see Jorion, 1986):

$$\hat{\mu}_r^{\text{bs}} = \left(1 - \hat{\delta}\right) \hat{\mu}_r + \hat{\delta} \hat{\mu}_r^{\text{mv}} \vec{1}_N \tag{34}$$

$$\hat{\Sigma}_r^{\text{bs}} = \left(1 + \frac{1}{T + \hat{\tau}}\right) \hat{\Sigma}_r + \frac{\hat{\tau}}{T(T + 1 + \hat{\tau})} \frac{\vec{1}_N \vec{1}_N^\top}{\vec{1}_N^\top \hat{\Sigma}_r^{-1} \vec{1}_N} \tag{35}$$

where

$$\hat{\tau} = \frac{T \hat{\sigma}_r}{1 - \hat{\sigma}_r} \tag{36}$$

$$\hat{\delta} = \frac{N + 2}{N + 2 + T(\hat{\mu}_r - \hat{\mu}_r^{\text{mv}})^\top \hat{\Sigma}_r^{-1} (\hat{\mu}_r - \hat{\mu}_r^{\text{mv}})} \tag{37}$$

It shrinks sample mean $\hat{\mu}_r$ towards the return to the global minimum-variance portfolio $\hat{\mu}_r^{\text{mv}}$. $\hat{\mu}_r^{\text{bs}}$ and $\hat{\Sigma}_r^{\text{bs}}$ are then plugged into the Equation (25) to compute portfolio weights:

$$\omega_{\text{bs}} = \frac{\left(\hat{\Sigma}_r^{\text{bs}}\right)^{-1} \hat{\mu}_r^{\text{bs}}}{\vec{1}_N^\top \left(\hat{\Sigma}_r^{\text{bs}}\right)^{-1} \hat{\mu}_r^{\text{bs}}} \tag{38}$$

E.10 Tangency Portfolio

MacKinlay and Pástor (2000) assume an exact but unobservable factor structure[12] in the asset returns, which implies a restriction in between mispicing and residual covariance matrix that is exploitable in order to improve portfolio selection problem:

$$r_t = \alpha + \nu_t \tag{39}$$

$$\Sigma_r = \alpha\alpha^\top \frac{1}{\mathcal{SR}_m^2} + \sigma_\nu^2 I_N \tag{40}$$

where α captures the mispricing, ν_t denotes unobservable factor(s), and $\mathcal{SR}_m$ is the Sharpe ratio of the market portfolio (e.g., a strong belief in CAPM). Then the portfolio weights of the tangency portfolio are derived analytically:

$$\omega_{\text{tp}} = \frac{\hat{\mu}_r}{\vec{1}_N^\top \hat{\mu}_r} \tag{41}$$

E.11 Bayesian Data-and-Model Method

Pástor (2000), Pástor and Stambaugh (2000) suggest a Bayesian data-and-model method that allows investors to combine information from sample data with their beliefs in asset pricing models, from which the asset returns are generated, such as CAPM. Wang (2005) demonstrates that the Bayesian estimator of expected returns and covariance

[12] They also show that the benefits of relaxing this strict assumption are small due to the fact that model misspecification may still exist.

matrix can be written as follows:

$$\hat{\mu}_r^{\mathrm{dm}} = \hat{\delta}\bar{\beta}\hat{\mu}_m + \left(1 - \hat{\delta}\right)\hat{\mu}_r \tag{42}$$

$$\Sigma_r^{\mathrm{dm}} = \frac{T+1}{T-3}\tilde{\beta}\tilde{\beta}^\top \hat{\sigma}_m^2 + \frac{T}{T-N-2}\left[\hat{\delta}\bar{\rho} + \left(1-\hat{\delta}\right)\hat{\rho}\right]\left[\hat{\delta}\bar{\Sigma}_\varepsilon + \left(1-\hat{\delta}\right)\hat{\Sigma}_\varepsilon\right] \tag{43}$$

where

$$\hat{\delta} = \frac{1}{1 + \left[T\tau / \left(1 + \widehat{\mathcal{SR}}_m^2\right)\right]} \tag{44}$$

$$\tilde{\beta} = \hat{\delta}\bar{\beta} + \left(1-\hat{\delta}\right)\hat{\beta} \tag{45}$$

$$\bar{\rho} = \frac{T(T-2)+1}{T(T-3)} - \frac{4\widehat{\mathcal{SR}}_m^2}{T(T-3)\left(1+\widehat{\mathcal{SR}}_m^2\right)} \tag{46}$$

$$\hat{\rho} = \frac{(T-2)(T+1)}{T(T-3)} \tag{47}$$

$\left(\bar{\beta}\bar{\Sigma}_\varepsilon\right)$ and $\left(\hat{\beta}, \hat{\Sigma}_\varepsilon\right)$ represent the maximum likelihood estimates of $(\beta, \Sigma_\varepsilon)$ without and with a constant, respectively; τ measures the degrees of beliefs in terms of a total weight attached to alternative models other than CAPM. It shrinks sample mean $\hat{\mu}_r$ towards $\bar{\beta}\hat{\mu}_m$. $\hat{\mu}_r^{\mathrm{dm}}$ and $\hat{\Sigma}_r^{\mathrm{dm}}$ are then plugged into Equation (25) to compute portfolio weights:

$$\omega_{\mathrm{dm}} = \frac{\left(\hat{\Sigma}_r^{\mathrm{dm}}\right)^{-1}\hat{\mu}_r^{\mathrm{dm}}}{\vec{1}_N^\top \left(\hat{\Sigma}_r^{\mathrm{dm}}\right)^{-1}\hat{\mu}_r^{\mathrm{dm}}} \tag{48}$$

E.12 Multi-Prior Max-Min Approach

By introducing additional constraints in standard Markowitz mean-variance optimization, Garlappi, Uppal, and Wang (2007) propose a multi-prior max-min approach that explicitly accounts for estimation errors in expected returns μ_r, assuming that investors are averse to ambiguity and that uncertainty in the measurement of covariance matrix

Σ_r is negligible:

$$\max_{\tilde{\omega}_{\text{mm}}} \min_{\mu_r} \; U(\tilde{\omega}_{\text{mm}}) = \tilde{\omega}_{\text{mm}}^\top \mu_r - \frac{\gamma}{2} \tilde{\omega}_{\text{mm}}^\top \Sigma_r \tilde{\omega}_{\text{mm}} \qquad s.t. \;\; \vec{1}_N^\top \tilde{\omega}_{\text{mm}} = 1 \;\text{ and }\; f(\mu_r, \hat{\mu}_r, \Sigma_r) \leq \epsilon \tag{49}$$

where ϵ in the second constraint may be understood as the product of common ambiguity aversion across assets and asset-specific ambiguity. When normalizing the degree of ambiguity aversion to 1, we can interpret ϵ as the confidence interval if we restrict the priors to be Gaussian. Instead of specifying the confidence intervals individually, we choose to handle them jointly. Then the max-min problem in Equation (49) is equivalent to the following maximization problem:

$$\max_{\tilde{\omega}_{\text{mm}}} \; U(\tilde{\omega}_{\text{mm}}) = \tilde{\omega}_{\text{mm}}^\top \hat{\mu}_r - \frac{\gamma}{2} \tilde{\omega}_{\text{mm}}^\top \hat{\Sigma}_r \tilde{\omega}_{\text{mm}} - \sqrt{\varepsilon \tilde{\omega}_{\text{mm}}^\top \hat{\Sigma}_r \tilde{\omega}_{\text{mm}}} \qquad s.t. \;\; \vec{1}_N^\top \tilde{\omega}_{\text{mm}} = 1 \tag{50}$$

where $\varepsilon \equiv \epsilon \frac{(T-1)N}{T(T-N)}$. Garlappi, Uppal, and Wang (2007) derive the analytical solution for optimal portfolio weights as below:

$$\tilde{\omega}_{\text{mm}} = \frac{\tilde{\sigma}_p}{\sqrt{\epsilon} + \gamma \tilde{\sigma}_p} \hat{\Sigma}_r^{-1} \left[\hat{\mu}_r - \frac{1}{A} \left(B - \frac{\sqrt{\epsilon} + \gamma \tilde{\sigma}_p}{\tilde{\sigma}_p} \right) \vec{1}_N \right] \tag{51}$$

where $\tilde{\sigma}_p$ is the volatility of the optimal portfolio, which can be obtained by solving the following polynomial equation:

$$A\gamma^2 \sigma_p^4 + 2A\gamma\sqrt{\epsilon}\sigma_p^3 + (A\epsilon - AC + B^2 - \gamma^2)\sigma_p^2 - 2\gamma\sqrt{\epsilon}\sigma_p - \epsilon = 0 \tag{52}$$

where $A = \vec{1}_N^\top \hat{\Sigma}_r^{-1} \vec{1}_N$, $B = \hat{\mu}_r^\top \hat{\Sigma}_r^{-1} \vec{1}_N$, and $C = \hat{\mu}_r^\top \hat{\Sigma}_r^{-1} \hat{\mu}_r$. The normalized portfolio weights are then:

$$\omega_{\text{mm}} = \frac{\tilde{\omega}_{\text{mm}}}{\vec{1}_N^\top \tilde{\omega}_{\text{mm}}} \tag{53}$$

