

Essays in Empirical Dynamic Asset Pricing: Methods and Applications in Foreign Exchange

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Chapter I

Introduction

The thesis consists of three independently readable essays dealing with the estimation of dynamic linear factor pricing models and the dynamic factor structure of currency return cross-sections. The first essay introduces a likelihood-based approach to estimate linear factor models with time-varying risk premia, where risk exposures (betas) and risk prices (lambdas) are updated in each period, such that the one-step ahead prediction error is reduced given the current observation. For illustration purposes, among others, an empirical application of the novel method to the factor structure of currency carry trades is conducted. The second essay develops this idea further and provides an empirical study of time-varying risk premia in style-based currency investing strategies that employs methodological results from the first chapter. It shows that risk premia dynamics in the three currency trading strategies carry, momentum and value are heterogeneous and supports the view that they compensate for different sources of risk. Essay 3 investigates an economic interpretation of the currency cross-section that the second essay analyzes technically from a dynamic perspective. It empirically supports an intermediation-based model for currency cross-sections, in which the financial conditions of the biggest three foreign exchange (FX) dealers by market share serves as a risk factor. The contents and merits of the essays are summarized in greater detail in the following.

Likelihood-based Dynamic Asset Pricing

The paper is single-authored. It has been presented at the 12th International Conference on Computational and Financial Econometrics (December 2018), the Brown Bag Seminar at University of Kiel (July 2019) and the Doctoral Workshop at the 26th Annual Meeting of the German Finance Association (September 2019).

Financial theory states that expected excess returns reflect a compensation for risk exposure. A very popular approach to measure these so-called risk premia is to estimate linear factor models with the two-pass estimation approach of Fama and MacBeth (1973) (FMB) or a generalized method of moments (GMM) framework. Despite contradictory evidence in the literature, lambdas and betas are commonly assumed to be constant, neglecting time-variation in risk attitudes for example. Recent approaches to incorporate risk price dynamics into linear factor models, as for example proposed by Gagliardini et al. (2016) and Adrian

et al. (2015), generate time-variation with instruments that are established return forecasters, such as the dividend yields.

This paper proposes a likelihood-based approach that allows for filtering time-varying lambdas and betas without employing instrument variables. This is particularly useful in applications where no appropriate instruments are known or where possible misspecification should be avoided. The framework assumes a factor model specification with a beta representation relating asset returns to a risk premium, factor innovations and idiosyncratic disturbances. Residuals are assumed to follow elliptical distributions, which are popular in financial modeling and risk management. The main novelty of the approach is that the time-varying lambdas and betas follow an updating scheme derived from martingale difference sequences, being proportional to the score of the observation density, i.e. the derivative of the logarithmic observation density with respect to lambda and beta. This score-driven approach, originally introduced by Creal et al. (2013), has been successfully employed in volatility and copula modeling, for example. The intuitive idea behind the approach is to update the lambdas and betas each period in the direction in which we achieve the steepest increase in likelihood of the observation density. Put differently, the idea is to reduce the one-step ahead forecast error with information from current observations.

Local likelihood optimal updating schemes are derived in the paper to establish a score-driven likelihood-based asset pricing model (SLAPM). They intuitively perform a scaled updating according to currently observed cross-sectional (for lambdas) as well as time series general least squares (GLS) regression errors. A particular striking result is that the optimal updating scheme for elliptical distributions is unique up to a scalar multiplier. The specific choice of the elliptical distribution, therefore, does not alter the update direction of parameters. Estimation and inference can be conducted with standard maximum likelihood methods.

A Monte-Carlo study shows that a Gaussian version of the SLAPM with constant betas is able to filter even persistent risk price dynamics in a realistic setting. The performance of the SLAPM is compared to that of a dynamic asset pricing model according to Adrian et al. (2015) (in the following referred to as DAPM) employing noisy signals of different strength of the true instrument factor driving the lambda dynamics of the data-generating process. In an asset return panel of 25 assets and 500 time observations, a DAPM would need to be informed with a signal containing at least 80% of the information from the true data-generating process to be able to at least compete with a SLAPM as measured by the root mean squared error (RMSE) of forecasting lambdas and corresponding Diebold and Mariano (1995) tests.

Two applications illustrate the ability of the SLAPM procedure to filter risk price dynamics from panel data of asset returns. A dynamic version of the traditional three-factor model

of Fama and French (1993) illustrates the ability of the SLAPM procedure to filter risk price dynamics from panel data of asset returns. Resulting risk price series show cyclical variations around fairly stable average risk prices in a cross-section of 25 equity portfolios covering roughly the last 90 years. Huge risk price volatility is found during financial crises whereas pure economic crisis show less impact. The second application contributes to the rapidly growing literature on explaining currency cross-sections, as started by Lustig et al. (2011) and Menkhoff et al. (2012a). Risk prices explaining carry trade premia are found to be highly time-varying and persistent but with several sudden downfalls.

Risk-Premia Dynamics in Style-based Currency Investing

The paper is single-authored.

Recent literature documents attractive significant returns to currency speculation strategies. Portfolios are sorted based on different currency characteristics such as carry (Lustig et al. (2011)), FX momentum (Menkhoff et al. (2012b)), and FX value (Menkhoff et al. (2017)). These trading strategies are of practical relevance in currency trading as well. For example, Deutsche Bank offers exchange-traded funds that invest according to the considered portfolio strategies, such as the Global Currency Harvest, the DB Momentum index and the DB valuation index.

In particular, carry trades are well-known to generate attractive returns but are highly speculative as they are prone to financial crisis and currency crashes (Brunnermeier et al. (2008)). A better understanding of their risk dynamics and associated predictability would, therefore, be of interest to avoid big losses.

A likelihood-based filter is applied to extract and analyze time-varying risk premia from currency portfolio cross-sections. Filtered risk premia for high-minus-low carry and FX value returns are found to be significantly varying and persistent whereas premia for FX momentum do not show crucial time-variation. The latter strategy is therefore particularly suitable for investors preferring a rather steady rate of return.

Superior out-of-sample predictability for carry trade returns is found with respect to a random walk as well as a constant risk price benchmark. The predictability mainly stems from the predictability of returns in safe-haven currencies that tend to be included in the short-leg of the carry trade. Out-of-sample predictability is in contrast not verified for FX momentum

as well as FX value strategies.

Time variation in carry risk premia can mainly be explained by recent carry gains and FX market volatility, supporting the view of Brunnermeier et al. (2008), who argue that predictable returns to the carry trade can be understood as compensations for currency crash risk exposure. In this way, the results of the paper unify the time series findings of Brunnermeier et al. (2008) with the cross-sectional factor structure proposed by Lustig et al. (2011). Moreover, the results guide exchange rate theory in the sense that currency crashes should be tightly connected to carry trade returns that are bets on uncovered interest parity (UIP) deviations. A connection to real economic developments as FX value returns are bets on purchasing power parity alignments is not evidenced.

