The parametrization of an international equity portfolio: A decomposition of global momentum returns.

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JEL classification: F31, F37, G11, G15

Keywords: Portfolio choice, international equity, momentum returns

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1 Introduction

A common practice in the academic momentum literature is to form winner and loser portfolios based on the past cumulative performance, and subsequently invest into the winner portfolio, financed by the loser portfolio. While this is straight forward when winner and loser portfolios are in the same market, an inevitable issue arises when currency exchange rates come into play. In this paper, I show how investors can form international stock momentum portfolios, while exploiting the dependencies among global equity returns, currency exchange rates, and interest rate differentials.[1] Furthermore, this paper contributes to the existing literature on empirical asset pricing, by providing new insights into the composition of global equity profits, by decomposing momentum returns into an equity part, currency part, and inflation part.

Every investment that is denominated in a foreign (un-pegged) currency inherits the risk of currency exchange rate fluctuations. Therefore, strategies that would yield profits in foreign markets are still subject to exchange rate gains and losses when converting into the home currency. Though future currency spot rates are nearly impossible to forecast out-of-sample (Meese and Rogoff (1983)), a tremendous amount of research investigates the profitability of currency exchange rate strategies. A widely used strategy is the carry trade: a profitable strategy,[2] exploiting the violation of the uncovered interest rate parity (UIP), which hypothesizes that a high interest-rate foreign currency is expected to depreciate by the interest-rate differential between the foreign and domestic risk-free rate.[3] Boudoukh, Richardson, and Whitelaw (2005) find that a fundamental factor for forecasting expected exchange rate movements are interest-rate differentials, or equivalently inflation differences, between countries. Lustig, Roussanov, and Verdelhan (2011) provide evidence that currencies with higher average interest rates tend to earn higher average profits.[4] Therefore, any correlation between exchange rates and interest rate differentials has the potential to directly implicate the expected excess returns from holding foreign assets (Bansal and Dahlquist (2000)).

In addition to currency exchange rate fluctuations, this paper also shows how sophisticated

[1] Campbell, Medeiros, and Viceira (2010) find that currency hedging can substantially reduce the risk of global investments, when the optimal portfolio choice problem of stocks and currency positions is jointly solved. Jylhae and Suominen (2009) show that currency carry trades have a low correlation with both equity and bond returns.

[2] Burnside, Eichenbaum, and Rebelo (2011) argue that carry-trades provide large diversification gains and make profits as long as there is a difference between the forward rates and spot rates, or equivalently, an interest rate differential between the domestic currency and the foreign currency.

[3] For an overview of the UIP see Bilson (1981), Fama (1984), Hodrick (1987) and Engel (1996).

[4] Engel and West (2006), Alquist and Chinn (2008), Mark (2009) and Engel (2011) are additional studies that establish the empirical link between real interest rates and real exchange rates.

investors can exploit the impact of inflation on equity returns. If we consider equities to be real assets, investments in local securities should provide a natural hedge against increases in local prices, because they are claims to real cash flows that are produced domestically. In line with a vast amount of literature finding a negative relation between stocks returns and inflation,[5] Campbell, Shiller, and Viceira (2009) show that the inflation risk premium is time-varying and the Fisher hypothesis does not hold.[6]

I begin my analysis by forming pure global momentum portfolios. Looking at the past cumulative returns of international equity indices, I find momentum strategies (going long past winners, and short past losers) to be profitable for both developed and emerging markets.[7] Contributing to the existing literature on momentum strategies, I show that the U.S. dollar-denominated momentum returns are affected by both currency exchange rates and local inflation. In general, I find that exchange rate gains contribute positively to the overall return, whereas high inflation rates lessen the overall return. I then use the decomposed sub-parts of momentum returns to model future equity profits, based on the individual past performance of the components. My results indicate that there is a positive relation between future U.S. dollar profits and past equity momentum (in local currency), and a negative impact of foreign currency appreciation and high inflation rates.

Based on this information, I form an optimal equity portfolio using the parametric portfolio approach of Brandt, Santa-Clara, and Valkanov (2009). This framework allows me to model the optimal portfolio weights, purely based on characteristics, without modeling the joint distribution explicitly.[8] My main empirical result is that the portfolio parametrization of momentum strategies can be significantly improved by decomposing momentum returns. Comparing the optimal pure momentum portfolio with the decomposed momentum portfolio, the out-of-sample certainty equivalent (CE) and Sharpe ratio can be increased by almost 60 and 36 percent, respectively. The optimal decomposed portfolio choice overweights international equities with positive momentum, whereas it underweights countries with past appreciating currency exchange rates[9] and high inflation rates.

[5]See, for example, Lintner (1975), Nelson (1976), Fama and Schwert (1977), Fama (1981), Boudoukh and Richardson (1993), Buraschi and Jiltsov (2005), Lin (2009) and Bekaert and Wang (2010), among others.

[6]Irving Fisher finds that equity returns should be positively related to expected inflation, because they represent claims to real assets.

[7]See, for example, Asness, Moskowitz, and Pedersen (2013) for a good overview of momentum across different asset classes.

[8]Pastor and Stambaugh (2000) stretch the importance of a portfolio perspective, to assess which characteristics matter jointly for the optimal portfolio allocation.

[9]This might seem intuitively puzzling, given that the U.S. dollar-denominated return of a foreign investment increases when the foreign currency depreciates. But the optimization exploits the negative correlation between currencies and global stock markets that has been shown by Campbell et al. (2010) and others.

In a next step, I consider several modifications and extensions of the model. Since the framework optimizes portfolio weights as the deviation from a benchmark portfolio, it might not be feasible in practice to short stocks. To address this issue, I provide results for an optimal long-only portfolio that produces a 50 percent gain in the Sharpe Ratio and three times the CE, compared to an value weighted benchmark. Another natural extension of the framework is the incorporation of transaction costs. Using different levels of transaction costs I show that the optimal portfolio remains profitable if transaction costs are incorporated. When I take both restrictions into account, the optimal out-of-sample parametrization produces almost twice the CE and a 28 percent Sharpe ratio gain, compared to a value weighted benchmark.

In a final step, I propose several robustness checks to the initial estimation. First, I consider that there might be a non-constant relationship among equity market returns and currency exchange rates and thus perform a rolling sample approach to estimate optimal portfolios. Second, I substitute the inflation coefficient by a coefficient modeling the cross-sectional differences in 10-year government bond yields. Consistent with my main findings, the optimal portfolio choice overweights countries with a positive equity momentum and a depreciating currency, and underweights countries with high interest-rate differentials. In a third robustness check, I substitute the currency exchange rate and consumer price parameters with the real effective exchange rate, which is the geometric weighted average of bilateral exchange rates, adjusted by the relative consumer prices. It thus incorporates both coefficients in a single measure. Again, consistent with my earlier findings, the optimal portfolio consists of countries with positive past stock market momentum and underweights countries with an appreciating real effective exchange rate.

The rest of the paper is organized as follows. Section 2 describes the proposed momentum measure and documents the impact of currency exchange rate fluctuations and price change effects on global equity returns. Section 3 provides the methodology for the parametric portfolio optimization approach and its extensions, while Section 4 presents the empirical results and robustness checks. A final section concludes.

2 Momentum in global equity markets

I use a comprehensive panel-dataset from Reuters Datastream containing 52 developed and emerging markets. For each country in the sample, I collect monthly observations of the MSCI stock market total return index (in local currency as well as in U.S. dollars), the exchange rate quoted against the U.S. dollar and the local Consumer Price Index (CPI). The sample starts in January 1970, and ends in April 2017, resulting in 568 monthly observations. Details and descriptive statistics are displayed in Appendix A.1.

2.1 Momentum measure

I begin my analysis by examining the profitability of buying past strong performers and selling past weak performers of global equity markets. I follow a common measure of momentum in the finance literature and sort winners to losers based on past cumulative returns between months $t-h$ and $t-2$, for various lengths h, ranging from 3 to 24 months:[10]

$$r_{i,t-1} = log(P_{i,t-2}) - log(P_{i,t-h}), \tag{1}$$

where $P_{i,t}$ is the total return price of stock market index i at time t.

I then weight past winners and losers as the proportional difference between the individual stock market and the cross-sectional average across all markets, $r_{m,t-1}$. This results in greater absolute weights for those markets that deviate more from the mean, ensuring that portfolio weights are unbiased by any cut-off limits:[11]

$$w_{i,t} = \frac{1}{N_t}[r_{i,t-1} - r_{m,t-1}]. \tag{2}$$

Since the weights can be arbitrarily scaled to obtain any level of profits, I normalize them by the absolute amount invested in the long and short positions $\frac{1}{2}\sum_{j=1}^{N_t}|w_{j,t}|$. The resulting portfolio return, at time t, is therefore:

$$\pi_t = \frac{\sum_{i=1}^{N_t} w_{i,t} r_{i,t}}{\frac{1}{2}\sum_{j=1}^{N_t}|w_{j,t}|}. \tag{3}$$

[10] I skip the last month to avoid 1-month reversal in stock returns, which is standard in the momentum literature. See, for example, Jegadeesh and Titman (1993), Fama and French (1996), Asness et al. (1997), Richards (1997), Grinblatt and Moskowitz (2003) and Asness, Moskowitz, and Pedersen (2013), among others.

[11] As a robustness check I also calculated the weights for different breakpoints. After sorting momentum returns from lowest to highest, the strategy takes a long position in the top percentiles and shorts the bottom percentiles. Overall, smaller (greater) cut-offs yield higher (lower) mean returns, but also higher (lower) standard deviations, resulting in similar Sharpe Ratios.

2.2 Decomposition of global equity momentum profits

In order to show the statistical and economic profitability of momentum returns, I extend the decomposition model of Chan et al. (2000) and Bhojraj and Swaminathan (2006) by an inflation term. Profits from international momentum strategies are subsequently split up into an equity component, currency component, inflation component, and interaction components. For an U.S. investor, the continuously compounded return can be decomposed into:

$$r_{i,t}^{USD} \approx r_{i,t}^{LCY} + f_{i,t} + c_{i,t}, \tag{4}$$

where $r_{i,t}^{USD}$ is the nominal U.S. dollar return, $r_{i,t}^{LCY}$ the assets real return (in local currency), $f_{i,t}$ the change in the currency exchange rate, and $c_{i,t}$ the change in price levels of country i at time t. This implies that the U.S. dollar return from Equation (3), can be re-written as:

$$\pi_t = \sum_{i=1}^{N} w_{i,t} r_{i,t}^{USD} = \frac{1}{N}\sum_{i=1}^{N}\left[r_{i,t-1}^{USD} - r_{m,t-1}^{USD}\right] r_{i,t}^{USD} \tag{5}$$

$$\approx \frac{1}{N}\sum_{i=1}^{N}\left[(r_{i,t-1}^{LCY} + f_{i,t-1} + c_{i,t-1}) - (r_{m,t-1}^{LCY} + f_{m,t-1} + c_{m,t-1})\right](r_{i,t}^{LCY} + f_{i,t} + c_{i,t}). \tag{6}$$

Figure 1 shows average portfolio returns π_t, for different sample sizes (all countries, OECD countries and emerging markets), and for various lengths h, defined in Equation (1). The black bars present average returns quoted in U.S. dollars. The dark gray bars display the return contribution from the equity part, the light gray bars display the return contribution from the currency exchange rate change, and the white bars show the return contribution stemming from the price change rate.[12]

[FIGURE 1 ABOUT HERE]

Forming future portfolios, based on the past momentum performance, highlights a clear pattern. I find consistent positive average momentum returns across all measurement lengths h, with a clear peak on the one-year horizon. The explicitly displayed return contribution

[12] Table 16 in Appendix B.1 displays the results explicitly.

shows positive values for the equity and the exchange rate part, but a negative contribution for inflation. This result is also consistent if I restrict the sample to OECD countries.

Since the decomposed return contribution displays only the past $t-h$ equity, currency exchange rate and inflation part, one cannot infer how the past performance of each part individually impacts future equity returns. Therefore, by examining the sub-components explicitly, I expand the equation to its cross products:

$$\begin{aligned}\pi_t = \frac{1}{N}\Bigg[&\sum_{i=1}^{N}(r_{i,t-1}^{LCY} - r_{m,t-1}^{LCY})r_{i,t}^{LCY} + \sum_{i=1}^{N}(f_{i,t-1} - f_{m,t-1})r_{i,t}^{LCY} + \sum_{i=1}^{N}(c_{i,t-1} - c_{m,t-1})r_{i,t}^{LCY} \\ &+ \sum_{i=1}^{N}(r_{i,t-1}^{LCY} - r_{m,t-1}^{LCY})f_{i,t} + \sum_{i=1}^{N}(f_{i,t-1} - f_{m,t-1})f_{i,t} + \sum_{i=1}^{N}(c_{i,t-1} - c_{m,t-1})f_{i,t} \\ &+ \sum_{i=1}^{N}(r_{i,t-1}^{LCY} - r_{m,t-1}^{LCY})c_{i,t} + \sum_{i=1}^{N}(f_{i,t-1} - f_{m,t-1})c_{i,t} + \sum_{i=1}^{N}(c_{i,t-1} - c_{m,t-1})c_{i,t}\Bigg]. \end{aligned} \tag{7}$$

The result of the decomposition is divided into 9 decomposed profit components (π_t^i) and is reported along with the sum for all dollar returns ($\pi_t = \sum_{i=1}^{9} \pi_t^i$) in Table 1.[13] To evaluate the economic significance of the returns, the table also displays Newey and West (1987) autocorrelation-corrected t-statistics in parenthesis.

[13] Table 1 shows the decomposed profit due to predictability of equity returns based on past equity performance

$$\pi_t^1 = \frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1}^{LCY} - r_{m,t-1}^{LCY})r_{i,t}^{LCY}, \tag{8}$$

profits due to predictability of equity returns based on past exchange rate performance

$$\pi_t^2 = \frac{1}{N}\sum_{i=1}^{N}(f_{i,t-1} - f_{m,t-1})r_{i,t}^{LCY}, \tag{9}$$

and profits due to predictability of equity returns based on past price change performance

$$\pi_t^3 = \frac{1}{N}\sum_{i=1}^{N}(c_{i,t-1} - c_{m,t-1})r_{i,t}^{LCY}, \tag{10}$$

and several interaction terms. These are profits due to predictability of exchange rate returns based on past equity performance ($\pi_t^4 = \frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1}^{LCY} - r_{m,t-1}^{LCY})f_{i,t}$), past exchange rate performance ($\pi_t^5 = \frac{1}{N}\sum_{i=1}^{N}(f_{i,t-1} - f_{m,t-1})f_{i,t}$), past price change performance $\pi_t^6 = \frac{1}{N}\sum_{i=1}^{N}(c_{i,t-1} - c_{m,t-1})f_{i,t}$, and in interaction terms for profits due to predictability of price change returns based on past equity performance ($\pi_t^7 = \frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1}^{LCY} - r_{m,t-1}^{LCY})c_{i,t}$), past exchange rate performance ($\pi_t^8 = \frac{1}{N}\sum_{i=1}^{N}(f_{i,t-1} - f_{m,t-1})c_{i,t}$) and past price change performance $\pi_t^9 = \frac{1}{N}\sum_{i=1}^{N}(c_{i,t-1} - c_{m,t-1})c_{i,t}$.

