Optimal Factor Strategy in FX Markets*

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Abstract

We construct a dynamic currency trading strategy that earns a remarkable out-of-sample Sharpe ratio of 1.04 before and 0.78 after transaction costs. It substantially outperforms other popular carry trade strategies in terms of Sharpe ratio, skewness, kurtosis, maximum drawdown, expected recovery time, and percentage of positive returns. Popular factor pricing models in international finance do not explain the superior performance. Our strategy predicts future (1- to 24-month ahead) returns and changes in global FX market volatility. A pricing model using our trading strategy as a single factor outperforms and subsumes the popular "Dollar"-"Carry" two factor pricing model.

JEL-Classification: F31, F37, G11, G12, G15, G17.

Keywords: Foreign Exchange, Factor Pricing Model, Dollar, Carry Trade, Maximum Sharpe Ratio, Predictability, Principal Component.

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1 Introduction

Currency carry trade strategies are well-known to earn high Sharpe ratios. The literature typically suggests to sort currencies according to country-specific characteristics such as interest rates, power purchase parity adjusted exchange rates or past exchange rate appreciation and use an equal weighting scheme to construct trading strategies. In turn, such trading strategies are then used as pricing factors to price assets in foreign exchange (FX) markets. A prominent pricing model is the DOL-HML two factor model (Lustig et al., 2011), where DOL is the "dollar" factor (borrow USD, equally lend in all other currencies) and HML is the "carry" factor (borrow low, lend high interest rate currencies). Equal weighting schemes are, however, suboptimal and there is no theoretical guidance why these profitable trading strategies are suitable pricing factors which are able to explain expected asset returns in the cross-section.

We construct a currency trading strategy which outperforms many well-known carry trade strategies out-of-sample. Moreover, our strategy earns economically large and statistically significant abnormal returns according to popular factor pricing models, suggesting that current pricing factors fail to explain important priced risks in FX markets. Finally, a pricing model which uses our trading strategy as a single factor performs better than and subsumes the prominent DOL-HML factor pricing model.

In theory, our strategy is perfectly negatively correlated with the stochastic discount factor (SDF) estimated according to a standard projection approach as described by Hansen and Jagannathan (1991),[1] and thus, earns the theoretically maximum attainable Sharpe ratio in FX markets. We call this strategy the *Maximum Sharpe Ratio* (MSR) strategy. It is equal to the optimal portfolio of an investor with log-utility (Merton, 1971).

As suggested by Maurer et al. (2015), we use principal component analysis (PCA) to span a risk space containing the most important FX market risks, onto which we project the SDF. PCA helps us to reduce estimation noise. Addressing estimation error and parameter uncertainty concerns is important (see Brandt (2005) for an overview). That is, by

[1] Following Maurer et al. (2015), first, principal component analysis (PCA) is used to map out the FX market risk space. Second, a cross-sectional regression of currency pair carry trade returns (borrow USD, lend currency I) is employed to estimate market prices of risk and construct country-specific SDFs.

construction our MSR strategy earns the maximum Sharpe ratio *in-sample*, but this does not guarantee a strong *out-of-sample* performance. For instance, DeMiguel et al. (2009) show that in equity markets an equally weighted strategy outperforms optimized portfolios out-of-sample (due to parameter uncertainty). In contrast to this strong finding in equity markets, we find that our optimized portfolio performs well in FX markets because there is a strong factor structure which is an ideal environment to reduce noise in the estimation of expected returns and covariances.

Besides the fact that MSR is constructed from an SDF projection, Maurer et al. (2015) document that this approach yields country-specific SDF estimates which are correlated to fluctuations in output gap, which is a proxy for macroeconomic uncertainty. In particular, countries with more volatile SDFs feature a higher output gap volatility and changes in output gap are negatively correlated with shocks to estimated SDFs. Thus, this empirical relationship is evidence that the superior performance of MSR as a trading strategy and pricing factor has a risk-based explanation related to economic fundamentals.

We implement MSR at a monthly frequency and find that it earns a high Sharpe ratio and outperforms other popular carry trade strategies across various performance measures and for diverse subsamples between 1977 and 2016.[2] For our set of 15 developed countries, which feature a large active trading volume and liquidity, we find that MSR earns a Sharpe ratio of 1.04 before and 0.78 after accounting for transaction costs. This is in comparison to a Sharpe ratio of 0.62 and 0.56 respectively for the HML strategy, which borrows (lends) a portfolio of currencies with low (high) interest rates (Lustig and Verdelhan, 2007). The outperformance is even larger during NBER recessions when MSR earns a Sharpe ratio of 0.67 after transaction costs, while HML earns 0.05. We also confirm the superior performance of MSR outside NBER recession periods and in pre- and post-Euro subsamples.

We further find that the monthly return distribution of MSR is positively skewed, which is a desirable property since it indicates large upside potential and relatively limited downside risk. Many other currency strategies have a less favorable negative skewness. Moreover, the

[2]For the implementation we only use available information, that is, at the end of each month, when we rebalance our portfolio, we estimate all necessary parameters (in PCA and cross-sectional regressions) using only historical data. Thus, our results are not subject to a look-ahead bias.

maximum drawdown for MSR is less severe than for other popular currency strategies. The expected recovery time from a maximum drawdown is also substantially shorter for MSR. Consistent with Bekaert and Panayotov (2016) and Daniel et al. (2014) our finding of a limited downside risk suggests that crash risk does not appear to fully explain the large expected returns in FX markets.

MSR earns statistically significant and economically large abnormal returns according to popular factor pricing models in FX markets. This suggests that current pricing factors fail to explain important risk sources which are compensated by sizable average excess returns. Building on this finding we test the ability of MSR as a pricing factor. We document that MSR is an important pricing factor and is able to explain much of the cross-sectional variation in expected returns in FX markets. Time-series and cross-sectional asset pricing tests indicate that a model using MSR as a single factor outperforms the popular DOL-HML two factor model in pricing assets in FX markets. Moreover, DOL and HML do not contain any additional information relevant for pricing beyond what is already captured by MSR. Thus, the MSR single factor model appears to subsume the DOL-HML two factor pricing model.

We argue that there are two important dimensions of MSR's investment. First, MSR optimally trades off conditional risks and market prices, i.e., it invests in the Markowitz (1952) tangency portfolio. Second, MSR allocates capital between the risk-free asset (bond in home currency) and the risky tangency portfolio such that the conditional volatility of MSR matches the conditional volatility of the estimated SDF. This time variation in the capital allocation is essentially *market timing*. MSR invests more (or increases leverage) in the risky tangency portfolio when market prices of risk are high and less (or decreases leverage) during times of low risk compensations. Notice that times of high (low) market prices (i.e., SDF volatility) do not necessarily coincide with times of high (low) FX market volatility. Thus, the market timing of MSR is different to volatility managed portfolios such as in Della Corte et al. (2009), Daniel et al. (2014) and Moreira and Muir (2016). MSR's market timing ability is valuable and MSR earns a higher unconditional Sharpe ratio than other strategies (e.g. the tangency portfolio), which have the same risky asset portfolio composition but do not dynamically adjust their leverage. MSR is also found to outperform volatility managed portfolios particularly during NBER recessions and in the post-Euro subsample.

In support of the idea that MSR is able to time the market, we find that the amount of leverage taken by MSR in month t predicts future (1- to 24-month ahead) returns of many FX strategies as well as future changes in global FX market volatility. In contrast, changes in global FX market volatility do not have such predictive power, suggesting that MSR is able to time the market more efficiently than volatility managed portfolios.

To address estimation error concerns discussed in the literature on portfolio optimization under parameter uncertainty, we exploit the strong factor structure in FX markets. A strong structure on expected returns and covariances helps to reduce noise in the estimation of these moments. We use interest rate differentials to proxy for expected carry trade returns and remove unimportant principal components when estimating exchange rate growth covariances. Removing principal components with little explanatory power ensures that the underlying model excludes near-arbitrage opportunities (Kozak et al., 2015).[3] It is also similar to shrinkage methods or portfolio constraints to prevent extreme portfolio positions which generate large in-sample but small out-of-sample returns.

Our paper is organized as follows. First, we relate our paper to the relevant literature. The data and all tested carry trade strategies are described in section 2. We report and compare the performance of all strategies in section 3: section 3.1 compares strategies without accounting for transaction costs, 3.2 reports the performance after accounting for transaction costs, 3.3 reports results in diverse subsamples, and 3.4 investigates whether popular pricing factors can explain the large excess returns of MSR. Section 4 demonstrates MSR's ability to predict future currency returns and FX market volatility. Motivated by the findings in the previous sections, section 5 delivers the key result of the paper, demostrating the power of MSR as a single pricing factor to explain the cross-section of expected FX market returns. Section 6 concludes. Appendix A describes the construction of MSR and its relation to the tangency portfolio in Markowitz (1952) and the non-parametric SDF estimation approach in Maurer et al. (2015). Appendix B and C describe the data sources and all relevant tables.

[3] In a similar spirit, Ross (1976) suggests factors should be constructed such that the maximum attainable Sharpe ratio is bounded.

The accompanying Internet Appendix replicates all results in this paper for a larger set of 48 emerging and developed countries and demonstrates the robustness of our findings.

Related Literature

Our paper is related to the literature which analyzes risk factors in FX markets and constructs profitable carry trade strategies. Lustig and Verdelhan (2007, 2011) and Burnside (2011, 2012) discuss the connection between carry trade returns, aggregate consumption growth (CCAPM) and popular stock market pricing factors. Recently, many new FX risk factors were introduced: carry factor (Lustig et al., 2011), global volatility factor (Menkhoff et al., 2012a; Christiansen et al., 2011), momentum factor (Burnside et al., 2011; Menkhoff et al., 2012b), global currency skewness factor (Rafferty, 2012), FX correlation risk factor (Mueller et al., 2013), dollar factor (Verdelhan, forthcoming; Lustig et al., 2014), downside beta risk factor (Dobrynskaya, 2014; Lettau et al., 2014; Galsband and Nitschka, 2013), FX liquidity risk factor (Mancini et al., 2013), economic size factor (Hassan, 2013), surplus-consumption risk factor (Riddiough, 2014). Brusa et al. (2015) introduce an international CAPM model with one global equity factor and two currency factors. Daniel et al. (2014) show that dollar-neutral carry trades and dollar-exposed strategies are fundamentally different and usual risk factors appear to explain only dollar-neutral returns. Bekaert and Panayotov (2016) show that excluding the Australian dollar, Japanese Yen, and Norwegian Krone from the asset universe substantially improves the Sharpe ratio and lowers the downside risk of carry trade strategies. For most of our analysis we focus on the well-known and dominant DOL and HML factors as a benchmark. We show that our trading strategy loads on important risks not spanned by these pricing factors and outperforms the DOL-HML two factor model.

Some research attempts to link currency carry trade returns and pricing factors to macroeconomic fundamentals (Habib and Stracca, 2012; Cenedese, 2012; Dobrynskaya, 2015; Filippou and Taylor, forthcoming; Menkhoff et al., 2015). Our companion paper, Maurer et al. (2015) shows that estimated SDFs, which correspond to MSR, are inherently related to fluctuations in output gap.

There is a large literature on trading strategies in FX markets. Our MSR strategy is closely related to the mean-variance efficient currency portfolios by Baz et al. (2001) and Della Corte et al. (2009), but there are several important differences. Baz et al. (2001) build portfolios of short term bonds in 5 developed currencies to minimize the conditional variance given a conditional expected target return. Thus, similar to MSR, their strategy holds the tangency portfolio, but opposite to MSR, their strategy decreases (increases) the investment in the tangency portfolio when market prices are high (low) because the expected target return is constant through time. Accordingly, the conditional Sharpe ratio is identical but the unconditional Sharpe ratio of their strategy is lower than the one of MSR. Della Corte et al. (2009) construct portfolios of short term bonds in 4 developed currencies to maximize the conditional expected return given a conditional target volatility. While their strategy decreases (increases) leverage in response to an increase (decrease) in the global FX market volatility, MSR adjusts its leverage in response to time variations in market prices of risk. Notice that FX market volatility and market prices are likely negatively correlated but the correlation is not perfect. Daniel et al. (2014) and Moreira and Muir (2016) also document that volatility managed portfolios in FX markets earn large risk adjusted returns, and Daniel et al. (2014) further analyzes the downside/crash risk of such strategies. One of our main results is to analyze abnormal returns of MSR, predictability of FX market returns and the possibility to use MSR as a pricing factor, while Baz et al. (2001), Della Corte et al. (2009), Daniel et al. (2014) and Moreira and Muir (2016) only study the performance of trading strategies.

Levich and Thomas (1993), Taylor and Allen (1992), Silber (1994) and LeBaron (1999), provide evidence that technical analysis can generate substantial risk-adjusted returns in FX markets. Jorda and Taylor (2012) show that conditioning on purchase power parity (PPP) information can improve the performance of naive carry trade strategies. Sager and Taylor (2014) build on the exchange rate predictability results from a cointegration relationship in Clarida and Taylor (1997) and generate large trading profits. Employing the portfolio optimization method of Brandt et al. (2009), which maps asset characteristics into portfolio weights, Laborda et al. (2014) and Barroso and Santa-Clara (2015) construct optimal carry trade portfolios, which perform well out-of-sample. Della Corte et al. (forthcoming) construct a profitable carry trade strategy based on option implied variance risk premia. Dahlquist and

Hasseltoft (2016) document a strong relationship between economic momentum (trends in fundamental variables) and average carry trade returns and build trading strategies. Bekaert and Panayotov (2016) construct carry trades based on a restricted set of "good" currencies and earn large risk adjusted returns with limited downside risk.

Finally, our paper is related to a large literature on portfolio optimization under parameter uncertainty. Markowitz (1952) derives a theoretical formula to construct the maximum Sharpe ratio (or tangency) portfolio. The implementation is, however, challenging because conditional expected returns and covariances have to be estimated from the data. Estimation errors can lead to a poor out-of-sample performance of a strategy, even though the in-sample performance is deceptively outstanding (Brandt (2005) provides an extensive review). Popular methods to deal with estimation errors include: shrinkage to reduce noise in estimates of expected returns and covariances (James and Stein, 1961; Jorion, 1986; Frost and Savarino, 1986), minimization of expected loss due to parameter uncertainty (Kan and Zhou, 2007; Tu and Zhou, 2011; Kan et al., 2016), portfolio constraints to restrict extreme positions which are likely due to estimation errors (Frost and Savarino, 1988; Jagannathan and Ma, 2003), and imposing factor structures to reduce noise in estimates of expected returns and covariances (Sharpe, 1963; Chan et al., 1999; MacKinlay and Pastor, 2000). Given that FX markets feature a strong factor structure, our paper employs the last approach and imposes a factor model to overcome estimation errors.

2 Data and Carry Trade Strategies

2.1 Data

Exchange Rate: We collect daily spot and 1-month forward bid, ask and mid exchange rates from Barclays Bank International and Reuters via Datastream. Our sample consists of 15 developed countries: Australia, Belgium, Canada, Denmark, Euro Area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom. These are the countries identified as developed by Lustig et al. (2011). Exchange rates are defined against USD (US-dollar) and our sample starts on January 2nd, 1976 and ends on March 2nd, 2016.[4]

Trading frictions are typically lower for currencies of developed countries (e.g., they have a large active trading volume, there are less capital controls, liquidity is higher, transaction costs are lower) than for emerging countries. Thus, our set of 15 developed countries fits our theoretical frictionless model better than a larger set of developed and emerging countries. Moreover, investors typically prefer to implement a trading strategy using currencies of developed countries because of liquidity risks and trading costs. Since our paper develops a profitable trading strategy, we focus on our results for the set of 15 developed countries. The results for a larger set of 48 emerging and developed markets are similar and we report them in the Internet Appendix.

Purchasing power parity (PPP): OECD provides annual PPP data (national foreign currency per USD) for all of the countries in our sample. Annual PPP data is released in March and we assume PPP is constant from March until February in the following year in order to construct monthly observations.

NBER Recession: We collect the NBER recession time-series from the Federal Reserve Bank of St. Louis. NBER based Recession Indicators for the USA are defined as the Period following the Peak through the Trough.

2.2 Carry Trade Returns and Transaction Costs

We denote spot and 1-month forward exchange rates of units of currency I per USD at time t by $EX_{I/US,t}$ and $F_{I/US,t}$. By no-arbitrage the covered interest rate parity (CIP) implies $F_{I/US,t} = EX_{I/US,t} e^{\left(r_{I,t} - r_{US,t}\right)\Delta t}$, where $r_{US,t}$, $r_{I,t}$ are (continuously compounded and annualized) risk-free 1-month spot interest rates in USD and currency I, and $\Delta t = \frac{1}{12}$ is a 1 month investment horizon. Akram et al. (2008) show that the CIP holds closely in the data at daily and lower frequencies. We define the realized carry trade return denominated in USD of borrowing 1 USD and lending $EX_{I/USD,t}$ units of currency I for 1 month ($\Delta t = \frac{1}{12}$)

[4] The sample from January 2nd, 1976 to October 11th, 1983 is quoted against the British Pound, and we convert all data to exchange rates against USD.

as,

$$\begin{aligned} CT^{US}_{-US/+I,t+\Delta t} &= \frac{EX_{I/US,t}}{EX_{I/US,t+\Delta t}} e^{r_{I,t}\Delta t} - e^{r_{US,t}\Delta t} = e^{r_{US,t}\Delta t}\left(\frac{EX_{I/US,t}}{EX_{I/US,t+\Delta t}} e^{\left(r_{I,t}-r_{US,t}\right)\Delta t} - 1\right) \\ &= e^{r_{US,t}\Delta t}\left(\frac{F_{I/US,t}}{EX_{I/US,t+\Delta t}} - 1\right) \approx e^{r_{US,t}\Delta t} \ln\left(\frac{F_{I/US,t}}{EX_{I/US,t+\Delta t}}\right). \end{aligned}$$

Note that carry trade returns are net-zero investments and thus, they are excess returns. We use quotes of the last day of the month to compute monthly returns. Since $r_{US,t}$ is locally-deterministic, we rescale the carry trade returns to $\widehat{CT}^{US}_{-US/+I,t+\Delta t} \approx \ln\left(\frac{F_{I/US,t}}{EX_{I/US,t+\Delta t}}\right)$, that is, borrow $e^{-r_{US,t}\Delta t}$ USD and lend $e^{-r_{US,t}\Delta t} EX_{I/USD,t}$ units of currency I.