Foreign Exchange Dealer Asset Pricing

The paper is joint work with Stefan Reitz. My contribution has been the empirical data work and implementation of econometric methods in R for the empirical analysis. The writing and exposition of the paper has been conducted jointly with Stefan Reitz to equal shares. The paper has been presented at the 11th International Conference on Computational and Financial Econometrics (December 2017), the 2nd Workshop on Financial Econometrics and Empirical Modeling of Financial Markets (May 2018), the German Economic Association Annual Conference (September 2018), the Bundesbank Research Seminar (April 2019), the Workshop on Monetary and Financial Macroeconomics (June 2019), and the 2019 Econometric Society European Meeting (August 2019).

The FX market with a turnover of 5,067 billion US dollar in 2016 (BIS 2016) can be considered as the biggest over-the-counter (OTC) market in the world, where a set of specialized dealers provide FX liquidity for a large variety of customers and trade heavily among each other. Particularly large foreign exchange dealers may be perceived as internationally-active financial intermediaries potentially being marginal for pricing FX assets and it is their marginal value of wealth which may propagate a stochastic discount factor. Regarding the intermediaries' specific metric for asset pricing information in general recent empirical contributions stress the importance of balance sheet variables for explaining the cross-section of excess returns in a number of asset classes (He et al. 2017; Adrian et al. 2014).

This paper provides a detailed analysis of the role of FX dealers' balance sheet constraints for currency pricing. Our empirical results show that dealers' capital ratio performs remarkably well as a priced risk factor in a variety of currency portfolio cross-sections. The key insight, however, is that the balance sheet information of the biggest three FX dealers by market

share, as identified by data collected from the yearly EuroMoney FX survey, is sufficient to describe the cross-sectional variation of currency portfolio returns. Empirical asset pricing tests within a generalized method of moments (GMM) framework reveal that this factor outperforms the HKM factor calculated from the broader set of financial intermediaries listed as the New York Fed’s primary dealers as used in He et al. (2017). The empirical analysis, therefore, suggests that excess returns in currency markets can reasonably be explained by the financial wealth of the three most active FX dealers or core dealers who are the relevant marginal dealers, while the additional explanatory power that arises from including more peripheral dealers’ capital ratios is negligible.

Besides providing insights into the pricing ability of top-tier dealers for currency portfolio returns, the analysis is extended by performing asset pricing tests separately on cross-sections sorted by carry, momentum and value. In particular, our top three FX dealer factor shows a remarkably good pricing ability for carry trade portfolios and is even able to outperform the HKM factor in a horse race. This points towards a risk-based explanation of carry trade returns related to balance-sheet conditions of main FX dealers. Currency trading at a high forward discount tends to pay off poorly when the capital ratio decreases and balance sheet constraints are tightening. In contrast, the negative beta of currencies with a forward premium suggests that these provide a hedge for times with decreasing capital ratios. With respect to other portfolio sorts, however, little pricing ability of the intermediary factors is found to explain value portfolios and almost none for currency portfolios sorted on exchange rate momentum implying that these portfolios seem to exert little impact on core FX dealers’ balance sheets. The heterogeneity in the pricing ability with respect to different characteristics is also evident in a analysis of the bilateral rates, where well-known high and low interest rates show a particularly strong positive or negative exposure to financial conditions of the core FX dealers.

An analysis of the pricing power in other asset classes reveals that our FX core dealer factor provides less pricing power in non-FX asset classes than the factor of He et al. (2017). This strengthens the point that the pricing power of core FX dealers’ financial wealth for currency returns does not solely stem from the exposure to the financial wealth of the whole intermediary sector in general but includes information that is specific to foreign exchange markets due to market segmentation.

Chapter II

Likelihood-based Dynamic Asset Pricing

Abstract

This paper proposes a new parametric approach to estimate linear factor models with time-varying risk premia. In contrast to recent contributions to the literature, the framework presented abstains from introducing instrument variables to describe the time variation of risk prices. This is particularly useful in situations where instrument variables are unavailable or of poor quality and misspecification should be circumvented. Risk prices and exposures are derived from a generalized autoregressive score (GAS) model where parameter dynamics are driven by the scaled score of the observation density and therefore reduce its one-step ahead prediction error at the current observation. Estimation and inference are conducted through standard likelihood maximization. A Monte Carlo study assesses the potential improvement in predicting risk prices. Applications to the classical Fama-French three-factor asset pricing model as well as a currency carry trade cross-section illustrate the novel approach.

Keywords: Dynamic Asset Pricing, Generalized Autoregressive Score Models, Time-varying Risk Premia

JEL Codes: G12, G17, C58

1 Introduction

Risk premia for holding financial assets vary over time (Campbell and Shiller (1988), Fama and French (1989), Lettau and Ludvigson (2001), Lettau and Ludvigson (2001), Cochrane (2011)). Traditional factor asset pricing models (for example, Fama and French (1993) and Carhart (1997)) describe this compensation using the market prices of risk (λ s) that are demanded by investors for each unit of exposure (beta) to a financial or macroeconomic source of risk.

Although the predominant methods to test asset pricing models like the two-step regression procedure of Fama and MacBeth (1973) (in the following referred to as the FMB procedure) rely on constant λ s and betas, the appropriateness of this assumption has been largely doubted (Jagannathan and Wang (1996), Ghysels (1998)). In addition, post-crisis macro-finance models incorporating financial frictions in dynamic macroeconomic frameworks such as He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) imply factor model representations including risk prices and exposures depending on other macroeconomic or financial variables. Recent empirical frameworks and estimation methods developed, for example, in Adrian et al. (2015) and Gagliardini et al. (2016) formulate in that sense λ s as affine-linear functions of instrument variables generating the risk price dynamics. However, this approach opens the door to possible misspecifications when inappropriate explaining instruments are employed. Moreover, candidates for driving the dynamics have to be guessed or derived from theory but looking at things the other way around, theoretical models would strongly benefit from empirical studies that employ methods for exploring risk price dynamics independently.

The method presented in this paper allows for estimating dynamic asset pricing models but refrains from incorporating instruments that drive the dynamics. Instead, betas and λ s are modeled as unobserved components driven by the scaled score of the observation density as proposed by Creal et al. (2013). This scaled score step automatically reduces the one-step-ahead prediction error at the current observation. The resulting class of dynamic

asset pricing models allows the filtering of lambda and beta series from asset returns and risk factors only. Estimation and inference can be conducted using the standard maximum-likelihood machinery.

This paper contributes to the existing literature in several ways. The main contribution is the introduction of a general framework for dynamic asset pricing models with score-driven parameter dynamics following the idea of generalized autoregressive score (GAS) models, as introduced by Creal et al. (2013), that has been applied successfully in numerous areas.¹ The resulting score-driven likelihood-based asset pricing model (SLAPM) works for every linear factor model that can be analyzed using the traditional FMB procedure and generates latent risk price and exposure dynamics.