E.13 Three-Fund Rule

Kan and Zhou (2007) propose to a “three-fund rule” that combines the global minimum-variance portfolio with tangency portfolio in order to reduce estimation errors if estimation errors are not perfectly correlated. It essentially allocates capital in the sample global minimum-variance portfolio, sample tangency portfolio, and the risk-free asset. Its portfolio weights are given by:

$$\tilde{\omega}_{\text{tfr}} = \frac{(T-N-1)(T-N-4)}{\gamma T(T-2)} \left[\hat{\eta}\hat{\Sigma}_r^{-1}\hat{\mu}_r + (1-\hat{\eta})\hat{\Sigma}_r^{-1}\vec{1}_N\hat{\mu}_r^{\text{mv}}\right] \tag{54}$$

where

$$\hat{\eta} = \frac{\hat{\psi}^2}{\hat{\psi}^2 + N/T} \tag{55}$$

$$\hat{\psi}^2 = \frac{(T-N-1)\bar{\psi}^2 - (N-1)}{T} + \frac{2(\bar{\psi}^2)^{(N-1)/2}(1+\bar{\psi}^2)^{-(T-2)/2}}{TB_{\bar{\psi}^2/(1+\bar{\psi}^2)}((N-1)/2,(T-N+1)/2)} \tag{56}$$

$$\bar{\psi}^2 = (\hat{\mu}_r - \hat{\mu}_r^{\text{mv}})^\top \hat{\Sigma}_r^{-1}(\hat{\mu}_r - \hat{\mu}_r^{\text{mv}}) \tag{57}$$

where $B_x(a,b) = \int_0^x y^{a-1}(1-y)^{b-1}\text{d}y$ is the incomplete beta function. The fraction of wealth allocated to global minimum-variance portfolio increases with N/T, as the parameters of tangency portfolio become more difficult to estimate. The normalized portfolio weights can then be calculated as:

$$\omega_{\text{tfr}} = \frac{\tilde{\omega}_{\text{tfr}}}{\vec{1}_N^\top\tilde{\omega}_{\text{tfr}}} \tag{58}$$

E.14 Combination of Minimum Variance with $1/N$

DeMiguel, Garlappi, and Uppal (2009) consider a portfolio strategy that combines naive diversification with minimum-variance portfolio as follows:

$$\omega_{\text{cmv}} = \hat{\delta}\omega_{\text{nd}} + (1-\hat{\delta})\omega_{\text{mv}} \qquad s.t.\ \ \vec{1}_N^\top\tilde{\omega}_{\text{cmv}} = 1 \tag{59}$$

where δ is chosen to maximize the expected utility of a mean-variance investor.[13]

E.15 Combination of Maximum Sharpe Ratio with $1/N$

Tu and Zhou (2011) further suggest the combination of naive diversification with tangency (or equivalently, maximum Sharpe-ratio) portfolio to reduce estimation risk. The resulting portfolio weights can be written as:

$$\omega_{\text{ctp}} = \frac{\hat{\pi}_2}{\hat{\pi}_1 + \hat{\pi}_2}\omega_{\text{nd}} + \frac{\hat{\pi}_1}{\hat{\pi}_1 + \hat{\pi}_2}\omega_{\text{msr}} \tag{60}$$

where

$$\hat{\pi}_1 = \omega_{\text{nd}}^\top \hat{\Sigma}_r \omega_{\text{nd}} - \frac{2}{\gamma}\omega_{\text{nd}}^\top \hat{\mu}_r + \frac{\hat{\psi}^2}{\gamma^2} \tag{61}$$

$$\hat{\pi}_2 = \frac{\hat{\psi}^2}{\gamma^2}\left[\frac{(T-2)(T-N-2)}{(T-N-1)(T-N-4)} - 1\right] + \frac{(T-2)(T-N-2)N}{\gamma^2(T-N-1)(T-N-4)T} \tag{62}$$

$$\hat{\psi}^2 = \frac{(T-N-2)\bar{\psi}^2 - N}{T} + \frac{2(\bar{\psi}^2)^{N/2}(1+\bar{\psi}^2)^{-(T-2)/2}}{TB_{\bar{\psi}^2/(1+\bar{\psi}^2)}(N/2,(T-N)/2)} \tag{63}$$

$$\bar{\psi}^2 = \hat{\mu}_r^\top \hat{\Sigma}_r^{-1}\hat{\mu}_r \tag{64}$$

E.16 Combination of Three-Fund Rule with $1/N$

Tu and Zhou (2011) also show how to combine the $1/N$ rule with three-fund rule proposed by Kan and Zhou (2007). The portfolio weights are given by:

$$\omega_{\text{ctf}} = \left(1 - \frac{\hat{\pi}_1 - \hat{\pi}_{13}}{\hat{\pi}_1 - 2\hat{\pi}_2 + \hat{\pi}_3}\right)\omega_{\text{nd}} + \frac{\hat{\pi}_1 - \hat{\pi}_{13}}{\hat{\pi}_1 - 2\hat{\pi}_2 + \hat{\pi}_3}\omega_{\text{tfr}} \tag{65}$$

where

$$\hat{\pi}_3 = \frac{\hat{\psi}^2}{\gamma^2} - \frac{(T-N-1)(T-N-4)}{\gamma^2(T-2)(T-N-2)}\left(\hat{\psi}^2 - \frac{\hat{\eta}N}{T}\right) \tag{66}$$

[13] Note that the utility function can be other types, such as power utility.

$$\hat{\pi}_{13} = \frac{\hat{\psi}^2}{\gamma^2} - \frac{1}{\gamma}\omega_{\text{nd}}^\top\hat{\mu}_r + \frac{(T-N-1)(T-N-4)}{\gamma(T-2)(T-N-2)}\left[\hat{\eta}\omega_{\text{nd}}^\top\hat{\mu}_r + (1-\hat{\eta})\hat{\mu}_r^{\text{mv}}\omega_{\text{nd}}^\top\vec{1}_N\right]$$
$$+\frac{1}{\gamma}\left[\hat{\eta}\hat{\mu}_r^\top\hat{\Sigma}_r^{-1}\hat{\mu}_r + (1-\hat{\eta})\hat{\mu}_r^{\text{mv}}\hat{\mu}_r^\top\hat{\Sigma}_r^{-1}\vec{1}_N\right] \quad (67)$$

F Predictive Regression Methods

In this paper, we consider various penalized regression methods and other regression methods designed to tackle the curse of high dimensionality.

F.1 Elastic Net

Zou and Hastie (2005) propose a regularized regression method that linearly combines ℓ_1-norm penalty (LASSO)[14] and ℓ_2-norm (ridge) penalties. The LASSO tends to select one variable from a group of correlated variables and ignore others in the group. To some extent, it is indifferent to the choice among a set of strong but correlated variables (sparse solution), while the ridge regression overcomes this limitation by shrinking the coefficients of correlated variables toward each other (averaged solution). The compromised beta is estimated by:

$$\hat{\beta} \equiv \underset{\beta}{\text{argmin}}\left(\|y - X\beta\|_2^2 + \Psi(1-\varrho)\|\beta\|_1 + \Psi\varrho\|\beta\|_2^2\right) \quad (68)$$

where Ψ denotes the penalizing parameter, and ϱ is the mixing parameter between ridge and LASSO. The model is fitted with coordinate descent algorithm.

F.2 Adaptive LASSO

Zou (2006) further suggest a weighted penalty form of LASSO, called adaptive LASSO:

$$\hat{\beta} \equiv \underset{\beta}{\text{argmin}}\left(\|y - X\beta\|_2^2 + \Psi w_{\text{OLS}}\|\beta\|_1\right) \quad (69)$$

[14] It is as knowned as least absolute shrinkage and selection operator.

where $w_{\text{OLS}} = 1/|\tilde{\beta}|^{\vartheta}$ represents the weight attached to coefficients; $\tilde{\beta}$ is the OLS estimates and $\vartheta > 0$. The model can be fitted via least-angle regression (LARS) algorithm.

F.3 Group LASSO

In some circumstances, variables belong to pre-defined categories and it may be desirable to shrink and select certain members of variables from a group, which can be achieved by group LASSO that minimizes a convex criterion (see Bach, 2008; Jacob, Obozinski, and Vert, 2009, for details)

$$\hat{\beta} \equiv \underset{\beta}{\operatorname{argmin}} \left(\|y - X\beta\|_2^2 + \Psi\sqrt{\varphi}\|\beta\|_2 \right) \tag{70}$$

where $\sqrt{\varphi}$ accounts for changes in group size, and $\|\cdot\|_2$ is the Euclidean norm (not squared). As a result, this procedure encourages sparsity at group level. We fit the standard group LASSO using coordinate descent algorithm and simple soft-thresholding while assuming an orthonormal (not just orthogonal) design matrix for each group.[15]

F.4 Bayesian Model Averaging

While the aforementioned forecasting methods are particularly useful in handling parameter uncertainty, Bayesian model averaging is known for its capacity to deal with model uncertainty via model probability and obtain probability-weighted forecasts via model combination (see Raftery, Madigan, and Hoeting, 1997, for details). The posterior distribution of dependent variable y given the information set Φ and N_m models or combinations of predictive variables can be written as:

$$\Pr(y_{t+1}|\Phi_t) = \sum_{k=1}^{N_m} \Pr(y_{t+1}|\mathcal{M}_k, \Phi_t) \Pr(\mathcal{M}_k|\Phi_t) \tag{71}$$

[15] Please refer to Simon, Friedman, Hastie, and Tibshirani (2013) for general design matrices.