We compute carry trade returns before and after transaction costs. We use mid exchange rate quotes for $EX_{I/US,t}$ and $F_{I/US,t}$ to compute returns before transaction costs. To account for transaction costs we use bid-ask quotes, indicated by superscript ^{b} and ^{a}. We implement two measures of transaction costs: (i) full round-trip costs (a conservative measure) and (ii) costs assuming no roll-over fees for forward contracts (arguably more realistic measure). We present our results for both types of transaction costs. Accounting for full round-trip transaction costs for a long position in the "borrow USD lend I" trade we have the return net of transaction costs $\widehat{CT}^{L,US}_{-US/+I,t+\Delta t} \approx \ln\left(\frac{F^b_{I/US,t}}{EX^a_{I/US,t+\Delta t}}\right)$, and for a short position in the same trade we have $\widehat{CT}^{S,US}_{-US/+I,t+\Delta t} \approx -\ln\left(\frac{F^a_{I/US,t}}{EX^b_{I/US,t+\Delta t}}\right)$.

Accounting every month for full round-trip transaction costs is conservative because it is relatively cheap to roll a contract over from month to month. The literature recognizes this and often assumes no roll-over fees and only accounts for transaction costs if there is a change in a position (Menkhoff et al., 2012a,b; Della Corte et al., forthcoming). Specifically, if a position was open before time t and stays open after the end of the month, then we compute the realized return without transaction costs (mid exchange rate quotes). If a long position was open before time t and is closed at the end of the month, then we calculate the return as $\widehat{CT}^{L,US}_{-US/+I,t+\Delta t} \approx \ln\left(\frac{F_{I/US,t}}{EX^a_{I/US,t+\Delta t}}\right)$. If a long position was newly opened at time t but stays open at the end of the month, then we calculate the return as $\widehat{CT}^{L,US}_{-US/+I,t+\Delta t} \approx \ln\left(\frac{F^b_{I/US,t}}{EX_{I/US,t+\Delta t}}\right)$. Similar, if a short position was open before time t and is closed at the end of the month, then we calculate the return as $\widehat{CT}^{S,US}_{-US/+I,t+\Delta t} \approx -\ln\left(\frac{F_{I/US,t}}{EX^b_{I/US,t+\Delta t}}\right)$. If a short position was newly opened at time t but stays open at the end of the month, then we calculate the return as $\widehat{CT}^{S,US}_{-US/+I,t+\Delta t} \approx -\ln\left(\frac{F^a_{I/US,t}}{EX_{I/US,t+\Delta t}}\right)$.

If a currency does not have a bid, ask of mid quote for the spot or the forward exchange rate at some time t or $t+\Delta t$, then we exclude the currency from our sample at time t. We also exclude a currency at time t if the absolute value of the annualized forward premium $12 \times \left|\frac{F_{I/US,t}}{EX_{I/US,t}}\right|$ or equivalently the annualized implied interest rate differential $12 \times |r_{I,t} - r_{US,t}|$ is larger than 30%. Interest rate differentials of more than 30% are rare and we believe such large values likely indicate the presence of severe trading frictions, sizable sovereign default risk or an extraordinary large currency devaluation. This selection removes only 0.1% of observations in our sample of 15 developed countries between January 1976 and March 2016. Our results are robust to various choices of this threshold value.

2.3 Trading Strategies

MSR: The theoretical motivation and a detail derivation of the maximum Sharpe ratio (MSR) strategy is described in Appendix A. In the main text we focus on the empirical implementation of the strategy.

MSR invests in a portfolio of foreign short term bonds with weights

$$\theta_{US,t} = \vartheta \widetilde{W}_t \widetilde{\Lambda}_t^{-1} \widetilde{W}_t^T ECT_t,$$

where ϑ is a time invariant scaling factor, $ECT_t = E_t\left[CT^{US}_{-US/+I,t+\Delta t}\right]$ is a vector of conditional expected excess returns and $\widetilde{W}_t \widetilde{\Lambda}_t^{-1} \widetilde{W}_t^T$ represents the inverse of the conditional covariance matrix of exchange rate growth Σ_t after a spectral decomposition (or PCA) with $\widetilde{W}_t$ the matrix of eigenvectors and $\widetilde{\Lambda}_t$ the diagonal matrix of eigenvalues. The implementation of MSR requires the estimation of the conditional moments Σ_t and ECT_t. On the last day of every month t we collect daily exchange rate returns over the past 6 months. We exclude the most recent daily return to ensure that our portfolio construction $\theta_{US,t}$ at time t only uses information available prior to t. We exclude a currency at time t and set its weight to zero in the MSR portfolio if more than 20% of its daily exchange rate returns are missing over the past 6 months. We use an exponentially weighted moving average (EWMA) of squared, demeaned returns to estimate the current conditional covariance matrix Σ_t.[5] We set the EWMA weight equal to 0.95, which implies a half-life of an exchange rate growth observation of 14 trading days. Our strategy is robust to various choices of the window length and the EWMA weight; we have tested window lengths between 3 and 12 months and EWMA weights between 0.9 and 1, and our findings remain essentially unchanged. We use the most recent interest rate differential $(r_{I,t} - r_{US,t})\,\Delta t$ (or equivalently the forward premium $\ln\left(\frac{F_{I/US,t}}{EX_{I/US,t}}\right)$) as a proxy for the conditional expected return $E_t\left[CT^{US}_{-US/+I,t+\Delta t}\right]$. Thus, the underlying assumption is that the representation $E_t\left[\widehat{CT}^{US}_{-US/+I,t+\Delta t}\right] = \alpha_t + \beta_t\,(r_{I,t} - r_{US,t})\,\Delta t$ with $\beta_t > 0$ holds $\forall I$ at time t.

Our theoretical derivation assumes that there are no transaction costs or other trading frictions. Transaction costs are most of the time small for our set of 15 developed countries. In contrast, transaction costs can be substantial for emerging countries and affect the profitability of MSR. The issue of transaction costs can be mitigated if we compute the current bid-ask spread relative to the mid exchange rate quote at every time t and exclude currencies with relative spreads larger than 1%. When we account for monthly full round-trip transaction costs, then a 1% spread implies annual costs of 12%. It is natural to exclude assets with large costs from the portfolio selection. This filter removes 0.2% of the monthly observations for our 15 developed countries (all of which are before August 1993). Our results are robust to changes in this threshold value.

We drop principal components (i.e., an eigenvector and eigenvalue) with little explanatory power to exclude near-arbitrage opportunities in the constructed SDF. In particular, we drop a principal component k if $\frac{\lambda_{k,t}}{\sum_{h=1}^{N}\lambda_{h,t}}$ is less than 1%. The results are robust to changes in this threshold value. This also helps to further mitigate the problem of transaction costs. As explained in more detail in Appendix A transaction costs imply that the exchange rate is not exactly equal to the ratio of country-specific SDFs (equation (2) in the Appendix). Instead the relationship holds approximately because transaction costs limit arbitrage opportunities.

[5] Element (I,J) of Σ_t is $Cov_t\left(\widehat{CT}^{US}_{-US/+I,t+\Delta t}, \widehat{CT}^{US}_{-US/+J,t+\Delta t}\right) = \frac{\sum_{\tau<t}\delta^{t-\tau}\overline{CT}^{US}_{-US/+I,\tau}\overline{CT}^{US}_{-US/+J,\tau}}{\sum_{\tau<t}\delta^{t-\tau}}$, where $\overline{CT}^{US}_{-US/+I,\tau}$ is the demeaned realized carry trade return denominated in USD of borrowing USD and lending I at time τ, and weight $\delta \in (0,1]$. Returns are demeaned within the 6 month rolling window.

In turn, this implies that carry trade returns (equation (3) in the Appendix) will be exposed to small unpriced fluctuations. Removing principal components which explain almost no common variation in the data from our analysis helps to remove such unpriced fluctuations of the exchange rate around the ratio of SDFs.

The variance of MSR is by construction equal to the variance of the SDF in the US. Thus, we scale the portfolio weights in our strategy by a constant factor of $\vartheta = 0.02$ so that the volatility is of a similar magnitude to the volatility of HML. Scaling the portfolio by a constant ϑ is not material because MSR is a net-zero investment strategy and its returns are always excess returns.

$\mathbf{MSR}_V$, $\mathbf{MSR}_I$, $\mathbf{MSR}_{CV}$, $\mathbf{MSR}_{I,CV}$, TAN: Besides MSR, we implement five related strategies. MSR_V and MSR_I explore the importance of the covariance matrix in the construction of MSR. MSR_V ignores all correlations and assumes the covariance matrix is simply a diagonal matrix with exchange rate variances on the diagonal. The portfolio weights are $\theta_{V,t} = D_t^{-1} ECT_t$ where the diagonal of D_t is equal to the diagonal of $\widetilde{W}_t \widetilde{\Lambda}_t^{-1} \widetilde{W}_t^T$ and all off-diagonal elements are zero. MSR_I further ignores the variances and the portfolio weights are $\theta_{I,t} = ECT_t$. Using the full covariance matrix undoubtedly improves the in-sample performance of the optimal portfolio and thus MSR is expected to outperform MSR_V and MSR_I. However, out-of-sample this may not be true because of estimation errors. For instance, DeMiguel et al. (2009) document that a naive, equally weighted portfolio outperforms the tangency portfolio out-of-sample in equity markets.

MSR_{CV} adjusts MSR to keep its conditional volatility (or risk exposure) constant through time, $\theta_{CV,t} = \frac{1}{\sqrt{\widetilde{\eta}_{US,t}^T \widetilde{\eta}_{US,t}}} \theta_{US,t}$. Accordingly, the difference between MSR and the adjusted strategy MSR_{CV} is due to market timing. MSR takes into account time variations in market risk premia and dynamically changes its risk exposure. More specifically, MSR increases (decreases) its risk exposure when the compensation for risk is large (small), which increases the unconditional Sharpe ratio of the strategy. In contrast, MSR_{CV} is constructed to keep its risk exposure constant through time and does not take advantage of changes in market risk premia. Similarly, we construct $MSR_{I,CV}$ which adjusts MSR_I to keep the conditional volatility constant. This strategy is also discussed by Daniel et al. (2014) and is related to the research by Moreira and Muir (2016). The portfolio is $\theta_{I,CV,t} = \frac{\sigma_{I,CV}}{\sqrt{ECT_t^T \widetilde{W}_t \widetilde{\Lambda}_t \widetilde{W}_t^T ECT_t}} ECT_t$, which has constant conditional volatility $\sigma_{I,CV}$. Finally, TAN is the tangency portfolio $\phi_t = \frac{\theta_{US,t}}{1_{N\times 1}^T \theta_{US,t}}$.

DOL, D-DOL, HML: The Dollar (DOL) and High-minus-Low interest rate (HML) strategies are introduced by Lustig et al. (2011). DOL is a net-zero investment strategy of borrowing 100% in USD and investing all of the borrowed money equally in risk-free bonds in all other currencies, i.e. the return on DOL is simply $\sum_{I=1}^{N} \frac{1}{N} \widehat{CT}_{-US/+I,t+\Delta t}^{US}$. The dynamic Dollar ($D$-$DOL$) takes a long (short) position in DOL when the interest rate in USD is below (above) the median interest rate across all countries. For the HML strategy we first sort currencies on the last day of every month t according to their current risk-free interest rates relative to the rate in the US, i.e. $r_{I,t} - r_{US,t}$ or equivalently the forward premium $\frac{F_{I/US,t}}{EX_{I/US,t}}$ into quintiles. Within each quintile we build a net-zero investment strategy of borrowing 100% in USD and investing all of the borrowed money equally in risk-free bonds in all other currencies within the quintile. We denote these five portfolios by $IntP_i \; \forall i \in \{1, \ldots, 5\}$. The HML strategy takes a long position in the high interest rate currency portfolio $IntP_5$ and a short position in the low interest rate portfolio $IntP_1$. HML is well-known to earn a high Sharpe ratio.

MOM: Momentum (MOM) strategies are popular in equity and FX markets. For instance Burnside et al. (2011) and Menkhoff et al. (2012b) analyze momentum returns in FX markets and report high Sharpe ratios. They show that the momentum returns do not change much if either the formation period or the investment horizon changes, or whether the portfolios are constructed based on past carry trade returns or solely exchange rate growths. On the last day of every month t we compute for each currency I the average carry trade return of borrowing USD and lending currency I over the past 12 months. We, then, sort currencies according to the past performance into quintiles (the top quintile contains the winner currencies and the bottom quintile the loser currencies) and build equally weighted currency portfolios for each quintile. We denote these five portfolios by $MomP_i \; \forall i \in \{1, \ldots, 5\}$. MOM takes a long position in the winner currency portfolio $MomP_5$ and a short position in the loser currency portfolio $MomP_1$. We exclude a currency from our sample at time t if we do not observe any returns of that currency over the past 12 months.

VAL: The value (VAL) strategy assumes that the uncovered interest rate parity holds in the long run and (in real terms) undervalued currencies appreciate against overvalued currencies. This idea arguably goes back to Bilson (1984) who analyzes an FX trading strategy based on deviations of the exchange rate from its equilibrium level when the PPP relationship holds. On the last day of every month t we sort currencies according to their real exchange rates against the USD into quintiles, where the top quintile contains overvalued and the bottom quintile undervalued currencies. The real exchange rate of currency I per USD is equal to the purchasing power parity at time t (quoted as currency I per USD) divided by nominal exchange rate $EX_{I/US,t}$. We construct equally weighted currency portfolio for each quintile, denoted by $ValP_i$ $\forall i \in \{1, \ldots, 5\}$. VAL takes a long position in the portfolio of undervalued currencies $ValP_1$ and a short position in the portfolio of overvalued currencies $ValP_5$.

3 Performance of Trading Strategies

Table 3 reports the correlation matrix of monthly returns of all strategies. Correlations are estimated using returns before transaction costs. The correlation between MSR and all other strategies (except for MSR_{CV}, MSR_V and $MSR_{I,CV}$ where the correlation is 77%, 61% and 51%) is relatively small. MSR has a moderate correlation of roughly 35% with both MSR_I and HML. MSR's correlation to TAN, DOL, MOM and VAL is close to zero. This cross-correlation pattern indicates that MSR is distinct from the existing carry trade strategies in the literature.

Tables 4 through 10 in the Appendix summarize the performance of the eleven trading strategies MSR, MSR_V, MSR_I, MSR_{CV}, $MSR_{I,CV}$, TAN, HML, DOL, D-DOL, MOM and VAL described in section 2.3. All trading strategies use information available at the end of month t to construct a portfolio which we then hold until the end of the subsequent month $t + 1$. Thus, all returns are out-of-sample and none of the trading strategies suffers from a look-ahead bias. We report annualized average excess returns (Mean), volatility (Vol) and Sharpe ratio (SR) (these three values are measured in percentage in the tables).

Moreover, we characterize the distribution of returns and estimate the skewness (Skew), kurtosis (Kurt), and the 10th-, 50th- and 90th-percentiles (10-%, 50-% and 90-%) of monthly returns. We further compute what percentage of monthly returns are positive (% positive) and we estimate the auto-correlation (AC) of monthly returns. MDD measures the maximum drawdown in percentage, which is defined as the maximum loss from peak to trough a strategy has experienced during the entire sample period. Moreover, ‖MDD‖/Mean measures the expected time in years to recover from the maximum drawdown. Equivalently, ‖MDD‖/Mean also measures the maximum downside risk (in percentage) a strategy is exposed to per 1% expected return.

Tables 11 through 15 report annualized abnormal returns of MSR according to several popular factor pricing models in international finance. We use DOL, D-DOL, HML, MOM, VAL and a proxy for changes in global FX market volatility as pricing factors.

As a brief preview of our results, MSR and some of its variations dominate popular carry trade strategies (HML, DOL, D-DOL, MOM, VAL) across all performance measures. MSR pays statistically significant and economically large abnormal returns according to the investigated pricing models. This is evidence that MSR is indeed close to the true maximum Sharpe ratio strategy in FX markets and current popular FX pricing factors are not able to explain important FX market risks.

3.1 Performance Before Transaction Costs

Table 4 reports results for monthly excess returns without accounting for transaction costs (i.e., returns computed using mid exchange rate quotes) for our set of 15 developed countries for the period starting at the end of January 1977 to the end of February 2016.[6] Consistent with the literature HML earns a sizable Sharpe ratio of 0.62 (Lustig et al., 2011). D-DOL earns a comparably high Sharpe ratio of 0.58. MOM and VAL perform slightly worse with Sharpe ratios of 0.32 and 0.53. DOL earns a much lower Sharpe ratio of only 0.08. MSR

[6] Though our data starts in January 1976, the construction of MOM uses 12 months of past returns and thus, we measure the performance of our strategies starting only in January 1977.

dominates all strategies by a large amount and earns a remarkable Sharpe ratio of 1.04.[7]

TAN performs substantially worse than MSR with a Sharpe ratio of 0.32. Remember that both MSR and TAN earn the same conditional Sharpe ratio. The difference is due to the market timing of MSR. MSR_{CV} also earns a lower Sharpe ratio than MSR, 0.96 but the difference is not as stark as between MSR and TAN. The outperformance of MSR over MSR_{CV} is also due to the better market timing on MSR. By construction, MSR_{CV} has a constant conditional volatility and does not take advantage of changes in market prices of risk. The conditional volatility of TAN changes through time but not in an optimal way. In contrast, MSR loads more (less) on a risk source when its market price is large (small). Dynamically adjusting the exposure to risk depending on the size of the compensation increases the unconditional Sharpe ratio. We will further show in section 3.3 that MSR's ability to time the market is particularly beneficial during recessions.

Interestingly, with a Sharpe ratio of 1.08 and 1.05 MSR_V and $MSR_{I,CV}$ slightly outperform MSR, which implies that estimating the correlation structure of exchange rate growths is not beneficial or even harmful for the out-of-sample performance. This is due to estimation errors (Brandt, 2005): knowing the correlation matrix undoubtedly improves the in-sample performance of an optimized portfolio, but estimation errors can lead to a suboptimal allocation and poor performance out-of-sample. For the construction of MSR_V and $MSR_{I,CV}$ we have to estimate far less parameters than for MSR, and thus, estimation uncertainty is a more prevalent issue in the case of MSR. This is similar to the finding by DeMiguel et al. (2009) in stock markets, where a naive, equally weighted strategy is found to outperform mean-variance efficient portfolios out-of-sample. The difference between MSR_V and $MSR_{I,CV}$ is small, which implies that controlling for only overall portfolio variance or managing the variance of each asset does not matter much. In contrast, we find the Sharpe ratio of MSR_I is substantially smaller, 0.74, which implies that the value to estimate exchange rate variances is large when constructing a trading strategy.

[7] Note that if our theory is correct, then there is an upper bound on the Sharpe ratio of MSR. Since $\theta_{J,t} = 0.02 \times \widetilde{W}_t \widetilde{\Lambda}_t \widetilde{W}_t^T ECT_t$, then $\theta_{US,t}^T \Sigma_t \theta_{US,t} \approx 0.02 \times \theta_{US,t}^T ECT_t$ and thus, $0.02\times$ the unconditional Sharpe ratio has to be less or equal to the unconditional volatility of MSR. Empirically, we observe an unconditional volatility of 11.36% which is almost 5.5 times larger than $0.02\times$the unconditional Sharpe ratio 1.04. Thus, the performance of our strategy is in accordance with the restrictions set by our theoretical model.