Optimal updating schemes for time-varying lambdas and betas with respect to the observational likelihood are derived in case of elliptically distributed asset returns and show an intuitive relation to the FMB estimates. The updating corrects lambdas and betas with respect to local cross-sectional and time-series errors that are produced when employing FMB with constant parameters. Moreover, the updating downweights the impact of extreme observations when considering heavy-tailed distributions which make the filtered lambdas and betas more prone to outliers.

A Monte Carlo study shows that a Gaussian version of the SLAPM with constant betas is able to filter even persistent risk price dynamics in a realistic setting. The performance of the SLAPM is compared to that of a dynamic asset pricing model developed by Adrian et al. (2015) (in the following referred to as DAPM) which employs noisy signals of different strengths of the true instrument factor driving the lambda dynamics of the data-generating process. In an asset return panel of 25 assets and 500 time observations, a DAPM would need to be informed with a signal containing at least 80% of the information from the true data-generating process to at least be able to compete with an SLAPM as measured by the root mean squared error (RMSE) of forecasting lambdas and the corresponding Diebold and

¹See, for example, Harvey and Lange (2017) and Gorgi et al. (2019) for applications in volatility modeling or Oh and Patton (2018) and Bernardi and Catania (2019) for systemic risk applications.

Mariano (1995) tests.

Two applications illustrate the ability of the SLAPM procedure to filter risk price dynamics from panel data of asset returns. The first one is a dynamic version of the traditional three-factor model of Fama and French (1993). The filtered risk price series show some short-run variations around fairly stable average risk prices in a cross-section of 25 equity portfolios covering roughly the last 90 years. The results generally speak in favor of static risk price methods like two-step FMB regressions but risk prices show huge volatility during financial crises in which they are better covered by dynamic approaches. Interestingly, a pure economic crisis appears to have less impact on risk price variability. The second application contributes to the rapidly growing literature on explaining currency cross-sections as started by Lustig et al. (2011) and Menkhoff et al. (2012a). Risk prices explaining carry trade premia are found to be highly time-varying and persistent but with several sudden downfalls.

The method possibly closest to the one employed here is presented in Adrian et al. (2015). The two main differences are that they specify forecasting variables to drive the time-variation in risk prices in an affine-linear fashion and suggest a three-step estimation approach based on linear regressions. Adrian et al. (2019) include a similar approach that allows for a non-linear relation between risk prices and forecast variables. Risk prices and exposures being affine-linear transformations of instruments are also employed in Gagliardini et al. (2016) with a focus on large cross-sections of individual stock returns.

Early contributions already allow for instrument-free dynamics of risk prices and exposures by conducting the FMB regressions period by period as in Fama and MacBeth (1973) and Ferson and Harvey (1991). The approach presented in the following differs from that by explicitly modelling an intertemporal relation between betas and lambdas of different time periods that can be fitted and analyzed whereas the period-by-period FMB procedures produce parameters that are not explicitly connected over time.

The paper is organized as follows. Section 2 introduces and discusses the proposed score-driven dynamic asset pricing framework and closes by laying out a strategy for likelihood-

based estimation and inference. A Monte-Carlo study evaluating the performance of the SLAPM is conducted in Section 3. Empirical applications are illustrated in Section 5 and Section 6 concludes the paper.

2 A Score-driven Likelihood Asset Pricing Framework

The following chapter introduces a framework for score-driven likelihood-based asset pricing models. The model setup is described first and is followed by a derivation for optimal parameter-updating schemes in case of elliptical distributions. Before turning to the applications in the following section, the estimation strategy is explained and discussed.

2.1 Model Setup

The basic model setup outlined in the following is in line with the approach presented in Adrian et al. (2015) but differs in the specification of risk price and exposure dynamics that are driven by scores of the observation density instead of forecasting variables.

Let $r_t = (r_t^1, \dots, r_t^N)^\top$ denote the N-dimensional vector representing the excess returns of N different assets at time $t \in \{0, \dots, T\}$. Assume the underlying data-generating processes to be defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ that is equipped with a filtration $\mathcal{F}_t = \sigma(\{r_t, \dots, r_0\})$ representing the set of information available at time t.

Suppose the risk in the economy is described in terms of K risk factors covered in the state vector f_t that follows an adapted $VAR(1)$ process given by

$$f_{t+1} = \mu + \Phi f_t + u_{t+1}, \quad t = 0, \dots, T-1. \quad (1)$$

with u_t being i.i.d. disturbances. The modelling approach is not restricted to this choice and more general models like $VAR(p)$ processes may be taken into consideration to better capture the distribution of f_t as this is particularly important for maximum likelihood (ML) estimation. I decide to stick to the $VAR(1)$ model for the sake of brevity and because factors

are mostly returns with if-at-all first order auto-correlation (as is the case for Fama and French (1993) and Carhart (1997)).

The existence of a unique stochastic discount factor (SDF) m_t that prices every asset $i \in \{1, \dots, N\}$ according to

$$\mathbb{E}_t(m_{t+1}r_{t+1}^i) = 0 \quad (2)$$

is assumed. The Euler equation (2) can be reformulated to

$$Cov_t(m_{t+1}, r_{t+1}^i) = -\mathbb{E}_t(m_{t+1})\mathbb{E}_t(r_{t+1}^i) \quad (3)$$

with \mathbb{E}_t and Cov_t denoting the conditional expectation and covariance with respect to time t information \mathcal{F}_t . Let the $K \times K$ matrix $\Sigma_{u,t}$ be the possibly time-varying covariance matrix of the risk factor innovations u_t . Regressing the demeaned return of asset i on the factor innovations u_{t+1} yields an idiosyncratic noise term $e_{i,t+1}$ that is orthogonal to u_{t+1} . Taken together with (3) the return can be decomposed to

$$r_{t+1}^i = \mathbb{E}_t(r_{t+1}^i) + (r_{t+1}^i - \mathbb{E}_t(r_{t+1}^i)) \quad (4)$$

$$= -\frac{Cov_t(m_{t+1}, r_{t+1}^i)}{\mathbb{E}_t(m_{t+1})} + \beta_i^\top u_{t+1} + e_{i,t+1} \quad (5)$$

with $\beta_{i,t} = \Sigma_{u,t}^{-1}Cov_t(u_{t+1}, r_{t+1}^i)$ being the K -dimensional vector of risk exposures. Further, assume that the SDF is affine-linear in the economy's risk factor innovations i.e.