which is an average of posterior distributions of each model considered. The posterior probability for model k (denoted by $\mathcal{M}_k$ where $y_{t+1} = \hat{\beta}_k x_{k,t} + u_{k,t}$) is given by:

$$\Pr(\mathcal{M}_k|\Phi_t) = \frac{\Pr(\Phi_t|\mathcal{M}_k)\Pr(\mathcal{M}_k)}{\sum_{l=1}^{N_m}\Pr(\Phi_t|\mathcal{M}_l)\Pr(\mathcal{M}_l)} \tag{72}$$

where

$$\Pr(\Phi_t|\mathcal{M}_k) = \int \Pr(\Phi_t|\Theta_k, \mathcal{M}_k)\Pr(\Theta_k|\mathcal{M}_k)\,\mathrm{d}\Theta_k \tag{73}$$

is the integrated likelihood of $\mathcal{M}_k$, Θ_k represents the vector of parameters of $\mathcal{M}_k$, $\Pr(\Theta_k|\mathcal{M}_k)$ is the prior density of Θ_k under $\mathcal{M}_k$, $\int \Pr(\Phi_t|\Theta_k, \mathcal{M}_k)$ denotes the likelihood, and $\Pr(\mathcal{M}_k)$ is the prior probability that $\mathcal{M}_k$ is the true model, given that one of the models considered is true. The posterior mean (point forecast) of y is then computed as:

$$\mathbb{E}[y_{t+1}|\Phi_t] = \sum_{k=0}^{N_m} \hat{y}_{k,t+1}\Pr(\mathcal{M}_k|\Phi_t) \tag{74}$$

We follow the procedure of Raftery, Madigan, and Hoeting (1997) to specify the prior distribution for Bayesian estimations.

F.5 Complete Subset Regression

Elliott, Gargano, and Timmermann (2013) explore the trade-off of bias and variance of forecasting errors via the choice of model complexity measured by the number of regressors specified in the model. They propose an estimation method that uses equally-weighted combinations of forecasts based on all possible models with a subset of predictors:

$$y_{t+1} = \frac{1}{N_c N_s}\sum_{i=1}^{N_c}\sum_{j=1}^{N_s} \hat{\beta}_{i,j} x_{i,j,t} + v_{i,j,t} \tag{75}$$

where $x_{i,j,t}$ denotes a subset i of predictive variables with a given number of j selected from all available predictors N_c and up to N_s are selected; $\hat{y}_{t+1}$ is the equally-weighted average forecast of all possible combinations $C_{N_s}^{N_c}$ of predictive models. They prove that:

$$\hat{\beta}_{N_s,N_c} = \left(\frac{1}{N_s} \sum_{k=1}^{N_s} z_k \right) \hat{\beta}_{\text{OLS}} \tag{76}$$

where z represents a $N_c \times N_c$ matrix with all elements of zeros, and $\hat{\beta}_{\text{OLS}}$ is the OLS estimator. Elliott, Gargano, and Timmermann (2013) also show that complete subset regression can produce forecasts with comparable accuracy to those generated via bagging, ridge, and BMA.

F.6 Partial Least Squares

The partial least squares (PLS) is designed to solve the problem of highly correlated variables in regressions while a small subset of variables are associated with the dependent variable. Accurate predictions would not be available if the selected subsets are not enough. Similarly to PCA, PLS adopts a latent variable approach to model the covariance structures in the spaces of both predictive and dependent variables:

$$X = AB^T; \quad Y = PQ^T \tag{77}$$

where A and P are the projections (scores) of X and Y, respectively, while B and Q are the orthogonal loading matrices; and $P = A\varpi$. Then we have:

$$Y = PQ^T = A\varpi Q^T = XB\varpi Q^T \tag{78}$$

We fit the model using nonlinear iterative partial least squares (NIPALS) algorithm. Light, Maslov, and Rytchkov (2017) employ the PLS method to aggregate the information from a large set of characteristics for explaining the cross section of stock returns.

F.7 Three-Pass Regression Filter

Kelly and Pruitt (2015) propose a three-pass regression filter to deal with the problem of forecasting (target y) with many predictors. It can be calculated in closed form and easily represented as a set of OLS regressions.

The first (error-in-variable) pass is to run N separate time-series regressions for each of the predictive variables where predictors X are dependent variables and proxies Z are regressors. This procedure estimates the sensitivity of each predictors to the factors represented by the proxies, and it requires that common components of the proxies span the space of the target-relevant factors. The second (factor rotation) pass uses the coefficients estimated in the first pass to run T separate cross-sectional regressions at each point of time where predictors are again dependent variables while the coefficients estimated in the first pass are regressors. The fluctuations in the latent factors compress the cross section of predictors. These two stages of parameter estimates accomplish a two-way variable mapping. The third and final pass is to deliver a consistent forecast of the target with the predictive factors $\hat{G}$ produced via the first two stages.

$$\hat{y}_{t+1} = \iota_T \bar{y}_t + \hat{G}_t \hat{\beta} \tag{79}$$

$$\hat{G}_t^\top = H_{ZZ,t}(W_{XZ,t}^\top H_{XZ,t})^{-1}(W_{XZ,t} X_t)^\top \tag{80}$$

$$\hat{\beta} = H_{ZZ,t} W_{XZ,t} H_{XZ,t}(W_{XZ,t}^\top H_{XX,t} W_{XZ,t})^{-1} W_{XZ,t}^\top h_{Xy,t} \tag{81}$$

where $\bar{y}_t = \iota_T^\top y_t / T$, $W_{ZZ,t} \equiv L_N X_t^\top L_T Z_t$, $H_{ZZ,t} \equiv X_t^\top J_T X_t$, $H_{XZ,t} \equiv X_t^\top J_T Z_t$, $h_{Xy,t} \equiv X_t^\top J_T y_t$, $L_N \equiv I_N - \iota_N \iota_N^\top / N$, and $L_t \equiv I_T - \iota_T \iota_T^\top / T$, with I as an identity matrix and ι as a vector of ones. They also show that PLS is a special case of TPF.

G Performance Fees

The performance fee is a measure of economic values to investors introduced by Fleming, Kirby, and Ostdiek (2001, 2003) in evaluating portfolio management. The maximum performance fee is determined by a state when a representative agent with a quadratic utility of wealth is indifferent between using factor-based mean-variance model (FB) and the competing models denoted by CM in general. A performance fee lower than this threshold induces investors to switch from a CM to the alternative FB model. The maximum performance fee $\mathcal{F}$ is estimated by satisfying the out-of-sample condition of average utility with relative risk aversion (RRA) γ as below:

$$\sum_{t=T_{IS}+1}^{T_{OOS}} \left[(1+\mu_{p,t+1}^{FB} - \mathcal{F}) - \frac{\gamma}{2(1+\gamma)}(1+\mu_{p,t+1}^{FB} - \mathcal{F})^2 \right] = \sum_{t=T_{IS}+1}^{T_{OOS}} \left[(1+\mu_{p,t+1}^{CM}) - \frac{\gamma}{2(1+\gamma)}(1+\mu_{p,t+1}^{CM})^2 \right] \tag{82}$$

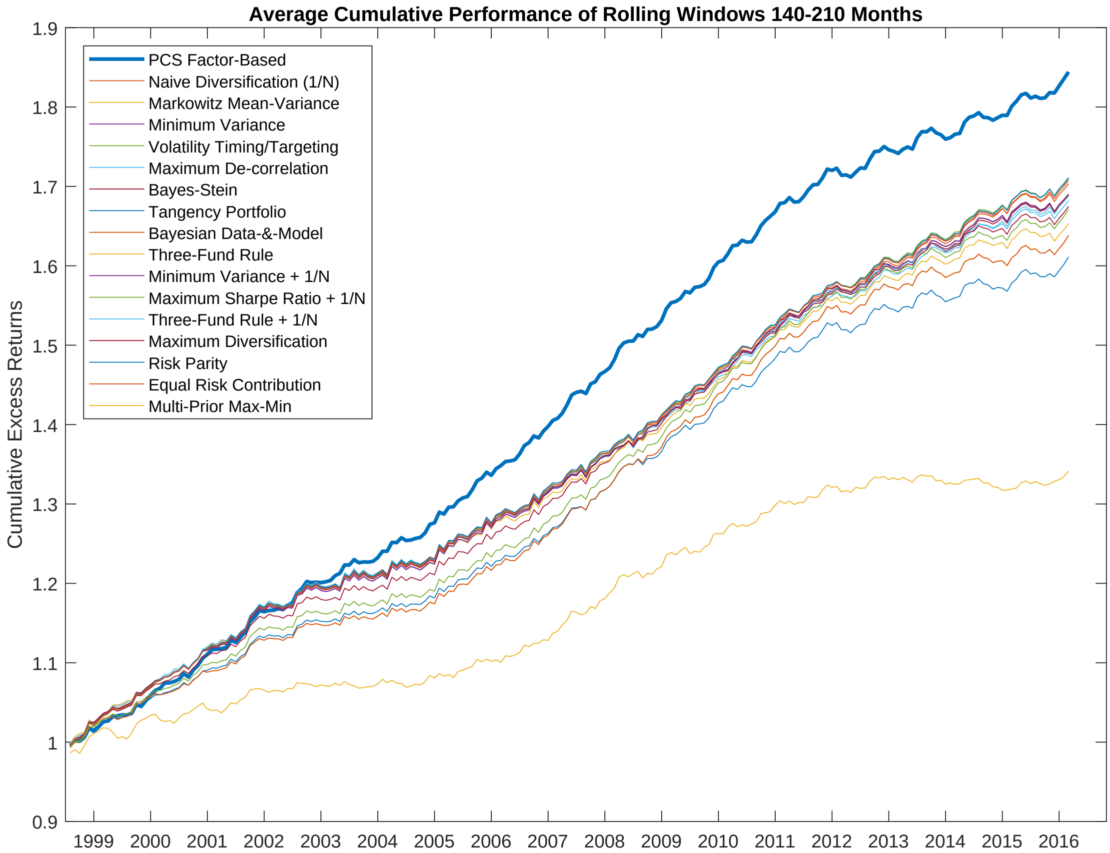
Goetzmann, Ingersoll, Spiegel, and Welch (2007) further define a manipulation-proof performance measure $\mathcal{P}$ robust to return distributions as follows:

$$\mathcal{P} = \frac{1}{1-\gamma} \ln \left[\frac{1}{T} \sum_{t=T_{IS}+1}^{T_{OOS}} \left(\frac{1+\mu_{p,t+1}^{FB}}{1+r_t} \right)^{1-\gamma} \right] - \frac{1}{1-\gamma} \ln \left[\frac{1}{T} \sum_{t=T_{IS}+1}^{T_{OOS}} \left(\frac{1+\mu_{p,t+1}^{CM}}{1+r_t} \right)^{1-\gamma} \right] \tag{83}$$

It does not require to specify a utility function but shares the same economic intuition as the maximum performance fee. We can interpret it as certainty equivalent portfolio excess returns. Both $\mathcal{F}$ and $\mathcal{P}$ are reported in percentage and annualized.

H Further Robustness Checks

Figure H.1.: Strategic Asset Allocation: Out-of-Sample Performance of Portfolio Optimizers with Multiple Risk Premia ($\gamma = 2$)



This figure shows the cumulative average performance (excess returns after transaction costs) of currency factor-investing portfolio strategies across different rolling-window lengths spanning 2-3 business cycles (according to NBER), and using various optimizers, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). The out-of-sample period is from August 1998 to March 2016. All series are adjusted to the same risk profile as the factor-based portfolio strategy, in terms of portfolio volatility, for comparison.

Table H.1.: Strategic Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 2$)

	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Rolling Window: 140M																	
Mean (%)	4.37	3.30	3.51	3.32	3.30	3.32	3.41	3.48	3.51	3.50	3.32	3.41	3.42	3.32	3.35	3.31	1.88
Std.Dev. (%)	4.89	4.27	5.10	4.46	4.31	4.38	4.67	5.13	5.10	4.82	4.46	4.72	4.54	4.41	4.30	4.36	4.84
Sharpe Ratio	**0.89**	0.77	0.69	0.74	0.77	0.76	0.73	0.68	0.69	0.73	0.74	0.72	0.75	0.75	0.78	0.76	0.39
Sortino Ratio	**1.26**	1.09	0.90	0.99	1.06	1.05	0.97	0.91	0.90	0.99	0.99	0.98	1.04	1.02	1.09	1.05	0.52
CEQ	**4.13**	3.12	3.25	3.12	3.12	3.12	3.20	3.22	3.25	3.27	3.12	3.18	3.21	3.12	3.17	3.12	1.65
Omega Ratio	**1.07**	1.06	0.97	1.04	1.04	1.05	0.94	0.98	0.97	1.00	1.04	0.92	1.04	1.03	1.04	1.05	0.93
Calmar Ratio	**0.39**	0.30	0.30	0.32	0.30	0.32	0.33	0.26	0.30	0.38	0.32	0.31	0.35	0.32	0.31	0.31	0.12
$\mathcal{F}$ (%)	-	0.59	1.00	0.73	0.62	0.67	0.80	1.05	1.00	0.82	0.73	0.84	0.69	0.69	0.56	0.65	2.47
$\mathcal{P}$ (%)	-	0.59	1.00	0.73	0.62	0.66	0.79	1.05	1.00	0.82	0.73	0.84	0.68	0.69	0.56	0.65	2.47
LW Test	-	0.10	0.02	0.08	0.10	0.09	0.07	0.01	0.02	0.09	0.08	0.04	0.07	0.09	0.10	0.09	0.00
Rolling Window: 150M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	4.64	3.13	3.57	3.21	3.13	3.20	3.33	3.51	3.57	3.27	3.21	3.39	3.21	3.22	3.19	3.17	2.15
Std.Dev. (%)	4.86	4.27	5.15	4.44	4.31	4.35	4.65	5.06	5.15	4.63	4.43	4.75	4.43	4.37	4.31	4.34	5.10
Sharpe Ratio	**0.96**	0.73	0.69	0.72	0.73	0.74	0.72	0.69	0.69	0.71	0.72	0.71	0.72	0.74	0.74	0.73	0.42
Sortino Ratio	**1.37**	1.03	0.91	0.98	1.00	1.03	0.97	0.96	0.91	0.99	0.98	0.97	1.02	1.02	1.03	1.01	0.53
CEQ	**4.41**	2.95	3.30	3.01	2.94	3.02	3.12	3.26	3.30	3.05	3.01	3.16	3.01	3.03	3.00	2.98	1.89
Omega Ratio	1.07	1.05	0.94	1.00	1.03	1.04	0.95	1.02	0.94	1.03	1.02	0.92	**1.09**	1.04	1.04	1.04	0.91
Calmar Ratio	**0.59**	0.28	0.28	0.30	0.29	0.30	0.31	0.28	0.28	0.38	0.30	0.29	0.33	0.30	0.29	0.29	0.12
$\mathcal{F}$ (%)	-	1.08	1.28	1.13	1.12	1.06	1.16	1.27	1.28	1.21	1.12	1.18	1.12	1.06	1.05	1.10	2.60
$\mathcal{P}$ (%)	-	1.08	1.27	1.12	1.12	1.06	1.16	1.27	1.27	1.21	1.12	1.18	1.12	1.06	1.05	1.09	2.59
LW Test	-	0.04	0.00	0.04	0.04	0.04	0.01	0.00	0.00	0.01	0.04	0.01	0.02	0.05	0.05	0.04	0.00

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with other popular approaches in practice, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Table H.2.: Strategic Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 2$)

	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Rolling Window: 160M																	
Mean (%)	5.05	3.51	4.06	3.61	3.51	3.60	3.84	4.08	4.06	3.85	3.61	3.92	3.71	3.59	3.54	3.57	2.72
Std.Dev. (%)	4.80	4.21	5.06	4.39	4.26	4.28	4.58	4.88	5.06	4.50	4.38	4.66	4.33	4.32	4.26	4.28	4.98
Sharpe Ratio	**1.05**	0.83	0.80	0.82	0.82	0.84	0.84	0.83	0.80	0.86	0.82	0.84	0.85	0.83	0.83	0.83	0.55
Sortino Ratio	**1.53**	1.20	1.08	1.15	1.17	1.22	1.18	1.19	1.08	1.24	1.15	1.19	1.24	1.18	1.18	1.19	0.75
CEQ	**4.82**	3.33	3.80	3.42	3.33	3.42	3.63	3.84	3.80	3.65	3.42	3.70	3.52	3.41	3.36	3.38	2.47
Omega Ratio	1.06	1.12	1.01	1.09	1.11	1.10	1.02	1.11	1.01	1.14	1.09	1.02	**1.18**	1.10	1.09	1.11	0.92
Calmar Ratio	**0.65**	0.44	0.41	0.43	0.44	0.44	0.45	0.50	0.41	0.48	0.43	0.46	0.46	0.43	0.43	0.44	0.18
$\mathcal{F}$ (%)	-	1.06	1.21	1.10	1.10	1.02	1.03	1.05	1.21	0.95	1.10	1.02	0.95	1.07	1.07	1.06	2.44
$\mathcal{P}$ (%)	-	1.05	1.20	1.10	1.10	1.02	1.02	1.05	1.20	0.94	1.10	1.02	0.95	1.06	1.06	1.05	2.43
LW Test	-	0.04	0.00	0.04	0.04	0.04	0.02	0.00	0.00	0.03	0.04	0.01	0.04	0.04	0.04	0.04	0.00
Rolling Window: 170M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	5.28	3.92	4.56	4.18	3.94	4.13	4.25	4.36	4.56	4.01	4.17	4.32	3.97	4.15	4.00	4.05	3.37
Std.Dev. (%)	4.81	4.16	4.91	4.26	4.20	4.20	4.45	4.84	4.91	4.40	4.25	4.61	4.26	4.22	4.19	4.20	4.92
Sharpe Ratio	**1.10**	0.94	0.93	0.98	0.94	0.98	0.95	0.90	0.93	0.91	0.98	0.94	0.93	0.98	0.95	0.96	0.69
Sortino Ratio	**1.56**	1.36	1.36	1.44	1.34	1.47	1.40	1.31	1.37	1.32	1.44	1.38	1.35	1.45	1.38	1.41	1.07
CEQ	**5.05**	3.75	4.32	3.99	3.77	3.95	4.05	4.13	4.32	3.82	3.99	4.11	3.79	3.97	3.82	3.87	3.13
Omega Ratio	1.06	1.17	1.08	1.20	1.16	1.20	1.12	1.11	1.08	1.21	1.20	1.08	**1.25**	1.24	1.15	1.18	1.05
Calmar Ratio	**0.69**	0.49	0.51	0.51	0.49	0.52	0.52	0.52	0.51	0.54	0.51	0.51	0.52	0.52	0.49	0.51	0.22
$\mathcal{F}$ (%)	-	0.74	0.81	0.56	0.76	0.55	0.69	0.94	0.81	0.89	0.56	0.77	0.79	0.56	0.70	0.65	1.98
$\mathcal{P}$ (%)	-	0.74	0.80	0.56	0.76	0.54	0.68	0.94	0.80	0.89	0.56	0.77	0.79	0.56	0.69	0.64	1.97
LW Test	-	0.07	0.02	0.10	0.07	0.10	0.06	0.00	0.02	0.04	0.10	0.03	0.07	0.10	0.08	0.09	0.00