Interestingly, the skewness of MSR is positive. Many other strategies have a negative skewness (including MSR_{CV} and $MSR_{I,CV}$). MSR_I, MOM and VAL have a slightly positive but basically zero skewness. A positive skewness is a favorable property of a trading strategy, while a negative skewness is undesirable. With a positive skewness we frequently observe large positive returns (large upside potential), while negative returns are relatively close to the mean (limited downside risk). A negative skewness implies the opposite, the upside potential is (or positive returns are) relatively limited, and the downside risk is (or negative returns are) relatively large. The kurtosis is larger than that of a normal distribution and the return distribution features fat tails. Fat tails are generally desirable (undesirable) in combination with a positive (negative) skewness. The 10th and 90th percentiles draw a similar picture: while MSR earns among the largest 90th percentile returns, its 10th percentile return is less negative than that of other strategies.

The maximum drawdown of MSR is only -16%, which is the smallest maximum loss among all strategies. In comparison, HML has a maximum drawdown of -43%, DOL -73%, $D\text{-}DOL$ -24%, MOM -30%, VAL -23%. The MDD of MSR_V (-19%) is slightly worse than the MDD of MSR (-16%). It appears that estimating the correlation structure between exchange rate growths has the benefit to limit maximum losses. TAN has a MDD of -30% and MSR_I, MSR_{CV} and MSR have MDDs in excess of -40%. The small maximum loss of MSR is particularly remarkable since MSR earns an annualized expected return of 11.9%, which is substantially larger than the expected return of most other strategies. In comparison, only MSR_V earns a slightly larger expected return of 12.6%. $MSR_{I,CV}$ earns 11.7%, MSR_{CV} 9%, MSR_I 7.6%, HML 5.7% and expected returns of DOL, $D\text{-}DOL$, MOM, VAL and TAN are all well below 5%. In other words, the expected recovery time from the maximum drawdown (or equivalently the maximum downside risk per 1% expected return) is only 1.35 years for MSR while it is 1.54 years for MSR_V, 3.56 years for $MSR_{I,CV}$, 4.5 years for MSR_{CV}, 4.99 years for $D\text{-}DOL$, and well above 5 years for all other strategies. We conclude that MSR faces substantially less downside risk than any of the other strategies, and the market timing and information from the covariance matrix estimation is useful to limit maximum losses.

Monthly returns are about 65% of the time positive for MSR, HML, MSR_V, MSR_I,

MSR_{CV}, $MSR_{I,CV}$ and TAN, 58% for $D\text{-}DOL$, 56% for MOM and VAL, and 53% for DOL. The auto-correlation is slightly positive for almost all strategies: 23% for MSR_I, 18% for MSR_V, 15% for MSR and MSR_{CV}, 10% for $MSR_{I,CV}$ and HML, 5% for TAN and VAL, 4% for DOL, and virtually 0 for $D\text{-}DOL$ and MOM.

3.2 Performance After Transaction Costs

Table 5 reports results for returns after transaction costs assuming that there is no fee to roll over a forward contract. As explained in section 2.2, we compute returns after transaction costs by accounting for bid-ask spreads when portfolio weights change over time. That is, transaction costs are paid for any turnover in the portfolio. This definition of transaction costs is widely used in the literature (Menkhoff et al., 2012a,b; Della Corte et al., forthcoming). MSR again outperforms all other strategies except for MSR_V and $MSR_{I,CV}$ across all performance dimensions. The outperformance of MSR_V and $MSR_{I,CV}$ again suggests that there is no value in estimating the correlation matrix between exchange rate growths. Transaction costs are larger for MSR than for other strategies but the outperformance of MSR over popular trading strategies remains economically large. We observe a sizable drop in the Sharpe ratio of MSR from 1.04 to 0.78. Similarly, the Sharpe ratio of MSR_{CV} drops from 0.96 to 0.7 and of TAN from 0.32 to 0.18. This is in contrast to all other strategies where the Sharpe ratio is never reduced by more than 0.08. Comparing MSR, MSR_{CV} and TAN, all of whom need an estimation of the correlation matrix, to MSR_V, MSR_I and $MSR_{I,CV}$, all of whom ignore the correlation structure, suggests that the time variations in estimated correlations between exchange rate growths induce substantial turn over and transaction costs. Thus, ignoring the correlation structure and only managing variances of exchange rate growths reduces transaction costs substantially.

We observe a similar effect of transaction costs on all other performance measures: the skewness becomes smaller, the maximum drawdown worse, the expected recovery time longer and percentage of positive returns lower after transaction costs. Moreover, this effect is generally stronger for MSR than for other strategies. But our conclusion remains unchanged: MSR dominates all popular trading strategies HML, DOL, $D\text{-}DOL$, MOM and VAL.

In table 6 we account for full round-trip transaction costs. This measure assumes that the entire portfolio is liquidated every month, which is a rather conservative way to implement transaction costs. For instance Lustig et al. (2011) use this conservative way to account for transaction costs. The Sharpe ratio for MSR is still surprisingly high, 0.51. Other performance measures are also negatively affected after accounting for full round-trip transaction costs. Again, our conclusion remains unchanged that MSR outperforms all other popular strategies.

3.3 Performance in Subsamples (After Transaction Costs)

Next, we investigate the performance in diverse subsamples. Throughout this section we work with returns after transaction costs (but not full round-trip costs). First, we split our sample into NBER recession and non-NBER recession subsamples. The following time periods, which span 56 months, are NBER recessions between 1977 and 2016: February 1980 to July 1980, August 1981 to November 1982, August 1990 to March 1991, May 2001 to November 2001, and January 2008 to June 2009. In table 7 we condition on non-NBER recessions. The results and our conclusion are similar as in the full sample. MSR outperforms all strategies except for MSR_V and MSR_I, CV in good times. The Sharpe ratio of MSR is 0.80. Thus, the Sharpe ratio in good times is only slightly higher than in the entire sample (cf. table 5). The Sharpe ratio of all other strategies except for VAL are substantially higher in good times than in the full sample.

More interesting, table 8 reports results when we condition on NBER recessions. First, we observe that MSR and VAL perform incredibly well during recessions while all other strategies perform poorly. The Sharpe ratios of MSR and VAL are 0.67 and 0.95 during recessions.[8] MSR_V earns a comparably much smaller Sharpe ratio of 0.34 and $MSR_{I,CV}$ a ratio of only 0.13. All other strategies earn either negative average excess returns or a Sharpe ratio close to zero. The outperformance of MSR over MSR_V and $MSR_{I,CV}$ suggests that estimating the correlation matrix of exchange rate growths adds value to the portfolio

[8] Though VAL outperforms MSR during recessions, it performs much worse than MSR during good times, and 88% of the time the economy was not in a recession between 1977 and 2016. Moreover, the performance of MSR is more stable across good and bad times than the performance of VAL.

construction in bad times. This is consistent with the common belief that correlations increase in bad times and thus, ignoring correlations is likely a costly mistake. Moreover, given the almost identical performance of MSR and MSR_{CV} in good times but the large outperformance of MSR over MSR_{CV} during recessions, we conclude that the market timing of MSR is particularly valuable in bad times. In bad times market prices are arguably more volatile and timing the market/ adjusting leverage is important to earn a high unconditional Sharpe ratio.

Finally, we split the sample into pre- and post-Euro subsamples, because trading strategies may be affected by the introduction of the Euro. For instance, if a strategy has earned large profits trading European currencies against each other, the introduction of the Euro would eliminate much of these profits since many European countries have joined the currency union. Moreover, the introduction of the Euro may have non-trivial implications on global FX markets in equilibrium, which may substantially affect carry trade profits. All strategies but VAL and TAN have earned a higher Sharpe ratio in the pre-Euro era than in the post-Euro era. While the Sharpe ratio of MSR drops only slightly from 0.86 to 0.79, it drops substantially for many other strategies. For instance, the Sharpe ratio of MSR_V declines from 1.21 to 0.66 and the ratio of $MSR_{I,CV}$ from 1.26 to 0.56. Thus, it appears that estimating the correlation matrix of exchange rate growths was not valuable in the pre-Euro era but has become valuable after the introduction of the Euro. Similarly, the Sharpe ratio of MSR_{CV} drops from 0.85 to 0.52 and the ratio of MSR_I from 0.82 to 0.57. It appears that the market timing of MSR was profitable in the pre-Euro era but even more so after the introduction of the Euro. The Sharpe ratio of HML decreases from 0.68 to 0.45 and the one of MOM from 0.35 to only 0.09. The Sharpe ratio of DOL and $D\text{-}DOL$ is almost identical across the two subsamples. The poor performance of MOM in recent years is also pointed out for instance by Della Corte et al. (forthcoming). The Sharpe ratio slightly increases for VAL from 0.45 to 0.53 and for TAN from 0.09 to 0.26. Overall, MSR is more stable across the two subsamples than other strategies. A similar conclusion can be drawn for other performance measures.

In summary, we find that MSR outperforms popular carry trade strategies (HML, DOL, $D\text{-}DOL$, MOM, VAL) by a large amount across diverse performance measures and within various subsamples. We also find that MSR earns a higher unconditional Sharpe ratio than other strategies (MSR_{CV}, TAN), which have the same risky asset portfolio composition as MSR but only differ with respect to the time variation in leverage. This is evidence that MSR is able to time the market and invest more (less) aggressive when market prices are high (low). Finally, we document that MSR_V and $MSR_{I,CV}$, which ignore the correlation structure and only manage the portfolio variance outperform MSR in good times or during the pre-Euro era. This suggests that estimation errors outweigh the benefits of taking the correlation matrix into account in the portfolio optimizaiton. However, we also document that MSR substantially outperforms MSR_V and $MSR_{I,CV}$ during NBER recessions or in the post-Euro era, i.e., taking the correlation structure into account is valuable during bad times or in more recent times. Moreover, we find that MSR's performance is roughly the same across subsamples while other strategies have less stable performances.

3.4 "Abnormal" Returns of MSR

According to our theoretical derivation in section A expected excess returns earned by MSR are compensation for risk and there is no (statistical) arbitrage. We start with the premise that MSR pays the maximum attainable Sharpe ratio because it is perfectly negatively correlated to the SDF (or the projection of the SDF into the FX market risk space) and loads on all relevant priced risks (in FX markets). This derivation offers a compelling economic justification for the outstanding empirical performance of MSR reported in tables 4 through 10. Next, we test whether the excess returns earned by MSR can be explained by existing pricing factors. When we talk about abnormal returns in this section, we do not refer to (statistical) arbitrage, but rather, it is with respect to a specific pricing model. When MSR earns abnormal returns, then we conclude that the pricing model under investigation is inadequate to explain priced risks (in FX markets). Indeed, we find that MSR earns statistically significant and economically large abnormal returns according to popular factor pricing models in international finance.

The literature has introduced and discussed many possible pricing factors. We focus on the trading strategies in section 2.3 as factors. DOL and HML are popular pricing factors in the international finance literature since Lustig et al. (2011), Verdelhan (forthcoming) and Lustig et al. (2014). Menkhoff et al. (2012a) show that HML is highly negatively correlated with a currency portfolio (FM_{VOL}) which mimics unexpected changes in global FX volatility (VOL). Following Menkhoff et al. (2012a) we estimate global FX volatility at the end of month t,

$$\sigma_t^{FX} = \frac{1}{T_t \times N} \sum_{\tau=1}^{T_t} \sum_{I=1}^{N} \left| \frac{dEX_{US/I,\tau}}{EX_{US/I,\tau}} \right|$$

where T_t is the number of trading days τ in month t. The measure uses absolute instead of squared returns so that outliers are less accentuated. The VOL index is the time series of residuals after estimating an AR(1) process for σ_t^{FX}, and thus, captures unexpected changes in volatility. Moreover, as in Menkhoff et al. (2012a), we construct a VOL factor mimicking currency portfolio FM_{VOL}. Therefore, we regress VOL on five equally weighted currency portfolios sorted by interest rates. We confirm the finding by Menkhoff et al. (2012a) that FM_{VOL} takes long (short) positions in low (high) interest rate currencies, and the correlation between FM_{VOL} and HML is close to -1.

Tables 11 through 15 report the results of the time-series regressions,

$$MSR_t = \alpha + \sum_i \beta_i F_{i,t} + \varepsilon_t,$$

where MSR_t is the monthly excess return of MSR in month t, α measures the abnormal return of MSR, $F_{i,t}$ are the pricing factors DOL, $D\text{-}DOL$, HML, FM_{VOL}, MOM and VAL, β_i is the factor loading of MSR on pricing factor i, and ε_t is an error term with mean 0 and uncorrelated to all factors. We use excess returns before transaction costs in all our regressions. We consider five different pricing models with factors: (1) DOL and HML, (2) DOL and FM_{VOL}, (3)-(4) are as (1)-(2) but adding $D\text{-}DOL$, MOM and VAL, and (5) combines all six pricing factors. Although HML and FM_{VOL} are highly negatively correlated, the correlation is not perfect, and thus, there is value in analyzing factor models with both factors. Overall, MSR earns statistically significant and economically large abnormal returns, suggesting that all six pricing factors fail to explain important priced risks.[9]

Table 11 reports results for the entire sample period from January 1977 to February 2016 for our set of 15 developed countries. MSR hardly loads on DOL, $D\text{-}DOL$, MOM or VAL. It does, however, load positively on HML and negatively on FM_{VOL}. When combining all factors, HML is the most important factor to capture the risk in MSR. The R^2 of all regressions is less than 15%, indicating that the time variation/ risk of MSR is not well captured by the investigated factors. The estimated abnormal return α of MSR according to the factor models is highly statistically significant and between 8.1% and 9.6% per year. Thus, the unexplained risk in MSR is compensated with large expected returns. Notice that the volatility of the unexplained risk is about 10%, since the total volatility of MSR is 11% and $R^2 = 1 - \frac{\text{unexplained variance}}{\text{total variance}} \approx 15\%$. In turn, this implies that the compensation for the unexplained variation in MSR is between 81% to 96%, which is an economically larger market price of risk. This is strong evidence that the popular pricing factors DOL, HML, FM_{VOL}, $D\text{-}DOL$, MOM and VAL fall short to capture important risks in FX markets.

We further analyze several subsamples to check for robustness. First, table 12 describes the results outside NBER recessions. The results are basically identical to the results in the entire sample. Second, table 13 reports our findings for NBER recession periods. The most notable change is that MSR loads significantly positively on MOM in bad times. Unfortunately, there are only 56 monthly observations for NBER recessions, which limits the power of our test, and our estimated abnormal returns are only significant on the 10% level. The size of the estimated α is, however, economically large and ranges between 12.7% and 13.9% per year.

Finally, we also investigate the pre- and post-Euro subsamples in tables 14 and 15. MSR is positively exposed to risks captured by DOL, HML and VAL, negatively to FM_{VOL}, and not (statistically significantly) to $D\text{-}DOL$ and MOM risk in the pre-Euro era, while it positively loads on $D\text{-}DOL$ and MOM but neither on DOL nor VAL in the post-Euro subsample. R^2 is comparably low in pre- and post-Euro subsamples. Finally, abnormal

[9] For statistical tests, we use Newey and West (1987) heteroskedasticity and auto-correlation robust covariance estimates. The regression residuals appear uncorrelated. Nevertheless, we include $T^{0.25}$ (where T is the number of monthly observations) auto-correlation lags in the estimation of the robust covariance matrix of residuals. Changing the number of lags does not affect our results.

returns are statistically significant and positive, but economically roughly three times as large in the pre-Euro era.

4 Market Timing of MSR and Predictability of FX Market Returns

An integral feature of MSR is its market timing ability. MSR dynamically adjusts its leverage in response to time variations in market prices of risk. Increasing (decreasing) leverage when market prices are high (low) allows MSR to outperform and earn an unconditionally higher Sharpe ratio than other strategies (e.g. MSR_{CV} or TAN), which have the same risky asset portfolio composition as MSR but only differ with respect to the time variation in leverage. To support this argument, we provide evidence that MSR is indeed able to predict future returns and volatility in FX markets. The idea is that if MSR is able to time the market and adjust its leverage based on time variations in market prices, then MSR should be able to predict future returns.

We construct predictors based on the portfolio holdings of MSR and run several predictive regressions,

$$Y_{t,t+h} = c_o + \sum_i c_i x_{i,t} + \varepsilon_t,$$

where the dependent variable $Y_{t,t+h} = \frac{1}{h}\sum_{\tau=1}^{h} Y_{t+\tau}$ is the average realization of Y over the subsequent h months after month t, $x_{i,t}$ is the realization of predictor i in month t, ε_t is white noise, and c_0 and c_i are the regression coefficients.

Our first predictor is the sum over all absolute portfolio weights of MSR, $x_{1,t} = \sum_i \|\theta_{i,US,t}\|$. This quantity measures the total dollar exposure of (or notional amount invested in) MSR in month t. Our second measure of risk exposure is the leverage defined by the sum over all portfolio weights but the risk-free asset in the USA, $x_{2,t} = \sum_{i\theta_{i,US,t}}$. The third predictor is the sign of $x_{2,t}$, $x_{3,t} = sign(x_{2,t})$. It indicates when MSR lends versus borrows in the risk-free asset in the USA. Fourth, we investigate whether the USD interest rate versus interest rate in other currencies can predict future returns. Predictor $x_{4,t} = sign\left(median(\{r_{J,t}\}) - r_{US,t}\right)$ is 1 (-1) if the US interest rate is smaller (larger) than the median interest rate across all currencies, and zero otherwise. This measure is identical to the conditioning variable used to construct *D-DOL*. Fifth, we use changes in global FX market volatility $x_{5,t} = VOL$ as described in section 3.4 as a predictor. Finally, we use the most recent realization of the dependent variable in our predictive regressions as a predictor, $x_{6,t} = Y_t$.

The dependent variables to predict (Y) are future returns in MSR, HML, DOL, *D-DOL*, MOM and VAL as well as future changes in global FX market volatility VOL. We consider prediction horizons h between 1 and 24 months, i.e., we test whether our predictors x_i are able to explain 1-month or up to 24-month ahead realizations of our dependent variables Y.