$$\frac{m_{t+1} - \mathbb{E}_t(m_{t+1})}{\mathbb{E}_t(m_{t+1})} = -\lambda_t^\top \Sigma_{u,t}^{-1} u_{t+1} \quad (6)$$

with time-invariant price of risk vector λ_t of dimension K . Plugging the SDF into the return decomposition (5) yields a standard beta representation given by

$$r_{t+1}^i = \lambda_t^\top \Sigma_{u,t}^{-1} \text{Cov}_t(u_{t+1}, r_{t+1}^i) + \beta_i^\top u_{t+1} + e_{i,t+1} \quad (7)$$

$$= \beta_{i,t}^\top \lambda_t + \beta_{i,t}^\top u_{t+1} + e_{i,t+1}. \quad (8)$$

The decomposition (8) therefore consists of a predictable risk premium $\beta_{i,t}^\top \lambda_t$ that prices risk exposures and another unpredictable component $\beta_{i,t}^\top u_{t+1}$ depending on risk factor innovations. Representation (8) may be interpreted as a system of seemingly unrelated regressions (SUR) with time-varying coefficients and identical regressors that can be stacked to

$$r_{t+1} = \beta_t(\lambda_t + u_{t+1}) + e_{t+1} \quad (9)$$

with $\beta_t = (\beta_{1,t}, \dots, \beta_{N,t})^\top$. What essentially distinguishes the approach proposed here from prior contributions is the specification of the dynamics of the time-varying $(N + 1)K$ -dimensional parameter vector $\theta_t = (\lambda_t^\top, \text{vec}(\beta_t)^\top)^\top$.² Whereas for example Adrian et al. (2015) assume that λ_t is affine-linear in a forecasting variable that has to be specified and time-varying betas are derived from a non-parametric kernel-based approach, the approach discussed here suggests to use a data driven approach for both sets of varying parameters. The GAS model³ proposed by Creal et al. (2013) provides an opportunity to introduce time variation into general models with specified observation densities. Their basic idea is to let the time-varying parameters of a model be updated proportionally to the score of the observation density i.e. the derivative of the logarithmic density with respect to the parameter that should become time-varying. Thus, the parameter vector is pushed in the direction indicated by the gradient. This is the direction in which the update would yield the steepest increase in the observation density. The approach can therefore be understood as a param-

² K lambdas and N betas per lambda.

³Models of this type are also known as dynamic conditional score (DCS) or score-driven models. See Harvey (2013).

eter update optimizing the local likelihood in period t .

In the framework described above, asset returns r_t as well as risk factor realizations f_t are observed and the conditional observation density $p(r_t, f_t | \mathcal{F}_{t-1}, \theta_{t-1})$ has to be specified. Given such a specification, the GAS updating scheme for the dynamic vector of risk prices and exposures is then given by:

$$\theta_t = \omega + \sum_{i=1}^p A_i s_{t-i+1} + \sum_{j=1}^q B_j \theta_{t-j} \quad (10)$$

$$s_t = \mathcal{I}_t^{-1} \nabla_t, \quad \nabla_t = \frac{\partial \ln p(r_t, f_t | \mathcal{F}_{t-1}, \theta_{t-1})}{\partial \theta_{t-1}}. \quad (11)$$

Equation (10) determines the updating mechanism for the time-varying parameter θ_t . Here, ω is an $(N+1)K$ -dimensional vector of intercepts and A_i, B_j are $(N+1)K \times (N+1)K$ matrices of coefficients for $i = 1, \dots, p$ and $j = 1, \dots, q$. The updating process therefore consists of a constant part, an adjustment of the observation density score, and an autoregressive part.

The centerpiece of score-driven models is the specification of the innovation sequence s_t . This is done by setting s_t proportional to the so-called score ∇_t defined in (2.3). Creal et al. (2013) leave open to scale the impact of the score sequence to make models more robust to outliers. I follow their proposal to employ the inverted Fisher information matrix \mathcal{I}_t^{-1} for scaling. The specific definition in our framework is $\mathcal{I}_t = \mathbb{E}_{t-1}(\nabla_t \nabla_t')$ with \mathbb{E}_{t-1} being the expectation operator with respect to $p(r_t, f_t | \mathcal{F}_{t-1}, \theta_{t-1})$. This bears the advantage that the scaling depends directly on the variance of the score and yields an intuitive interpretation of the updating scheme if elliptically distributed residuals are assumed as will be shown below.⁴

Given that $\mathbb{E}(\nabla_t \nabla_t')$ is finite, the innovation s_t is a martingale difference sequence implying that θ_t in (10) is an ARMA process that inherits the features of this class of time series.

This holds particularly for stationarity conditions.

⁴Other popular scalings use an identity matrix or the Cholesky factor of the inverse Fisher information. The latter choice may be attractive to achieve unit variance of the scaled score process s_t .

2.2 Optimal Parameter Updating for Elliptically Distributed Returns

To compute the score ∇_t , assumptions on the distributions of the innovations u_t and e_t have to be made. I consider the distribution families from the general class of elliptical distributions⁵ to allow for flexibility in fitting the data while keeping the framework tractable. The general N-dimensional density of such distributions can be formulated as $p(x) = |\Omega|^{-\frac{1}{2}} \psi(x' \Omega^{-1} x, \nu)$ with a dispersion matrix $\Omega \in \mathbb{R}^{N \times N}$, a degrees-of-freedom parameter $\nu \in \mathbb{R}_{>0}$, and a characteristic generator $\psi : \mathbb{R}_{\geq 0} \times \mathbb{R}_{>0} \rightarrow \mathbb{R}_{\geq 0}$ ⁶. The elliptical class includes not only the normal distribution, as can be seen by choosing the generator to be $\psi(x, \nu) = (2\pi)^{-N/2} \exp(-x/2)$, but also many other distributions like the Laplace and the Student's t-distribution that are popular for fitting financial returns.

Quite intuitive formulas can be derived for the driving martingale difference sequences s_t of time-varying risk prices and exposures can be derived when assuming zero cross-information quantities i.e. $\mathcal{I}_t^{\lambda, \beta} = \mathcal{I}_t^{\beta, \lambda} = 0$. This assumption additionally assures the validity of the derived updating schemes below, when betas or lambdas are assumed to be constant what often yields more parsimonious models. Explicit calculations can be found in Appendix A. The scaled scores turn out to be

$$\begin{pmatrix} s_t^\lambda \\ s_t^\beta \end{pmatrix} = C(\tilde{e}_t, \psi^e) \begin{pmatrix} (\beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1})^{-1} \beta_{t-1}^\top \Omega_e^{-1} r_t - (\lambda_{t-1} + u_t) \\ (\lambda_{t-1} + u_t)^\top ((\lambda_{t-1} + u_t)(\lambda_{t-1} + u_t)^\top)^{-1} r_t - \beta_{t-1} \end{pmatrix} \quad (12)$$

with

$$C(\tilde{e}_t, \psi^e) = -\frac{N \frac{\psi_1^e}{\psi^e}}{2\mathbb{E}_{t-1} \left(\|\tilde{e}_t\|^2 \left(\frac{\psi_1^e}{\psi^e} \right)^2 \right)}.$$

⁵See Fang et al. (1990) or Chapter 6 of Embrechts et al. (2015) for a comprehensive treatment of elliptical distributions.