[TABLE 1 ABOUT HERE]

The first column represents the predictability of future U.S. dollar profits by decomposing the past nominal U.S. dollar performance into an equity part and currency exchange rate part. The profit generated by the predictability of equity returns based on past equity performance (π_t^1) is positive and highly significant, whereas I find a highly significant negative profit generated by the predictability of equity returns based on past currency exchange rate performance (π_t^2). The predictability of future exchange rate changes based on past equity performance (π_t^4) is not significantly different from zero, and the profit generated by the predictability of exchange rate changes based on past currency exchange rate performance (π_t^5) is significantly positive. These results are in line with Chan et al. (2000) and Bhojraj and Swaminathan (2006).

The second column represents the predictability of future U.S. dollar profits by decomposing the past nominal U.S. dollar performance into an equity part and a price change part. Again, the profit generated by the predictability of equity returns based on past equity performance (π_t^1) is positive and highly significant. This is also the case for the predictability of price change returns based on past price change performance (π_t^9). For the interaction terms, (π_t^3) and (π_t^7), I find significant negative profits based on the past performance for both equity and price change performance.

The third column represents the predictability of future U.S. dollar profits by decomposing past nominal U.S. dollar performance into the 9 cross products, defined in Equation (7). Consistent with columns 1 and 2, I find a significant positive profit generated by the predictability of equity returns based on past equity performance (π_t^1), and negative profits due to the predictability of equity returns based on past currency exchange rate performance and past price change performance. Even though past exchange rate returns and past price change returns may not have a significant (direct) impact on the predictability of equity returns, they have the right sign and contribute a major part interchangeably to the overall profits via their interaction terms.

Given the relationship of future equity returns with past equity returns, currency exchange rate movements and price changes, a profitable strategy would impose an overweighting in past equity winners, while exploiting the negative relationship with past currency exchange rate appreciation and price changes.

3 Parametric portfolio optimization

To form optimal equity portfolios, I follow the parametric portfolio optimization approach in Brandt, Santa-Clara, and Valkanov (2009). Assuming that certain characteristics convey relevant information about the assets' condition distribution of return, the model does not require a quadratic utility function or estimated positive definite covariance matrix to form optimal portfolio weights.[14] Instead of modeling the joint distribution of returns and characteristics, their framework guarantees that only N portfolio weights are estimated. Therefore, regardless of the investors utility function and distribution of assets, the portfolio policy is reduced in dimensionality and prevents common statistical problems of imprecise coefficient estimates and over-fitting. The portfolio weights $w_{i,t}$ are parametrized as the simple linear specification for the portfolio weight function with respect to the assets' characteristics $w_{i,t} = f(x_{i,t}; \theta)$:

$$w_{i,t} = \bar{w}_{i,t} + \frac{1}{N_t}\theta^T \hat{x}_{i,t}, \tag{11}$$

where $\bar{w}_{i,t}$ is the weight of asset i at time t of the benchmark portfolio, θ represents the vector of coefficients to be estimated, and $\hat{x}_{i,t}$ are the cross-sectionally standardized characteristics of the asset.[15]

Suppose, at time t, there are N_t assets in the investable universe, and each asset i has a return $r_{i,t+1}$ from time t to $t+1$. For a certain portfolio to be optimal, it must maximize the investor's conditional expected utility of the portfolio's return $r_{p,t+1}$ by choosing weights $w_{i,t}$ for each asset:

$$\max_{(w_{i,t})_{i=1}^{N_t}} E_t[u(r_{p,t+1})] = E\left[u\left(\sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}\right)\right]. \tag{12}$$

[14] If the investors' utility function is not quadratic, it is almost impossible to estimate a covariance matrix that guarantees positive definitiveness, since it requires not only the conditional skewness of each asset to be estimated but also the numerous high-order cross-moments.

[15] Brandt, Santa-Clara, and Valkanov (2009) use standardized characteristics for three reasons. First, the standardization implies that the cross-sectional average of $\theta^T \hat{x}_{i,t}$ is zero, meaning that the sum of the portfolio weights is always one, resulting in a purely long-short strategy deviating from the benchmark portfolio. Second, the cross-sectional distribution of the standardized $\hat{x}_{i,t}$ is stationary over time, while the non-standardized characteristics may not. Thus, coefficients that maximize the investor's conditional expected utility at time t maximize the investor's conditional expected utility for all T, and hence also maximize the investor's unconditional expected utility. Third, the coefficients are constant across assets, implying that the weight of each asset in the portfolio depends only on the asset's characteristics and not on the historical return performance. In order to use an arbitrary and time-varying number of assets for the optimization, the term $1/N_t$ normalizes the portfolio weight function.

Assuming that the characteristics are constant across assets and through time, the conditional optimization can be re-written as the unconditional optimization with respect to the estimated θ coefficients:

$$\max_{\theta} E[u(r_{p,t+1})] = E\left[u\left(\sum_{i=1}^{N_t} f(x_{i,t};\theta) r_{i,t+1}\right)\right]. \tag{13}$$

In other words, it is the average utility over time,

$$\max_{\theta} \frac{1}{T}\sum_{t=0}^{T-1} u(r_{p,t+1}) = \frac{1}{T}\sum_{t=0}^{T-1} u\left(\sum_{i=1}^{N_t} f(x_{i,t};\theta) r_{i,t+1}\right), \tag{14}$$

optimized for some constant relative risk aversion utility function:

$$\max_{\theta} \frac{1}{T}\sum_{t=0}^{T-1} u\left(\sum_{i=1}^{N_t}\left(\bar{w}_{i,t} + \frac{1}{N_t}\theta^T \hat{x}_{i,t}\right) r_{i,t+1}\right). \tag{15}$$

This framework allows the investor to perform a numerically robust optimization over a large number of assets, without the risk of in-sample over-fitting, given the relatively low dimensionality of the parameter vector. Furthermore, since the optimization does not require covariance matrices, the computational burden lies purely in the number of characteristics.[16]

3.1 Objective function

In contrast to using a mean-variance utility function, which takes only the first two moments of the distribution of returns into account, I follow common practice in the finance literature and use a constant relative risk aversion utility function that penalizes negative skewness and kurtosis:[17]

$$u(r_{p,t+1}) = \frac{(1 + r_{p,t+1})^{1-\gamma}}{1-\gamma}, \tag{16}$$

[16]The optimization takes the relation between the characteristics and expected returns, variances, covariances, and even higher-order moments of returns into account, to the extent that they affect the distribution of the optimized portfolio return, and consequently the investors expected utility (Brandt, Santa-Clara, and Valkanov (2009)).

[17]Experimental evidence from Gordon, Paradis, and Rorke (1972) shows that most individuals have a concave utility function. Kraus and Litzenberger (1976) find that investors have a preference for positive skewness and kurtosis.

and assume a constant relative risk aversion coefficient of $\gamma = 5$.[18]

3.2 Portfolio constraints and modifications

Deviating from the optimal portfolio choice problem (12) can be due to various reasons. This section describes specifications for real-life applications, such as short-selling constraints and the impact of transaction costs.

3.2.1 Long-only portfolio optimization

A very common requirement in practice is the implementation of long-only portfolios, where the investor is restricted from selling short assets that impose a negative expected return (Jacobs, Levy, and Starer (1999)). This modification can easily be applied by truncating the optimal weights (11) at zero and normalizing them to one:

$$w_{i,t}^{+} = \frac{max[0, w_{i,t}]}{\sum_{j=1}^{N} max[0, w_{j,t}]}. \tag{17}$$

3.2.2 Transaction costs

In the presence of transaction costs, theoretical returns of a profitable strategy can be substantially reduced. Keim and Madhavan (1997) and Lesmond, Schill, and Zhou (2004), for example, find that relative strength strategies require frequent trading in disproportionally high-cost securities, which can substantially reduce or possibly outweigh the expected value created by an investment strategy.[19] Especially short positions can be particularly costly, due to borrowing costs and higher margin requirements for short versus long positions (Diamond and Verrecchia (1987) and D'Avolio (2002)).

Examining transaction costs for developed and emerging markets, I find a substantial variation in the execution costs of international equities. For example, in emerging markets, trading costs are generally higher than in developed markets and vary systematically with market capitalization, market liquidity and return volatility (Lesmond, Schill, and Zhou

[18] Brandt, Santa-Clara, and Valkanov (2009) use a risk aversion coefficient of 5 and Barroso and Santa-Clara (2015) use $\gamma = 4$. Bliss and Panigirzoglou (2004) estimate γ empirically in 1-month options on the Standard & Poor's (S&P) and Financial Times Stock Exchange (FTSE) and find values close to 4.

[19] Korajczyk and Sadka (2004), for example, investigate the price impact of trading costs on the profitability of momentum strategies.

(2004)).[20] In addition to the cross-sectional differences, there is also a substantial time-series variation in trading costs (Lesmond, Ogden, and Trzcinka (1999)). Wermers (2000), for example, reports annual trading costs in 1994 to be one third of the level in 1975.

Therefore, the portfolio's turnover constitutes an essential part in the portfolio optimization when considering transaction costs. I define it as the sum of absolute net changes in the optimal portfolio weights (11) from period $t-1$ to t:

$$T_t = \sum_{i=1}^{N_t} |w_{i,t} - w_{i,t-1}|. \tag{18}$$

The resulting portfolio return, after transaction costs, can be re-written as

$$r_{p,t+1} = \sum_{i=1}^{N_t} w_i r_{i,t+1} - c_{i,t}|w_{i,t} - w_{i,t-1}|, \tag{19}$$

where $c_{i,t}$ reflects the proportional transaction costs of asset i at time t.

Given the tremendous impact of global transaction costs on the portfolio's return, I merge the one-way equity transaction costs of Table 1 in Domowitz, Glen, and Madhaven (2001) and Table 5 in Chiyachantana et al. (2004) to model global equity transaction costs. The average one-way trading cost is 86.25 basis points (BP) and ranges from 226 BP (Czech Republic in 1970) to a minimum of 15 BP (Japan in 2017). Table 12 in Appendix A.3 displays average mean one-way total equity trading costs of the merged dataset.

4 Empirical application

4.1 Characteristics

As mentioned in Section 3, I form optimal portfolio weights purely based on characteristics that are assumed to convey relevant information about the assets' condition distribution of return (see Equation (11)). Given the previous results in Section 2, I construct the following four factors:

[20] Keim and Madhavan (1997) and Chiyachantana et al. (2004) observe a negative relation between trading costs and market capitalization. Sercu and Vanpee (2008) also show that implicit transaction costs are substantially higher in emerging markets than in developed markets.

$$r_{i,t}^{USD} = log(\frac{P_{i,t-2}^{USD}}{P_{i,t-12}^{USD}}) \qquad \text{stock market momentum (in U.S. dollar),} \tag{20}$$

$$r_{i,t}^{LCY} = log(\frac{P_{i,t-2}^{LCY}}{P_{i,t-12}^{LCY}}) \qquad \text{stock market momentum (in local currency),} \tag{21}$$

$$f_{i,t} = log(\frac{FX_{i,t-2}}{FX_{i,t-12}}) \qquad \text{currency exchange rate change,} \tag{22}$$

$$c_{i,t} = log(\frac{CPI_{i,t-2}}{CPI_{i,t-12}}) \qquad \text{price change,} \tag{23}$$

where $P_{i,t}^{USD}$ and $P_{i,t}^{LCY}$ are the U.S. dollar and local currency-denominated total return prices of the MSCI stock market index, $FX_{i,t}$ is the U.S. dollar per foreign currency exchange rate,[21] and $CPI_{i,t}$ is the seasonally adjusted Consumer Price Index of country i at time t.[22]

Given the lack of previous research on realized inflation as a macroeconomic characteristic for parametric portfolio optimization, I use the same time horizon as for the other characteristics. Two reasons emerge for this approach. First, it seems reasonable to use the same time horizon for realized inflation as for stock market momentum, if one believes equities to be effective hedges against inflation. Second, since consumer price indices are published with a 2 to 4 week lag, I naturally avoid forward-looking biases.

4.2 Optimal portfolios and benchmarks

Following common practice in the finance literature, I provide results for both in- and out-of-sample estimates. The in-sample optimization starts in January 1971 (I lose the first year to form characteristics) and ends in April 2017, using all 556 monthly observations to calculate optimal θ estimates. For the out-of-sample optimization, I use the first 240 months to estimate initial coefficients of the portfolio policy and then re-estimate them using an expanding window until the end of the sample period, yielding optimal coefficients each point in time.[23] All results are presented for the out-of-sample period, i.e. January 1991

[21] All exchange rates are quoted against the U.S. dollar, which means that even if all currencies depreciate against the U.S. dollar, after standardizing, those that fall less will have positive momentum.

[22] Bekaert and Wang (2010) show that one of the most successful models to predict inflation rates is the random walk model, which simply uses the current inflation rate to forecast future inflation rates. Lustig, Roussanov, and Verdelhan (2011) use the lagged one-year change in log Consumer Price Index as a proxy for inflation. Brunnermeier, Nagel, and Pedersen (2009) add inflation to their analysis, since it is a more natural complement for the UIP with the assumption that purchasing power parity holds in the long run.

[23] In addition to this expanding window approach, in Section 4.8, I use a rolling window optimization to estimate optimal coefficients.

until April 2017.

In order to make results more comparable, I introduce two different benchmarks. The equally weighted (EW) benchmark, where all stock markets in the data sample have a constant equal weight of $1/N$, and the value weighted (VW) benchmark, where all stock markets are weighed according to their market capitalization (see Table 11 in Appendix A.2 for the market capitalization weights).

4.3 Pure momentum return parametric portfolio optimization

In a first step, I restrict the optimization to a single characteristic, i.e. the pure momentum returns defined in Equation (20). Table 2 presents the results of the parametrization. The first set of rows display the optimal θ_{mom}^{USD} parameter of the portfolio policy and the average out-of-sample estimate with bootstrapped standard errors. The next set of rows shows statistics of the portfolio weights over time, followed by annualized measures of portfolio performance.

[TABLE 2 ABOUT HERE]

Table 2 illustrates that the parametrization loads positively on past winners, as expected, and creates an annualized CE of 0.081, compared to -0.034 and 0.013 for the equal and value weighted benchmarks, respectively. The optimal portfolio more than doubles the average return and Sharpe ratio, but also significantly increases the turnover in the portfolio. In addition, the mean return generated by individual countries is positive for both OECD and emerging markets, as is the average return for the long and short side of the portfolio.