Tables 16 and 17 report the results of our predictive regression. We also run predictive regressions for each predictor individually and the results are the same.[10] All dependent variables except for VAL are well forecast across all horizons. R^2 is large even at the 1-month horizon.[11] For instance, future returns of MSR are extremely well predicted with R^2 ranging from 14% at the 1-month horizon to over 25% at 1- and 2-year horizons. Changes in global FX market volatility VOL are also very well forecast at the 1-month horizon with an R^2 of 10%. Though, the predictability of VOL worsens at longer horizons. Surprisingly our predictors are also able to forecast future returns in HML, *D-DOL* and MOM.[12] To our knowledge we are the first to document such strong predictabilities in these returns. The predictability of DOL is less surprising. The construction of *D-DOL* is based on the predictability of DOL using $sign\left(median(\{r_{J,t}\}) - r_{US,t}\right)$ as a signal.

Our three measure of leverage of MSR ($\sum_i \|\theta_{i,US,t}\|$, $\sum_i \theta_{i,US,t}$, $sign\left(\sum_i \theta_{i,US,t}\right)$) are by far the most powerful predictors. The slope coefficient of at least one of the three MSR leverage variables is significant in almost every predictive regression (except for the regressions where VAL is the dependent variable). In contrast, $sign\left(median(\{r_{J,t}\}) - r_{US,t}\right)$ only has power

[10] We do not report predictive regressions with single predictors to save space.

[11] An R^2 of even 0.5% is considered substantial in predictive regressions of asset returns at a 1 month horizon.

[12] Notice that MOM is cross-sectional (not time-series) momentum and thus, there is no reason why it should be predictable.

to predict future returns in DOL but none of the other variables. Similarly, VOL forecasts itself at a 1 month horizon but nothing else. Finally, the most recent realization of any dependent variable does not have any power to predict its own future realizations. We take the strong predictive power of our three leverage measures of MSR as evidence that the time variation in expected returns and risk (or equivalently market prices) is well forecast. In turn, this predictive power allows our MSR strategy to time the market and dynamically adjust leverage in response to changes in market prices and earn a high unconditional Sharpe ratio.

5 MSR as a Single Pricing Factor

Motivated by our theoretical derivation of MSR we test the ability of MSR as a pricing factor and show that a pricing model with MSR as a single factor subsumes the prominent DOL-HML two factor model. This finding is arguably the economically most important result of our paper. We use the following 21 test assets: 5 interest rate sorted portfolios ($IntP_i$ $\forall i \in 1, \ldots, 5$), 5 momentum sorted portfolios ($MomP_i$ $\forall i \in 1, \ldots, 5$), 5 value sorted portfolios ($ValP_i$ $\forall i \in 1, \ldots, 5$), D-DOL, MSR_V, MSR_I, MSR_{CV}, $MSR_{I,CV}$, TAN.[13]

5.1 Time-Series Test

We run a separate time-series regression for each test asset j with excess return $R_{j,t}$ on a constant and the contemporaneous excess return of MSR,

$$R_{j,t} = \alpha_j + \beta_{MSR,j} MSR_t + \varepsilon_{j,t},$$

where $\varepsilon_{t,j}$ is white noise. We do not report the coefficient estimates of all 21 regressions to save space. Overall we find that abnormal returns α_j are close to zero. We test the joint hypothesis of all abnormal returns α_j being equal to 0. In particular, we calculate

[13] DOL, HML, MOM and VAL are captured by the 15 $IntP_i$, $MomP_i$ and $ValP_i$ portfolios. We do not include individual currency pairs as test assets because many currency pairs have missing observations. Working with portfolios is more convenient because we do not have to truncate the data and can apply standard econometric methods for hypothesis testing.

the F-statistic $\frac{T-N-K}{N}\left(1+E[F]^T\Sigma_F^{-1}E[F]\right)^{-1}\alpha^T\Sigma_\varepsilon^{-1}\alpha$, which is distributed according to a F-distribution with N and $T-N-K$ degrees of freedom, where T is the number of monthly return observations, N is the number of test assets, K is the number of pricing factors, $E[F]$ is a column vector of average factor returns, Σ_F is the covariance matrix of pricing factors, α is a column vector of estimated abnormal returns of all test assets and Σ_ε is the covariance matrix of residuals in the time-series regressions of all test assets. The last panel (last two rows) in table 18 report F-statistics. For abnormal returns of the 15 $IntP_i$, $MomP_i$ and $ValP_i$ portfolios the F-statistic is 1.069, which is insignificant (p-value of 38.3%). Thus, the single MSR factor model cannot be rejected based on abnormal returns in time series regressions. However, the F-statistic for abnormal returns of all 21 test assets is 1.460, which is significant at the 10% level (p-value of 8.7%). Thus, the single MSR factor model is rejected, though only at a low significant level.

We also estimate a 2-factor model which uses DOL and HML as pricing factors to place the results from the single MSR factor model into perspective,[14]

$$R_{j,t} = \alpha_j + \beta_{DOL,j}DOL_t + \beta_{HML,j}HML_t + \varepsilon_{j,t}.$$

The DOL-HML model is a popular pricing model in the literature (Lustig et al., 2011). The model explains the expected returns of the interest rate sorted portfolios ($IntP_i$), but abnormal returns of other portfolios are economically large and and highly statistically significant. The joint hypothesis that all abnormal returns are equal to 0 is rejected for both the smaller set of 15 test assets as well as for the larger set of 21 assets. The F-statistic for abnormal returns of the 15 portfolios is 1.560, which is significance at the 10% (p-value is 8.1%). Even more striking, the F-statistic for the larger set of 21 assets is 2.710, which is highly statistically significant (p-value of 0.008%). In comparison, the single MSR factor model performs much better in time-series tests than the two factor DOL-HML model.

[14] To save space we only compare the single factor MSR model to the popular 2-factor DOL-HML model.

5.2 Cross-Sectional Test

We run cross-sectional regressions to estimate the market price of risk of the factors. We also estimate abnormal returns in the cross-sectional regressions and test the joint hypothesis that all abnormal returns are equal to zero. Columns 2 and 4 of the top 3 panels in table 18 report the estimates of the cross-sectional regression,

$$E[R_j] = \beta_{MSR,j}\gamma_{MSR} + \alpha_j^*,$$

where $E[R_j]$ is the average annualized return of asset j, $\beta_{MSR,j}$ is the estimated factor loading from the time-series regression above, γ_{MSR} is the estimated market price of the MSR risk factor and α_j^* the abnormal return in the cross-sectional regression. We do not include a constant in our cross-sectional regression, though the results are robust if we include a constant. Column 2 reports estimates of the regression with only the 15 interest rate, momentum and value portfolios as test assets, while column 4 also includes all 21 test assets. The estimated market price of risk γ_{MSR} is large (roughly 20%) and significantly different from 0. The point estimate of γ_{MSR} is somewhat larger than the average return of MSR. The R^2 of the cross-sectional regression is large: 81% for the 15 portfolios, and 91% for all 21 test assets. The MSR single factor model does a very good job explaining the cross-sectional variation of average returns in FX markets. We also report the χ^2 test statistic $\alpha^T\left(\frac{1}{T}(I-\beta(\beta^T\beta)^{-1}\beta^T)\Sigma_\varepsilon(I-\beta(\beta^T\beta)^{-1}\beta^T)(1+\gamma^T\Sigma_F\gamma)\right)^{-1}\alpha$ which is distributed according to a χ^2 distribution with $N-K-1$ degrees of freedom, where α are the abnormal return estimates from the cross-sectional regression, I is an identity matrix, β are the factor loading estimates from the time-series regressions, Σ_ε is the covariance matrix of the residuals of the time-series regressions, γ are the market price of risk estimates from the cross-sectional regression, Σ_F is the covariance matrix of the pricing factors, N is the number of test assets and K is the number of pricing factors. In either case of 15 or 21 test assets we cannot reject the hypothesis that all abnormal returns α_j^* estimated in the cross-sectional regression are jointly 0 (χ^2-statistics 8.9 and 23.6, or p-values 77.9% and 21.1%), which is in support of our single factor MSR model.

Columns 3 and 5 of the top 3 panels in table 18 report the results of the equivalent cross-sectional regression for the DOL-HML model,

$$E[R_j] = \beta_{DOL,j}\gamma_{DOL} + \beta_{HML,j}\gamma_{HML} + \alpha_j^*.$$

Column 3 reports estimates for the 15 interest rate, momentum and value portfolios as test assets, while column 5 uses all 21 test assets. DOL does not carry a market price but HML is compensated with a large premium. The implied premium of HML is 6% for the 15 test assets but 15% for the 21 test assets. In the case of 15 test assets the premium is of a similar size as the average return of HML. The R^2s of the cross-sectional regressions are substantially lower than the values in the MSR single factor model. In the case of 15 portfolios R^2 is only 54%, for 21 test assets it is 68%. The χ^2 test suggests that the DOL-HML model is rejected based on the hypothesis that all abnormal returns α_j^* are jointly 0. For the set of 15 test assets the χ^2-statistic is 22.726, which is significant at the 5% level (p-value of 3.0%). For the larger set of 21 test assets χ^2-statistic is 51.290, which is highly significant (p-value of 0.005%). This is in stark contrast to the MSR model which could not be rejected. In summary, the cross-sectional results (R^2 and χ^2-tests) suggest that the MSR single factor model is a better pricing model than the popular 2-factor DOL-HML model to price assets in FX markets.

5.3 Single- versus Multi-Factor Pricing Model

The previous comparison of the MSR single factor model and the DOL-HML two factor model suggests that the MSR model prices assets more accurately. It is, then, not surprising that adding MSR to the DOL-HML two factor model improves the model's ability to price assets. More interesting is whether DOL and HML have any additional information beyond MSR to price assets. To answer the first question of whether MSR adds value to the DOL-HML two factor model, we first orthogonalize MSR with respect to DOL and HML, and then, add it as an additional pricing factor to the model. Indeed we find a significant market price for the orthogonalized factor, and conclude that MSR has important information for pricing beyond DOL and HML. Similarly, to address the question whether adding DOL and HML to the MSR single factor model improves pricing, we orthogonalize DOL and

HML with respect to MSR, and then, check whether market prices are significant for the orthogonalized factors. We document that market prices of the orthogonalized DOL and HML factor do not carry a market prices, and thus, we conclude that DOL and HML do not explain expected returns beyond what is already captured by MSR.[15]

With regard to the first question, we regress MSR on DOL and HML,

$$MSR = h_0 + h_1 DOL + h_2 HML + \epsilon$$

to define the orthogonalized factor $\widetilde{MSR} = h_0 + \epsilon$. $\widetilde{MSR}$ only contains information which is not captured by DOL and HML. We, then, estimate the time-series regression

$$R_{j,t} = \alpha_j + \beta_{\widetilde{MSR},j}\widetilde{MSR}_t + \beta_{DOL,j}DOL_t + \beta_{HML,j}HML_t + \varepsilon_{j,t},$$

for every test asset R_j, and subsequently the cross-sectional regression,

$$E[R_j] = \beta_{\widetilde{MSR},j}\gamma_{\widetilde{MSR}} + \beta_{DOL,j}\gamma_{DOL} + \beta_{HML,j}\gamma_{HML} + \alpha_j^*.$$

The coefficient estimates of the cross-sectional regression are reported in table 19. For the estimation with either 15 or 21 test assets the market price of the orthogonalized factor $\widetilde{MSR}$ is large and significant. We further document that the cross-sectional regression R^2 of the three factor model is substantially larger than the R^2 of the DOL-HML model. In the case of 15 test assets the R^2 increases from 54% to 88% when we add $\widetilde{MSR}$, and in the case of 21 test assets it increases from 68% to 91%. This is a substantial improvement and $\widetilde{MSR}$ explains much of cross-sectional variation in average returns beyond DOL and HML. Finally, once we add $\widetilde{MSR}$ to the DOL-HML model, the new three factor model is no longer rejected according to the joint tests of abnormal returns α_j and α_j^* being equal to zero. To sum up, adding MSR as a pricing factor to the DOL-HML model substantially improves the pricing model. In other words, MSR contains important information for pricing which is not captured by DOL and HML.

[15] Orthogonalizing factors to testi their importance for pricing beyond the information captured by other factors is suggested in the Empirical Asset Pricing lecture notes by John Cochrane, for instance.

With regard to the second question, we separately regress DOL and HML on MSR,

$$Y_i = h_{i,0} + h_{i,1} MSR + \epsilon_i$$

to define the orthogonalized factor $\widetilde{Y}_i = h_{i,0} + \epsilon_i$, $\forall Y_i \in \{DOL, HML\}$. $\widetilde{DOL}$ and $\widetilde{HML}$ only contain information which is not captured by MSR. We, then, estimate the time-series regression

$$R_{j,t} = \alpha_j + \beta_{MSR,j} MSR_t + \beta_{\widetilde{DOL},j} \widetilde{DOL}_t + \beta_{\widetilde{HML},j} \widetilde{HML}_t + \varepsilon_{j,t},$$

for every test asset R_j, and subsequently the cross-sectional regression,

$$E[R_j] = \beta_{MSR,j} \gamma_{MSR} + \beta_{\widetilde{DOL},j} \gamma_{\widetilde{DOL}} + \beta_{\widetilde{HML},j} \gamma_{\widetilde{HML}} + \alpha_j^*.$$

The coefficient estimates of the cross-sectional regression are reported in table 20. For the estimation with either 15 or 21 test assets the market prices of the orthogonalized factors $\widetilde{DOL}$ and $\widetilde{HML}$ are both close to zero and insignificant. Moreover, we find that the cross-sectional regression R^2 of the three factor model is similar to the R^2 of the MSR single factor model. In the case of 15 test assets the R^2 slightly increases from 81% to 88% when we add $\widetilde{DOL}$ and $\widetilde{HML}$, but in the case of 21 test assets it remains virtually unchanged at 91%. Thus, DOL and HML explain almost nothing in the cross-sectional variation in average returns beyond what is already explained by MSR. The three factor model slightly improves over the MSR single factor model with respect to the joint test of all abnormal returns α_j from time-series regressions of 21 test asset being equal to zero. The p-value slightly increases from 8.7% to 14.7%. However, in all other joint tests of abnormal returns (in time-series and cross-sectional regressions) neither the MSR single factor model nor the three factor model is rejected. To sum up, DOL and HML do not contain any additional information relevant for pricing beyond what is captured by MSR. In other words, the MSR single factor model subsumes the DOL-HML two factor pricing model.

6 Conclusion

We construct a currency carry trade strategy that aims to earn the theoretically maximum attainable Sharpe ratio in FX markets (we call it MSR strategy). We implement our MSR trading strategy at the end of every month from January 1977 to February 2016. MSR earns a high Sharpe ratio of 1.04 before and 0.78 after transaction costs and outperforms popular carry trade strategies by a large amount across diverse performance measures and within various subsamples. MSR's market timing ability is valuable and MSR earns a higher unconditional Sharpe ratio than other strategies, which have the same risky asset portfolio composition but do not dynamically adjust their leverage. In support of the idea that MSR is able to time the market, we find that the amount of leverage taken by MSR in month t predicts future returns of many FX strategies as well as future changes in global FX market volatility.

We further document that MSR earns statistically significant and economically large abnormal returns according to popular factor pricing models in FX markets. This suggests that current pricing factors fail to explain important priced risks. Time-series and cross-sectional asset pricing tests confirm that MSR is an important pricing factor. We further document that the MSR single factor model performs better in pricing assets in FX markets than the popular DOL-HML two factor model. Moreover, DOL and HML do not contain any additional information relevant for pricing beyond what is captured by MSR. In other words, the MSR single factor model subsumes the DOL-HML two factor pricing model.

References

Akram, Farooq, Dagfinn Rime, and Lucio Sarno, 2008, Arbitrage in the foreign exchange market: Turning on the microscope, *Journal of International Economics* 76, 237–253.

Barroso, Pedro, and Pedro Santa-Clara, 2015, Beyond the Carry Trade: Optimal Currency Portfolios, *Journal of Financial and Quantitative Analysis* 50, 1037–1056.

Baz, Jamil, Frances Breedon, Vasant Naik, and Joel Peress, 2001, Optimal Portfolios of Foreign Currencies, *The Journal of Portfolio Management* 28, 102–111.

Bekaert, Geert, and George Panayotov, 2016, Good Carry, Bad Carry, Working paper.

Bilson, John F. O., 1984, Purchasing Power Parity as a Trading Strategy, *Journal of Finance* 39, 715–724.

Brandt, M. W., P. Santa-Clara, , and R. Valkanov, 2009, Parametric Portfolio Policies: Exploiting Characteristics in the Cross-Section of Equity Returns, *Review of Financial Studies* 22, 3411–3447.

Brandt, Michael W., 2005, Portfolio choice problems, in Y. Ait-Shahalia, and L. P. Hansen, eds., *Handbook of Financial Econometrics*, chapter 5, 269–336 (Elsevier, Amsterdam).

Brusa, Francesca, Tarun Ramadorai, and Adrien Verdelhan, 2015, The International CAPM Redux, Working paper, University of Oxford.

Burnside, Craig, 2011, The Cross-Section of Foreign Currency Risk Premia and Consumption Growth Risk: Comment, *American Economic Review* 101, 3456–3476.

Burnside, Craig, 2012, Carry Trades and Risk, in J. James, I.W. Marsh, and L. Sarno, eds., *Handbook of Exchange Rates* (Hoboken: John Wiley & Sons).

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo, 2011, Carry trade and momentum in currency markets, *Annual Review of Financial Economics* 3, 511–535.

Cenedese, Gino, 2012, Safe Haven Currencies: A Portfolio Perspective, Working paper, Bank of England.

Chan, L., J. Karceski, and J. Lakonishok, 1999, On portfolio optimization: Forecasting covariances and choosing the risk model, *Review of Financial Studies* 12, 937974.

Christiansen, Charlotte, Angelo Ranaldo, and Paul Söderlind, 2011, The Time-Varying Systematic Risk of Carry Trade Strategies, *Journal of Financial and Quantitative Analysis* 46, 1107–1125.

Clarida, Richard H., and Mark P. Taylor, 1997, The term structure of forward exchange rate premiums and the forecastability of spot exchange rates: correcting the errors, *Review of Economics and Statistics* 79, 353–370.

Dahlquist, Magnus, and Henrik Hasseltoft, 2016, Economic Momentum and Currency Returns, Working paper.

Daniel, Kent, Robert J. Hodrick, and Zhongjin Lu, 2014, The Carry Trade: Risks and Drawdowns, Working paper, Columbia University.

Della Corte, Pasquale, Tarun Ramadorai, and Lucio Sarno, forthcoming, Volatility Risk Premia and Exchange Rate Predictability, *Journal of Financial Economics* .

Della Corte, Pasquale, Lucio Sarno, and Ilias Tsiakas, 2009, An Economic Evaluation of Empirical Exchange Rate Models, *Review of Financial Studies* 22, 3491–3530.

DeMiguel, Victor, Lorenzo Garlappi, and Raman Uppal, 2009, Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy?, *Review of Financial Studies* 22, 1915–1953.