⁶The general definition of elliptical distributions includes a location parameter vector $\mu \in \mathbb{R}^N$. However, a zero mean of the innovation terms is assumed throughout the paper and μ is therefore neglected for convenience.

The updating sequence can be seen as a scaled difference of the generalized least squares (GLS) coefficient estimate from cross-sectionally regressing r_t on β and the observed coefficient $\lambda_{t-1} + u_t$. The driving mechanism therefore intuitively corrects local deviations in the cross-section. This observation can be related to the very popular estimation approach of Fama and MacBeth (1973) in which constant risk prices are estimated with a cross-sectional regression of the average portfolio returns \bar{r} on their betas i.e. the risk price estimate is given by $(\beta^\top \Sigma_e^{-1} \beta)^{-1} \beta^\top \Sigma_e^{-1} \bar{r}$. The correction step proposed by (12) for the lambda essentially enforces this average prescription. Finding $\lambda_{t-1} + u_t$ to be greater than $(\beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1})^{-1} \beta_{t-1}^\top \Omega_e^{-1} r_t$ would be interpreted as an overestimation of the market price of risk plus factor innovation. The resulting s_t^λ would be negative (given that $C(\tilde{e}_t, \psi^e) > 0$) and would downsize the market price of risk for the next period. The term $C(\tilde{e}_t, \psi^e)$ as well as the coefficient matrices A_1, \dots, A_p reveal how much of the local estimation error can be possibly attributed to a change in risk prices and not to factor innovations u_t . This mechanism points out the difference of the proposed method to the time-varying lambda framework in Fama and MacBeth (1973) which would choose λ_t in each period to set the cross-sectional regression error to zero. This comes with the drawback that time-varying lambdas become unrealistically volatile because cross-sections are fitted independently period by period and do not offer insights into the connections between lambdas of different time periods.

Interestingly, the optimal beta updating analogously adjusts to the OLS error by locally estimating the stacked SUR model in (9). The discussion of the lambda updating holds accordingly for that of time-varying betas.

With regard to the distributional assumption it is striking that the particular choice of the elliptical distribution does not alter the direction of the score and therefore also does not alter the direction of the parameter updating. However, the scalar part depends on observed residuals that depend on t . Updating steps are therefore weighted with regard to the shape of the particular distribution. A particularly simple updating is achieved when assuming

normal distributions, as $C(\tilde{e}_t, \psi^e) \equiv 1$ holds in this case.⁷ The effect of the scaling becomes clear when looking on the Student's t-updating sequence, where the scalar part is given by $C(\tilde{e}_t, \psi^e) = \frac{\nu+N+2}{\nu+e'_t\Omega_e^{-1}e_t}$.⁸ The division by $\|\tilde{e}_t\|^2 = e'_t\Omega_e^{-1}e_t$ down-weighs the impact of scores when observing extreme values and therefore takes the more pronounced tails of the return distribution into account. Hence, imposing this updating structure makes the market price of risk more robust to outliers in the data. Therefore, it might henceforth be beneficial for tractability to assume a distribution that yields a simple updating scheme such as the Gaussian distribution. However, such a simplification would come at the cost of incorrectly weighting the magnitude of extreme observations.

Moreover, the updating scheme does not depend on the distribution of the factor innovations u_t . Hence, one could introduce some statistical features like heavy tails and asymmetries in the model without giving up a simple updating scheme by adjusting the distribution of u_t . However, this does not open up the possibility to allow for these features idiosyncratically for specific assets in the cross-section.

With the specified distributions for the residuals, (12) completes our dynamic asset pricing model framework consisting of the equations (62), (9), (10), and (12). We refer to it as the (elliptical) SLAPM of orders p and q (SLAPM(p,q)).

2.3 Estimation and Inference

The elliptical SLAPM discussed so far ends up with a reduced-form representation that can be estimated with an ML-procedure. The set of static parameter vectors and matrices to be estimated is given by $\omega, A_1, \dots, A_p, B_1, \dots, B_q, \mu, \Phi, \Omega_e, \Omega_c, \nu_e$, and ν_u . This collection of parameters needs to be chosen to maximize the log-likelihood function given by

$$\mathcal{L} = \sum_{t=1}^T \ln \psi^e(e'_t\Omega_e^{-1}e_t, \nu_e) + \ln \sum_{t=1}^T \psi^u(u'_t\Omega_u^{-1}u_t, \nu_u) - \frac{T}{2} (\ln |\Omega_e| + \ln |\Omega_u|). \quad (13)$$

⁷See Corollary 3 and its proof in the technical appendix.

⁸See Corollary 4 and its proof in the technical appendix.

Besides the problems associated with the enormous number of parameters, closed-form solutions of the ML-estimators are not available due to the strong dependencies of the parameters on each other. This makes it necessary to employ numerical optimization procedures.

The elliptical SLAPM(p,q) is quite general and can be simplified further by imposing technical or economic restrictions, which would result in a more parsimonious model. As an illustration of the framework, let us focus on a Gaussian SLAPM with constant betas which yields a reduced number of parameters. Although there is a large body of literature assuming time-varying betas, empirical studies such as Braun et al. (1995) and Ghysels (1998) document that changes in betas are rather slow-moving. Assuming constant betas and letting the dynamics kick in from time-varying lambdas to achieve a parsimonious model could therefore be justified in this regard. The Gaussianity of the asset's residual distribution represented by the characteristic generator ψ_e ensures a simple and tractable updating scheme for the time-varying lambda that adjusts for local Fama-MacBeth errors. These assumptions turn out to be sufficient to reasonably filter risk price dynamics for asset cross-sections. However, for prediction purposes, a more adequate fit to the statistical properties of return time series can be achieved by an alternative specification of the factor innovation distributions u_t as mentioned in the previous section.

The complete reduced form Gaussian constant beta SLAPM(p,q) is then given by

$$f_{t+1} = \mu + \Phi f_t + u_{t+1}, \quad t = 0, \dots, T-1 \quad (14)$$

$$r_{t+1} = \beta(\lambda_t + u_{t+1}) + e_{t+1} \quad (15)$$

$$\lambda_t = \omega^\lambda + \sum_{i=1}^p A_i^\lambda s_{t-i+1}^\lambda + \sum_{j=1}^q B_j^\lambda \lambda_{t-j} \quad (16)$$

$$s_t^\lambda = (\beta^\top \Omega_e^{-1} \beta)^{-1} \beta^\top \Omega_e^{-1} r_t - (\lambda_{t-1} + u_t) \quad (17)$$

The likelihood in (13) can be optimized in several steps. The parameters of the factor VAR model (14) are estimated independently in a first stage where the ML-estimator in the

Gaussian case is the usual OLS estimator given by

$$\begin{bmatrix} \hat{\mu}, \hat{\Phi} \end{bmatrix} = \sum_{t=1}^T f_t f_{t-1}^\top \left(\sum_{t=1}^T f_{t-1} f_{t-1}^\top \right)^{-1}. \quad (18)$$

This estimation approach may yield inefficiencies because the factor innovations u_t enter the idiosyncratic portfolio errors e_t via the return equation (15). However, this effect is found to be negligible.