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with other popular approaches in practice, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Table H.3.: Strategic Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 2$)

Rolling Window: 180M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	4.81	3.26	3.77	3.46	3.26	3.47	3.49	3.71	3.77	3.36	3.46	3.58	3.32	3.46	3.30	3.36	2.53
Std.Dev. (%)	4.75	4.02	4.72	4.10	4.06	4.04	4.28	4.69	4.72	4.26	4.10	4.44	4.12	4.07	4.06	4.05	4.72
Sharpe Ratio	**1.01**	0.81	0.80	0.84	0.80	0.86	0.82	0.79	0.80	0.79	0.84	0.81	0.80	0.85	0.81	0.83	0.53
Sortino Ratio	**1.44**	1.13	1.13	1.20	1.11	1.24	1.15	1.12	1.13	1.11	1.20	1.14	1.14	1.22	1.13	1.17	0.78
CEQ	**4.59**	3.10	3.55	3.29	3.09	3.31	3.31	3.49	3.55	3.18	3.29	3.38	3.15	3.29	3.13	3.20	2.30
Omega Ratio	1.09	1.12	1.00	1.14	1.09	1.18	1.02	1.08	1.00	**1.19**	1.14	1.02	1.17	1.17	1.09	1.13	0.95
Calmar Ratio	**0.62**	0.41	0.44	0.42	0.41	0.44	0.43	0.42	0.44	0.43	0.42	0.44	0.42	0.43	0.41	0.42	0.16
$\mathcal{F}$ (%)	-	0.96	1.02	0.80	1.00	0.73	0.94	1.06	1.02	1.07	0.80	0.98	0.99	0.78	0.96	0.87	2.27
$\mathcal{P}$ (%)	-	0.95	1.01	0.80	1.00	0.73	0.93	1.06	1.01	1.06	0.80	0.98	0.99	0.77	0.95	0.87	2.26
LW Test	-	0.07	0.00	0.09	0.06	0.10	0.02	0.00	0.01	0.02	0.09	0.01	0.03	0.10	0.06	0.08	0.00

Rolling Window: 190M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	4.38	2.81	3.45	2.89	2.79	2.93	3.15	3.41	3.45	3.12	2.89	3.25	2.99	2.90	2.85	2.85	1.92
Std.Dev. (%)	4.72	3.94	4.55	4.01	3.99	3.94	4.13	4.53	4.55	4.09	4.01	4.29	4.00	3.97	3.98	3.97	4.48
Sharpe Ratio	**0.93**	0.71	0.76	0.72	0.70	0.74	0.76	0.75	0.76	0.76	0.72	0.76	0.75	0.73	0.71	0.72	0.43
Sortino Ratio	**1.30**	0.99	1.12	0.99	0.95	1.05	1.09	1.10	1.12	1.11	0.99	1.11	1.07	1.01	0.99	0.99	0.63
CEQ	**4.16**	2.66	3.24	2.73	2.63	2.77	2.98	3.21	3.24	2.95	2.73	3.07	2.83	2.75	2.69	2.69	1.72
Omega Ratio	1.15	1.09	1.00	1.10	1.06	1.14	1.11	1.03	1.00	**1.24**	1.10	1.02	1.18	1.09	1.07	1.12	0.98
Calmar Ratio	**0.58**	0.35	0.40	0.36	0.35	0.37	0.39	0.42	0.40	0.42	0.36	0.39	0.39	0.36	0.35	0.36	0.15
$\mathcal{F}$ (%)	-	1.01	0.80	0.98	1.08	0.87	0.78	0.82	0.80	0.78	0.98	0.80	0.85	0.93	1.01	0.99	2.36
$\mathcal{P}$ (%)	-	1.01	0.80	0.98	1.07	0.86	0.78	0.82	0.80	0.78	0.98	0.80	0.85	0.93	1.00	0.99	2.35
LW Test	-	0.06	0.02	0.05	0.05	0.07	0.05	0.02	0.02	0.07	0.05	0.03	0.07	0.06	0.06	0.06	0.00

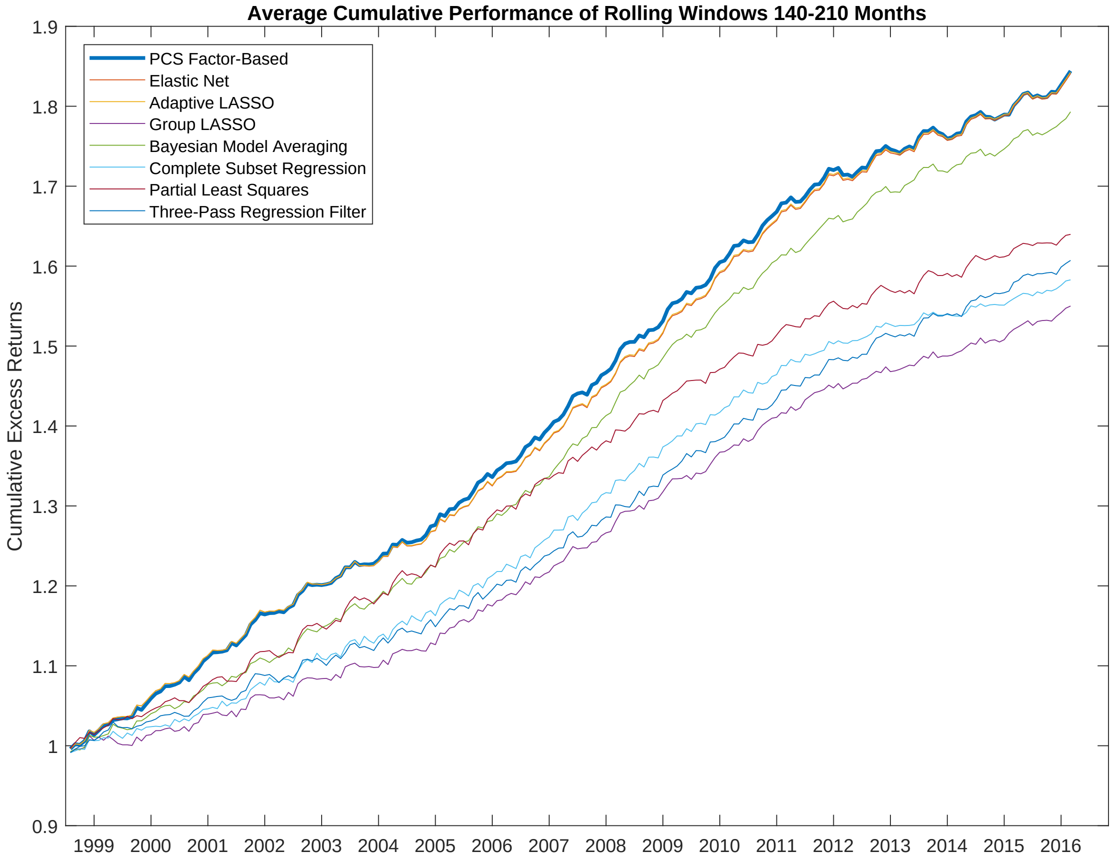
This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with other popular approaches in practice, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Table H.4.: Strategic Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 2$)