Dobrynskaya, Victoria, 2014, Downside Market Risk of Carry Trades, *Review of Finance* 18, 1885–1913.

Dobrynskaya, Victoria, 2015, Currency Exposure to Downside Risk: Which Fundamentals Matter?, Working paper, London School of Economics.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81, 607–636.

Filippou, Ilias, and Mark P. Taylor, forthcoming, Common macro factors and currency premia, *Journal of Financial and Quantitative Analysis* .

Frost, P. A., and J. E. Savarino, 1986, An empirical Bayes approach to efficient portfolio selection, *Journal of Financial and Quantitative Analysis* 21, 293–305.

Frost, P. A., and J. E. Savarino, 1988, For better performance: Constrain portfolio weights, *Journal of Portfolio Management* 15, 29–34.

Galsband, Victoria, and Thomas Nitschka, 2013, Currency Excess Returns and Global Downside Risk, Working paper, Deutsche Bundesbank.

Habib, Maurizio Michael, and Livio Stracca, 2012, Getting beyond Carry Trade: What Makes a Safe Haven Currency?, Working paper, European Central Bank.

Hansen, Lars Peter, and Ravi Jagannathan, 1991, Implications of Security Market Data for Models of Dynamic Economies, *Journal of Political Economy* 99, 225–262.

Hassan, Tarek, 2013, Country Size, Currency Unions, and International Asset Returns, *Journal of Finance* 68, 2269–2308.

Jagannathan, R., and T. Ma, 2003, Risk reduction in large portfolios:Why imposing the wrong constraints helps, *Journal of Finance* 58, 1651–1683.

James, W., and C. Stein, 1961, Estimation with quadratic loss, *Proceedings of the Fourth Berkeley Symposium on Mathematics and Statistics* 361–379.

Jorda, O., and A. M. Taylor, 2012, The Carry Trade and Fundamentals: Nothing to Fear but FEER Itself?, *Journal of International Economics* 88, 74–90.

Jorion, Philippe, 1986, Bayes-Stein estimation for portfolio analysis, *Journal of Financial and Quantitative Analysis* 21, 279–292.

Kan, Raymond, Xiaolu Wang, and Guofu Zhou, 2016, Optimal Portfolio Selection with and without Risk-free Asset, Working paper.

Kan, Raymond, and Guofu Zhou, 2007, Optimal portfolio choice with parameter uncertainty, *Journal of Financial and Quantitative Analysis* 42, 621–656.

Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh, 2015, Interpreting Factor Models, Working paper.

Laborda, Juan, Ricardo Laborda, and Jose Olmo, 2014, Optimal currency carry trade strategies, *International Review of Economics Finance* 33, 52–66.

LeBaron, Blake, 1999, Technical Trading Rule Profitability and Foreign Exchange Intervention, *Journal of International Economics* 49, 125–143.

Lettau, Martin, Matteo Maggiori, and Michael Weber, 2014, Conditional Risk Premia in Currency Markets and Other Asset Classes, *Journal of Financial Economics* 114, 197–225.

Levich, Richard, and Lee R. Thomas, 1993, The significance of technical trading-rule profits in the foreign exchange market: A bootstrap approach, *Journal of International Money and Finance* 12, 451–474.

Lustig, Hanno, Nick Roussanov, and Adrien Verdelhan, 2011, Common Risk Factors in Currency Returns, *Review of Financial Studies* 24, 3731–3777.

Lustig, Hanno, Nick Roussanov, and Adrien Verdelhan, 2014, Countercyclical Currency Risk Premia, *Jounal of Financial Economics* 111, 527–553.

Lustig, Hano, and Adrien Verdelhan, 2007, The Cross-section of Foreign Currency Risk Premia and Consumption Growth Risk, *American Economic Review* 97, 89–117.

Lustig, Hano, and Adrien Verdelhan, 2011, The Cross-section of Foreign Currency Risk Premia and Consumption Growth Risk: A Reply, *American Economic Review* 101, 3477–3500.

MacKinlay, A. C., and L. Pastor, 2000, Asset pricing models: implications for expected returns and portfolio selection, *Review of Financial Studies* 13, 883–916.

Mancini, Loriano, Angelo Ranaldo, and Jan Wrampelmeyer, 2013, Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums, *Journal of Finance* 68, 1805–1841.

Markowitz, Harry, 1952, Portfolio Selection, *Journal of Finance* 7, 77–91.

Maurer, Thomas A., Thuy-Duong To, and Ngoc-Khanh Tran, 2015, Pricing Risks across Currency Denominations, Working paper, Washington University.

Maurer, Thomas A., and Ngoc-Khanh Tran, 2015, Entangled Risks in Incomplete FX Markets, Working paper, Washington University.

Maurer, Thomas A., and Ngoc-Khanh Tran, 2016, Incomplete Asset Market View of the Exchange Rate Determination, Working paper, Washington University.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2012a, Carry Trades and Global Foreign Exchange Volatility, *Journal of Finance* 67, 681–718.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2012b, Currency Momentum Strategies, *Journal of Financial Economics* 106, 620–684.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2015, Currency Risk Premia and Macro Fundamentals, Working paper.

Merton, Robert, 1971, Optimum Consumption and Portfolio Rules in a Continuous-Time Model, *Journal of Economic Theory* 3, 373–413.

Moreira, Alan, and Tyler Muir, 2016, Volatility Managed Portfolios, *Journal of Finance* .

Mueller, Philippe, Andreas Stathopoulos, and Andrea Vedolin, 2013, International Correlation Risk, Working paper, London School of Economics and Political Science.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703708.

Rafferty, Barry, 2012, Currency Returns, Skewness and Crash Risk, Working paper, Duke University.

Riddiough, Steven, 2014, The Mystery of Currency Betas, Working paper, Warwick Business School.

Ross, Stephen A., 1976, The Arbitrage Theory of Capital Asset Pricing, *Journal of Economic Theory* 13, 341–360.

Sager, Michael, and Mark P. Taylor, 2014, Generating currency trading rules from the term structure of forward foreign exchange premia, *Journal of International Money and Finance* 44, 230–250.

Sharpe, W., 1963, A simplified model for portfolio analysis, *Management Science* 9, 277–293.

Silber, W., 1994, Technical trading: When it works and when it doesn't, *Journal of Derivatives* 1, 39–44.

Taylor, Mark P., and H. Allen, 1992, The use of technical analysis in the foreign exchange market, *Journal of International Money and Finance* 11, 304–314.

Tu, Jun, and Guofu Zhou, 2011, Markowitz meets Talmud: A combination of sophisticated and naive diversification strategies, *Journal of Financial Economics* 99, 204–221.

Verdelhan, Adrien, forthcoming, The Share of Systematic Risk in Bilateral Exchange Rates, *Journal of Finance* .

Appendix

A Maximum Sharpe Ratio (MSR) Strategy: Derivation and Comparison to the Tangency Portfolio

A.1 The Tangency Portfolio

Let $CT^J_{-J/+I,t+dt}$ be the carry trade return (denominated in the home currency J) of borrowing in the home currency J and lending in the foreign currency I over the time horizon $(t, t+dt]$.[16] Let the $N \times 1$ column vector $ECT_t = \left[E_t\left[CT^J_{-J/+1,t+dt}\right], \ldots, E_t\left[CT^J_{-J/+N,t+dt}\right]\right]^T$ denote the conditional expected returns and Σ_t the $N \times N$ conditional covariance matrix of N carry trade returns $\{CT^J_{-J/+I,t+dt}\}_{I\in\{1,\ldots,N\}}$ at time t. Markowitz (1952) shows that the tangency portfolio earns the maximum (conditional) Sharpe ratio (over the interval $(t, t+dt]$) and is given by,

$$\phi_{J,t} = \frac{1}{c_t}\Sigma_t^{-1} ECT_t,$$

where the N elements in vector $\phi_{J,t}$ are the portfolio weights of the N foreign bonds $I \in \{1, \ldots, N\}$, $c_t = 1^T_{N\times1}\Sigma_t^{-1}ECT_t$ and $1_{N\times1}$ is an $N \times 1$ column vector of ones. The scaling factor c_t ensures that the portfolio weights of $\phi_{J,t}$ add up to 1 and the tangency portfolio, by definition, only consists of risky assets/ foreign bonds.[17] Note that c_t crucially depends on the conditional moments of asset returns at time t, and thus, is time varying if there are shocks to the investment opportunity set.

Investing always all the wealth in the tangency portfolio implies that there is no market timing, i.e., no adjustments of the capital allocation between the risk-free asset and the risky portfolio. Thus, the tangency portfolio earns the maximum conditional Sharpe ratio, but its

[16] That is, $CT^J_{-J/+I,t+dt}$ takes a short position in the risk-free home bond J and a long position in foreign bond I.

[17] If we assume mean-variance preferences $u(w) = E_t[w] - \frac{\gamma}{2}Var_t[w]$ where γ characterizes risk aversion, then the optimal capital allocation between the risk-free (home) bond and the risky tangency portfolio leads to the foreign bond portfolio weights $\frac{1}{\gamma}\Sigma_t^{-1}ECT_t$ and the the risk-free (home) bond weight $1 - \frac{1}{\gamma}1^T_{N\times1}\Sigma_t^{-1}ECT_t$.

unconditional Share ratio may be far lower than the maximum attainable ratio in a dynamic setting with changes in the investment opportunity set. Intuitively, a strategy which only maximizes the conditional Sharpe ratio but ignores market timing earns unconditionally a lower Sharpe ratio than a dynamic strategy which takes advantage of changes in the investment opportunity set and invests more (less) in the risky asset portfolio (i.e., increase (decrease) leverage) in times when market prices of risk are high (low). We show in section A.2 that at every time t MSR, which is constructed as a mimicking portfolio of the inverse of the SDF, is equal to the tangency portfolio $\phi_{J,t}$ multiplied by c_t.Thus, MSR times the market and adjusts its risk exposure over time and earns a higher unconditional Sharpe ratio than the tangency portfolio.

When we implement our strategy, we do not observe the true conditional expected returns and covariances and have to estimate them from the data. Estimation errors often lead to extreme portfolio positions, which imply a high in-sample Sharpe ratio but typically lead to a poor out-of-sample performance (Brandt, 2005). To mitigate this problem, we exploit the strong factor structure in FX markets. We use interest rate differentials $r_{I,t} - r_{J,t}$ as a proxy for the conditional expected return $E_t\left[CT^J_{-J/+I,t+dt}\right]$. The assumption is that the representation $E_t\left[CT^J_{-J/+I,t+dt}\right] = \alpha_t + \beta_t\left(r_{I,t} - r_{J,t}\right)$ with $\beta_t > 0$ holds at time t. This assumption is motivated by the empirical fact that currency premia sort well with interest rate differentials.

For the conditional covariance matrix we use an exponentially weighted moving average (EWMA) of squared, demeaned returns to estimate the conditional covariance matrix Σ_t.[18] EWMA models share several desirable features with GARCH models but are much easier to estimate. Moreover, we diagonalize the covariance matrix Σ_t,

$$\Sigma_t W_t = W_t \Lambda_t, \tag{1}$$

where W_t is the $N \times N$ rotation matrix (whose columns are $N \times 1$ eigenvectors) and Λ_t

[18] Element (I, L) of Σ_t is $Cov_t\left(CT^J_{-J/+I,t+dt}, CT^J_{-J/+L,t+dt}\right) = \frac{\sum_{\tau<t}\delta^{t-\tau}\overline{CT}^J_{-J/+I,\tau}\overline{CT}^J_{-J/+L,\tau}}{\sum_{\tau<t}\delta^{t-\tau}}$, where $\overline{CT}^J_{-J/+I,\tau}$ is the demeaned realized carry trade return denominated in J of borrowing J and lending I at time τ, and weight $\delta \in (0, 1]$.

the $N \times N$ diagonal matrix with corresponding eigenvalues of Σ_t. We, then, remove an eigenvector and the corresponding eigenvalue from W_t and Λ_t if the eigenvalue is sufficiently small.[19] Let's denote the new matrices by $\widetilde{W}_t$ and $\widetilde{\Lambda}_t$. To construct the tangency portfolio we replace Σ_t^{-1} by $\widetilde{W}_t \widetilde{\Lambda}_t^{-1} \widetilde{W}_t^T$. This procedure reduces estimation errors in the covariance matrix in a similar spirit as shrinkage, and ensures absence of near-arbitrage opportunities in the underlying model (Kozak et al., 2015).

A.2 MSR and the SDF in a Diffusion Model

We derive now an expression for MSR with foreign bond weights $\theta_{J,t}$, which mimics the inverse of the SDF constructed according to the approach by Maurer et al. (2015).[20] This approach is a standard projection of the SDF into the FX market space, where Maurer et al. (2015) suggest to span the FX market space using the most important principal components of exchange rate growths. As the strategy which trades the projected SDF, MSR is equivalent to the optimal portfolio in a continuous time model with log-utility (Merton, 1971).

We assume financial markets are fully integrated, frictionless and free of arbitrage.[21] Let $\{\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t\geq 0}, \mathbb{P}\}$ be a standard filtered probability space, where $\{\mathcal{F}_t\}_{t\geq 0}$ is the natural filtration generated by the d-dimensional standard Brownian motion Z_t. For ease of exposition, we assume financial markets are complete. This ensures that in each country I there is a unique country-specific SDF M_I and the exchange rate is equal to the ratio of country-specific SDFs. Note that it is possible to relax the complete market assumption in a diffusion model. Maurer and Tran (2015, 2016) show that the pricing-consistent exchange rate is unique and equal to the ratio of projected SDFs in a model with incomplete markets and pure diffusion risks.

[19] See Section 2.3 for the specific choice of the threshold value.

[20] In this paper we go beyond the analysis in Maurer et al. (2015) and estimate our model dynamically (using rolling windows). This is particularly important when we implement a trading strategy.

[21] There are no direct or indirect trading costs and feasible portfolio weights are on the real line (continuous and unconstraint).

The unique SDF in country I, which prices all assets denominated in currency I, is,

$$\frac{dM_{I,t}}{M_{I,t}} = -r_{I,t}dt - \eta_{I,t}^T dZ_t.$$

The drift and diffusion terms describe the short rate $r_{I,t} \in \mathbb{R}$ and the d market prices of diffusion risks $\eta_{I,t} \in \mathbb{R}^d$ at time t in currency I. Our analysis holds conditionally at time t, for any $r_{I,t}$ and $\eta_{I,t}$ adapted to the filtration $\mathcal{F}_t$.

We define the exchange rate between currencies J and I at time t such that $EX_{J/I,t}$ units of currency J exchange for one unit of currency I. By no-arbitrage the exchange rate is equal to the ratio of country-specific SDFs I and J,

$$EX_{J/I,t} = \frac{M_{I,t}}{M_{J,t}}. \tag{2}$$

Applying Itô's Lemma, we compute the dynamics of the exchange rate,

$$\frac{dEX_{J/I,t}}{EX_{J/I,t}} = \left[r_{J,t} - r_{I,t} + \eta_{J,t}^T \left(\eta_{J,t} - \eta_{I,t}\right)\right] dt + \left(\eta_{J,t} - \eta_{I,t}\right)^T dZ_t.$$

Accordingly, we obtain the carry trade return denominated in currency J of borrowing currency J and lending currency I over the time horizon $(t, t+dt]$,

$$\begin{aligned} CT^J_{-J/+I,t+dt} &= \left(r_{I,t} - r_{J,t}\right) dt + \frac{dEX_{J/I,t}}{EX_{J/I,t}} \\ &= \eta_{J,t}^T \left(\eta_{J,t} - \eta_{I,t}\right) dt + \left(\eta_{J,t} - \eta_{I,t}\right)^T dZ_t. \end{aligned} \tag{3}$$

Note that the carry trade return $CT^J_{-J/+I,t+dt}$ is an excess return since it is a net-zero investment. We can write the conditional expected excess return in terms of market prices of risks,

$$E_t\left[CT^J_{-J/+I,t+dt}\right] = \eta_{J,t}^T \left(\eta_{J,t} - \eta_{I,t}\right) dt. \tag{4}$$

The challenge is that we observe neither the d risk sources Z_t nor the market prices $\eta_{I,t}$. However, realized carry trade returns are observable and based on equations (3) and (4), Maurer et al. (2015) propose a 2-step estimation procedure using PCA and linear regression analysis to construct country-specific SDFs. In the first step, PCA on carry trade returns is employed to transform the original risk sources Z_t into equivalent risk sources $\widetilde{Z}_t$. In the second step, market prices $\widetilde{\eta}_{I,t}$ of these new risk sources are estimated in a linear regression.[22]

More specifically, let,

$$x_{t+dt} = \begin{bmatrix} CT^J_{-J/+1,t+dt} - E_t\left[CT^J_{-J/+1,t+dt}\right] \\ \vdots \\ CT^J_{-J/+N,t+dt} - E_t CT^J_{-J/+N,t+dt} \end{bmatrix} = \begin{bmatrix} \left(\eta_{J,t} - \eta_{1,t}\right)^T dZ_t \\ \vdots \\ \left(\eta_{J,t} - \eta_{N,t}\right)^T dZ_t \end{bmatrix} \equiv \Delta\eta_t^T dZ_t, \tag{5}$$

be a $N \times 1$ column vector of (non-redundant) demeaned carry trade returns of borrowing currency J and lending currencies I, $\forall I \in \{1, \ldots, N\}$, $I \neq J$ over the time horizon $(t, t + dt]$ (cf. equation (3)) and $\Delta\eta_t$ is an $N \times d$ matrix of differential market prices.[23] Notice that x_{t+dt} is also equal to the vector of demeaned exchange rate growths. The $N \times N$ conditional covariance matrix of carry trade returns at time t is again denoted by $\Sigma_t = E_t\left[x_{t+dt}x^T_{t+dt}\right]$. The N principal components of the set of N carry trade returns are given by $W_t^T x_{t+dt}$, where W_t is the rotation matrix in (1). In the spirit of Kozak et al. (2015), dropping principal components with little explanatory power (i.e., we drop eigenvectors with small eigenvalues) ensures that the constructed SDF excludes near-arbitrage opportunities. Again we let $\widetilde{W}_t$ and $\widetilde{\Lambda}_t$ denote the $N \times K_t$ and $K_t \times K_t$ matrices corresponding to W_t and Λ_t after removing principal components with low explanatory power, where K_t is the number of principal components we retain in our analysis at time t.

We use the rotation matrix $\widetilde{W}_t$ to transform the d original risk sources Z_t into K_t new risk sources $\widetilde{Z}_t$, which are proportional to the first K_t principal components of the set of N

[22]The procedure is similar to the 2-stage Fama-MacBeth regression (Fama and MacBeth, 1973), but in the approach of Maurer et al. (2015) we do not have to estimate time-series regressions in the first stage because of the particular relationship between market prices and exchange rate loadings on risk sources, i.e., the exchange rate is equal to the ratio of SDFs. This reduces estimation errors. Moreover, it ensures that our identified risk sources are always priced risks (in contrast to possibly unpriced risk sources as it is the case with other asset classes; see below for details).