[FIGURE 2 ABOUT HERE]

Figure 2 plots the estimated out-of-sample coefficient for the pure stock market momentum θ_{mom}^{USD} over time. Though the coefficient varies over time, it is always positive, implying that the parametrization always overweights past strong performers. Figure 3 plots the portfolio performance of \$1 invested in January 1991. The continuous green line presents the portfolio performance of the in-sample optimization, the dashed line presents the out-of-sample performance. The blue an red lines display the equally weighted and value weighted benchmarks, respectively. The performance of the in- and out-of-sample portfolio choice displayed in Table 2 is not due to single outliers, but is continuous over a substantial time horizon. Even during global stock market crashes (e.g. 2001, 2008) the optimization seems to respond well.

[FIGURE 3 ABOUT HERE]

4.4 Decomposed momentum return portfolio optimization

Starting out from the single coefficient parametrization using the pure momentum returns only, Table 3 presents results for the decomposed momentum return portfolio optimization.

[TABLE 3 ABOUT HERE]

Generally, the optimization overweights countries with positive past stock market momentum and underweights countries with an appreciating currency or high price changes, resulting in positive estimates for θ_m and negative estimates for θ_f and θ_c. Figure 4 displays the out-of-sample theta coefficients over time. Though the coefficients vary over time, they seem to be roughly stationary, with the stock market momentum coefficient always being positive, and the exchange rate and price change coefficient always being negative.

[FIGURE 4 ABOUT HERE]

The optimal portfolio exhibits a maximum long (62.448 percent) and short (-41.166 percent) position that results in a yearly turnover of 11.531. The optimization delivers a CE, mean return and standard deviation of 0.128, 0.233 and 0.206, respectively, translating into a Sharpe Ratio of 1.002. Similar to the optimal portfolio, the out-of-sample optimization loads positively on past stock market momentum and negatively on appreciating foreign currencies and high price changes. Compared to the optimal portfolio, the estimated θ coefficients are lower in magnitude, resulting in lower average absolute weights, lower maximum and minimum weights, and consequently lower portfolio turnover (10.412).

Not surprisingly, the out-of-sample optimization delivers a lower performance than the optimal portfolio, but manages to outperform all benchmarks. The average yearly out-of-sample CE and mean return is 0.127 and 0.221, with a standard deviation of 0.195. This results in a Sharpe Ratio of 1.002, compared to the Sharpe Ratio of 0.212 and 0.367, for the equally weighted and value weighted benchmarks, respectively. For both the in- and out-of-sample parametrization, OECD countries contribute about 72 percent to the overall return, while the long sides of the portfolio contribute about 84 percent.

Table 3 also shows that the pure momentum return parametrization can be significantly improved by decomposing global momentum returns into an equity part, currency exchange rate part and inflation part. The pure momentum return parametrization gains almost 60 percent in CE, 37 percent in mean return and a 28 percent in Sharpe ratio, when the sub-components are jointly modeled. This evidence can also be seen in Figure 4 where I plot the portfolio performance of $1 invested in January 1991. The black lines present the decomposed momentum return performance, in- and out-of-sample. The green lines display the in- and out-of-sample performance of the pure momentum return optimization.

[FIGURE 5 ABOUT HERE]

4.5 Long-only optimization

So far, I have assumed that the optimal weights are not subject to any restrictions, which can be contrary to many real-life investment strategies. A very common deviation, compared to the unconstrained case, is the long-only optimization. In this scenario, the investor cannot exploit downside gains from holding short positions, which could be used to leverage exposure in long positions. In reality, a majority of equity portfolio managers tend to limit their investments from the possibility of downside gains.

Table 4 presents the results of a long-only portfolio policy using the no-short sale constraints (17) from Section 3.2.1. Higher than in the unconstrained case, the in-sample optimization overweights past stock market winners (θ_m of 3.386) and high price changes (θ_c of 0.045) and underweights appreciating currencies (θ_f of -0.671). The limitation to non-negative weights results in lower average weights, lower maximum weights, and 70 percent lower turnover.

[TABLE 4 ABOUT HERE]

Even though the optimal portfolio outperforms the equally weighted and value weighted benchmarks, the inability to hedge downside risk by taking short positions in the market is directly reflected in the return statistics. Compared to the unconstrained case, the annualized CE is reduced to 0.027, with a mean return of 0.112 and a Sharpe ratio of 0.488. Figure 6 and 7 in Appendix B.2 display the out-of-sample theta coefficients and portfolio performance, respectively.

4.6 Transaction costs

Managing transaction costs is particularly important, as the strategies employed are highly leveraged. Even a small increase in transaction costs can have a significant impact on the strategy imposed, given the high turnover of momentum strategies. Table 5 provides results for optimal portfolio policies under different levels of transaction costs: no transaction costs (No TC), constant one-way transaction costs of 100 basis points (100 BP),[24] and a merged dataset from Table 1 of Domowitz, Glen, and Madhaven (2001) and Table 5 of Chiyachantana et al. (2004) (Table 12).[25] The mean one-way equity transaction cost of the merged dataset, across all countries, is 86.251 basis points.[26] This number seems conservatively high, considering the introduction of exchange traded funds (ETFs) in the early 90s. Nevertheless, using the merged dataset I can capture the cross-sectional and time-series variation more accurately than with constant trading costs.

[TABLE 5 ABOUT HERE]

The impact of transaction costs on the optimal portfolio choice shows consistent results for the estimated parameter, weights and return statistics. All optimized θ coefficients have the right sign, but decline in magnitude, leading to lower maximum long and short positions in the portfolio, which is directly reflected by significantly reduced turnover.

For the constant one-way cost of 100 basis points the turnover can be reduced by almost 25 percent. The reduced magnitude of the estimated coefficients can clearly be seen in the return statistics. The out-of-sample portfolio delivers a CE of 0.071, mean return of 0.151, and Sharpe Ratio of 0.705. Using the merged dataset from Table 1 of Domowitz, Glen,

[24] A constant measure for transaction costs is not very realistic given the enormous cross-sectional and time series differences in transaction costs. Nevertheless, compared to other measures, it is fairly easy to estimate and interpret.

[25] See Table 12 in Appendix A.3. I assume trading costs to be 4 times higher in 1970 than in 2001 and interpolate values in between. This is consistent with Wermers (2000), who finds trading costs in 1994 to be one third their level in 1975.

[26] Grundy and Martin (2001) find that round-trip costs of 150 basis points would offset statistically significant net profits in momentum strategies.

and Madhaven (2001) and Table 5 of Chiyachantana et al. (2004), "Table 12", reduces the turnover by 20 percent. The optimal portfolio policy results in a CE of 0.093, mean return of 0.176, and a Sharpe ratio of 0.829. Figures 8, 9 and 10 in Appendix B.3 display the out-of-sample theta coefficient plots and portfolio performance, respectively.

4.7 Transaction costs and long-only constraint

This section describes the effects of transaction costs in the long-only framework. Table 6 compares the unconstrained case with the long-only portfolio, the parametrization with transaction costs from Table 12 introduced in the previous section, and a combination of the latter two.

[TABLE 6 ABOUT HERE]

Introducing both transaction costs and short-selling constraints clearly affects the optimal parametrization of the portfolio. In general, the out-of-sample "TC & long-only" portfolio exhibits lower average absolute weights, lower maximum weights and significantly lower (-65 percent) turnover when compared to the unconstrained case. This is also reflected in the portfolio performance, with an annualized CE, mean return and Sharpe ratio of 0.021, 0.103 and 0.448, respectively. Figures 11 and 12 in Appendix B.4 display the out-of-sample theta coefficient plot and portfolio performance, respectively.

4.8 Time specific correlation and rolling window optimization

Campbell, Medeiros, and Viceira (2010) find that many currencies are positively correlated with global stock markets for long periods, while others are negatively related to stock market movements. Engel (2011), argues that when a country's relative real interest rate is high, securities are expected to yield an excess return over foreign securities in the short run, but eventually yield lower returns in the long run.

Considering the non-constant correlation among equity markets, currency markets and the impact of inflation on those markets,[27] I introduce a similar approach to DeMiguel et al. (2009), who use a rolling sample approach to estimate optimal parameters. That means that instead of an expanding window (where I use the first 240 months to estimate initial

[27] Table 13 in Appendix A.4 displays correlation coefficients for different sample periods.

coefficients for the portfolio policy and then re-estimate the coefficients every subsequent point in time until the end of the sample period), I keep the optimization time-frame k constant. After an initial estimation period from $[t, t+k]$, yielding optimal coefficients for time $t+k+1$, the optimization adds the data for the next month and drops the data for the earliest month, moving the estimation period to $[t+1, t+k+1]$, yielding optimal coefficients for time $t+k+2$ etc., until the end of the sample period.

Taking Equation (15) from Section 3,

$$\max_{\theta} \frac{1}{T} \sum_{t=0}^{T-1} u\left(\sum_{i=1}^{N_t} \left(\frac{1}{N_t} \theta^T \hat{x}_{i,t} \right) r_{i,t+1} \right), \tag{24}$$

and re-writing T as $k+j$, where $j \in [0, T-k]$ and $k \in [60, 120, 240]$, I can define the rolling window optimization as:

$$\max_{\theta} \frac{1}{k+j} \sum_{t=j}^{k+j-1} u\left(\sum_{i=1}^{N_t} \left(\frac{1}{N_t} \theta^{k+j} \hat{x}_{i,t} \right) r_{i,t+1} \right). \tag{25}$$

Table 7 compares the results of the initial portfolio optimization, using an expanding window with the out-of-sample results of the rolling window optimization, using pre-specified constant time-frames of 60, 120 and 240 months.[28][29]

[TABLE 7 ABOUT HERE]

There is a clear negative relation between window length and the volatility of portfolio weights. Shrinking k leads to an absolute increase in optimal coefficients, which translates into more volatile portfolio weights and higher turnover. An increase in CE, mean return and alpha is accompanied by an increase in the standard deviation and decrease in β. Plots for the out-of-sample theta coefficients and the portfolio performance can be found in Appendix B.5.

[28] Note that the in-sample results of the rolling window optimization are identical to the expanding window optimization.

[29] Time-frames of 60, 120 and 240 months are chosen arbitrarily. I also employed the rolling window optimization approach with other window-lengths and find consistent results.

4.9 Interest rate differentials

It seems intuitively reasonable that equities are real assets, since they represent claims to real cash flows. Therefore, changes in the real rate of interest should be a true cause of ex-post stock returns, because an increase (decrease) in the real interest rate induces a reduction (increase) in all asset values (see Geske and Roll (1983)). Solnik (1983) uses interest rates as a proxy for expected inflation and finds that stock price movements signal (negative) revisions in inflationary expectations.

Frankel (1979) finds that the exchange rate is negatively related to the nominal interest rate, but positively related to the expected long-term inflation differential. The difference between the exchange rate and its equilibrium is proportional to the real interest differential (i.e. the nominal interest differential minus the expected inflation differential). Giovannini and Jorion (1987) document a negative correlation for both the stock market and foreign exchange market, whereas Jaffe and Mandelker (1976) find a stronger correlation between stock returns and the Treasury bill than between stock returns and inflation.

In a no-arbitrage framework, any variable that affects the pricing of the domestic yield curve has the potential to also affect the foreign exchange risk premium. In fact, Ang and Chen (2010) find an economically strong and statistically significant predictability of changes in the interest rates and slopes of the yield curve for foreign exchange rate returns.

Assuming that interest rate differentials convey information about the countries' condition distribution of stock market returns, I substitute the price change coefficient from Equation (23) in Section 4.1 with an interest rate differential coefficient to estimate optimal portfolio weights (11):

$$ird_{i,t} = \frac{Y_{i,t-1} - \bar{Y}_{t-1}}{\sigma_{t-1}}, \tag{26}$$

where $Y_{i,t-1}$ is the government bond yield of country i, $\bar{Y}_{t-1}$ is the average government bond yield and σ_{t-1} is the standard deviation of all government bond yields at time $t-1$. The data is obtained from Global Financial Data.[30]

[TABLE 8 ABOUT HERE]

[30] See Table 14 in Appendix A.5 for further statistical information. Due to data unavailability, I use 15-year government bond yields for Morocco and Peru, and exclude Jordan completely from the analysis.

The results from Table 8 are consistent with my earlier findings, i.e. the optimization overweights countries with past stock market winners and underweights those with an appreciating currency. The estimated θ_{ird} coefficient is even more negative than the θ_c coefficient. This results in more pronounced negative weights for countries with higher than average interest rates, and contributes to a higher CE, mean return and Sharpe ratio. Plots for the out-of-sample theta coefficients and the portfolio performance can be found in Appendix B.6.

4.10 Real effective exchange rate

An additional robustness check of my earlier findings is the substitution of the currency exchange rate and consumer price parameters with the real effective exchange rate (REER). The REER is the geometric weighted average of bilateral exchanges, adjusted by the relative consumer prices. This means the REER covers both the impact of the currency exchange rate changes and price levels. The data is obtained from the Bank for International Settlements.[31][32]

Similarly to all other measures, I define the *reer* coefficient as the cumulative change between month t-2 and month t-12 as:

$$reer_{i,t} = log(\frac{REER_{i,t-2}}{REER_{i,t-12}}), \tag{27}$$

where $REER_{i,t}$ is the real effective exchange rate of country i at time t. An increase in the index indicates an appreciation. The results are displayed in Table 9.

[TABLE 9 ABOUT HERE]

Consistent with the decomposed momentum return parametrization, the optimization overweights countries with positive stock market momentum and underweights those with an appreciating real effective exchange rate. Plots for the out-of-sample theta coefficients and the portfolio performance can be found in Appendix B.7.

[31] `https://www.bis.org/statistics/eer.htm`

[32] See Table 15 in Appendix A.6 for further statistical information. Due to data unavailability, I use only a subset of 25 countries, where data is available from January 1970 to April 2017. A broader dataset on real effective exchange rates is available from January 1994, including 48 out of my 52 countries. With only 280 monthly observations and a modified in-sample estimation period of 120 months, I receive similar results.

5 Conclusion

In this paper, I study equity momentum returns and their relation to currency exchange rates and interest rate differentials, for 52 developed and emerging markets, over the period 1970 to 2017. The empirical evidence in this paper suggests that there are significant momentum return premia among country stock market indices. The resulting mean returns and Sharpe ratios, of a simple cross-sectional weighting of past returns, are higher in developed markets and peak if weights are based on the past 12 month cumulative return.

Contributing to the existing momentum literature, I find that global stock momentum returns can be used to form international equity portfolios. Furthermore, I show that these returns can be decomposed into three parts. First, in an equity component, which reflects the change in asset prices denominated in its local currency. Second, a currency exchange rate component, which is the rate of change of the currency exchange rate compared to the U.S. dollar. Third, an inflation component, which reflects the change in local prices. With a decomposition analysis I explicitly determine the dollar profits of the single components. I find significantly positive profits by predicting future equity returns based on past equity performance, and negative profits based on past currency exchange rate appreciation and high inflation rates.