In the second step, the fitted residuals from (14) are plugged in and the likelihood is numerically optimized with respect to the remaining GAS parameters $\lambda_0, \omega^\lambda, A_1^\lambda, \dots, A_p^\lambda, B_1^\lambda, \dots, B_p^\lambda$ and β using a quasi-Newton procedure. Especially challenging is the problem that the covariance matrix Ω_e enters the updating scheme in (17) and therefore makes a direct evaluation of the likelihood impossible. A possible solution would be to assume cross-sectionally homoscedastic errors e_t in such a way that (17) simplifies to $s_t^\lambda = (\beta^\top \beta)^{-1} \beta^\top r_t - (\lambda_{t-1} + u_t)$, thus allowing direct computation of the likelihood. However, the computations in the following applications refrain from this assumption and instead compute the likelihood iteratively with general Σ_e . This is done by computing fitted residuals \hat{e}_t as an initial guess from the constant Fama-MacBeth procedure and estimating the residual covariance matrix with $\hat{\Sigma}_e = \sum_{t=1}^T e_t e_t^\top$. This is followed by a computation of the time-varying lambda sequence with the as well as risk exposures according to . Next, one must re-estimate \hat{e}_t and $\hat{\Sigma}_e$ with and repeat until convergence.

Inference is conducted in the standard fashion for ML-estimators as suggested by Creal et al. (2013) for GAS models in general. If ϑ stacks all the static parameters of the model, standard asymptotic theory for ML-estimators would suggest that under some regularity conditions the following holds:

$$\sqrt{T} \left(\hat{\vartheta} - \vartheta \right) \xrightarrow{d} \mathcal{N} \left(0, H^{-1} \right) \quad (19)$$

with $H = \lim_{T \rightarrow \infty} \mathbb{E} \left((\partial \mathcal{L} / \partial \theta) (\partial \mathcal{L} / \partial \theta') \right) / T$. Standard errors in the following are derived by numerically differentiating the score function with a finite difference approximation.

3 Scores vs Forecasters: A Monte Carlo Study

The performance of the Gaussian constant beta SLAPM is evaluated with a Monte Carlo study on forecasting risk prices in the following. The standard static approach of Fama and MacBeth (1973) and the DAPM of Adrian et al. (2015) are considered as benchmark methods for comparison. The latter approach assumes that factors in f_t may be risk price factors f_1 or forecasting factors f_2 in such a way that $f_t = (f_{1t}^\top, f_{2t}^\top)^\top$ and

$$r_{t+1} = \beta(\lambda_0 + \Lambda_1 f_{2t}) + \beta u_{1,t+1} + e_{t+1}$$

with $u_{1,t+1}$ being the components of the innovations risk factor VAR model (62) associated with the risk price factors.⁹ The DAPM can be estimated with a three-step linear regression approach and nests the constant risk price model of Fama and MacBeth (1973).

The data-generating process employed for simulations is in line with the DAPM modeling approach with exactly one risk factor f_{1t} and one forecasting factor f_{2t} . In order to generate realistic returns we orientate on a capital asset pricing model (CAPM) of an industrial portfolio cross-section from the Kenneth R. French data library. The pricing factor supposed to be the market return that is found to be fairly well represented by an ARMA(1,1)-process with GARCH(1,1)-residuals. Thus, the heteroscedasticity in the return series is modeled to be sourced from the risk factor process. To get a candidate process for the forecasting factor, a DAPM with two forecasting factors is fitted. The forecasting factors under consideration are the 10-year treasury yield obtained from the H.15 statistical release of the Board of Governors of the Federal Reserve System as well as the ten year dividend yield of the *S&P* – 500 index. Both series are found to be reasonable stock return predictors in the past.¹⁰ For simplicity, the two predictors are combined to form one forecast process

⁹Adrian et al. (2015) explicitly include the possibility for factors to be both risk and forecasting factors. We abstain from this for simplicity.

¹⁰See Keim and Stambaugh (1986), Campbell (1987), Fama and French (1989), Campbell and Thompson (2008) for evidence on long-run treasury yields and Campbell and Shiller (1988), Fama and French (1989), Campbell and Thompson (2008), Cochrane (2008) for dividend yields.

by computing the linear combination of the two weighted by coefficients from the fitted DAPM. The forecasting factor process dynamics are found to be well-described by an AR(1)-process given by $f_{2,t+1} = 0.005 + 0.98f_{2,t} + u_{2,t}$, $u_{2,t} \sim \mathcal{N}(0, \sigma_f^2)$ and $\sigma_f = 0.11$ that is used for simulation in the following. The high level of persistence with AR(1)-coefficients near unity is often observed for return forecasting factors (Campbell and Yogo (2006)). From the simulated risk and forecasting factor processes, the risk price process is derived as $\lambda_t = 0.38 + f_{2,t}$, where the intercept has been calibrated to the industry portfolio data. The simulated return values are finally derived from the beta representation according to (2.3) with betas uniformly drawn from the interval $[0.5, 1.5]$ that is roughly the range observed for portfolio exposures when regressing portfolio returns on the market risk factor.

Because $\mathbb{E}_T(R_{T+1}) = \beta\lambda_T$, predicting stock market returns for period $T + 1$ would need an accurate estimation of λ_T . Let us therefore evaluate the accuracy of the different approaches by the ability of predicting the one-period-ahead risk price. The predictions of the different approaches would be:

$$\text{SLAPM : } \quad \hat{\lambda}_T^{GAS} = \hat{\omega} + \hat{A}s_T + \hat{B}\hat{\lambda}_{T-1}^{GAS} \quad (20)$$

$$\text{FMB : } \quad \hat{\lambda}_T^{FMB} = \hat{\lambda}^{FMB} \quad (21)$$

$$\text{DAPM : } \quad \hat{\lambda}_T^{ACM} = \hat{\lambda}_0 + \hat{\Lambda}_1 f_{2,T} \quad (22)$$

Given the simulated data set, λ_T is predicted with the three approaches mentioned above. Since the part of the data-generating process concerning the market price of risk dynamics completely follows the specification in Adrian et al. (2015), the DAPM estimator has a trivially high information advantage over the other two approaches when using $f_{2,t}$. To circumvent this issue, the DAPM is fitted with employing a diffuse signal of the true forecast factor realization ranging from pure noise to perfectly non-diffused signal. The DAPM is

therefore estimated with a signal $\tilde{f}_{2,t}$ drawn from

$$\tilde{f}_{2,t} = \kappa f_{2,t} + (1 - \kappa)\epsilon_t, \quad \epsilon_t \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_f^2) \quad (23)$$

with $\kappa \in [0, 1]$. For $\kappa = 0$ the signal exhibits no information about the true factors and for $\kappa = 1$ the DAPM exploits the true forecasting factor series.