[23]Technically, J is the $(N + 1)$th currency.

carry trade returns,

$$d\widetilde{Z}_t = \sqrt{dt}\widetilde{\Lambda}_t^{-0.5}\widetilde{W}_t^T x_{t+dt}. \tag{6}$$

Given the new defined risk sources $\widetilde{Z}_t$, we obtain the cross-country differences in market prices of these new risks,

$$\widetilde{\Delta\eta}_t^T \equiv \begin{bmatrix} (\widetilde{\eta}_{J,t} - \widetilde{\eta}_{1,t})^T \\ \vdots \\ (\widetilde{\eta}_{J,t} - \widetilde{\eta}_{N,t})^T \end{bmatrix} = \frac{1}{\sqrt{dt}}\widetilde{W}_t\widetilde{\Lambda}_t^{0.5}.$$

This is because $\widetilde{\Delta\eta}_t$ has to satisfy $\widetilde{\Delta\eta}_t^T d\widetilde{Z}_t = x_{t+dt}$ (see (5)). Thus, PCA on N carry trade returns (or exchange rate growths) allows us to transform the original, unobservable risk space Z_t into an equivalent, observable risk space $\widetilde{Z}_t$, and at the same time we also observe the cross-country difference in market prices of risk $(\widetilde{\eta}_{J,t} - \widetilde{\eta}_{I,t})$ associated with the new defined risk sources.

To construct country-specific SDFs it is not enough to estimate the cross-country difference in market prices $(\widetilde{\eta}_{J,t} - \widetilde{\eta}_{I,t})$, but we need $\widetilde{\eta}_{J,t}$. We estimate $\widetilde{\eta}_{J,t}$ from the system of equations (4),

$$\widetilde{\eta}_{J,t} = \frac{1}{dt}\left[\widetilde{\Delta\eta}_t\widetilde{\Delta\eta}_t^T\right]^{-1}\widetilde{\Delta\eta}_t ECT_t, \tag{7}$$

and $\widetilde{\eta}_{I,t} = \widetilde{\eta}_{J,t} - (\widetilde{\eta}_{J,t} - \widetilde{\eta}_{I,t})$. $\widetilde{\eta}_{J,t}$ in (7) is the slope coefficient in a cross-sectional regression of expected carry trade returns ECT_t on factor loadings $\widetilde{\Delta\eta}_t$ (corresponding to the risk factors $d\widetilde{Z}_t$).

Finally, we construct the SDF in every country $I \in \{1, \ldots, N+1\}$,

$$\frac{d\widetilde{M}_{I,t}}{\widetilde{M}_{I,t}} = -r_{I,t}dt - \widetilde{\eta}_{I,t}^T d\widetilde{Z}_t. \tag{8}$$

For the SDF $\widetilde{M}_J$ in country J, the last term capturing the SDF's risk loadings (or the market prices) is equal to the unexpected return of a net-zero investment carry trade strategy with portfolio weights,

$$\theta_{J,t} = \widetilde{W}_t \widetilde{\Lambda}_t^{-1} \widetilde{W}_t^T ECT_t, \tag{9}$$

that is, $\widetilde{\eta}_{J,t}^T d\widetilde{Z}_t = \theta_{J,t}^T x_{t+dt}$.

Notice that if we keep all principal components in our construction of the SDF ($K_t = N$), then $\widetilde{W}_t = W_t$ and $\widetilde{\Lambda}_t = \Lambda_t$, and thus, $\widetilde{W}_t \widetilde{\Lambda}_t^{-1} \widetilde{W}_t^T = \Sigma_t^{-1}$ according to (1). However, as explained above, PCA is important because we want to drop principal components with low explanatory power to exclude near-arbitrage opportunities in our setting. As a result $\widetilde{W}_t \neq W_t$ and $\widetilde{\Lambda}_t \neq \Lambda_t$, and thus, $\widetilde{W}_t \widetilde{\Lambda}_t^{-1} \widetilde{W}_t^T \neq \Sigma_t^{-1}$, and we work with the adjusted covariance matrix $\widetilde{W}_t \widetilde{\Lambda}_t \widetilde{W}_t^T$ instead of Σ_t.

Equation (9) clearly reveals now that MSR is equivalent to the optimal portfolio of an investor with log-utility in Merton (1971). Moreover, by construction, strategy $\theta_{J,t}$ is perfectly negatively correlated with the SDF in country J, and thus, earns the maximum attainable Sharpe ratio (in FX markets) when denominated in currency J. We call $\theta_{J,t}$ the maximum Sharpe ratio (MSR) carry trade strategy to investor J. Notice that $\theta_{J,t} = c_t \phi_{J,t}$ and thus, MSR is not identical to the tangency portfolio. Though, both MSR and the tangency portfolio conditionally earn the maximum Sharpe ratio, the tangency portfolio does not adjust its risk exposure in response to changes in market prices. In contrast, MSR's risk exposure is perfectly correlated with the conditional volatility of the SDF, and thus, it times the market and earns a higher unconditional Sharpe ratio.[24]

The main objective of our paper is to implement the MSR strategy in USD, $\theta_{US,t}$ and compare its performance to other well-known carry trade strategies. Indeed, we show in section 3 that the Sharpe ratio earned by MSR exceeds the Sharpe ratios of other strategies. This empirical result is consistent with our theory and is evidence in favor of our approach to construct country-specific SDFs. Finally, a slight adjustment of strategy $\theta_{J,t}$ yields the MSR strategy to investor I (denominated in currency I), $\theta_{I,t} = \theta_{J,t} - i_I$, where i_I is a $N \times 1$ column vector with element I is equal to 1 and all other elements are equal to 0. Then, $\theta_{I,t}$ satisfies $\widetilde{\eta}_{I,t} d\widetilde{Z}_t = \theta_{I,t}^T x_{t+dt}$, which implies that $\theta_{I,t}$ is perfectly negatively correlated to the

[24]The quantitative importance of this market timing feature of MSR is demonstrated in section 3.

SDF in country I and it earns the maximum Sharpe ratio denominated in currency I.

Some comments are in order. First, the described approach to construct country-specific SDFs is non-parametric. For instance, we do not need any assumptions about preferences, wealth distributions or the structure of the economy. We also do not impose any specific statistical model or stochastic process to estimate the SDFs. The only restriction is that FX market returns are driven by pure-diffusion risks, and even this can be relaxed for the processes of $r_{I,t}$ and $\eta_{I,t}$, as long as they are adapted to the filtration $\mathcal{F}_t$ (and assuming some regularity to exclude pathological price behavior such as bubbles).

Second, the model holds conditionally. That is, given the risk-free short rates $r_{I,t}$, conditional expected carry trade returns ECT_t and covariance matrix Σ_t at time t, we can construct the observable risk sources $d\widetilde{Z}_t$ in (6), the corresponding conditional market prices $\widetilde{\eta}_{I,t}$ in (7), SDF growths $\frac{d\widetilde{M}_{I,t}}{\widetilde{M}_{I,t}}$ in (8) and the MSR strategy $\theta_{J,t}$ in (9). We describe the (dynamic) estimation of the model (i.e. the estimation of conditional quantities and the implementation of the MSR strategy) in more detail in section 2.3.

Third, an advantage of FX market data is that all risks are priced risks. This is clear from (3): the diffusion term of any carry trade return (or exchange rate growth) is equal to the difference in country-specific market prices of risks. Accordingly, carry trade returns never load on unpriced risks, because such risks by definition do not carry a market price. This is in stark contrast to other financial market instruments, which often are subject to unpriced shocks. Therefore, it is natural to work with FX market securities to construct SDFs.

Fourth, although all risks in FX markets are priced, this does not imply that all priced risks affect FX markets. In particular, if all $N+1$ countries assign identical market prices to some priced risk source (i.e., some element h in $\eta_{I,t}$ is identical across all countries I), then according to (3) no carry trade return is exposed to this risk source. Risks, which satisfy this knife edge condition on market prices, are not detected using FX market data and are missing in the constructed SDF in (8). Our constructed SDF is, however, a projection of the SDF into the FX market risk space. Accordingly, MSR earns the maximum attainable Sharpe ratio *in FX markets* but not necessarily the maximum attainable Sharpe ratio if we are able to invest in all (FX and non-FX) assets.

Finally, relaxing the assumption of frictionless trading – such as introducing transaction costs (bid-ask spreads) – may cause some distortions due to limits to arbitrage. In particular, in the presence of transaction costs, the exchange rate will only approximately but not exactly be equal to the ratio of country-specific SDFs in (2). If transaction costs are *large enough*, then it may not be possible to lock in an arbitrage profit even if (2) is violated and the exchange rate *slightly* deviates from the ratio of SDFs. This implies that in the presence of transaction costs, there may be some fluctuations in exchange rates which are not due to fundamental, priced shocks. No-arbitrage sets limits on the absolute size of these non-fundamental, unpriced fluctuations and the limits are proportional to the size of the transaction costs. But these unpriced fluctuations have an effect on the construction of the equivalent risks $\widetilde{Z}_t$ in (6), the corresponding market prices in (7), the country-specific SDFs in (8) and the MSR trading strategy in (9). Removing principal components which explain almost no common variation in the data in order to exclude near-arbitrage opportunities (as explained above) also helps to mitigate the problem of transaction costs. This is because unpriced fluctuations of the exchange rate around the ratio of SDFs, by their nature, are unsystematic and do not capture much of the common variation in exchange rates.

B Data Sources

Spot and Forward Exchange Rates

In Table 1 we list the Datastream mnemonics for spot and forward exchange rate quotes against the British pound, whereas those against the U.S. Dollar are listed in Table 2. To obtain mid-, bid- and ask-exchange rates, the suffixes (ER), (EB) and (EO) are added to the corresponding mnemonics.

Table 1: Datastream mnemonics for currency quotes against the British pound

Currency	Spot rate	Forward rate	Quote convention
Belgian franc	BELGLUX	BELXF1F	FCU/GBP
Canadian dollar	CNDOLLR	CNDOL1F	FCU/GBP
Danish krone	DANISHK	DANIS1F	FCU/GBP
French franc	FRENFRA	FRENF1F	FCU/GBP
German mark	DMARKER	DMARK1F	FCU/GBP
Italian lira	ITALIRE	ITALY1F	FCU/GBP
Japanese yen	JAPAYEN	JAPYN1F	FCU/GBP
Netherlands guilder	GUILDER	GUILD1F	FCU/GBP
Norwegian krone	NORKRON	NORKN1F	FCU/GBP
Swedish krona	SWEKRON	SWEDK1F	FCU/GBP
Swiss franc	SWISSFR	SWISF1F	FCU/GBP
U.S. dollar	USDOLLR	USDOL1F	FCU/GBP

C Strategy Performance

We consider the following trading strategies, which are described in detail in section 2.3:

- MSR is the maximum Sharpe ratio strategy, which is perfectly negatively correlated with the US SDF.
- MSR_V is constructed as MSR but for simplicity assumes that covariances between exchange rate growths are zero (i.e., use a diagonal matrix with exchange rate growth variances on the diagonal as the covariance matrix).
- MSR_I makes the additional simlifying assumption that variances across exchange rates are identical (i.e., use an identity matrix as the covariance matrix).
- $MSR_{I,CV}$ adjusts MSR_I to yield a constant conditional volatility.
- MSR_{CV} adjusts MSR to yield a constant conditional volatility.
- TAN is the tangency portfolio.
- DOL borrows USD and equally lends in all other currencies.

Table 2: Datastream mnemonics for currency quotes against the U.S. dollar

Currency	Spot rate	Forward rate	Quote convention
Australian dollar	BBAUDSP	BBAUD1F	FCU/USD
Belgian franc	BELGLU$	USBEF1F	FCU/USD
British pound	BBGBPSP	BBGBP1F	USD/FCU
Canadian dollar	BBCADSP	BBCAD1F	FCU/USD
Danish krone	BBDKKSP	BBDKK1F	FCU/USD
Euro	BBEURSP	BBEUR1F	FCU/USD
French franc	BBFRFSP	BBFRF1F	FCU/USD
German mark	BBDEMSP	BBDEM1F	FCU/USD
Italian lira	BBITLSP	BBITL1F	FCU/USD
Japanese yen	BBJPYSP	BBJPY1F	FCU/USD
Netherland guilder	BBNLGSP	BBNLG1F	FCU/USD
New Zealand dollar	BBNZDSP	BBNZD1F	FCU/USD
Norwegian krone	BBNOKSP	BBNOK1F	FCU/USD
Swedish krona	BBSEKSP	BBSEK1F	FCU/USD
Swiss france	BBCHFSP	BBCHF1F	FCU/USD

- *D-DOL* takes a long (short) position in *DOL* when the interest rate in USD is below (above) the median interest rate across all countries.
- *HML* buys (sells) the top 20% currencies with the highest (lowest) interest rate.
- *MOM* buys (sells) the top 20% currencies with the highest (lowest) past 12 month return.
- *VAL* buys (sells) the top 20% most undervalued (overvalued) currencies.
- $IntP_i$, $MomP_i$ and $ValP_i$ $\forall i \in \{1, \ldots, 5\}$ are equally weighted quintile portfolios sorted according to interest rates, past performance and value. Portfolios are constructed using information available at the end of month t and monthly returns are computed over the subsequent month (i.e. monthly return from the end of month t to the end of month $t + 1$).

Table 3 reports correlations between all strategies. Tables 4 through 10 report several performance measures:

- Mean: annualized average excess returns in %,
- Vol: annualized volatility in %,
- SR: annualized Sharpe ration in %,
- Skew: monthly return skewness,
- Kurt: monthly return kurtosis,
- MDD: maximum drawdown/ loss from peak to trough in %,
- ‖MDD‖/Mean: expected time to recover from maximum drawdown in years,
- AC: monthly auto-correlation of returns,
- % positive: percentage of positive returns in %,
- x-%: xth percentile of monthly returns.

Tables 11 through 15 show that MSR earns large abnormal returns and reports factor loadings according to several popular pricing factor model in international finance. Tables 16 and 17 report predictive regression results and shows that MSR is able to predict returns of popular carry trade strategies. Tables 18 and **??** show that MSR is able to price assets in FX markets and replaces the popular DOL and HML pricing factors.

Table 3: **Correlation Matrix of Trading Strategies**

	MSR	MSR_V	MSR_I	MSR_{CV}	$MSR_{I,CV}$	TAN	HML	DOL	$D\text{-}DOL$	MOM	VAL
MSR	1.00	0.61	0.37	0.77	0.51	0.12	0.36	0.06	0.14	0.04	0.12
MSR_V	0.61	1.00	0.64	0.50	0.76	0.08	0.35	0.21	0.51	0.13	-0.05
MSR_I	0.37	0.64	1.00	0.43	0.71	0.07	0.43	0.20	0.60	0.12	-0.09
MSR_{CV}	0.77	0.50	0.43	1.00	0.65	0.27	0.59	0.11	0.24	0.11	0.17
$MSR_{I,CV}$	0.51	0.76	0.71	0.65	1.00	0.10	0.56	0.18	0.62	0.18	0.06
TAN	0.12	0.08	0.07	0.27	0.10	1.00	0.22	0.01	0.01	0.09	0.06
HML	0.36	0.35	0.43	0.59	0.56	0.22	1.00	0.06	0.12	-0.03	0.24
DOL	0.06	0.21	0.20	0.11	0.18	0.01	0.06	1.00	0.31	-0.09	-0.31
$D\text{-}DOL$	0.14	0.51	0.60	0.24	0.62	0.01	0.12	0.31	1.00	0.17	-0.12
MOM	0.04	0.13	0.12	0.11	0.18	0.09	-0.03	-0.09	0.17	1.00	-0.18
VAL	0.12	-0.05	-0.09	0.17	0.06	0.06	0.24	-0.31	-0.12	-0.18	1.00

Notes: Correlation matrix of monthly currency strategy excess returns for our set of 15 developed countries from January 1977 to February 2016. Returns are without transaction costs. Details about the strategies are at the beginning of section C.

Table 4: **Performance Before Transaction Costs**

	MSR	HML	DOL	$D\text{-}DOL$	MOM	VAL
Mean	11.86	5.66	0.74	4.88	4.20	4.29
Vol	11.36	9.18	8.59	8.47	13.24	8.12
SR	1.04	0.62	0.09	0.58	0.32	0.53
Skew	2.35	-0.85	-0.20	-0.20	0.34	0.03
Kurt	18.77	5.82	3.90	4.04	6.90	4.66
MDD	-15.96	-43.18	-72.50	-24.34	-30.38	-22.79
‖MDD‖/Mean	1.35	7.62	98.27	4.99	7.23	5.31
AC	0.15	0.10	0.04	0.00	-0.00	0.05
% positive	64.73	64.52	53.12	57.54	56.13	55.70
90-%	4.04	3.60	3.08	3.32	4.70	3.00
50-%	0.44	0.58	0.08	0.38	0.28	0.23
10-%	-1.57	-2.85	-2.90	-2.43	-4.02	-2.36

	MSR	MSR_V	MSR_I	MSR_{CV}	$MSR_{I,CV}$	TAN
Mean	11.86	12.61	7.63	9.02	11.69	3.42
Vol	11.36	11.68	10.34	9.38	11.17	10.80
SR	1.04	1.08	0.74	0.96	1.05	0.32
Skew	2.35	3.14	0.07	-0.39	-0.47	8.64
Kurt	18.77	30.79	18.06	3.85	4.88	147.52
MDD	-15.96	-19.37	-47.51	-40.58	-41.65	-30.79
‖MDD‖/Mean	1.35	1.54	6.23	4.50	3.56	9.00
AC	0.15	0.18	0.23	0.15	0.10	0.05
% positive	64.73	67.31	67.53	64.73	67.53	64.73
90-%	4.04	4.51	3.18	4.03	4.81	0.62
50-%	0.44	0.58	0.47	0.77	1.09	0.08
10-%	-1.57	-1.54	-1.47	-2.87	-2.90	-0.35

Notes: Statistics of monthly currency strategy excess returns for our set of 15 developed countries from January 1977 to February 2016. Returns are before transaction costs. Details about the strategies and the performance measures are at the beginning of section C.