	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Rolling Window: 200M																	
Mean (%)	4.27	2.79	3.64	2.90	2.76	2.95	3.19	3.52	3.64	3.06	2.90	3.38	2.94	2.93	2.82	2.84	2.51
Std.Dev. (%)	4.70	3.99	4.53	4.03	4.03	3.97	4.14	4.53	4.53	4.09	4.03	4.30	4.02	4.00	4.03	4.01	4.49
Sharpe Ratio	**0.91**	0.70	0.80	0.72	0.69	0.74	0.77	0.78	0.80	0.75	0.72	0.79	0.73	0.73	0.70	0.71	0.56
Sortino Ratio	**1.26**	0.97	1.20	0.99	0.94	1.04	1.11	1.14	1.20	1.08	0.99	1.16	1.04	1.01	0.97	0.98	0.85
CEQ	**4.05**	2.63	3.44	2.74	2.60	2.79	3.02	3.31	3.44	2.89	2.74	3.20	2.78	2.77	2.66	2.68	2.31
Omega Ratio	1.11	1.10	0.97	1.07	1.07	1.11	1.03	1.03	0.97	**1.13**	1.07	1.01	1.12	1.08	1.06	1.11	0.98
Calmar Ratio	**0.58**	0.35	0.41	0.35	0.34	0.37	0.39	0.42	0.41	0.40	0.35	0.40	0.38	0.37	0.35	0.35	0.20
$\mathcal{F}$ (%)	-	0.98	0.50	0.89	1.05	0.78	0.64	0.62	0.50	0.75	0.89	0.57	0.83	0.82	0.98	0.94	1.64
$\mathcal{P}$ (%)	-	0.98	0.49	0.89	1.04	0.78	0.64	0.62	0.49	0.75	0.89	0.57	0.83	0.82	0.98	0.93	1.64
LW Test	-	0.07	0.08	0.07	0.06	0.10	0.09	0.04	0.08	0.08	0.07	0.07	0.08	0.09	0.07	0.07	0.01
Rolling Window: 210M																	
	FB	ND	MKW	MV	VT	MDC	JBS	MPS	WJM	KZ	DGU	TZ	KTZ	MD	RP	ERC	GUW
Mean (%)	4.38	2.79	3.59	2.87	2.76	2.92	3.12	3.54	3.59	2.96	2.87	3.33	2.88	2.90	2.81	2.82	2.61
Std.Dev. (%)	4.73	4.03	4.55	4.08	4.07	4.00	4.18	4.52	4.55	4.13	4.07	4.34	4.06	4.04	4.08	4.05	4.51
Sharpe Ratio	**0.93**	0.69	0.79	0.70	0.68	0.73	0.75	0.78	0.79	0.72	0.70	0.77	0.71	0.72	0.69	0.70	0.58
Sortino Ratio	**1.29**	0.96	1.17	0.96	0.92	1.02	1.07	1.17	1.17	1.04	0.96	1.12	1.01	0.99	0.95	0.96	0.87
CEQ	**4.16**	2.63	3.38	2.70	2.59	2.76	2.94	3.34	3.38	2.79	2.70	3.14	2.72	2.73	2.64	2.66	2.41
Omega Ratio	1.09	1.07	0.97	1.08	1.06	1.10	1.00	1.01	0.97	1.12	1.08	1.01	**1.14**	1.09	1.04	1.07	1.03
Calmar Ratio	**0.61**	0.35	0.41	0.35	0.34	0.36	0.38	0.43	0.41	0.38	0.35	0.40	0.37	0.36	0.35	0.35	0.22
$\mathcal{F}$ (%)	-	1.11	0.65	1.05	1.18	0.94	0.85	0.67	0.65	1.00	1.05	0.75	1.03	0.99	1.12	1.09	1.65
$\mathcal{P}$ (%)	-	1.11	0.65	1.05	1.18	0.94	0.85	0.67	0.65	0.99	1.05	0.75	1.02	0.99	1.12	1.08	1.64
LW Test	-	0.05	0.04	0.04	0.04	0.06	0.04	0.03	0.04	0.03	0.04	0.03	0.04	0.05	0.04	0.04	0.02

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with other popular approaches in practice, including naive diversification (ND), standard Markowitz mean-variance approach (MKW), minimum variance (MV), volatility timing (VT), maximum de-correlation (MDC), Jorion (1986) Bayes-Stein shrinkage estimator (JBS), MacKinlay and Pástor (2000) tangency portfolio (MPS), Bayesian data-and-model method (WJM) (see Pástor, 2000; Pástor and Stambaugh, 2000; Jagannathan and Ma, 2003; Wang, 2005, for details), Kan and Zhou (2007) three-fund rule (KZ), DeMiguel, Garlappi, and Uppal (2009) combination of minimum variance with $1/N$ (DGU), Tu and Zhou (2011) combination of maximum Sharpe ratio (tangency portfolio) with $1/N$ (TZ), Tu and Zhou (2011) combination of three-fund rule with $1/N$ (KTZ), maximum diversification (MD), risk parity (RP), Maillard, Roncalli, and Teïletche (2008) equal risk contribution (ERC), and Garlappi, Uppal, and Wang (2007) multi-prior max-min approach (GUW). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Figure H.2.: Tactical Asset Allocation: Out-of-Sample Performance of Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$ and $w_\varsigma = 0.50$)



This figure shows the cumulative average performance (excess returns after transaction costs) of currency factor-investing portfolio strategies across different rolling-window lengths spanning 2-3 business cycles (according to NBER), and using various forecasting methods on the residuals from the asset pricing tests, including Zou and Hastie (2005) elastic net (EN), Zou (2006) adaptive LASSO ($A - LASSO$), group LASSO ($G - LASSO$) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples), Raftery, Madigan, and Hoeting (1997) Bayesian model averaging (BMA), Elliott, Gargano, and Timmermann (2013) complete subset regression (CSR), partial least squares (PLS) (see Light, Maslov, and Rytchkov, 2017, for the application on stock markets), Kelly and Pruitt (2015) three-pass regression filter (TPF). The out-of-sample period is from August 1998 to March 2016. All series are adjusted to the same risk profile as the factor-based portfolio strategy, in terms of portfolio volatility, for comparison.

Table H.5.: Tactical Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$ and $w_\zeta = 0.50$)

	Rolling Window: 140M								Rolling Window: 150M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	4.37	4.44	4.45	4.46	6.42	5.01	5.89	5.88	4.64	4.78	4.78	5.11	5.02	4.17	4.12	3.74
Std.Dev. (%)	4.89	4.96	4.96	7.70	7.28	7.84	7.88	8.05	4.86	5.01	5.01	7.15	7.04	7.67	7.51	7.65
Sharpe Ratio	0.89	**0.90**	**0.90**	0.58	0.88	0.64	0.75	0.73	**0.96**	0.95	0.95	0.72	0.71	0.54	0.55	0.49
Sortino Ratio	1.26	1.25	1.25	0.76	**1.30**	0.93	1.23	1.14	**1.37**	**1.37**	**1.37**	0.92	1.03	0.80	0.85	0.72
CEQ	3.65	3.70	3.71	2.68	**4.83**	3.17	4.03	3.94	3.94	**4.03**	**4.03**	3.58	3.53	2.40	2.43	1.98
Omega Ratio	1.07	1.00	1.00	0.95	1.16	1.08	**1.18**	1.11	1.07	1.06	1.06	1.00	1.03	0.95	**1.13**	1.02
Calmar Ratio	0.39	0.41	0.41	0.16	**0.46**	0.22	0.35	0.27	**0.59**	0.52	0.52	0.33	0.25	0.19	0.25	0.31
$\mathcal{F}$ (%)	-	-0.01	-0.02	1.54	0.06	1.25	0.72	0.80	-	0.01	0.01	1.17	1.18	2.00	1.98	2.27
$\mathcal{P}$ (%)	-	-0.01	-0.02	1.54	0.05	1.23	0.70	0.78	-	0.01	0.01	1.16	1.17	1.99	1.96	2.26
LW Test	-	0.53	0.55	0.03	0.47	0.09	0.24	0.20	-	0.48	0.48	0.08	0.05	0.01	0.02	0.01

	Rolling Window: 160M								Rolling Window: 170M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	5.05	5.22	5.22	4.47	5.54	3.80	4.17	3.57	5.28	5.60	5.55	4.18	6.07	4.73	5.49	4.14
Std.Dev. (%)	4.80	5.04	5.03	7.29	7.08	7.44	7.72	7.63	4.81	5.00	5.00	7.22	6.94	7.53	7.30	7.61
Sharpe Ratio	**1.05**	1.04	1.04	0.61	0.78	0.51	0.54	0.47	1.10	**1.12**	1.11	0.58	0.87	0.63	0.75	0.54
Sortino Ratio	**1.53**	1.51	1.51	0.85	1.11	0.79	0.89	0.72	1.56	**1.60**	1.58	0.82	1.23	1.06	1.24	0.85
CEQ	4.36	**4.46**	**4.46**	2.88	4.03	2.14	2.38	1.83	4.58	**4.85**	4.80	2.61	4.62	3.03	3.89	2.40
Omega Ratio	1.06	1.08	1.08	0.98	0.99	1.00	**1.09**	1.06	1.06	1.06	1.05	1.03	1.12	1.13	**1.20**	1.18
Calmar Ratio	0.65	**0.64**	**0.64**	0.23	0.43	0.14	0.25	0.24	**0.69**	**0.69**	**0.69**	0.19	0.43	0.17	0.25	0.18
$\mathcal{F}$ (%)	-	0.09	0.08	2.11	1.30	2.60	2.47	2.81	-	-0.11	-0.06	2.50	1.08	2.26	1.66	2.66
$\mathcal{P}$ (%)	-	0.09	0.08	2.10	1.29	2.59	2.45	2.79	-	-0.11	-0.06	2.49	1.07	2.24	1.65	2.64
LW Test	-	0.30	0.31	0.01	0.03	0.00	0.00	0.00	-	0.81	0.70	0.00	0.08	0.01	0.05	0.00