Figure 2(a) shows an example draw of the simulated excess return of one portfolio from cross-section ($N = 25, T = 500$) together with its conditional excess return $\beta\lambda_{t-1}$. The conditional return in relation to the actual return can be regarded as only fairly small in magnitude. This fits the observation that stock returns show only little predictability, if at all. Therefore, it may be considered quite difficult to extract risk prices from a set of such return series. However the SLAPM seems to be quite effective in filtering λ_t , as indicated in Figure 2(b). The updating direction and turning points are anticipated correctly. Only peaks are hard to capture for the likelihood score-based filter. This means that extreme local cross-sectional errors resulting due to extreme changes in the risk price are devoted with a too large share to factor and idiosyncratic innovations. The full-information DAPM, as expected, better captures the peaks but has a slight tendency to overshoot.

Table 1 shows the RMSEs of the different forecasting approaches for different numbers of assets N and time observations T computed from 1000 simulations of each cross-section. Diebold and Mariano (1995) (DM) tests are additionally conducted on the null hypothesis that the SLAPM forecast is less accurate than or as accurate as the alternative forecast. The shaded areas indicate that the null hypothesis cannot be rejected for the respective forecast. The SLAPM prediction therefore shows a superior forecast accuracy than all forecasts that are not shaded.

At first sight, the SLAPM always shows a lower RMSE than the respective forecast from the Fama-McBeth regressions, and the null hypothesis of the DM test can be rejected indicating superior forecast accuracy with respect to the FMB forecast. The same holds for the DAPM

forecasts with pure noise forecasters. The evidence therefore suggests that the SLAPM succeeds in filtering information on the time variation in risk prices from the return series. For $T = 500, 1000$ the DAPM with $\kappa = 1$ shows the lowest RMSEs, as may be expected. However, for the short samples with $T = 100$, the DAPM performs much worse than the FMB forecast, irrespective of the employed signal. It can be seen that the DAPM suffers much more from a short sample length than the SLAPM, which still beats FMB for $T = 100$ despite performing worse than in situations with higher T . Surprisingly, in every N-T-combination considered, the SLAPM forecast is more accurate than the DAPM forecast using a signal that consists of less than 70% noise diffusion due to the DM test. This threshold is even lower for smaller samples. This points to a not negligible risk of misspecification when one is unsure about the correct forecast variable. For standard cross-sections with 25 to 100 portfolios, about 70% of the variation from the instrument supposed to explain the risk price time dynamics have to come from the true data generating process for the regression-based method to perform better than a method that uses none of this information.

Although an increase in time observations decreases the RMSE of instrument-based forecasts, their performance does not necessarily benefit from a richer cross-section. This suggests that the inappropriate instrument problem may not be resolved using larger panels or individual asset return cross-sections as in Gagliardini et al. (2016).

4 Empirical Applications

In the following, two empirical applications of the SLAPM framework are presented. The first one is a dynamic version of the popular three-factor model of Fama and French (1993) which prices a cross-section of 25 equity portfolios. The second one deals with the two-factor model of a carry trade cross-section studied in Lustig et al. (2011).

4.1 A Dynamic Fama-French 3-Factor Model

As a straightforward application of the SLAPM framework, a dynamic version of the well-known Fama-French three-factor model (FF3) from Fama and French (1993), is fitted to a cross-section of equity portfolios. The data has been obtained from Kenneth French's data library and consists of monthly returns of 25 portfolios formed on size and book-to-market as well as three series of risk factors. These are the equally weighted market portfolio return of all US stocks listed on the New York stock exchange (MKT), a small-minus-big (SMB) factor and a high-minus-low (HML) factor. The time-span starts in July 1926 and ends in March 2018.

A Gaussian constant beta SLAPM(1,1) is employed with non-diagonal elements of the parameter matrices in the updating scheme (16) restricted to be zero. In this way a more parsimonious model is obtained with three risk price updating equations given by

$$\lambda_t^i = \omega_i + A_i((\beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1})^{-1} \beta_{t-1}^\top \Omega_e^{-1} r_t - (\lambda_{t-1} + u_t))_i + B_i \lambda_{i,t-1} \quad (24)$$

$$= \omega_i + A_i((\beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1})^{-1} \beta_{t-1}^\top \Omega_e^{-1} r_t - u_t)_i + (B_i - A_i) \lambda_{i,t-1} \quad (25)$$

$$= \omega_i + \tilde{A}_i \tilde{s}_{i,t} + \tilde{B}_i \lambda_{i,t-1} \quad (26)$$

with $\tilde{A}_i = A_i$, $\tilde{B}_i = B_i - A_i$, $\tilde{s}_{i,t} = ((\beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1})^{-1} \beta_{t-1}^\top \Omega_e^{-1} r_t - u_t)_i$ and $i \in \{1, 2, 3\}$ or $i \in \{r^M, SMB, HML\}$ when identifying each component with the respective factor. The updating schemes in (26) are implemented to increase the stability of the optimization routine. Hence, the persistence of the risk price processes can be evaluated by computing $B_i = \tilde{A}_i + \tilde{B}_i$.

The parameter estimates for the lambda updating are presented in Table 2. The long-run risk prices can be computed as the unconditional mean of the ARMA interpretation of the updating schemes in (24) given by $\bar{\lambda} = \omega_i / (1 - B_i) = \omega_i / (1 - (\tilde{A}_i + \tilde{B}_i))$. They show values close to the FMB estimates assuming constant risk prices. This speaks in favor of a good average pricing ability of the unconditional FF3 model. However, the risk price dynamics

illustrated in Figure 2 provide evidence that unconditional pricing matters and reveals substantial differences in dynamic patterns of the three factors. MKT has the most volatile risk price series with the highest exposure to the FMB correction term as indicated by \tilde{A}_{MKT} being around 0.1451. It is particularly sensitive to financial crisis periods which are marked by substantial peaks and volatility clusters. However, the same pattern can not be observed in many general economic crises indicated by the shaded areas representing NBER recessions. Also striking is the rather high persistence of the SMB risk prices which is mirrored also in the estimated coefficient $B_{SMB} = \tilde{A}_{SMB} + \tilde{B}_{SMB} = 0.8764$ that is relatively high in comparison to those of the other two risk price series. In particular, the SMB risk price seems to evolve in cycles of four to five years. In contrast, the HML risk prices fluctuate closely around their unconditional mean with high volatility phases in periods of financial crisis.