Table 5: **Performance After Transaction Costs**

	MSR	HML	DOL	$D\text{-}DOL$	MOM	VAL
Mean	8.54	5.15	0.68	4.63	3.27	3.98
Vol	10.98	9.19	8.59	8.49	13.27	8.11
SR	0.78	0.56	0.08	0.54	0.25	0.49
Skew	1.04	-0.84	-0.20	-0.20	0.32	0.03
Kurt	17.16	5.80	3.90	4.04	6.85	4.66
MDD	-25.52	-43.58	-73.49	-24.42	-33.51	-22.95
‖MDD‖/Mean	2.99	8.47	108.67	5.28	10.24	5.76
AC	0.10	0.10	0.04	0.00	0.00	0.04
% positive	61.72	63.44	53.12	57.33	55.05	55.27
90-%	3.59	3.52	3.08	3.31	4.65	2.95
50-%	0.33	0.58	0.06	0.32	0.17	0.18
10-%	-1.85	-3.01	-2.90	-2.55	-4.05	-2.42

	MSR	MSR_V	MSR_I	MSR_{CV}	$MSR_{I,CV}$	TAN
Mean	8.54	11.46	7.14	6.58	10.80	1.84
Vol	10.98	11.43	10.33	9.35	11.16	10.09
SR	0.78	1.00	0.69	0.70	0.97	0.18
Skew	1.04	2.97	-0.03	-0.42	-0.51	7.87
Kurt	17.16	29.76	18.37	3.88	4.89	146.30
MDD	-25.52	-20.59	-48.42	-42.02	-42.05	-31.93
‖MDD‖/Mean	2.99	1.80	6.78	6.39	3.89	17.37
AC	0.10	0.16	0.22	0.15	0.10	0.05
% positive	61.72	65.59	67.31	61.29	67.31	60.86
90-%	3.59	4.46	3.13	3.83	4.71	0.50
50-%	0.33	0.50	0.46	0.58	0.99	0.04
10-%	-1.85	-1.61	-1.51	-3.01	-2.93	-0.48

Notes: Statistics of monthly currency strategy excess returns for our set of 15 developed countries from January 1977 to February 2016. Returns are after transaction costs/ accounting for bid-ask spreads (due to time variations in portfolio weights). Details about the strategies and the performance measures are at the beginning of section C.

Table 6: **Performance After Full Round-Trip Transaction Costs**

	MSR	HML	DOL	$D\text{-}DOL$	MOM	VAL
Mean	5.54	2.60	-0.68	3.46	1.48	1.41
Vol	10.86	9.18	8.59	8.48	13.26	8.12
SR	0.51	0.28	-0.08	0.41	0.11	0.17
Skew	0.20	-0.83	-0.22	-0.22	0.32	0.01
Kurt	19.74	5.77	3.90	4.08	6.90	4.68
MDD	-38.80	-46.56	-86.71	-27.55	-51.02	-31.66
‖MDD‖/Mean	7.00	17.88	-126.93	7.96	34.58	22.53
AC	0.07	0.10	0.04	0.00	-0.00	0.05
% positive	58.28	58.92	51.61	55.60	51.83	50.97
90-%	3.29	3.35	2.96	3.24	4.44	2.76
50-%	0.21	0.36	0.00	0.23	0.00	0.00
10-%	-1.98	-3.21	-3.03	-2.64	-4.28	-2.60

	MSR	MSR_V	MSR_I	MSR_{CV}	$MSR_{I,CV}$	TAN
Mean	5.54	9.81	5.61	3.64	8.42	1.46
Vol	10.86	11.24	10.25	9.28	11.10	10.07
SR	0.51	0.87	0.55	0.39	0.76	0.15
Skew	0.20	2.89	-0.22	-0.45	-0.56	7.88
Kurt	19.74	29.86	18.66	3.88	4.93	147.20
MDD	-38.80	-25.67	-52.37	-45.29	-48.12	-32.38
‖MDD‖/Mean	7.00	2.62	9.34	12.43	5.72	22.15
AC	0.07	0.14	0.21	0.13	0.09	0.05
% positive	58.28	63.44	63.66	58.28	63.66	58.28
90-%	3.29	4.11	3.02	3.59	4.49	0.47
50-%	0.21	0.42	0.37	0.30	0.77	0.02
10-%	-1.98	-1.78	-1.66	-3.28	-3.14	-0.51

Notes: Statistics of monthly currency strategy excess returns for our set of 15 developed countries from January 1977 to February 2016. Returns are after monthly full round-trip transaction costs/ accounting for bid-ask spreads (full turn over of portfolio every month). Details about the strategies and the performance measures are at the beginning of section C.

Table 7: **Performance during non-NBER Recessions**

	MSR	*HML*	*DOL*	*D-DOL*	*MOM*	*VAL*
Mean	8.42	5.73	1.26	5.18	4.02	3.30
Vol	10.52	8.57	8.26	8.13	12.24	7.87
SR	0.80	0.67	0.15	0.64	0.33	0.42
Skew	0.54	-0.67	-0.07	-0.07	-0.05	-0.05
Kurt	18.16	4.44	3.60	3.88	4.45	4.45
MDD	-25.52	-28.93	-64.13	-24.42	-29.38	-22.95
‖MDD‖/Mean	3.03	5.05	50.96	4.72	7.30	6.96
AC	0.04	0.04	0.01	0.03	0.01	0.02
% positive	62.62	63.59	54.13	58.88	55.34	54.85
90-%	3.66	3.55	3.10	3.29	4.67	2.87
50-%	0.36	0.57	0.14	0.42	0.19	0.15
10-%	-1.83	-2.48	-2.81	-2.26	-3.87	-2.45

	MSR	MSR_V	MSR_I	MSR_{CV}	$MSR_{I,CV}$	TAN
Mean	8.42	12.46	8.23	7.37	12.02	2.82
Vol	10.52	11.43	10.29	9.44	11.04	9.81
SR	0.80	1.09	0.80	0.78	1.09	0.29
Skew	0.54	3.37	0.23	-0.46	-0.53	11.04
Kurt	18.16	32.61	19.35	4.00	4.87	171.49
MDD	-25.52	-17.55	-48.42	-33.33	-42.05	-11.39
‖MDD‖/Mean	3.03	1.41	5.89	4.52	3.50	4.03
AC	0.04	0.16	0.26	0.14	0.10	0.05
% positive	62.62	66.50	67.96	61.89	67.96	61.89
90-%	3.66	4.47	3.42	3.86	4.89	0.52
50-%	0.36	0.61	0.47	0.63	1.11	0.05
10-%	-1.83	-1.55	-1.43	-2.97	-2.88	-0.41

Notes: Statistics of monthly currency strategy excess returns for our set of 15 developed countries for non-NBER Recession periods from January 1977 to February 2016. Returns are after transaction costs/ accounting for bid-ask spreads (due to time variations in portfolio weights). Details about the strategies and the performance measures are at the beginning of section C.

Table 8: **Performance during NBER Recessions**

	MSR	*HML*	*DOL*	*D-DOL*	*MOM*	*VAL*
Mean	9.47	0.66	-3.76	0.45	-2.45	9.21
Vol	14.06	13.04	10.83	10.88	19.50	9.74
SR	0.67	0.05	-0.35	0.04	-0.13	0.95
Skew	2.54	-0.92	-0.47	-0.47	1.13	0.18
Kurt	11.30	5.69	3.75	3.85	7.74	4.62
MDD	-11.60	-40.15	-34.35	-23.05	-47.82	-9.45
‖MDD‖/Mean	1.22	60.59	-9.13	51.49	-19.51	1.03
AC	0.22	0.29	0.14	-0.06	0.02	0.20
% positive	54.72	62.26	45.28	45.28	52.83	58.49
90-%	3.18	3.39	2.74	3.66	3.85	4.07
50-%	0.02	0.75	-0.20	-0.20	0.05	0.68
10-%	-2.29	-4.63	-3.70	-2.94	-6.83	-2.19

	MSR	MSR_V	MSR_I	MSR_{CV}	$MSR_{I,CV}$	TAN
Mean	9.47	3.83	-1.11	0.52	1.48	-5.68
Vol	14.06	11.33	10.42	8.50	11.75	11.89
SR	0.67	0.34	-0.11	0.06	0.13	-0.48
Skew	2.54	-0.10	-1.87	-0.15	-0.33	-5.60
Kurt	11.30	5.77	10.53	2.64	5.05	39.56
MDD	-11.60	-17.87	-23.60	-28.49	-27.38	-36.70
‖MDD‖/Mean	1.22	4.67	-21.18	54.80	18.44	-6.46
AC	0.22	0.11	-0.10	0.19	0.09	0.08
% positive	54.72	58.49	62.26	56.60	62.26	52.83
90-%	3.18	3.49	2.59	3.55	3.44	0.43
50-%	0.02	0.14	0.25	0.05	0.49	0.00
10-%	-2.29	-2.06	-2.87	-3.63	-4.46	-1.19

Notes: Statistics of monthly currency strategy excess returns for our set of 15 developed countries for NBER Recession periods from January 1977 to February 2016. Returns are after transaction costs/ accounting for bid-ask spreads (due to time variations in portfolio weights). Details about the strategies and the performance measures are at the beginning of section C.

Table 9: **Performance before Introduction of Euro**

	MSR	HML	DOL	$D\text{-}DOL$	MOM	VAL
Mean	11.70	5.57	0.76	4.90	4.50	3.62
Vol	13.64	8.16	8.72	8.63	12.87	8.03
SR	0.86	0.68	0.09	0.57	0.35	0.45
Skew	0.74	-0.90	-0.20	-0.20	-0.13	-0.05
Kurt	12.25	5.35	3.83	4.10	4.95	5.12
MDD	-25.52	-28.93	-73.49	-17.63	-31.44	-22.95
‖MDD‖/Mean	2.18	5.20	97.10	3.60	6.98	6.33
AC	0.08	0.06	0.04	0.06	-0.00	0.08
% positive	66.28	67.05	54.26	58.75	57.75	56.98
90-%	4.25	3.15	3.02	3.51	4.75	2.85
50-%	0.45	0.58	0.03	0.32	0.14	0.12
10-%	-2.52	-2.23	-2.96	-2.58	-3.87	-2.46

	MSR	MSR_V	MSR_I	MSR_{CV}	$MSR_{I,CV}$	TAN
Mean	11.70	16.36	10.68	7.73	14.47	0.27
Vol	13.64	13.50	13.06	9.14	11.47	2.94
SR	0.86	1.21	0.82	0.85	1.26	0.09
Skew	0.74	2.86	-0.22	-0.53	-0.39	-8.29
Kurt	12.25	25.04	12.54	4.90	4.61	120.62
MDD	-25.52	-15.38	-48.42	-25.03	-21.51	-11.39
‖MDD‖/Mean	2.18	0.94	4.53	3.24	1.49	42.12
AC	0.08	0.12	0.22	0.14	0.08	0.01
% positive	66.28	69.38	72.09	65.50	72.09	65.50
90-%	4.25	5.26	4.65	3.82	5.27	0.36
50-%	0.45	0.82	0.71	0.62	1.11	0.04
10-%	-2.52	-1.85	-2.35	-2.70	-2.71	-0.31

Notes: Statistics of monthly currency strategy excess returns for our set of 15 developed countries from January 1977 to December 1998. Returns are after transaction costs/ accounting for bid-ask spreads (due to time variations in portfolio weights). Details about the strategies and the performance measures are at the beginning of section C.

Table 10: **Performance after Introduction of Euro**

	MSR	HML	DOL	$D\text{-}DOL$	MOM	VAL
Mean	4.38	4.67	0.58	4.33	1.26	4.42
Vol	5.58	10.48	8.48	8.37	13.81	8.30
SR	0.79	0.45	0.07	0.52	0.09	0.53
Skew	0.79	-0.75	-0.20	-0.20	0.83	0.13
Kurt	5.45	5.44	3.92	3.89	8.89	3.99
MDD	-16.90	-43.58	-30.24	-24.42	-30.28	-14.43
‖MDD‖/Mean	3.86	9.33	52.02	5.64	24.08	3.26
AC	0.13	0.14	0.05	-0.07	0.01	0.03
% positive	55.88	58.82	51.47	55.88	51.47	52.45
90-%	2.35	3.93	3.25	3.31	4.46	3.11
50-%	0.15	0.58	0.14	0.40	0.21	0.20
10-%	-1.39	-3.55	-2.81	-2.41	-4.43	-2.32

	MSR	MSR_V	MSR_I	MSR_{CV}	$MSR_{I,CV}$	TAN
Mean	4.38	5.01	2.47	5.08	5.98	3.96
Vol	5.58	7.56	4.35	9.67	10.66	15.14
SR	0.79	0.66	0.57	0.52	0.56	0.26
Skew	0.79	0.60	-0.39	-0.29	-0.80	5.48
Kurt	5.45	7.00	6.37	2.74	5.18	67.14
MDD	-16.90	-20.59	-17.73	-42.02	-42.05	-31.93
‖MDD‖/Mean	3.86	4.11	7.18	8.28	7.03	8.06
AC	0.13	0.24	0.10	0.15	0.11	0.05
% positive	55.88	60.78	61.27	55.88	61.27	54.90
90-%	2.35	2.41	1.42	3.96	3.92	0.94
50-%	0.15	0.31	0.29	0.51	0.86	0.07
10-%	-1.39	-1.52	-0.98	-3.38	-3.19	-0.91

Notes: Statistics of monthly currency strategy excess returns for our set of 15 developed countries from January 1999 to February 2016. Returns are after transaction costs/ accounting for bid-ask spreads (due to time variations in portfolio weights). Details about the strategies and the performance measures are at the beginning of section C.

Table 11: **Alpha of MSR**

Factors	MSR				
α	9.304***	9.625***	8.257***	8.439***	8.144***
	(5.393)	(5.408)	(4.824)	(4.812)	(4.843)
DOL	0.051	-0.064	0.054	-0.046	0.227
	(0.677)	(-0.805)	(0.812)	(-0.659)	(1.589)
$D\text{-}DOL$			0.122*	0.130*	0.116
			(1.671)	(1.777)	(1.623)
HML	0.445***		0.410***		1.037***
	(6.683)		(6.466)		(2.744)
FM_{VOL}		-34.136***		-31.129***	51.676*
		(-6.190)		(-6.175)	(1.710)
MOM			0.044	0.045	0.044
			(1.135)	(1.147)	(1.155)
VAL			0.107	0.129*	0.088
			(1.500)	(1.812)	(1.223)
R^2	14	13	15	13	15
Obs	483	483	483	483	483

Notes: Linear regression $MSR_t = \alpha + \sum_i \beta_i F_{i,t} + \varepsilon_t$. α is the annualized abnormal return in percentage (with respect to the factor pricing model under consideration). We consider six pricing factors F_i: DOL, $D\text{-}DOL$, HML, FM_{VOL}, MOM, VAL. MSR and the factors are monthly excess returns and are described in detail in section 2.3. R^2 is in percentage and measures the regression fit, and Obs reports the number of monthly return observations in our sample. The data is our set of 15 developed countries from January 1977 to February 2016. Newey and West (1987) robust t-statistics are reported in parentheses below coefficient estimates. Significance at the 1%, 5% or 10% level are indicated by *,** or ***.

Table 12: **Alpha of MSR during non-NBER Recessions**

Factors	MSR				
α	8.436***	8.596***	7.731***	7.819***	7.732***
	(5.566)	(5.604)	(4.970)	(4.953)	(4.971)
DOL	0.100	0.027	0.086	0.029	0.076
	(1.221)	(0.327)	(1.305)	(0.428)	(0.907)
$D\text{-}DOL$			0.122	0.119	0.121
			(1.630)	(1.569)	(1.581)
HML	0.493***		0.452***		0.376
	(8.370)		(6.677)		(1.558)
FM_{VOL}		-46.517***		-42.257***	-7.548
		(-8.068)		(-6.427)	(-0.323)
MOM			-0.005	-0.005	-0.005
			(-0.110)	(-0.105)	(-0.120)
VAL			0.094	0.119	0.097
			(1.225)	(1.520)	(1.224)
R^2	17	16	17	17	17
Obs	427	427	427	427	427

Notes: Linear regression $MSR_t = \alpha + \sum_i \beta_i F_{i,t} + \varepsilon_t$. α is the annualized abnormal return in percentage (with respect to the factor pricing model under consideration). We consider six pricing factors F_i: DOL, $D\text{-}DOL$, HML, FM_{VOL}, MOM, VAL. MSR and the factors are monthly excess returns and are described in detail in section 2.3. R^2 is in percentage and measures the regression fit, and Obs reports the number of monthly return observations in our sample. The data is our set of 15 developed countries for non-NBER Recession periods from January 1977 to February 2016. Newey and West (1987) robust t-statistics are reported in parentheses below coefficient estimates. Significance at the 1%, 5% or 10% level are indicated by *,** or ***.

Table 13: **Alpha of MSR during NBER Recessions**

Factors	MSR				
α	12.701	13.946*	13.367*	13.262*	13.363*
	(1.618)	(1.684)	(1.813)	(1.719)	(1.824)
DOL	-0.114	-0.159	-0.016	-0.107	0.026
	(-0.668)	(-1.060)	(-0.072)	(-0.526)	(0.115)
$D\text{-}DOL$			0.019	0.135	-0.010
			(0.111)	(0.836)	(-0.050)
HML	0.332**		0.429***		0.505*
	(2.136)		(2.808)		(1.780)
FM_{VOL}		-10.195**		-11.856***	3.700
		(-2.183)		(-3.233)	(0.448)
MOM			0.200**	0.097	0.217**
			(2.477)	(1.630)	(2.094)
VAL			-0.022	0.109	-0.048
			(-0.105)	(0.536)	(-0.202)
R^2	8	6	12	7	12
Obs	56	56	56	56	56

Notes: Linear regression $MSR_t = \alpha + \sum_i \beta_i F_{i,t} + \varepsilon_t$. α is the annualized abnormal return in percentage (with respect to the factor pricing model under consideration). We consider six pricing factors F_i: DOL, $D\text{-}DOL$, HML, FM_{VOL}, MOM, VAL. MSR and the factors are monthly excess returns and are described in detail in section 2.3. R^2 is in percentage and measures the regression fit, and Obs reports the number of monthly return observations in our sample. The data is our set of 15 developed countries for NBER Recession periods from January 1977 to February 2016. Newey and West (1987) robust t-statistics are reported in parentheses below coefficient estimates. Significance at the 1%, 5% or 10% level are indicated by *,** or ***.