Deriving the components explicitly provides valuable information to form international stock market portfolios. A profitable strategy would overweight past equity winners, and underweight appreciating currencies and high inflation rate countries. Using the framework of Brandt, Santa-Clara, and Valkanov (2009) I find that past equity momentum, past exchange rate changes, and interest rate differentials convey relevant information about the conditional distribution of future equity returns, and can be used to parametrize global stock market portfolios. The optimal parametric portfolio policy increases the mean return and Sharpe ratio by more than 50 percent, compared to a pure momentum strategy, and is three times higher than an equally weighted or value weighted benchmark.

As robustness checks, a wide range of modifications and constraints can be applied. I find consistent results for long-only portfolios, different measures of transaction costs and a combination of the two. Furthermore, I applied a rolling sample approach, to model a possible non-constant relationship among equity markets, currency exchange rates and price changes. The optimization delivers similar results when I use 10-year government bond yields or real effective exchange rates, to proxy for interest rate differentials.

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Figure 1: Average returns for different momentum holding periods

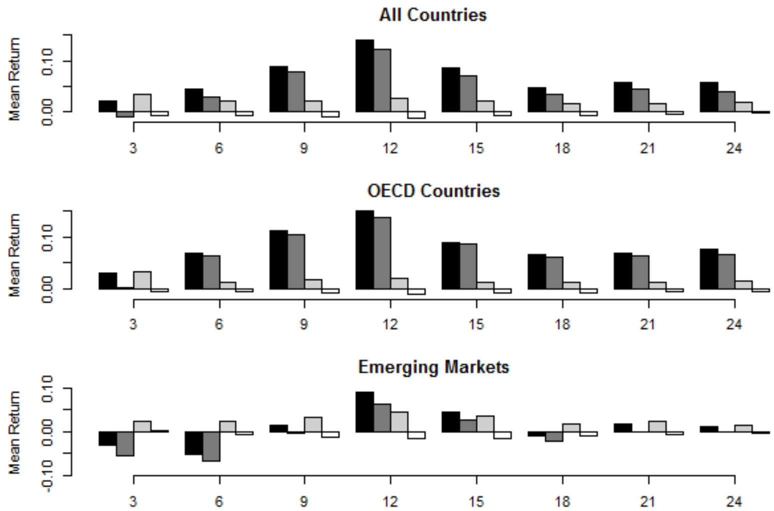
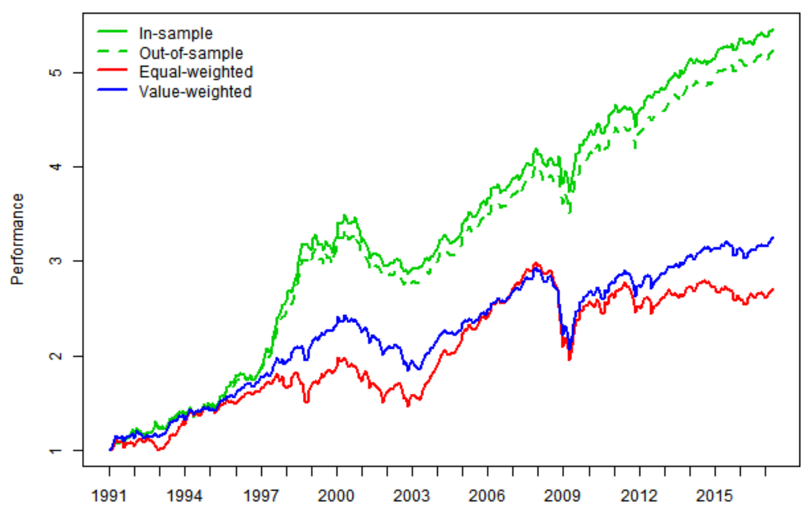


Figure 1 displays the decomposed returns for different holding periods of momentum portfolios defined in Equation (3). The portfolio weights are based on the proportional difference between the past $t-h$ individual stock market performance and the cross-sectional average of all markets (see Equation (2)). The horizontal axis represents h in Equation (1). The black bars show the overall return. The dark gray bars represent the return contribution from the equity part, the light gray bars display the return contribution from the currency exchange rate change and the white bars show the return contribution stemming from the price change rate. All returns are per annum and quoted in U.S. dollars. The upper panel contains all equity indices in the dataset, the middle and lower panels use only a subsample of OECD countries and emerging markets, respectively.

Figure 2: Theta plot for the pure momentum return portfolio optimization

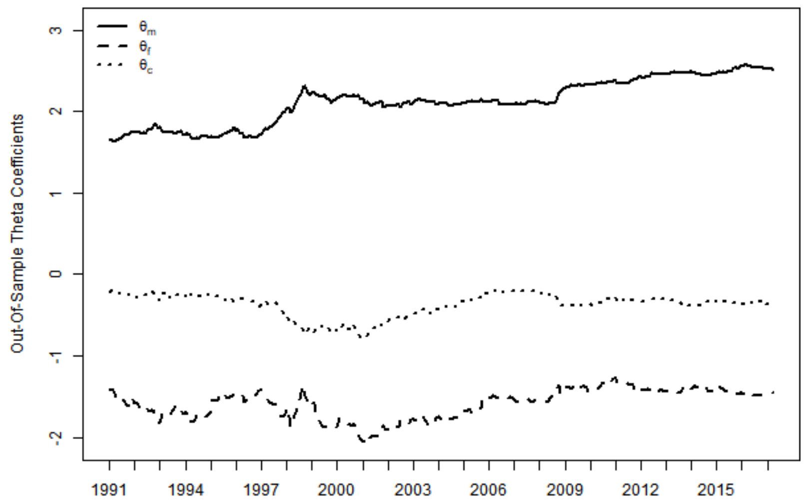
This figure displays the estimated out-of-sample θ_{mom}^{USD} coefficients (11) for the pure momentum return optimization from January 1991 to April 2017. The only characteristic used to parametrize the portfolio is the pure momentum return coefficient defined in Equation (20).

Figure 3: Performance plot for the pure momentum return portfolio optimization



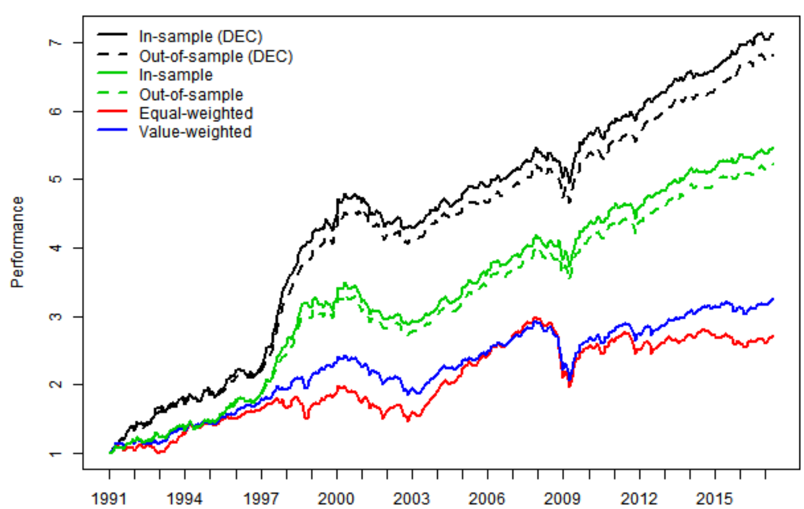
This figure displays the out-of-sample performance for the pure momentum optimization from January 1991 to April 2017. The continuous line displays the performance of the in-sample optimization, the dashed line plots the out-of-sample performance, the red and blue lines show the equally weighted and value weighted benchmarks, respectively.

Figure 4: Theta plot for the decomposed momentum return portfolio optimization



This figure displays the estimated out-of-sample θ coefficients (11) for the decomposed momentum return optimization from January 1991 to April 2017. The characteristics used to parametrize the portfolio are defined in Equation (21, 22, 23). The continuous line displays the estimated θ_m coefficient, the dashed line displays the θ_f coefficient, the dotted line displays the θ_c coefficient.

Figure 5: Performance plot for the decomposed momentum return portfolio optimization



This figure displays the out-of-sample performance from January 1991 to April 2017. The black lines present the decomposed momentum return performance, in- and out-of-sample. The green lines display the in- and out-of-sample performance of the pure momentum return optimization (see also Figure 3). The red and blue lines show the equally weighted and value weighted benchmarks, respectively.

Table 1: Decomposition of global equity momentum profits

	FX change	Price change	FX + Price change
π_t	0.142 (3.056)	0.164 (4.033)	0.163 (3.156)
$\pi_t^1 = \frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - r_{m,t-1})r_{i,t}$	0.170 (5.631)	0.174 (5.393)	0.144 (5.182)
$\pi_t^2 = \frac{1}{N}\sum_{i=1}^{N}(f_{i,t-1} - f_{m,t-1})r_{i,t}$	-0.103 (-3.156)		-0.031 (-1.109)
$\pi_t^3 = \frac{1}{N}\sum_{i=1}^{N}(c_{i,t-1} - c_{m,t-1})r_{i,t}$		-0.095 (-2.844)	-0.020 (-0.688)
$\pi_t^4 = \frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - r_{m,t-1})f_{i,t}$	-0.000 (-0.020)		0.026 (2.354)
$\pi_t^5 = \frac{1}{N}\sum_{i=1}^{N}(f_{i,t-1} - f_{m,t-1})f_{i,t}$	0.074 (3.275)		0.074 (3.251)
$\pi_t^6 = \frac{1}{N}\sum_{i=1}^{N}(c_{i,t-1} - c_{m,t-1})f_{i,t}$			-0.074 (-3.212)
$\pi_t^7 = \frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - r_{m,t-1})c_{i,t}$		-0.043 (-3.357)	-0.011 (-1.976)
$\pi_t^8 = \frac{1}{N}\sum_{i=1}^{N}(f_{i,t-1} - f_{m,t-1})c_{i,t}$			-0.072 (-3.879)
$\pi_t^9 = \frac{1}{N}\sum_{i=1}^{N}(c_{i,t-1} - c_{m,t-1})c_{i,t}$		0.127 (6.803)	0.127 (6.741)

This table reports the results for the decomposition of global momentum returns for all countries. The table shows a break-up of the dollar returns, divided into 9 decomposed profit components and their economic significance displayed by the Newey and West (1987) autocorrelation-corrected t-statistics. Each country's weight is based on the cumulative one-year performance of past winners and losers, as the proportional difference between the individual index and the cross-sectional average. The resulting decomposed profits are then normalized by the amount invested in the long and short positions. The first column displays the predictability U.S. dollar returns based on past equity momentum and currency exchange rate changes. The second column displays the predictability U.S. dollar returns based on past equity momentum and price changes. The third column takes past equity momentum, currency exchange rate and price changes into account. π_t is the overall dollar profit, π_t^1 shows profits due to predictability of equity returns based on past equity performance, π_t^2 reflects profits due to predictability of equity returns based on past currency exchange rate performance and π_t^3 displays the profits due to predictability of equity returns based on past price change performance. π_t^4, π_t^5, π_t^6, show the profits due to predictability of exchange rate returns based on past equity performance, past exchange rate performance and past price change performance, respectively. π_t^7, π_t^8, π_t^9, show the profits due to predictability of price change returns based on past equity performance, past exchange rate performance and past price change performance, respectively.

Table 2: Pure momentum return portfolio optimization

	EW	VW	IS	OOS
θ_{mom}^{USD}			1.907	1.618
Std. err.				0.011
$\lvert w_i \rvert$x 100	1.923	2.001	6.417	5.497
max w_i x 100	1.923	52.714	59.530	56.007
min w_i x 100	1.923	0.000	-26.471	-23.171
$\sum$ I(w_i <0)	0.000	0.000	-7.609	-6.305
Turnover	0.114	0.117	7.407	6.256
CE	-0.034	0.013	0.081	0.080
$\bar{r}$	0.065	0.085	0.169	0.161
$\sigma(r)$	0.184	0.162	0.184	0.175
Sharpe ratio	0.212	0.367	0.780	0.770
$\bar{r}_{OECD}$			0.135	0.129
$\bar{r}_{EM}$			0.035	0.032
$\bar{r}_{Long}$			0.147	0.135
$\bar{r}_{Short}$			-0.022	-0.026
α			0.095	0.085
β			0.821	0.832
TE			0.130	0.115
IR			0.686	0.707
Treynor			0.163	0.152

This table reports results for the pure momentum return parametric portfolio optimization compared to an equally weighted (EW) and value weighted (VW) benchmark portfolio. IS and OOS abbreviate the results for the in-sample and out-of-sample optimal parametric portfolio policy, respectively. The first set of rows display the estimated parameter of the portfolio policy, θ_{mom}^{USD}, with time-series average of coefficients and bootstrapped standard errors for the out-of-sample column. The next set of rows, report statistics of the portfolio weights over time, including the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average sum of negative weights in the portfolio and the turnover in the portfolio. The last part of the table represents annualized portfolio return statistics: certainty-equivalent return, mean return, standard deviation, Sharpe ratio, average returns for OECD and emerging markets, for the long and short side of the portfolio, alpha, beta, tracking error, information ratio and the Treynor index. The average risk-free rate in the sample is 0.048 (annualized).

Table 3: Decomposed momentum return portfolio optimization

	EW	VW	IS	OOS	IS^{DEC}	OOS^{DEC}
θ_m			1.907	1.618	2.524	2.122
Std. err.				0.011		0.016
θ_f					-1.463	-1.585
Std. err.						0.010
θ_c					-0.385	-0.371
Std. err.						0.008
$\lvert w_i \rvert$x 100	1.923	2.001	6.417	5.497	8.924	8.075
max w_i x 100	1.923	52.714	59.530	56.007	62.448	57.366
min w_i x 100	1.923	0.000	-26.471	-23.171	-41.166	-30.030
$\sum$ I(w_i <0)	0.000	0.000	-7.609	-6.305	-5.849	-5.209
Turnover	0.114	0.117	7.407	6.256	11.531	10.412
CE	-0.034	0.013	0.081	0.080	0.128	0.127
$\bar{r}$	0.065	0.085	0.169	0.161	0.233	0.221
$\sigma(r)$	0.184	0.162	0.184	0.175	0.206	0.195
Sharpe ratio	0.212	0.367	0.780	0.770	1.002	1.002
$\bar{r}_{OECD}$			0.135	0.129	0.172	0.161
$\bar{r}_{EM}$			0.035	0.032	0.060	0.060
$\bar{r}_{Long}$			0.147	0.135	0.201	0.186
$\bar{r}_{Short}$			-0.022	-0.026	-0.031	-0.035
α			0.095	0.085	0.157	0.145
β			0.821	0.832	0.838	0.849
TE			0.130	0.115	0.157	0.139
IR			0.686	0.707	1.016	1.061
Treynor			0.163	0.152	0.242	0.226

This table reports estimates of the pure momentum return portfolio optimization with the simple linear portfolio policy using the decomposed momentum characteristics from Equation (4). The labels IS and OOS abbreviate the in-sample and out-of-sample optimal parametric portfolio policy for the pure momentum returns, respectively. The labels IS^{DEC} and OOS^{DEC} abbreviate the in-sample and out-of-sample optimal parametric portfolio policy for the decomposed momentum returns, respectively.