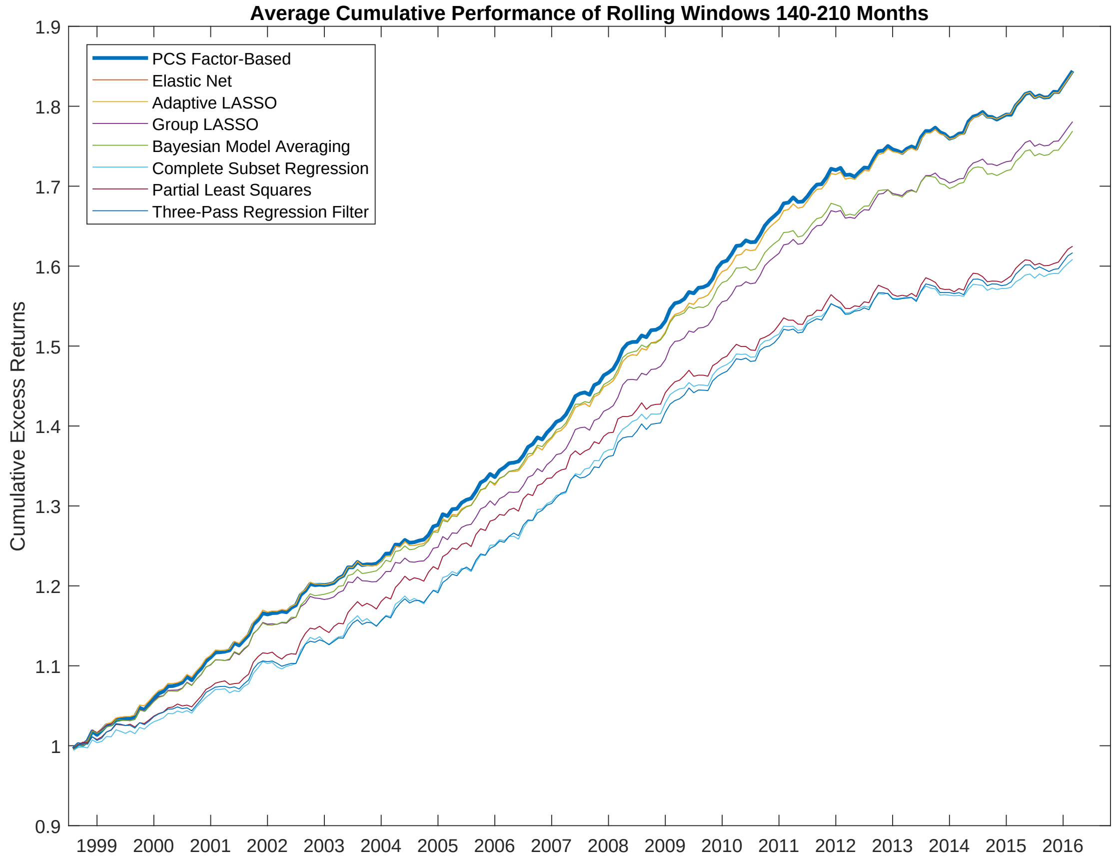
This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with an overlay of predicted regressions on the short-run deviations from expected returns using various forecasting methods on the residuals from the asset pricing tests, including Zou and Hastie (2005) elastic net (EN), Zou (2006) adaptive LASSO (AL), group LASSO (GL) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples), Raftery, Madigan, and Hoeting (1997) Bayesian model averaging (BMA), Elliott, Gargano, and Timmermann (2013) complete subset regression (CSR), partial least squares (PLS) (see Light, Maslov, and Rytchkov, 2017, for the application on stock markets), Kelly and Pruitt (2015) three-pass regression filter (TPF). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Table H.6.: Tactical Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$ and $w_\zeta = 0.50$)

	Rolling Window: 180M								Rolling Window: 190M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	4.81	5.04	5.04	2.77	4.17	3.78	3.27	3.95	4.38	4.67	4.67	1.92	3.10	4.06	3.04	3.53
Std.Dev. (%)	4.75	4.86	4.86	7.03	6.46	7.33	7.29	7.28	4.72	4.86	4.86	7.21	6.23	7.46	7.11	7.46
Sharpe Ratio	1.01	**1.04**	**1.04**	0.39	0.65	0.52	0.45	0.54	0.93	**0.96**	**0.96**	0.27	0.50	0.54	0.43	0.47
Sortino Ratio	1.44	**1.48**	**1.48**	0.50	0.91	0.87	0.71	0.93	1.30	**1.35**	**1.35**	0.35	0.69	0.91	0.73	0.82
CEQ	4.14	**4.33**	**4.33**	1.29	2.92	2.17	1.68	2.36	3.71	**3.97**	**3.97**	0.37	1.93	2.39	1.52	1.86
Omega Ratio	1.09	1.05	1.05	0.80	0.98	**1.16**	1.10	1.14	1.15	**1.18**	**1.18**	0.85	0.89	1.09	1.14	1.11
Calmar Ratio	0.62	**0.66**	**0.66**	0.16	0.22	0.16	0.12	0.21	0.58	**0.61**	**0.61**	0.09	0.17	0.17	0.14	0.23
$\mathcal{F}$ (%)	-	-0.11	-0.11	2.94	1.75	2.36	2.68	2.23	-	-0.16	-0.16	3.12	2.04	1.81	2.36	2.14
$\mathcal{P}$ (%)	-	-0.11	-0.11	2.94	1.74	2.34	2.66	2.21	-	-0.16	-0.16	3.12	2.03	1.79	2.34	2.12
LW Test	-	0.91	0.91	0.00	0.01	0.01	0.00	0.02	-	0.95	0.95	0.00	0.00	0.03	0.01	0.02
	Rolling Window: 200M								Rolling Window: 210M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	4.27	4.47	4.47	2.80	4.08	4.98	3.92	3.70	4.38	4.54	4.53	3.37	3.16	5.28	4.27	3.41
Std.Dev. (%)	4.70	4.82	4.82	7.21	5.89	7.46	7.52	7.65	4.73	4.85	4.86	7.51	6.23	7.67	7.68	7.52
Sharpe Ratio	0.91	**0.93**	**0.93**	0.39	0.69	0.67	0.52	0.48	0.93	**0.94**	0.93	0.45	0.51	0.69	0.56	0.45
Sortino Ratio	1.26	**1.29**	**1.29**	0.57	0.96	1.12	0.93	0.83	1.29	**1.31**	1.30	0.67	0.68	1.20	0.98	0.78
CEQ	3.61	**3.77**	**3.77**	1.24	3.04	3.31	2.23	1.94	3.71	**3.84**	3.83	1.67	1.99	3.52	2.49	1.71
Omega Ratio	1.11	**1.14**	**1.14**	0.85	0.95	1.20	1.23	1.05	1.09	1.12	1.12	1.00	0.91	1.17	**1.22**	1.08
Calmar Ratio	**0.58**	**0.58**	**0.58**	0.15	0.31	0.32	0.27	0.22	0.61	**0.62**	**0.62**	0.16	0.24	0.29	0.31	0.21
$\mathcal{F}$ (%)	-	-0.09	-0.09	2.45	1.01	1.13	1.82	2.00	-	-0.05	-0.03	2.26	1.99	1.12	1.76	2.24
$\mathcal{P}$ (%)	-	-0.09	-0.09	2.43	1.01	1.12	1.79	1.98	-	-0.05	-0.03	2.25	1.98	1.11	1.74	2.22
LW Test	-	0.84	0.84	0.01	0.09	0.10	0.05	0.03	-	0.73	0.65	0.01	0.00	0.10	0.05	0.02

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with an overlay of predicted regressions on the short-run deviations from expected returns using various forecasting methods on the residuals from the asset pricing tests, including Zou and Hastie (2005) elastic net (EN), Zou (2006) adaptive LASSO (AL), group LASSO (GL) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples), Raftery, Madigan, and Hoeting (1997) Bayesian model averaging (BMA), Elliott, Gargano, and Timmermann (2013) complete subset regression (CSR), partial least squares (PLS) (see Light, Maslov, and Rytchkov, 2017, for the application on stock markets), Kelly and Pruitt (2015) three-pass regression filter (TPF). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Figure H.3.: Tactical Asset Allocation: Out-of-Sample Performance of Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$, $w_\zeta = 0.95$, Differentiating L/S Legs)



This figure shows the cumulative average performance (excess returns after transaction costs) of currency factor-investing portfolio strategies across different rolling-window lengths spanning 2-3 business cycles (according to NBER), and using various forecasting methods on the residuals from the asset pricing tests, including Zou and Hastie (2005) elastic net (EN), Zou (2006) adaptive LASSO ($A - LASSO$), group LASSO ($G - LASSO$) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples), Raftery, Madigan, and Hoeting (1997) Bayesian model averaging (BMA), Elliott, Gargano, and Timmermann (2013) complete subset regression (CSR), partial least squares (PLS) (see Light, Maslov, and Rytchkov, 2017, for the application on stock markets), Kelly and Pruitt (2015) three-pass regression filter (TPF). The out-of-sample period is from August 1998 to March 2016. All series are adjusted to the same risk profile as the factor-based portfolio strategy, in terms of portfolio volatility, for comparison.