Table 14: **Alpha of MSR before Introduction of Euro**

Factors	MSR				
α	11.921***	12.347***	10.616***	11.012***	10.612***
	(4.926)	(5.062)	(4.166)	(4.217)	(4.155)
DOL	0.263**	0.051	0.314***	0.118	0.275**
	(2.120)	(0.441)	(3.109)	(1.170)	(2.365)
$D\text{-}DOL$			0.078	0.110	0.081
			(0.779)	(1.093)	(0.790)
HML	0.765***		0.698***		0.567**
	(6.316)		(5.340)		(2.143)
FM_{VOL}		-58.621***		-52.567***	-11.575
		(-6.287)		(-5.084)	(-0.528)
MOM			0.063	0.032	0.056
			(1.089)	(0.492)	(0.900)
VAL			0.226*	0.245*	0.222*
			(1.809)	(1.942)	(1.747)
R^2	18	17	20	18	20
Obs	276	276	276	276	276

Notes: Linear regression $MSR_t = \alpha + \sum_i \beta_i F_{i,t} + \varepsilon_t$. α is the annualized abnormal return in percentage (with respect to the factor pricing model under consideration). We consider six pricing factors F_i: DOL, $D\text{-}DOL$, HML, FM_{VOL}, MOM, VAL. MSR and the factors are monthly excess returns and are described in detail in section 2.3. R^2 is in percentage and measures the regression fit, and Obs reports the number of monthly return observations in our sample. The data is our set of 15 developed countries from January 1977 to December 1998. Newey and West (1987) robust t-statistics are reported in parentheses below coefficient estimates. Significance at the 1%, 5% or 10% level are indicated by *,** or ***.

Table 15: **Alpha of MSR after Introduction of Euro**

Factors	MSR				
α	3.893***	4.399***	3.180***	3.634***	3.163***
	(2.850)	(3.184)	(2.651)	(2.940)	(2.649)
DOL	-0.040	-0.071	-0.115	-0.137*	-0.111
	(-0.631)	(-1.123)	(-1.599)	(-1.865)	(-1.522)
$D\text{-}DOL$			0.186***	0.180***	0.187***
			(2.993)	(3.050)	(2.992)
HML	0.260***		0.265***		0.279***
	(5.149)		(6.456)		(2.845)
FM_{VOL}		-16.460***		-16.556***	1.145
		(-4.984)		(-7.045)	(0.194)
MOM			0.053*	0.059**	0.053*
			(1.725)	(2.208)	(1.698)
VAL			-0.045	-0.027	-0.045
			(-0.956)	(-0.542)	(-0.961)
R^2	28	24	30	26	30
Obs	204	204	204	204	204

Notes: Linear regression $MSR_t = \alpha + \sum_i \beta_i F_{i,t} + \varepsilon_t$. α is the annualized abnormal return in percentage (with respect to the factor pricing model under consideration). We consider six pricing factors F_i: DOL, $D\text{-}DOL$, HML, FM_{VOL}, MOM, VAL. MSR and the factors are monthly excess returns and are described in detail in section 2.3. R^2 is in percentage and measures the regression fit, and Obs reports the number of monthly return observations in our sample. The data is our set of 15 developed countries from January 1999 to February 2016. Newey and West (1987) robust t-statistics are reported in parentheses below coefficient estimates. Significance at the 1%, 5% or 10% level are indicated by *,** or ***.

Table 16: **Predictive Regressions**

	h = 1						
Predictors	$MSR_{t,t+h}$	$VOL_{t,t+h}$	$HML_{t,t+h}$	$DOL_{t,t+h}$	$D\text{-}DOL_{t,t+h}$	$MOM_{t,t+h}$	$VAL_{t,t+h}$
$\sum_i \lVert\theta_{i,US,t}\rVert$	0.286***	-0.011***	0.086**	-0.033	0.089**	0.226***	0.020
$\sum_i \theta_{i,US,t}$	-0.030	0.010***	-0.080	0.076	-0.244**	-0.438***	-0.052
$sign\left(\sum_i \theta_{i,US,t}\right)$	0.139	-0.008	-0.100	0.290**	0.077	-0.131	0.143
$sign\left(median(\{r_{J,t}\}) - r_{US,t}\right)$	-0.012	-0.000	-0.078	0.456***	0.142	0.115	-0.199*
VOL_t	-1.300	-0.203***	-0.103	-0.779	-2.049*	1.570	1.319
Y_t	0.062	NaN	0.087	-0.007	0.002	-0.012	0.042
R^2 (adjusted)	13.62	10.42	0.47	5.30	1.17	1.15	-0.04

	h = 6						
Predictors	$MSR_{t,t+h}$	$VOL_{t,t+h}$	$HML_{t,t+h}$	$DOL_{t,t+h}$	$D\text{-}DOL_{t,t+h}$	$MOM_{t,t+h}$	$VAL_{t,t+h}$
$\sum_i \lVert\theta_{i,US,t}\rVert$	0.214***	-0.001	0.054*	-0.050*	0.034	0.124***	-0.008
$\sum_i \theta_{i,US,t}$	-0.201**	-0.004*	-0.106**	0.132**	-0.038	-0.189***	0.048
$sign\left(\sum_i \theta_{i,US,t}\right)$	0.266***	-0.005*	0.037	0.061	-0.082	0.027	0.060
$sign\left(median(\{r_{J,t}\}) - r_{US,t}\right)$	-0.061	0.006*	-0.018	0.307***	0.063	-0.027	-0.076
VOL_t	-0.088	0.003	-0.069	-0.161	0.157	-0.329	0.708**
Y_t	-0.009	NaN	-0.004	0.027	0.011	-0.025	-0.038***
R^2 (adjusted)	21.74	5.15	0.35	10.35	0.09	4.12	0.35

Notes: Predictive regression $Y_{t,t+h} = c_0 + \sum_i c_i x_{i,t} + \varepsilon_t$. $Y_{t,t+h} = \frac{1}{h}\sum_{\tau=1}^{h} Y_{t+\tau}$. We check the predictability of the carry trade returns of MSR, HML, DOL, $D\text{-}DOL$, MOM, VAL, and cahnges to global FX market volatility VOL. We use the following predictors x_i: $\sum_i \lVert\theta_{i,US,t}\rVert$ is the dollar amount risk exposure of MSR at time t, $\sum_i \theta_{i,US,t}$ measures the leverage of MSR, i.e. exposure to the tangency portfolio, $sign\left(\sum_i \theta_{i,US,t}\right)$ indicates whether MSR takes a long or short position in the tangency portfolio, $sign\left(median(\{r_{J,t}\}) - r_{US,t}\right)$ indicates whether the interest rate in the US is above or below the median interest rate across all currencies, VOL_t is the change in global FX market volatility at time t, Y_t is the most recent realization of the variable to predict. R^2 (adjusted) is in percentage and measures the regression fit. The data is our set of 15 developed countries from January 1977 to February 2016. Significance of predictor x_i at the 1%, 5% or 10% level are indicated by *,** or ***.

Table 17: **Predictive Regressions**

Predictors	**h = 12**						
	$MSR_{t,t+h}$	$VOL_{t,t+h}$	$HML_{t,t+h}$	$DOL_{t,t+h}$	$D\text{-}DOL_{t,t+h}$	$MOM_{t,t+h}$	$VAL_{t,t+h}$
$\sum_i \|\theta_{i,US,t}\|$	0.156***	-0.000	0.053**	-0.055*	0.053**	0.087***	0.001
$\sum_i \theta_{i,US,t}$	-0.102*	-0.002	-0.133***	0.153***	-0.076*	-0.110**	-0.008
$sign\left(\sum_i \theta_{i,US,t}\right)$	0.248***	-0.005*	0.072	0.067	-0.012	0.043	0.083*
$sign\left(median(\{r_{J,t}\}) - r_{US,t}\right)$	-0.131	0.005*	-0.058	0.250***	0.091	-0.005	-0.098*
VOL_t	0.009	0.027	0.189	0.267	0.476	-0.022	0.364
Y_t	-0.000	NaN	0.003	0.016	0.006	-0.035***	-0.014
R^2 (adjusted)	25.75	4.67	2.54	15.38	2.89	5.68	1.66

Predictors	**h = 24**						
	$MSR_{t,t+h}$	$VOL_{t,t+h}$	$HML_{t,t+h}$	$DOL_{t,t+h}$	$D\text{-}DOL_{t,t+h}$	$MOM_{t,t+h}$	$VAL_{t,t+h}$
$\sum_i \|\theta_{i,US,t}\|$	0.119***	-0.000	0.051***	-0.048**	0.038***	0.061***	0.000
$\sum_i \theta_{i,US,t}$	-0.087*	-0.002	-0.107***	0.122***	-0.075***	-0.060**	-0.016
$sign\left(\sum_i \theta_{i,US,t}\right)$	0.237***	-0.005**	0.124***	-0.015	0.050	0.009	0.069**
$sign\left(median(\{r_{J,t}\}) - r_{US,t}\right)$	-0.125*	0.001	0.010	0.195***	-0.012	-0.080*	-0.059*
VOL_t	0.114	0.012	0.273	0.149	0.308	0.204	0.209
Y_t	0.009	NaN	0.000	0.008	-0.004	-0.019***	-0.011
R^2 (adjusted)	25.01	5.44	6.96	13.37	2.76	13.02	1.96

Notes: Predictive regression $Y_{t,t+h} = c_0 + \sum_i c_i x_{i,t} + \varepsilon_t$. $Y_{t,t+h} = \frac{1}{h}\sum_{\tau=1}^{h} Y_{t+\tau}$. We check the predictability of the carry trade returns of MSR, HML, DOL, $D\text{-}DOL$, MOM, VAL, and changes in global FX market volatility VOL. We use the following predictors x_i: $\sum_i \|\theta_{i,US,t}\|$ is the dollar amount risk exposure of MSR at time t, $\sum_i \theta_{i,US,t}$ measures the leverage of MSR, i.e. exposure to the tangency portfolio, $sign\left(\sum_i \theta_{i,US,t}\right)$ indicates whether MSR takes a long or short position in the tangency portfolio, $sign\left(median(\{r_{J,t}\}) - r_{US,t}\right)$ indicates whether the interest rate in the US is above or below the median interest rate across all currencies, VOL_t is the changes in global FX market volatility at time t, Y_t is the most recent realization of the variable to predict. R^2 (adjusted) is in percentage and measures the regression fit. The data is our set of 15 developed countries from January 1977 to February 2016. Significance of predictor x_i at the 1%, 5% or 10% level are indicated by *,** or ***.

Table 18: MSR **vs.** DOL-HML **Pricing Factors**

Factors	**15 Test Assets** ($IntP$, $MomP$, $ValP$)		**21 Test Assets**	
γ_{MSR}	21.031*		20.283***	
	(1.807)		(6.581)	
γ_{DOL}		0.643		0.983
		(0.457)		(0.698)
γ_{HML}		5.957***		14.668***
		(3.835)		(6.783)
R^2	80.746	54.230	90.632	68.043
$\gamma_{MSR} - E[MSR]$	8.710		7.962**	
	(0.748)		(2.583)	
$\gamma_{DOL} - E[DOL]$		-0.123		0.216
		(-0.087)		(0.154)
$\gamma_{HML} - E[HML]$		0.074		8.786***
		(0.048)		(4.063)
Joint Test of Cross-Sectional Regression α_j^*:				
χ^2-test ($\alpha_j^* = 0$, $\forall j$)	8.924	22.726**	23.634	51.290***
(p-value)	(0.779)	(0.030)	(0.211)	(0.000)
Joint Test of Time-Series Regression α_j:				
F-test ($\alpha_j = 0$, $\forall j$)	1.069	1.560*	1.460*	2.710***
(p-value)	(0.383)	(0.081)	(0.087)	(0.000)

Notes: Two stage regression test of pricing factors: Time-Series (TS): $R_{j,t} = \alpha_j + \sum_i F_{i,t}\beta_{i,j} + \varepsilon_{j,t}$, Cross-Section (CS): $E[R_j] = \sum_i \beta_{i,j}\gamma_i + \alpha_j^*$. Test assets R_j: Columns 2-3 use 15 test assets $IntP_i$, $MomP_i$, $ValP_i$ $\forall i \in \{1, \ldots, 5\}$, columns 4-5 use the same 15 test assets and add MSR_V, MSR_I, MSR_{CV}, $MSR_{I,CV}$, TAN and D-DOL. Pricing Factors F_i: Columns 2 and 4 report results for the single factor pricing model MSR, columns 3 and 5 for the 2-factor model DOL-HML. α_j and α_j^* are abnormal returns of test asset j in TS and CS regressions. $\beta_{i,j}$ is the loading of asset j on factor i. γ_i is the market price of risk of factor i. t-statistics are in parentheses below coefficient estimates. R^2 is the CS regression fit of the pricing model. $\gamma_{F_i} - E[F_i]$ for $F_i \in \{MSR, DOL, HML\}$ is the difference between the estimated market price of factor F_i and the average return of factor F_i; t-statistic is in parenthesis below. χ^2-test is the joint test statistic of $\alpha_j^* = 0$ $\forall j$ in the CS regression. F-test is the joint test statistic of $\alpha_j = 0$ $\forall j$ in the TS regression. The data is our set of 15 developed countries from January 1977 to February 2016. Significance at the 1%, 5% or 10% level are indicated by *,** or ***.

Table 19: **Additional Information of MSR to DOL-HML Two Factor Model**

Factors	**15 Test Assets** ($IntP$, $MomP$, $ValP$)	**21 Test Assets**
$\gamma_{\widetilde{MSR}}$	33.288***	16.287***
	(3.119)	(6.079)
γ_{DOL}	0.814	0.830
	(0.578)	(0.590)
γ_{HML}	5.925***	6.905***
	(3.719)	(4.045)
R^2	88.006	90.968
$\gamma_{\widetilde{MSR}} - E[\widetilde{MSR}]$	23.624**	6.623**
	(2.214)	(2.472)
$\gamma_{DOL} - E[DOL]$	0.047	0.064
	(0.034)	(0.045)
$\gamma_{HML} - E[HML]$	0.043	1.023
	(0.027)	(0.599)
Joint Test of Cross-Sectional Regression α_j^*:		
χ^2-test ($\alpha_j^* = 0$, $\forall j$)	5.898	23.018
(p-value)	(0.880)	(0.149)
Joint Test of Time-Series Regression α_j:		
F-test ($\alpha_j = 0$, $\forall j$)	0.925	1.336
(p-value)	(0.536)	(0.147)

Notes: We orthogonalize MSR with respect to DOL and HML, $MSR = h_0 + h_1 DOL + h_2 HML + \epsilon$. We test the importance of $\widetilde{MSR} = h_0 + \epsilon$ as a pricing factor in addition to DOL and HML. Two stage regression test of pricing factors: Time-Series (TS): $R_{j,t} = \alpha_j + \sum_i F_{i,t}\beta_{i,j} + \varepsilon_{j,t}$, Cross-Section (CS): $E[R_j] = \sum_i \beta_{i,j}\gamma_i + \alpha_j^*$. Test assets R_j: Columns 2 uses 15 test assets $IntP_i$, $MomP_i$, $ValP_i$ $\forall i \in \{1, \ldots, 5\}$, columns 3 use the same 15 test assets and adds MSR_V, MSR_I, MSR_{CV}, $MSR_{I,CV}$, TAN and D-DOL. Pricing Factors F_i: $\widetilde{MSR}$, DOL, HML. α_j and α_j^* are abnormal returns of test asset j in TS and CS regressions. $\beta_{i,j}$ is the loading of asset j on factor i. γ_i is the market price of risk of factor i. t-statistics are in parentheses below coefficient estimates. R^2 is the CS regression fit of the pricing model. $\gamma_{F_i} - E[F_i]$ for $F_i \in \{\widetilde{MSR}, DOL, HML\}$ is the difference between the estimated market price of factor F_i and the average return of factor F_i; t-statistic is in parenthesis below. χ^2-test is the joint test statistic of $\alpha_j^* = 0$ $\forall j$ in the CS regression. F-test is the joint test statistic of $\alpha_j = 0$ $\forall j$ in the TS regression. The data is our set of 15 developed countries from January 1977 to February 2016. Significance at the 1%, 5% or 10% level are indicated by *,** or ***.

Table 20: **Additional Information of DOL and HML to MSR Single Factor Model**

Factors	**15 Test Assets** ($IntP$, $MomP$, $ValP$)	**21 Test Assets**
γ_{MSR}	35.967***	19.403***
	(3.370)	(6.948)
$\gamma_{\widetilde{DOL}}$	-0.813	-0.047
	(-0.551)	(-0.034)
$\gamma_{\widetilde{HML}}$	-4.593	1.231
	(-1.328)	(0.736)
R^2	88.006	90.968
$\gamma_{MSR} - E[MSR]$	23.646**	7.082**
	(2.215)	(2.536)
$\gamma_{\widetilde{DOL}} - E[\widetilde{DOL}]$	-1.022	-0.256
	(-0.692)	(-0.182)
$\gamma_{\widetilde{HML}} - E[\widetilde{HML}]$	-6.872*	-1.048
	(-1.987)	(-0.626)
Joint Test of Cross-Sectional Regression α_j^*:		
χ^2-test ($\alpha_j^* = 0$, $\forall j$)	5.898	23.018
(p-value)	(0.880)	(0.149)
Joint Test of Time-Series Regression α_j:		
F-test ($\alpha_j = 0$, $\forall j$)	0.925	1.336
(p-value)	(0.536)	(0.147)

Notes: We orthogonalize DOL and HML with respect to MSR, $Y_i = h_{i,0} + h_{i,1}MSR + \epsilon_i$, and $\widetilde{Y_i} = h_{i,0} + \epsilon_i \ \forall Y_i \in \{DOL, HML\}$. We test the importance of $\widetilde{DOL}$ and $\widetilde{HML}$ as pricing factors in addition to MSR. Two stage regression test of pricing factors: Time-Series (TS): $R_{j,t} = \alpha_j + \sum_i F_{i,t}\beta_{i,j} + \varepsilon_{j,t}$, Cross-Section (CS): $E[R_j] = \sum_i \beta_{i,j}\gamma_i + \alpha_j^*$. Test assets R_j: Columns 2 uses 15 test assets $IntP_i$, $MomP_i$, $ValP_i$ $\forall i \in \{1, \ldots, 5\}$, columns 3 use the same 15 test assets and adds MSR_V, MSR_I, MSR_{CV}, $MSR_{I,CV}$, TAN and $D\text{-}DOL$. Pricing Factors F_i: MSR, $\widetilde{DOL}$, $\widetilde{HML}$. α_j and α_j^* are abnormal returns of test asset j in TS and CS regressions. $\beta_{i,j}$ is the loading of asset j on factor i. γ_i is the market price of risk of factor i. t-statistics are in parentheses below coefficient estimates. R^2 is the CS regression fit of the pricing model. $\gamma_{F_i} - E[F_i]$ for $F_i \in \{MSR, \widetilde{DOL}, \widetilde{HML}\}$ is the difference between the estimated market price of factor F_i and the average return of factor F_i; t-statistic is in parenthesis below. χ^2-test is the joint test statistic of $\alpha_j^* = 0 \ \forall j$ in the CS regression. F-test is the joint test statistic of $\alpha_j = 0 \ \forall j$ in the TS regression. The data is our set of 15 developed countries from January 1977 to February 2016. Significance at the 1%, 5% or 10% level are indicated by *,** or ***.