Table 4: Decomposed momentum return portfolio optimization: Long-only

	EW	VW	Unconstrained IS	Unconstrained OOS	Long-only IS	Long-only OOS
θ_m			2.524	2.122	3.386	4.163
Std. err.				0.016		0.068
θ_f			-1.463	-1.585	-0.671	-0.836
Std. err.				0.010		0.088
θ_c			-0.385	-0.371	0.045	0.008
Std. err.				0.008		0.027
$\lvert w_i \rvert$x 100	1.923	2.001	8.924	8.075	3.215	3.364
max w_i x 100	1.923	52.714	62.448	57.366	31.837	36.357
min w_i x 100	1.923	0.000	-41.166	-30.030	0.000	0.000
$\sum$ I(w_i <0)	0.000	0.000	-5.849	-5.209	0.000	0.000
Turnover	0.114	0.117	11.531	10.412	3.422	3.765
CE	-0.034	0.013	0.128	0.127	0.027	0.031
$\bar{r}$	0.065	0.085	0.233	0.221	0.112	0.117
$\sigma(r)$	0.184	0.162	0.206	0.195	0.176	0.177
Sharpe ratio	0.212	0.367	1.002	1.002	0.488	0.514
$\bar{r}_{OECD}$			0.172	0.161	0.085	0.088
$\bar{r}_{EM}$			0.060	0.060	0.027	0.029
$\bar{r}_{Long}$			0.201	0.186	0.112	0.117
$\bar{r}_{Short}$			-0.031	-0.035	0.000	0.000
α			0.157	0.145	0.025	0.031
β			0.838	0.849	1.018	1.019
TE			0.157	0.139	0.061	0.064
IR			1.016	1.061	0.423	0.492
Treynor			0.242	0.226	0.071	0.076

This table compares the decomposed momentum return case (Unconstrained case) with the long-only optimal portfolio policy defined in Equation (17). The labels IS and OOS abbreviate the in-sample and out-of-sample optimal parametric portfolio policy, respectively.

Table 5: Decomposed momentum return portfolio optimization: Transaction costs

			In-sample			Out-of-sample		
	EW	VW	No TC	100 BP	Table 12	No TC	100 BP	Table 12
θ_m			2.524	2.151	2.258	2.122	1.731	1.834
Std. err.						0.016	0.017	0.017
θ_f			-1.463	-0.934	-1.073	-1.585	-0.928	-1.059
Std. err.						0.010	0.008	0.008
θ_c			-0.385	-0.199	-0.243	-0.371	-0.171	-0.210
Std. err.						0.008	0.007	0.007
$\|w_i\|$x 100	1.923	2.001	8.924	7.441	7.845	8.075	6.257	6.650
max w_i x 100	1.923	52.714	62.448	59.822	60.564	57.366	55.977	56.302
min w_i x 100	1.923	0.000	-41.166	-33.420	-35.543	-30.030	-24.350	-25.516
$\sum$ I(w_i <0)	0.000	0.000	-5.849	-4.825	-5.109	-5.209	-4.006	-4.286
Turnover	0.114	0.117	11.531	9.254	9.874	10.412	7.741	8.346
CE	-0.035	0.013	0.128	0.067	0.093	0.127	0.071	0.093
$\bar{r}$	0.065	0.085	0.233	0.158	0.187	0.221	0.151	0.176
$\sigma(r)$	0.184	0.162	0.206	0.190	0.194	0.195	0.177	0.181
Sharpe ratio	0.212	0.365	1.002	0.692	0.830	1.002	0.705	0.829
$\bar{r}_{OECD}$			0.172	0.113	0.139	0.161	0.109	0.130
$\bar{r}_{EM}$			0.060	0.045	0.048	0.060	0.042	0.045
$\bar{r}_{Long}$			0.201	0.146	0.167	0.186	0.132	0.150
$\bar{r}_{Short}$			-0.031	-0.012	-0.020	-0.035	-0.019	-0.026
α			0.157	0.081	0.111	0.145	0.074	0.099
β			0.838	0.852	0.848	0.849	0.861	0.857
TE			0.157	0.132	0.139	0.139	0.111	0.118
IR			1.016	0.568	0.777	1.061	0.631	0.831
Treynor			0.242	0.141	0.180	0.226	0.133	0.166

This table compares estimates of the decomposed momentum return case with different levels of transaction costs. The first column of each section, describes the result for no transaction costs (No TC), the second column shows results for constant one-way trading costs of 100 basis points (100 BP), and the third column exhibits the results for a merged transaction cost dataset from Table 1 in Domowitz, Glen, and Madhaven (2001) and Table 5 in Chiyachantana et al. (2004) (Table 12).

Table 6: Decomposed momentum return portfolio optimization: TC and long-only

			Unconstrained		Long-only		TC Table 12		TC & Long-only	
	EW	VW	IS	OOS	IS	OOS	IS	OOS	IS	OOS
θ_m			2.524	2.122	3.386	4.163	2.258	1.834	2.286	3.032
Std. err.				0.016		0.068		0.017		0.070
θ_f			-1.463	-1.585	-0.671	-0.836	-1.073	-1.059	-0.452	-0.423
Std. err.				0.010		0.088		0.008		0.047
θ_c			-0.385	-0.371	0.045	0.008	-0.243	-0.210	0.021	-0.259
Std. err.				0.008		0.027		0.007		0.043
$\|w_i\|$x 100	1.923	2.001	8.924	8.075	3.215	3.364	7.845	6.650	2.975	3.115
max w_i x 100	1.923	52.714	62.448	57.366	31.837	36.357	60.564	56.302	34.289	37.344
min w_i x 100	1.923	0.000	-41.166	-30.030	0.000	0.000	-35.543	-25.516	0.000	0.000
$\sum$ I(w_i <0)	0.000	0.000	-5.849	-5.209	0.000	0.000	-5.109	-4.286	0.000	0.000
Turnover	0.114	0.117	11.531	10.412	3.422	3.765	9.874	8.346	2.992	3.641
CE	-0.034	0.013	0.128	0.127	0.027	0.031	0.093	0.093	0.019	0.021
$\bar{r}$	0.065	0.085	0.233	0.221	0.112	0.117	0.187	0.176	0.100	0.103
$\sigma(r)$	0.184	0.162	0.206	0.195	0.176	0.177	0.194	0.181	0.172	0.172
Sharpe ratio	0.000	0.367	1.002	1.002	0.488	0.514	0.830	0.829	0.431	0.448
$\bar{r}_{OECD}$			0.172	0.161	0.085	0.088	0.139	0.130	0.077	0.079
$\bar{r}_{EM}$			0.060	0.060	0.027	0.029	0.048	0.045	0.023	0.024
$\bar{r}_{Long}$			0.201	0.186	0.112	0.117	0.167	0.150	0.100	0.103
$\bar{r}_{Short}$			-0.031	-0.035	0.000	0.000	-0.020	-0.026	0.000	0.000
α			0.157	0.145	0.025	0.031	0.111	0.099	0.014	0.017
β			0.838	0.849	1.018	1.019	0.848	0.857	1.012	1.006
TE			0.157	0.139	0.061	0.064	0.139	0.118	0.051	0.053
IR			1.016	1.061	0.423	0.492	0.777	0.831	0.277	0.322
Treynor			0.242	0.226	0.071	0.076	0.180	0.166	0.060	0.063

This table compares the decomposed momentum return case (Unconstrained) with the long-only optimal portfolio policy (Long-only), the Table 12 transaction costs estimates (Table 12) and a combined approach for both long-only optimization and transaction costs (TC & long-only). Transaction costs are modeled using a merged dataset from Table 1 in Domowitz, Glen, and Madhaven (2001) and Table 5 in Chiyachantana et al. (2004).

Table 7: Decomposed momentum return portfolio optimization: Rolling window

			Expanding window		Rolling window		
	EW	VW	IS	OOS	60 months	120 months	240 months
θ_m			2.524	2.122	3.795	3.078	2.441
Std. err.				0.016	0.171	0.101	0.050
θ_f			-1.463	-1.585	-2.796	-1.915	-1.875
Std. err.				0.010	0.131	0.065	0.019
θ_c			-0.385	-0.371	-0.783	-0.798	-0.795
Std. err.				0.008	0.208	0.079	0.032
$\lvert w_i \rvert$x 100	1.923	2.001	8.924	8.075	17.842	12.269	9.466
max w_i x 100	1.923	52.714	62.448	57.366	128.276	68.340	61.235
min w_i x 100	1.923	0.000	-41.166	-30.030	-136.822	-77.170	-51.238
$\sum$ I(w_i <0)	0.000	0.000	-5.849	-5.209	-11.796	-8.358	-6.486
Turnover	0.114	0.117	11.531	10.412	22.579	15.204	12.267
CE	-0.034	0.013	0.128	0.127	0.204	0.133	0.129
$\bar{r}$	0.065	0.085	0.233	0.221	0.477	0.300	0.237
$\sigma(r)$	0.184	0.162	0.206	0.195	0.348	0.265	0.208
Sharpe ratio	0.212	0.367	1.002	1.002	1.294	1.037	1.015
$\bar{r}_{OECD}$			0.172	0.161	0.278	0.212	0.187
$\bar{r}_{EM}$			0.060	0.060	0.199	0.088	0.051
$\bar{r}_{Long}$			0.201	0.186	0.321	0.228	0.180
$\bar{r}_{Short}$			-0.031	-0.035	-0.156	-0.072	-0.058
α			0.157	0.145	0.422	0.233	0.165
β			0.838	0.849	0.495	0.695	0.784
TE			0.157	0.139	0.349	0.244	0.169
IR			1.016	1.061	1.255	0.931	0.976
Treynor			0.242	0.226	0.958	0.387	0.265

This table compares estimates of the decomposed momentum return case (Expanding window), where I use the first 240 months to estimate initial coefficients for the portfolio policy and then re-estimate the coefficient using an expanding window until the end of the sample period, with a rolling window optimization (see Equation 25), where the time frame of the estimation is held constant (Rolling window). The labels ”60 Months”, ”120 Months”, and ”240 Months” display the out-of-sample results using a 60, 120, 240 month ’rolling window’.

Table 8: Decomposed momentum return portfolio optimization: Gov. bond yield

			Unconstrained		Gov. bond yield	
	EW	VW	IS	OOS	IS	OOS
θ_m			2.524	2.122	2.527	2.143
Std. err.				0.016		0.015
θ_f			-1.463	-1.585	-1.758	-1.753
Std. err.				0.010		0.010
θ_c			-0.385	-0.371	-1.270	-0.849
Std. err.				0.008		0.017
$\|w_i\|$x 100	1.923	2.001	8.924	8.075	9.882	8.582
max w_i x 100	1.923	52.714	62.448	57.366	67.404	58.789
min w_i x 100	1.923	0.000	-41.166	-30.030	-52.573	-41.275
$\sum$ I(w_i <0)	0.000	0.000	-5.849	-5.209	-7.039	-5.865
Turnover	0.114	0.117	11.531	10.412	12.257	10.912
CE	-0.034	0.013	0.128	0.127	0.158	0.151
$\bar{r}$	0.065	0.085	0.233	0.221	0.271	0.246
$\sigma(r)$	0.184	0.162	0.206	0.195	0.217	0.198
Sharpe ratio	0.212	0.367	1.002	1.002	1.132	1.112
$\bar{r}_{OECD}$			0.172	0.161	0.202	0.178
$\bar{r}_{EM}$			0.060	0.060	0.070	0.068
$\bar{r}_{Long}$			0.201	0.186	0.221	0.196
$\bar{r}_{Short}$			-0.031	-0.035	-0.051	-0.050
α			0.157	0.145	0.201	0.174
β			0.838	0.849	0.754	0.787
TE			0.157	0.139	0.183	0.155
IR			1.016	1.061	1.118	1.148
Treynor			0.242	0.226	0.328	0.281

This table compares estimates of the decomposed momentum return case (Unconstrained) with the parametric portfolio optimization using interest rate differentials, proxied by government bond yields (see Equation 26). Table 14 in Appendix A.5 displays further statistical information.

Table 9: Decomposed momentum return portfolio optimization: REER

	EW	VW	Unconstrained IS	Unconstrained OOS	REER IS	REER OOS
θ_m			2.524	2.122	2.557	2.175
Std. err.				0.016		0.011
θ_f			-1.463	-1.585		
Std. err.				0.010		
θ_c			-0.385	-0.371		
Std. err.				0.008		
θ_{reer}					-0.959	-0.991
Std. err.						0.004
$\|w_i\|$x 100	1.923	2.001	8.924	8.075	6.860	6.168
max w_i x 100	1.923	52.714	62.448	57.366	76.329	71.381
min w_i x 100	1.923	0.000	-41.166	-30.030	-47.603	-45.306
$\sum$ I(w_i <0)	0.000	0.000	-5.849	-5.209	-8.733	-7.627
Turnover	0.114	0.117	11.531	10.412	10.770	9.357
CE	-0.034	0.013	0.128	0.127	0.101	0.100
$\bar{r}$	0.065	0.085	0.233	0.221	0.189	0.180
$\sigma(r)$	0.184	0.162	0.206	0.195	0.186	0.177
Sharpe ratio	0.212	0.367	1.002	1.002	0.875	0.868
$\bar{r}_{OECD}$			0.172	0.161	0.178	0.168
$\bar{r}_{EM}$			0.060	0.060	0.011	0.012
$\bar{r}_{Long}$			0.201	0.186	0.180	0.165
$\bar{r}_{Short}$			-0.031	-0.035	-0.009	-0.015
α			0.157	0.145	0.116	0.106
β			0.838	0.849	0.782	0.799
TE			0.157	0.139	0.141	0.126
IR			1.016	1.061	0.792	0.819
Treynor			0.242	0.226	0.199	0.185

This table compares estimates of the decomposed momentum return case (Unconstrained) with the parametric portfolio optimization using real effective exchange rates (see Equation 27). Table 15 in Appendix A.6 displays further statistical information.

A Appendix: Data

A.1 Data sample

This study uses a broad dataset consisting of 52 developed and emerging market countries: Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Lithuania, Luxembourg, Malaysia, Mexico, Morocco, the Netherlands, New Zealand, Norway, Peru, the Philippines, Poland, Portugal, Russian Federation, Singapore, Slovak Republic, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom and the United States.

For each month, I gather data of the value weighted stock market, proxied by the Morgan Stanley Capital International (MSCI) Total Return Index of each country, quoted in local currency and U.S. dollars, the currency exchange rate quoted against the U.S. dollar (U.S. dollars per foreign currency) and the local Consumer Price Index (CPI). The risk free rate is obtained from Kenneth French's database. The sample starts in January 1970 and ends in April 2017, resulting in 568 monthly observations.

Choosing a specific domestic stock market index, to capture the full movement of all listed equities, introduces a trade-off between data availability and accuracy. Therefore, if not otherwise stated, I use the country MSCI total return index. Except for Iceland, Luxembourg and Slovakia, where I use the domestic stock exchange index (i.e. SE ICEX 15, LuxX, SAX 16, respectively). The market capitalization weights are obtained from Global Financial Data.