Table H.7.: Tactical Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$, $w_\zeta = 0.95$, Differentiating L/S Legs)

	Rolling Window: 140M								Rolling Window: 150M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	4.37	4.45	4.45	4.26	4.53	4.24	4.99	4.87	4.64	4.79	4.78	4.55	4.66	5.06	4.38	3.92
Std.Dev. (%)	4.89	4.96	4.96	5.09	5.42	6.51	7.08	6.90	4.86	5.01	5.01	5.16	5.41	6.63	6.94	6.82
Sharpe Ratio	0.89	**0.90**	**0.90**	0.84	0.84	0.65	0.70	0.71	**0.96**	0.95	0.95	0.88	0.86	0.76	0.63	0.57
Sortino Ratio	**1.26**	1.25	1.25	1.17	1.20	0.90	1.00	1.02	**1.37**	**1.37**	**1.37**	1.27	1.22	1.09	0.91	0.82
CEQ	3.65	**3.71**	**3.71**	3.48	3.65	2.97	3.48	3.45	3.94	**4.03**	**4.03**	3.75	3.78	3.75	2.93	2.52
Omega Ratio	**1.07**	1.00	1.00	1.00	0.97	0.96	1.01	1.04	1.07	1.07	1.06	1.01	**1.08**	0.98	0.96	0.96
Calmar Ratio	0.39	**0.41**	**0.41**	0.31	0.36	0.23	0.30	0.32	**0.59**	0.52	0.52	0.40	0.34	0.29	0.25	0.27
$\mathcal{F}$ (%)	-	-0.02	-0.02	0.28	0.28	1.19	0.93	0.91	-	0.00	0.01	0.36	0.46	0.93	1.58	1.85
$\mathcal{P}$ (%)	-	-0.02	-0.02	0.28	0.28	1.18	0.92	0.91	-	0.00	0.01	0.36	0.46	0.92	1.57	1.84
LW Test	-	0.55	0.55	0.10	0.10	0.04	0.09	0.09	-	0.49	0.48	0.06	0.08	0.09	0.02	0.01
	Rolling Window: 160M								Rolling Window: 170M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	5.05	5.22	5.22	4.88	5.01	5.64	4.57	3.95	5.28	5.55	5.55	5.30	5.41	5.30	5.24	4.83
Std.Dev. (%)	4.80	5.03	5.03	5.19	5.39	6.51	6.89	6.80	4.81	5.00	5.00	5.10	5.25	6.49	6.67	6.67
Sharpe Ratio	**1.05**	1.04	1.04	0.94	0.93	0.87	0.66	0.58	1.10	**1.11**	**1.11**	1.04	1.03	0.82	0.79	0.72
Sortino Ratio	**1.53**	1.51	1.51	1.35	1.30	1.23	0.92	0.81	1.56	**1.58**	**1.58**	1.48	1.49	1.23	1.12	1.03
CEQ	4.36	**4.46**	**4.46**	4.08	4.14	4.37	3.15	2.56	4.58	**4.80**	**4.80**	4.52	4.59	4.04	3.91	3.49
Omega Ratio	1.06	**1.08**	**1.08**	**1.08**	1.06	1.07	0.98	0.97	1.06	1.05	1.05	1.11	1.09	**1.12**	0.97	1.02
Calmar Ratio	**0.65**	0.64	0.64	0.46	0.35	0.45	0.32	0.26	**0.69**	**0.69**	**0.69**	0.56	0.43	0.42	0.42	0.36
$\mathcal{F}$ (%)	-	0.08	0.08	0.54	0.60	0.90	1.87	2.27	-	-0.06	-0.06	0.28	0.32	1.35	1.50	1.80
$\mathcal{P}$ (%)	-	0.08	0.08	0.54	0.60	0.89	1.86	2.26	-	-0.06	-0.06	0.28	0.32	1.33	1.49	1.79
LW Test	-	0.31	0.31	0.02	0.04	0.09	0.01	0.00	-	0.70	0.70	0.07	0.10	0.03	0.03	0.01

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with an overlay of predicted regressions on the short-run deviations from expected returns using various forecasting methods on the residuals from the asset pricing tests, including Zou and Hastie (2005) elastic net (EN), Zou (2006) adaptive LASSO (AL), group LASSO (GL) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples), Raftery, Madigan, and Hoeting (1997) Bayesian model averaging (BMA), Elliott, Gargano, and Timmermann (2013) complete subset regression (CSR), partial least squares (PLS) (see Light, Maslov, and Rytchkov, 2017, for the application on stock markets), Kelly and Pruitt (2015) three-pass regression filter (TPF). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

Table H.8.: Tactical Asset Allocation: Performance Comparison among Portfolio Optimizers with Multiple Risk Premia ($\gamma = 6$, $w_\zeta = 0.95$, Differentiating L/S Legs)

	Rolling Window: 180M								Rolling Window: 190M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	4.81	5.04	5.04	4.69	4.55	4.96	4.43	4.39	4.38	4.67	4.67	4.19	4.24	4.57	4.23	4.31
Std.Dev. (%)	4.75	4.86	4.86	4.96	5.16	5.79	6.29	6.11	4.72	4.86	4.86	5.03	5.05	5.71	6.14	6.15
Sharpe Ratio	1.01	**1.04**	**1.04**	0.95	0.88	0.86	0.70	0.72	0.93	**0.96**	**0.96**	0.83	0.84	0.80	0.69	0.70
Sortino Ratio	1.44	**1.48**	**1.48**	1.35	1.24	1.30	1.08	1.09	1.30	**1.35**	**1.35**	1.18	1.18	1.21	0.98	1.05
CEQ	4.14	**4.33**	**4.33**	3.95	3.75	3.96	3.24	3.27	3.71	**3.97**	**3.97**	3.43	3.48	3.59	3.10	3.17
Omega Ratio	1.09	1.05	1.05	1.08	1.02	**1.15**	1.07	1.04	1.15	**1.18**	**1.18**	1.08	1.06	1.08	1.05	1.11
Calmar Ratio	0.62	**0.66**	**0.66**	0.55	0.34	0.46	0.46	0.37	0.58	**0.61**	**0.61**	0.38	0.34	0.41	0.40	0.36
$\mathcal{F}$ (%)	-	-0.11	-0.11	0.32	0.62	0.74	1.47	1.40	-	-0.16	-0.16	0.45	0.41	0.60	1.13	1.07
$\mathcal{P}$ (%)	-	-0.11	-0.11	0.32	0.62	0.73	1.45	1.39	-	-0.16	-0.16	0.45	0.41	0.59	1.12	1.06
LW Test	-	0.91	0.91	0.02	0.02	0.08	0.03	0.04	-	0.95	0.95	0.04	0.09	0.10	0.07	0.09
	Rolling Window: 200M								Rolling Window: 210M							
	FB	EN	AL	GL	BMA	CSR	PLS	TPF	FB	EN	AL	GL	BMA	CSR	PLS	TPF
Mean (%)	4.27	4.47	4.47	4.06	4.13	5.02	4.75	5.06	4.38	4.53	4.53	4.15	4.15	5.20	4.76	4.89
Std.Dev. (%)	4.70	4.82	4.82	4.96	5.03	5.57	6.01	6.03	4.73	4.86	4.86	5.02	5.08	5.52	5.91	5.95
Sharpe Ratio	0.91	**0.93**	**0.93**	0.82	0.82	0.90	0.79	0.84	0.93	0.93	0.93	0.83	0.82	**0.94**	0.81	0.82
Sortino Ratio	1.26	1.29	1.29	1.14	1.16	**1.36**	1.13	1.29	1.29	1.30	1.30	1.16	1.17	**1.41**	1.20	1.22
CEQ	3.61	3.77	3.77	3.32	3.37	**4.09**	3.66	3.97	3.71	3.83	3.83	3.40	3.37	**4.29**	3.72	3.83
Omega Ratio	1.11	**1.14**	**1.14**	1.03	1.02	1.07	1.07	1.13	1.09	**1.12**	**1.12**	1.07	1.07	1.10	1.08	1.01
Calmar Ratio	**0.58**	**0.58**	**0.58**	0.39	0.35	0.55	0.48	0.46	0.61	**0.62**	**0.62**	0.39	0.34	0.60	0.47	0.44
$\mathcal{F}$ (%)	-	-0.09	-0.09	0.43	0.41	0.03	0.56	0.32	-	-0.03	-0.03	0.47	0.52	-0.08	0.57	0.49
$\mathcal{P}$ (%)	-	-0.09	-0.09	0.42	0.41	0.02	0.55	0.31	-	-0.03	-0.03	0.47	0.52	-0.08	0.56	0.48
LW Test	-	0.84	0.84	0.04	0.10	0.48	0.09	0.09	-	0.65	0.65	0.05	0.07	0.10	0.09	0.09

This table reports the out-of-sample performance metrics of factor-based (FB) currency portfolio optimization with multiple risk premia applying the principal component slope factor (PCS) to the mean-variance framework, in comparison with an overlay of predicted regressions on the short-run deviations from expected returns using various forecasting methods on the residuals from the asset pricing tests, including Zou and Hastie (2005) elastic net (EN), Zou (2006) adaptive LASSO (AL), group LASSO (GL) (see Bach, 2008; Jacob, Obozinski, and Vert, 2009; Simon, Friedman, Hastie, and Tibshirani, 2013, for examples), Raftery, Madigan, and Hoeting (1997) Bayesian model averaging (BMA), Elliott, Gargano, and Timmermann (2013) complete subset regression (CSR), partial least squares (PLS) (see Light, Maslov, and Rytchkov, 2017, for the application on stock markets), Kelly and Pruitt (2015) three-pass regression filter (TPF). $\mathcal{F}$ and $\mathcal{P}$ reveal the annualized economic value of the PCS. $\mathcal{F}$ is a performance fee that a risk-averse investor is willing to pay for switching from the competing models to our alternative factor-based mean-variance approach; $\mathcal{P}$ is a manipulation-proof performance measure. The $p-value$ corresponds to the robust (bootstrapped) measure for no outperformance in Sharpe ratio proposed by Ledoit and Wolf (2008). The rolling-window length is 2-3 average business cycle durations (70 months on average). The same period is from February 1981 to March 2016.

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