Table 10 reports the full sample annualized mean, standard deviation, skewness and kurtosis of the MSCI stock market return, the currency exchange rate and the domestic inflation (i.e. yearly change in Consumer Price Index), for all countries, OECD countries and emerging markets.

Table 10: Descriptive statistics

	Mean	Std. Dev.	Skewness	Kurtosis
Panel A: Value weighted stock market return				
All countries	0.084	0.274	-0.228	1.997
OECD countries	0.078	0.255	-0.354	2.040
Emerging markets	0.096	0.309	0.012	1.914
Panel B: Value weighted stock market return (in U.S. dollars)				
All countries	0.065	0.303	-0.481	1.933
OECD countries	0.065	0.287	-0.507	2.344
Emerging markets	0.066	0.334	-0.433	1.156
Panel C: Currency exchange rate (per U.S. dollar)				
All countries	-0.025	0.122	-0.899	4.259
OECD countries	-0.020	0.116	-0.350	0.932
Emerging markets	-0.035	0.133	-1.907	10.358
Panel D: Consumer price index change				
All countries	0.070	0.099	1.651	4.907
OECD countries	0.064	0.074	1.355	3.213
Emerging markets	0.081	0.147	2.211	8.106

This table displays summary statistics of the data sample. Panels A and B show the local currency and U.S. dollar-denominated MSCI stock market mean return, standard deviation, skewness and kurtosis for all countries and sub-samples, such as OECD countries and emerging markets, in the dataset. Panels C and D provide statistics of the change in the currency exchange rate against the U.S. dollar and the change in the Consumer Price Index, respectively. All estimates are annualized.

A.2 Market capitalization weights

Table 11: Market capitalization weights

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Australia	0.000	1.358	1.589	1.626	2.017	2.655
Austria	0.040	0.095	0.146	0.148	0.184	0.369
Belgium	0.326	0.538	0.592	0.603	0.690	0.951
Brazil	0.000	0.350	0.701	0.817	1.134	2.821
Canada	0.000	2.123	2.537	2.382	3.195	4.561
Chile	0.000	0.066	0.228	0.222	0.331	0.624
China	0.000	0.000	0.266	2.410	2.773	12.493
Colombia	0.000	0.011	0.049	0.090	0.110	0.483
Czech Republic	0.000	0.000	0.000	0.026	0.049	0.145
Denmark	0.000	0.282	0.338	0.321	0.407	0.549
Egypt	0.000	0.013	0.040	0.063	0.096	0.255
Estonia	0.000	0.000	0.000	0.003	0.005	0.022
Finland	0.000	0.118	0.262	0.293	0.393	1.035
France	1.150	2.527	3.052	3.088	3.568	4.933
Germany	2.474	2.667	3.145	3.289	3.819	4.954
Greece	0.017	0.080	0.131	0.189	0.309	0.583
Hong Kong	0.000	0.772	1.671	2.064	2.885	5.223
Hungary	0.000	0.000	0.008	0.248	0.042	10.878
Iceland	0.000	0.000	0.004	0.010	0.012	0.069
India	0.000	0.000	0.449	0.798	1.375	2.978
Indonesia	0.000	0.002	0.085	0.198	0.322	0.824
Ireland	0.000	0.000	0.000	0.113	0.221	0.581
Israel	0.009	0.069	0.201	0.197	0.303	0.415
Italy	0.000	0.741	1.094	1.148	1.555	2.421
Japan	4.794	8.060	11.843	14.853	20.303	40.338
Jordan	0.000	0.022	0.035	0.039	0.056	0.108
Lithuania	0.000	0.000	0.000	0.004	0.006	0.019
Luxembourg	0.000	0.094	0.133	0.145	0.179	0.495
Malaysia	0.000	0.365	0.511	0.538	0.615	1.579
Mexico	0.000	0.062	0.424	0.406	0.665	1.438
Morocco	0.000	0.000	0.001	0.003	0.004	0.024
Netherlands	0.000	1.126	1.260	1.266	1.568	2.316
New Zealand	0.000	0.000	0.066	0.066	0.116	0.287
Norway	0.000	0.140	0.213	0.239	0.334	0.552
Peru	0.000	0.008	0.036	0.051	0.071	0.189
Philippines	0.014	0.076	0.124	0.162	0.210	0.423

Table 11 – continued from previous page

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Poland	0.000	0.000	0.020	0.094	0.206	0.347
Portugal	0.000	0.004	0.090	0.091	0.160	0.242
Russia	0.000	0.000	0.000	0.404	0.628	2.347
Singapore	0.000	0.246	0.474	0.565	0.929	1.411
Slovakia	0.000	0.000	0.000	0.005	0.010	0.030
Slovenia	0.000	0.000	0.001	0.008	0.012	0.045
South Africa	0.538	1.193	1.419	1.480	1.666	3.030
South Korea	0.025	0.195	0.878	0.872	1.442	2.175
Spain	0.334	1.012	1.316	1.474	2.043	2.810
Sweden	0.493	0.767	0.923	0.888	1.036	1.207
Switzerland	1.154	1.685	2.072	2.014	2.301	2.906
Taiwan	0.042	0.232	1.066	0.844	1.263	2.052
Thailand	0.000	0.048	0.184	0.271	0.491	0.936
Turkey	0.000	0.000	0.141	0.156	0.271	0.560
United Kingdom	3.834	6.896	7.667	7.410	8.198	12.177
USA	28.704	37.041	42.970	45.304	51.479	74.815

This table reports the minimum, first quantile, median, mean, third quantile and maximum market capitalization weights for all countries in the dataset. The data sample is obtained from Global Financial Data and starts in 1970 and ends in 2016. I use 2016 as a proxy for 2017. All numbers are multiplied by 100.

A.3 Transaction costs

Table 12: Transaction costs

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Std. Dev.
Australia	25.000	25.000	77.919	69.193	106.414	106.414	37.446
Austria	30.075	35.288	82.502	82.809	130.000	130.000	45.744
Belgium	24.000	24.000	65.152	64.154	102.158	102.158	36.951
Brazil	30.140	39.820	73.033	66.826	91.484	91.484	25.053
Canada	30.118	38.309	72.424	68.413	97.000	97.000	28.349
Chile	35.488	48.670	106.150	93.765	132.967	132.967	40.358
China	35.708	45.839	111.896	97.654	141.427	141.427	45.066
Colombia	30.161	41.331	122.772	103.241	153.787	153.787	52.838
Czech Republic	39.506	54.179	180.947	149.813	226.658	226.658	80.689
Denmark	30.043	33.022	59.243	57.993	82.000	82.000	23.432
Egypt	35.708	45.839	111.896	97.654	141.427	141.427	45.066
Estonia	35.708	45.839	111.896	97.654	141.427	141.427	45.066
Finland	25.000	25.000	71.692	67.727	106.414	106.414	38.003
France	22.000	22.000	58.300	58.473	93.645	93.645	34.082
Germany	24.000	24.000	66.640	64.504	102.158	102.158	36.749
Greece	32.810	44.996	82.477	75.354	103.313	103.313	28.461
Hong Kong	28.000	28.000	84.584	75.234	115.000	115.000	40.013
Hungary	35.488	48.670	180.305	147.331	225.598	225.598	82.514
Iceland	31.415	35.333	88.888	80.215	119.118	119.118	39.072
India	43.523	59.689	90.158	86.028	112.935	112.935	27.004
Indonesia	47.541	65.199	127.053	114.647	159.150	159.150	45.492
Ireland	61.000	86.883	164.577	148.663	206.153	206.153	58.747
Israel	31.415	35.333	88.888	80.215	119.118	119.118	39.072
Italy	22.000	22.000	61.220	59.160	93.645	93.645	33.669
Japan	15.000	15.000	51.424	42.616	63.849	63.849	22.308
Jordan	35.708	45.839	111.896	97.654	141.427	141.427	45.066
Lithuania	31.415	35.333	88.888	80.215	119.118	119.118	39.072
Luxembourg	30.108	37.554	80.337	71.482	100.632	100.632	29.871
Malaysia	36.158	49.588	111.691	98.094	139.907	139.907	43.126
Mexico	30.118	38.309	77.692	69.778	97.320	97.320	28.139
Morocco	35.708	45.839	111.896	97.654	141.427	141.427	45.066
Netherlands	21.000	21.000	63.386	57.636	89.388	89.388	31.610
New Zealand	30.054	33.777	87.069	85.803	136.000	136.000	48.814
Norway	21.000	21.000	64.709	57.948	89.388	89.388	31.506
Peru	21.000	21.000	120.631	95.170	151.106	151.106	59.426
Philippines	40.175	55.098	141.911	121.883	177.762	177.762	58.043

Table 12 – continued from previous page

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Std. Dev.
Poland	57.585	78.973	170.807	151.107	213.958	213.958	64.672
Portugal	24.000	24.000	78.952	66.132	98.897	98.897	34.210
Russia	35.708	45.839	111.896	97.654	141.427	141.427	45.066
Singapore	30.022	31.511	103.860	89.209	136.210	136.210	48.115
Slovakia	31.415	35.333	88.888	80.215	119.118	119.118	39.072
Slovenia	31.415	35.333	88.888	80.215	119.118	119.118	39.072
South Africa	30.129	39.065	102.750	88.122	128.708	128.708	42.142
South Korea	32.810	44.996	202.471	144.634	208.572	208.572	78.773
Spain	23.000	23.000	67.043	62.565	97.901	97.901	34.845
Sweden	26.000	26.000	69.415	69.225	110.671	110.671	40.200
Switzerland	38.500	54.474	77.337	88.352	125.000	125.000	35.455
Taiwan	30.075	35.288	93.936	80.694	117.667	117.667	38.323
Thailand	52.228	71.627	112.194	106.132	140.538	140.538	34.623
Turkey	30.118	38.309	81.344	72.421	101.894	101.894	30.208
United Kingdom	30.000	30.000	87.364	81.587	127.697	127.697	45.458
USA	28.000	28.000	47.035	44.175	58.000	58.000	13.831

This table reports the mean one-way total equity trading costs in basis points for a merged dataset comprising Table 1 of Domowitz, Glen, and Madhaven (2001) and Table 5 of Chiyachantana, Jain, Jiang, and Wood (2004). I assume trading costs to be 4 times higher in 1970 than in 2001 and interpolate values in between. This is consistent with Wermers (2000), who finds trading costs in 1994 to be one third their level in 1975. The average one-way trading cost is 86.251 basis points with a maximum of 226.658 (Czech Republic in 1970) and a minimum of 15 (Japan in 2017).

A.4 Correlation matrix for different sample periods

Table 13: Correlation matrix for different sample periods

	$log(P_{i,t}^{USD}/P_{i,t-1}^{USD})$	$r_{i,t}^{LCY}$	$f_{i,t}$	$c_{i,t}$
Full sample: 1970 - 2017				
$log(P_{i,t}^{USD}/P_{i,t-1}^{USD})$	1			
$r_{i,t}^{LCY}$	0.001	1		
$f_{i,t}$	0.012	0.124	1	
$c_{i,t}$	-0.063	-0.116	-0.013	1
1970 - 1985				
$log(P_{i,t}^{USD}/P_{i,t-1}^{USD})$	1			
$r_{i,t}^{LCY}$	-0.008	1		
$f_{i,t}$	-0.031	-0.168	1	
$c_{i,t}$	-0.065	-0.408	0.160	1
1985 - 2000				
$log(P_{i,t}^{USD}/P_{i,t-1}^{USD})$	1			
$r_{i,t}^{LCY}$	-0.027	1		
$f_{i,t}$	0.117	-0.175	1	
$c_{i,t}$	-0.098	-0.435	-0.169	1
2000 - 2017				
$log(P_{i,t}^{USD}/P_{i,t-1}^{USD})$	1			
$r_{i,t}^{LCY}$	0.022	1		
$f_{i,t}$	-0.072	0.412	1	
$c_{i,t}$	-0.265	0.224	0.518	1

This table reports correlation coefficients among U.S. dollar equity returns ($log(P_{i,t}^{USD}/P_{i,t-1}^{USD})$), local currency equity momentum ($r_{i,t}^{LCY}$) defined in Equation (21), currency exchange rate changes ($f_{i,t}$) defined in Equation (22) and price changes ($c_{i,t}$) defined in Equation (23). The upper panel of the table reports correlation coefficients for the full sample (i.e. from 1970 till 2017), while the bottom three panels report 15 year sub sample estimates.

A.5 10-year government bond yield

Table 14: 10-year government bond yield

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Std. Dev.
Australia	1.873	5.538	6.880	8.172	10.420	16.500	3.556
Austria	0.103	4.111	6.835	6.162	8.102	11.460	2.586
Belgium	0.150	4.210	7.205	6.792	8.812	14.250	3.222
Brazil	5.580	7.963	11.469	11.632	13.558	29.394	4.551
Canada	1.000	4.338	7.385	7.117	9.438	17.660	3.454
Chile	3.910	5.000	5.550	5.828	6.420	7.790	1.194
China	2.736	3.297	3.572	3.638	4.035	4.890	0.506
Colombia	5.895	6.835	8.020	9.654	12.884	19.000	3.452
Czech Republic	0.250	2.300	3.930	3.611	4.710	7.650	1.764
Denmark	0.015	4.220	8.560	8.581	11.505	23.060	5.426
Egypt	13.600	15.250	15.980	16.039	17.000	17.970	1.075
Estonia	3.500	4.900	7.520	7.879	10.590	15.270	3.056
Finland	0.029	4.095	7.910	7.444	10.925	15.280	3.909
France	0.101	4.090	7.500	7.251	10.092	17.320	3.913
Germany	-0.150	4.040	6.235	5.824	7.960	10.830	2.612
Greece	3.350	5.470	10.450	11.686	17.200	36.620	6.679
Hong Kong	0.560	1.992	3.778	3.998	5.845	10.450	2.359
Hungary	2.880	6.250	7.190	6.974	8.140	12.250	1.880
Iceland	4.898	6.227	7.144	7.333	8.164	12.667	1.458
India	5.000	6.510	7.945	8.835	11.143	15.820	2.719
Indonesia	5.199	7.043	7.854	7.761	8.530	11.090	1.332
Ireland	0.331	4.718	8.775	8.569	11.930	19.160	4.432
Israel	1.471	2.039	2.412	2.862	3.761	4.677	0.993
Italy	1.106	4.576	8.475	9.120	13.282	22.370	5.013
Japan	-0.225	1.400	4.580	4.225	7.099	9.973	2.903
Jordan							
Lithuania	0.400	3.880	5.055	6.395	8.520	17.950	4.217
Luxembourg	-0.080	4.228	6.680	5.941	7.600	10.860	2.557
Malaysia	3.105	4.233	6.750	6.727	8.600	11.742	2.306
Mexico	4.540	6.143	7.700	7.672	8.607	11.170	1.613
Morocco	3.200	3.670	4.505	4.895	5.768	7.380	1.225
Netherlands	0.009	4.047	6.360	6.059	8.170	12.510	2.721
New Zealand	2.210	5.667	6.655	8.140	10.160	18.900	3.709
Norway	1.002	4.539	6.275	7.191	9.957	14.190	3.570
Peru	4.200	5.770	6.080	6.060	6.590	7.810	0.941
Philippines	3.100	5.280	8.000	9.805	13.875	22.875	5.074

Table 14 – continued from previous page

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Std. Dev.
Poland	1.970	4.570	5.650	6.006	6.518	13.310	2.440
Portugal	1.751	4.683	7.089	9.599	14.885	22.800	5.559
Russia	5.260	7.260	8.350	10.959	11.490	48.620	7.468
Singapore	1.300	2.276	2.687	2.905	3.520	5.690	0.923
Slovakia	0.230	3.882	4.810	6.918	8.200	28.850	6.003
Slovenia	0.614	3.720	4.385	4.347	5.090	9.620	1.847
South Africa	6.010	8.500	10.583	11.573	14.815	18.380	3.368
South Korea	1.382	3.430	4.830	4.502	5.410	8.250	1.504
Spain	0.886	4.484	8.940	8.761	12.320	18.110	4.453
Sweden	0.100	4.196	7.360	7.360	10.718	14.320	3.824
Switzerland	-0.570	2.668	4.059	3.769	4.990	7.410	1.823
Taiwan	0.675	1.410	2.230	3.056	5.155	7.630	1.999
Thailand	1.710	4.155	7.500	7.753	10.750	15.150	3.691
Turkey	6.280	8.762	9.475	9.247	9.947	11.180	1.114
United Kingdom	0.640	4.632	8.455	7.972	10.990	17.240	3.980
USA	1.460	4.338	6.425	6.534	8.115	15.840	3.008

This table reports summary statistics of the 10-year government bond yields (in percent) across all countries in the sample. The data is obtained from Global Financial Data and starts in January 1970 and ends in April 2017. Due to data unavailability, I use 15-year government bond yields for Morocco and Peru and exclude Jordan completely from the analysis.

A.6 Real effective exchange rate

Table 15: Real effective exchange rate

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Std. Dev.
Australia	62.200	75.775	91.040	89.066	100.887	122.410	14.722
Austria	80.300	92.082	96.800	95.314	99.765	104.030	5.555
Belgium	89.110	95.297	98.305	98.829	100.880	117.320	5.668
Canada	69.260	83.470	92.480	92.505	100.507	115.010	11.743
Denmark	82.660	90.777	94.605	94.288	97.820	105.250	5.079
Finland	88.170	98.388	101.830	105.121	112.100	131.270	9.484
France	92.610	99.540	102.215	102.937	106.335	117.810	5.251
Germany	91.310	98.317	101.030	102.377	105.985	126.480	6.148
Greece	65.390	79.177	83.865	84.854	90.688	101.820	8.332
Hong Kong	81.350	102.097	110.090	112.997	124.210	158.430	15.589
Ireland	72.650	83.392	88.605	89.630	95.718	113.580	8.325
Italy	76.710	92.430	97.395	97.268	101.233	114.250	7.277
Japan	53.200	77.495	92.525	90.864	103.953	143.050	17.912
Mexico	50.170	88.507	102.115	99.393	109.440	138.340	16.970
Netherlands	87.280	93.967	97.820	97.543	100.403	109.870	4.673
New Zealand	70.230	85.867	92.880	93.615	100.823	119.350	10.323
Norway	82.930	92.167	95.440	95.833	99.373	110.180	5.122
Portugal	68.280	80.505	93.735	89.917	99.280	104.670	10.042
Singapore	80.520	90.467	100.375	101.087	110.780	138.850	12.963
South Korea	68.360	102.922	117.675	118.601	130.470	178.590	18.086
Spain	69.310	84.647	89.575	90.050	97.773	105.480	8.906
Sweden	88.420	105.375	119.485	124.532	144.920	174.350	22.678
Switzerland	67.540	89.028	92.780	93.041	97.005	120.610	9.488
United Kingdom	92.900	111.125	121.670	121.308	128.102	158.450	13.621
USA	92.940	101.300	108.230	111.610	118.537	147.010	13.067

This table reports summary statistics of real effective exchange rates across all countries in the sample. The data is obtained from the Bank for International Settlements and starts in January 1970 and ends in April 2017. Due to data unavailability, I use a narrow sample of 25 countries for the analysis.

B Appendix: Additional Results And Robustness Checks

B.1 Momentum in global equity markets

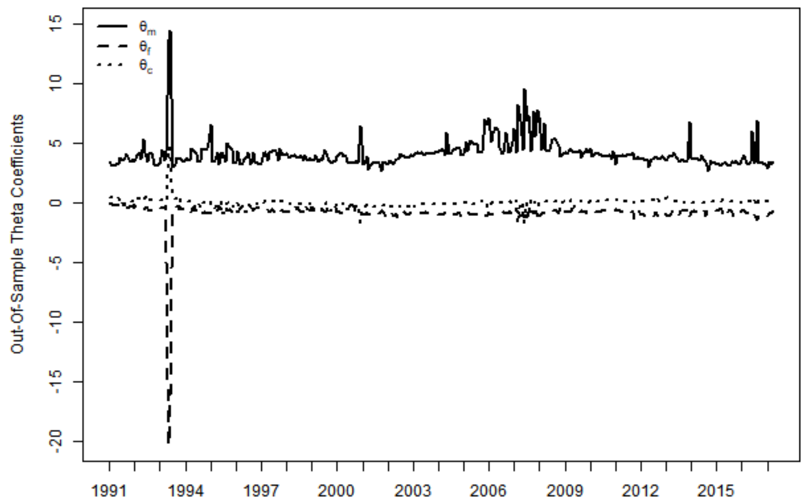
Table 16: Return contribution of global equity momentum profits

h	3	6	9	12	15	18	21	24
Panel A: All countries								
π_r	-0.008	0.031	0.077	0.123	0.072	0.035	0.044	0.041
π_f	0.035	0.021	0.023	0.028	0.022	0.018	0.016	0.018
π_c	-0.006	-0.007	-0.010	-0.011	-0.008	-0.005	-0.004	-0.001
$\sum \pi$	0.021	0.044	0.090	0.141	0.087	0.048	0.057	0.059
Std. dev.	0.187	0.202	0.197	0.204	0.209	0.198	0.195	0.189
Sharpe ratio	0.110	0.218	0.454	0.688	0.414	0.242	0.290	0.311
Panel B: OECD countries								
π_r	0.003	0.064	0.104	0.139	0.087	0.062	0.063	0.066
π_f	0.032	0.011	0.017	0.021	0.012	0.011	0.012	0.015
π_c	-0.006	-0.006	-0.009	-0.010	-0.008	-0.007	-0.006	-0.005
$\sum \pi$	0.030	0.069	0.112	0.150	0.090	0.066	0.069	0.076
Std. dev.	0.177	0.194	0.192	0.200	0.200	0.183	0.178	0.172
Sharpe ratio	0.168	0.356	0.581	0.749	0.451	0.361	0.385	0.444
Panel C: Emerging markets								
π_r	-0.056	-0.067	-0.003	0.062	0.026	-0.020	0.000	-0.001
π_f	0.022	0.023	0.033	0.044	0.037	0.019	0.024	0.016
π_c	0.002	-0.008	-0.014	-0.017	-0.016	-0.009	-0.007	-0.003
$\sum \pi$	-0.031	-0.052	0.016	0.089	0.046	-0.011	0.016	0.012
Std. dev.	0.284	0.271	0.285	0.279	0.265	0.266	0.266	0.260
Sharpe ratio	-0.110	-0.193	0.055	0.320	0.174	-0.041	0.061	0.045

This table reports the results for the decomposition of global momentum returns for all countries, OECD countries, and emerging markets. The table shows the overall dollar returns ($\sum \pi$) and a break-up of the dollar returns contributed by the local currency momentum (π_r), the exchange rate change (π_f), and the price rate change (π_c). The columns represent the past momentum measure h defined in Equation (3).

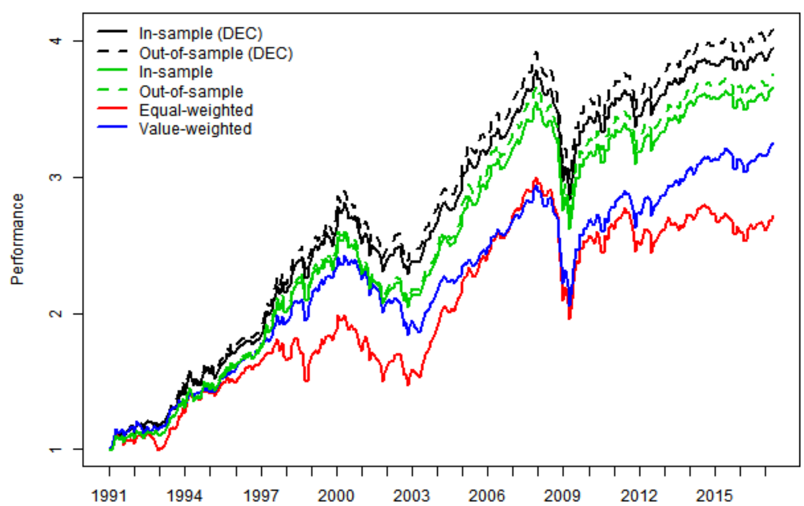
B.2 Long-only optimization

Figure 6: Theta plot for the long-only optimization



This figure displays the estimated out-of-sample θ coefficients (11) for the long-only optimization from January 1991 to April 2017.

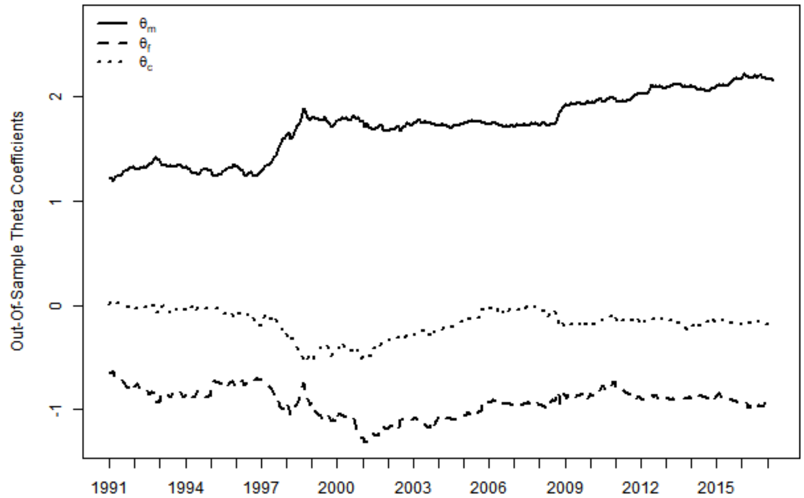
Figure 7: Performance plot for the long-only optimization



This figure displays the out-of-sample performance of the long-only optimization from January 1991 to April 2017.

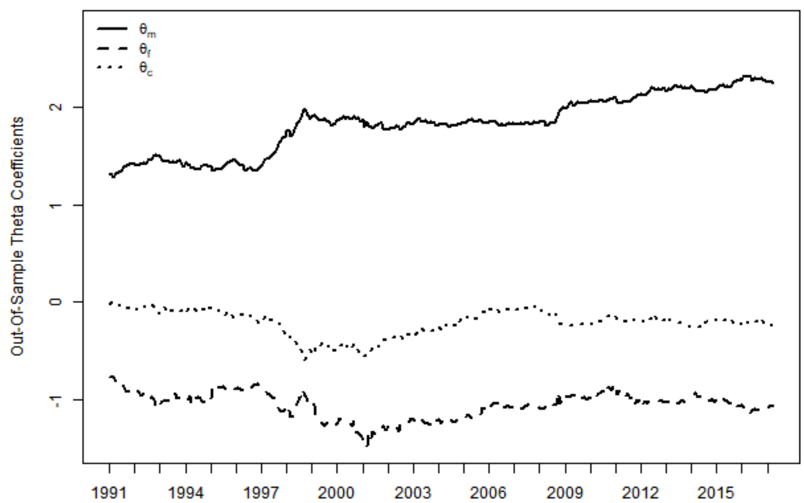
B.3 Transaction costs

Figure 8: Theta plot for transaction cost optimization (100 basis points)



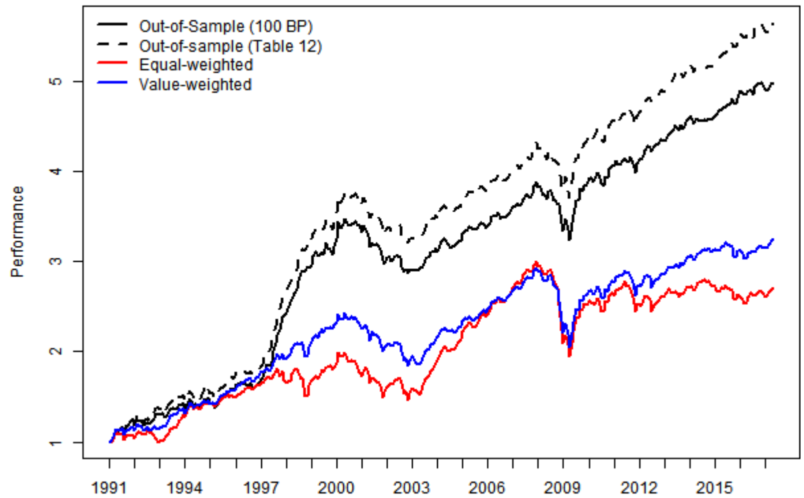
This figure displays the estimated out-of-sample θ coefficients (11) for the constant one-way equity transaction cost optimization of 100 basis points from January 1991 to April 2017.

Figure 9: Theta plot for transaction cost optimization (Table 12)



This figure displays the estimated out-of-sample θ coefficients (11) for the Table 12 transaction cost optimization from January 1991 to April 2017.

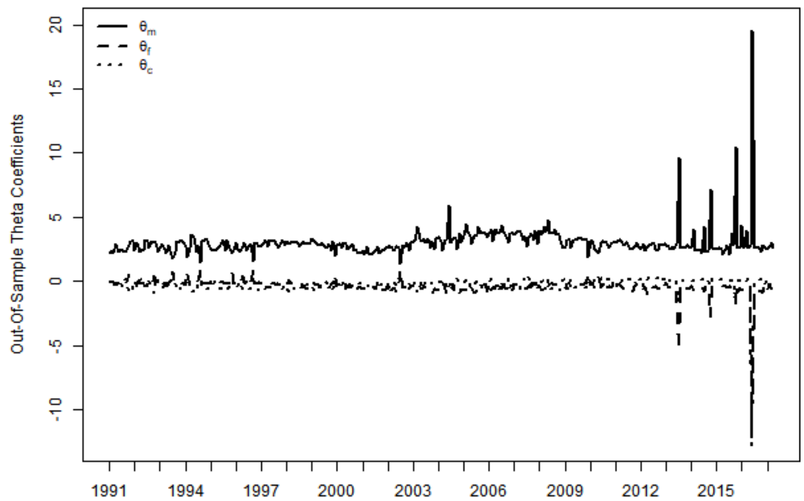
Figure 10: Performance plot for transaction cost optimizations



This figure displays the out-of-sample performance from January 1991 to April 2017 for different levels of transaction costs. The continuous line displays the performance for constant one-way equity trading costs of 100 basis points. The dashed line shows the performance for the optimization with the merged dataset from Table 1 in Domowitz, Glen, and Madhaven (2001) and Table 5 in Chiyachantana et al. (2004) to model global equity transaction costs (see Section 3.2.2, and Table 12 in Appendix A.3).

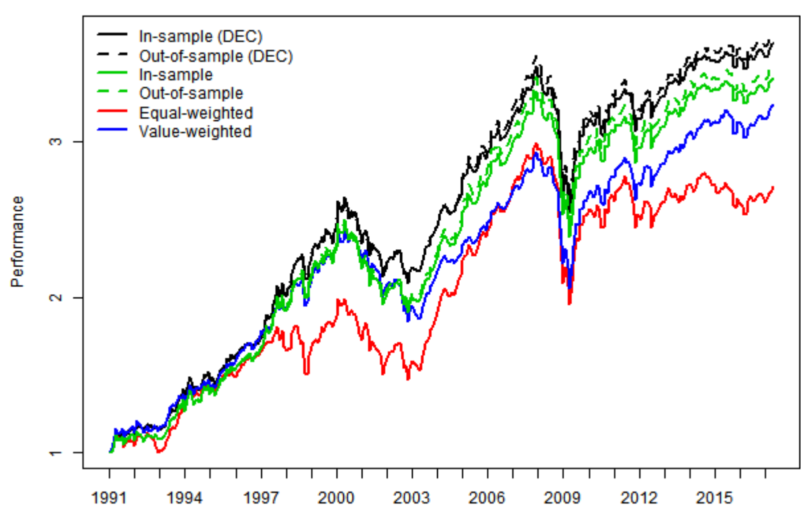
B.4 Transaction costs and long-only constraint

Figure 11: Theta plot for long-only and transaction cost optimization (Table 12)



This figure displays the estimated out-of-sample θ coefficients (11) for the combined long-only and Table 12 transaction cost optimization from January 1991 to April 2017.

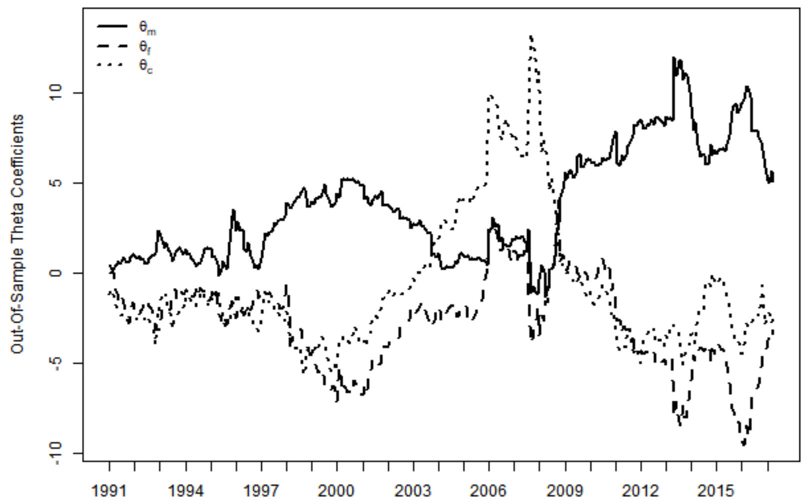
Figure 12: Performance plot for long-only and transaction cost optimizations



This figure displays the out-of-sample performance of the combined long-only and Table 12 transaction cost optimization from January 1991 to April 2017. The transaction costs are modeled through a merged dataset from Table 1 in Domowitz, Glen, and Madhaven (2001) and Table 5 in Chiyachantana et al. (2004) (see Section 3.2.2, and Table 12 in Appendix A.3).

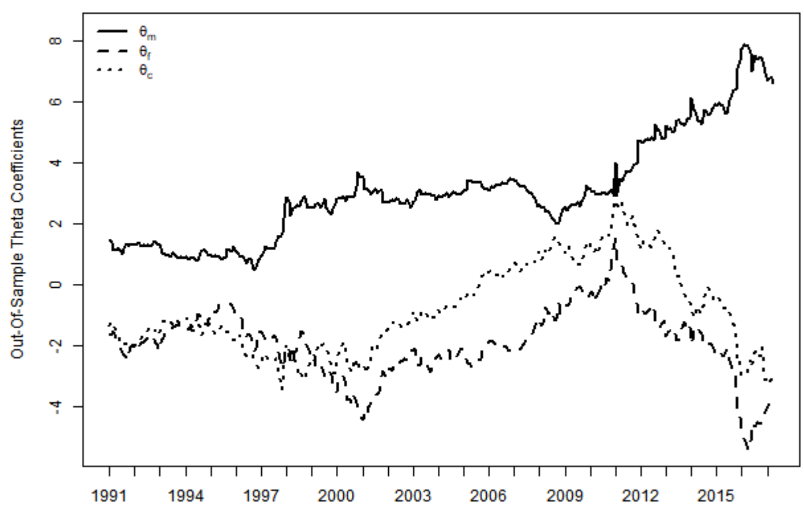
B.5 Rolling window optimization

Figure 13: Theta plot for the rolling window approach (60 months)



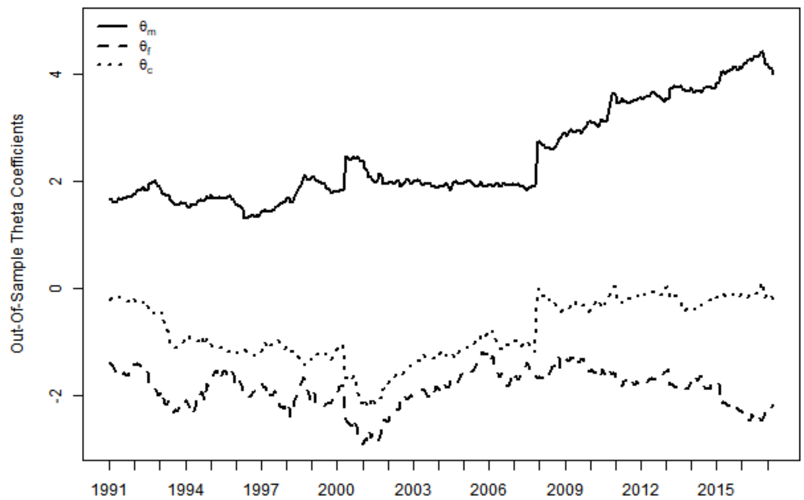
This figure displays the estimated out-of-sample θ coefficients (11) for the 60-month rolling window optimization from January 1991 to April 2017.

Figure 14: Theta plot for the rolling window approach (120 months)



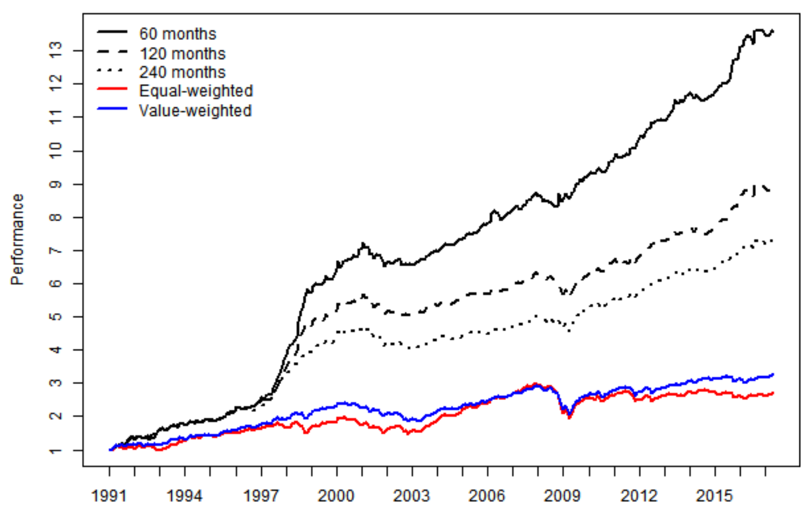
This figure displays the estimated out-of-sample θ coefficients (11) for the 120-month rolling window optimization from January 1991 to April 2017.

Figure 15: Theta plot for the rolling window approach (240 months)



This figure displays the estimated out-of-sample θ coefficients (11) for the 240-month rolling window optimization from January 1991 to April 2017.

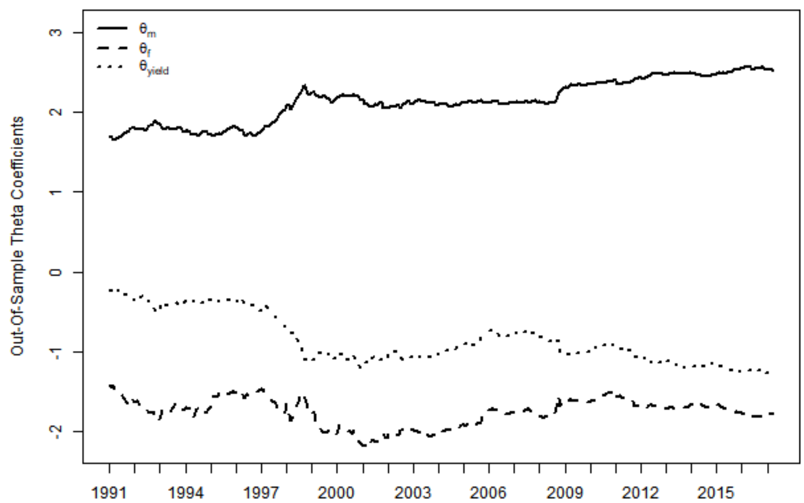
Figure 16: Performance plot for the rolling window approach



This figure displays the out-of-sample performance of the 60, 120 and 240 month rolling window optimization from January 1991 to April 2017. The continuous line displays the 60-month, the dashed line shows the 120-month and the dotted line presents the 240-month performance.

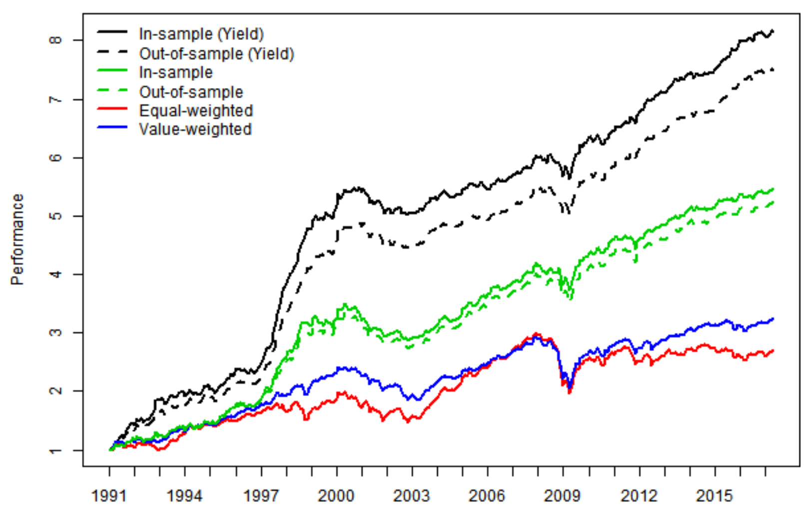
B.6 Interest rate differentials

Figure 17: Theta plot for the government bond yield optimization



This figure displays the estimated out-of-sample θ coefficients (11) for the government bond yield optimization from January 1991 to April 2017.

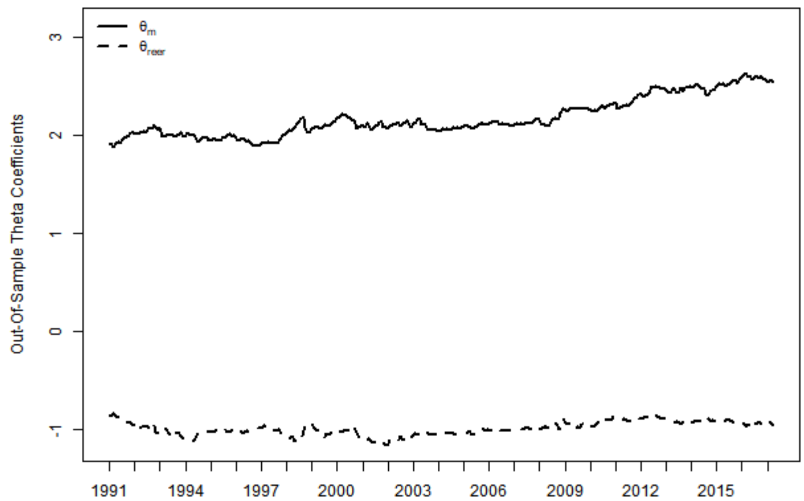
Figure 18: Performance plot for the government bond yield optimization



This figure displays the out-of-sample performance for the government bond yield optimization from January 1991 to April 2017.

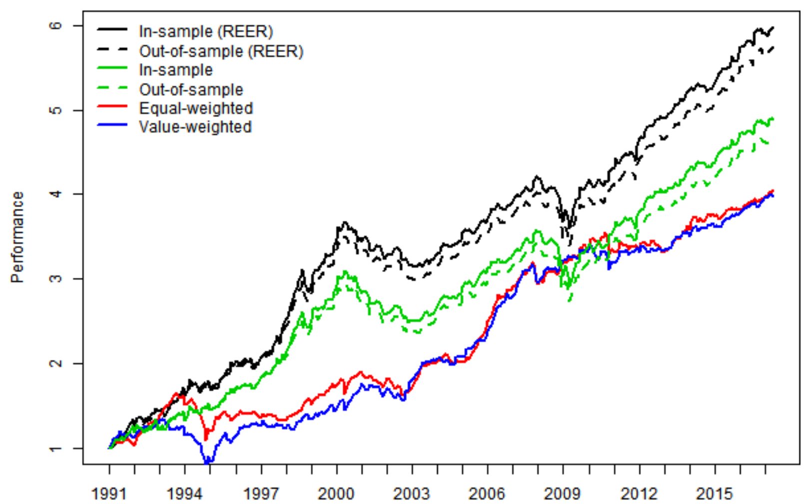
B.7 Real effective exchange rates

Figure 19: Theta plot for the real effective exchange rate optimization



This figure displays the estimated out-of-sample θ coefficients (11) for the real effective exchange rate optimization from January 1991 to April 2017.

Figure 20: Performance plot for the real effective exchange rate optimization



This figure displays the out-of-sample performance for the real effective exchange rate optimization from January 1991 to April 2017.