The empirical illustration shows that the Gaussian constant beta SLAPM(1,1) offers enough flexibility to filter a diverse range of differing risk price dynamics in a factor model simultaneously. The evidential statistical patterns revealed may improve our understanding of the associated risk factors when analyzed in further research. Also promising would be to clarify whether the occurrence of peaks in economic and financial recessions can help to measure or understand economic uncertainty. Since risk prices represent the premium demanded by investors per unit of exposure to a specific risk factor, taking time-varying lambdas as uncertainty indicators would be a straight-forward interpretation.

4.2 The Cross-Section of Carry Trade Returns

The Monte Carlo study in Section 3 provides evidence that in small cross-sections the SLAPM still provides good estimates of risk prices compared to the DAPM of Adrian et al. (2015). A small cross-section that has been studied recently can be found in Lustig et al. (2011) who find that the cross-section of five or six carry trade portfolios respectively can be reason-

ably priced by a two-factor model. Carry trades are popular speculative currency trading strategies that usually invest money in currencies bearing high interest rates and finance this investment with a credit in currencies with low interest rates. The predictable part of carry trade returns in the model of Lustig et al. (2011) is again given by the product of risk prices and associated risk exposures. Knowledge about the time dynamics of lambdas may help speculators to evaluate better the profitability of their carry trade positions. However, applying the DAPM would require good instruments that are possibly hard to find since the exchange rate disconnect puzzle of Meese and Rogoff (1983) refers to the weak relations of exchange rates and macroeconomic fundamentals that would come to mind as candidates otherwise. Applying the SLAPM to this problem therefore appears reasonable and one finds persistent risk price dynamics that may be exploited.

The data set consists of 48 spot exchange rates and one-month-forward exchange rates from Thomson-Reuters Datastream with the US-dollar being the base currency. The data covers the period from January 1984 to February 2017. Transaction costs are adjusted by considering bid and ask quotes. All available currencies are sorted into five equally weighted portfolios. The first portfolio (C1) therefore includes the fifth of currencies with the lowest interest rate differential to the US interest rates and the fifth portfolio (C5) the fifth of currencies with the highest interest rate differential. A first risk factor of the model from Lustig et al. (2011) is the return series of a currency market portfolio referred to as DOL-portfolio that holds an equally-weighted position in each currency. This may be seen as an equivalent of the market return factor in the CAPM for equity cross-sections. The second is the return of a portfolio that holds a long position in the high interest rate portfolio financed through a short position in the low interest rate portfolio. The latter factor is referred to as HML. A Gaussian constant beta SLAPM(1,1) with DOL and HML employed as risk factors is fitted to the five carry trade portfolios return cross-section. To avoid over-parametrization, the non-diagonal elements of the GAS parameter matrices are set to zero again. The updating

equations for both risk factors thus take the form

$$\lambda_t^{DOL} = \omega_{DOL} + \tilde{A}_{DOL}\tilde{s}_{1t} + \tilde{B}_{DOL}\lambda_{t-1}^{DOL} \quad (27)$$

$$\lambda_t^{HML} = \omega_{HML} + \tilde{A}_{HML}\tilde{s}_{2t} + \tilde{B}_{HML}\lambda_{t-1}^{HML} \quad (28)$$

with scalar parameters $\omega_{DOL}, \omega_{\eta}, \tilde{A}_{DOL}, \tilde{A}_{\eta}, \tilde{B}_{DOL}$, and \tilde{B}_{η} .

Estimates of the GAS parameters are presented in Table 3. The beta estimates shown in the right-hand panel are qualitatively similar to what can be observed using the FMB procedure with constant lambdas. Betas of the DOL factor are around unity and the DOL risk can therefore be interpreted as a general compensation for currency market risk, whereas the spread in the HML factor betas indicate that the risk associated with this factor generates the carry trade returns. The left-hand panel of Table 3 shows that both factor risk price processes are quite persistent, with HML risk prices being on a higher level and exhibiting a higher variance as can also be seen from the plots in Figure 3. Hence, the predictable component of carry trade returns varies over time with some persistence that may be exploited for forecasting. An out-of-sample analysis on predictability would be necessary to clarify this conjecture but is out of scope for this paper and left for further research.

5 Conclusions

The paper introduced an empirical dynamic asset pricing framework that allows for time-varying lambdas and betas which are unobserved processes filtered from the cross-section of asset returns and the asset pricing model's factor structure in line with the more general GAS model from Creal et al. (2013). It is applicable to a wide range of linear factor models in the finance literature. A main advantage is that no forecasters or instruments are required to describe the time dynamics of risk prices or exposures. A Monte-Carlo study provides evidence that this is a non-negligible source of possible misspecification that can be circumvented by employing a SLAPM. Updating schemes for the class of SLAPM models

with elliptically distributed innovations have been derived. It turns out that the updating direction within this class is unaffected by the distributional assumptions but the magnitude of risk parameter movements depends on the shape of the corresponding probability density function. A particular treatable model with respect to complexity and computational burden for estimation is the presented Gaussian constant beta SLAPM(1,1) model. It has been illustrated with empirical applications to the traditional FF3 model as well as a currency carry trade cross-section.

Due to the generality of the modeling framework, many applications are imaginable as being fairly out of the scope of the present paper to be seen as a methodological foundation for a promising alternative in dynamic risk premia modeling. Further research can also be conducted on the methodological front. The Gaussian constant beta SLAPM poses crucial distributional assumptions on the innovations that may be further relaxed to capture more statistical features of financial returns like negative skewness and excess kurtosis. This may be particularly important if the purpose is not mainly devoted to first moments as is the case when filtering lambdas in the present paper but if tail properties as in risk management applications are of interest.

Appendix

The following technical derivations prove the main results of SLAPM models with elliptically distributed innovations. To be clear about the setting in which the following results hold the elliptical SLAPM(p,q)-model is summarized in the following definition:

Definition 1 Let $(r_t)_{t=1}^T$ and $(f_t)_{t=1}^T$ time series of dimensions N and K respectively. We define the **elliptical SLAPM(p,q)-model** as the system given by

$$f_{t+1} = \mu + \Phi f_t + u_{t+1} \quad (29)$$

$$r_{t+1} = \beta_t \lambda_t + \beta_t u_{t+1} + e_{t+1} \quad (30)$$

$$\theta_t = \omega + \sum_{i=1}^p A_i s_{t-i+1} + \sum_{j=1}^q B_j \theta_{t-j}, \quad \theta_t = \begin{pmatrix} \lambda_t \\ \text{vec}(\beta_t) \end{pmatrix} \quad (31)$$

$$s_t = \begin{pmatrix} s_t^\lambda \\ s_t^\beta \end{pmatrix} = \begin{pmatrix} \mathcal{I}_t^\lambda & \mathcal{I}_t^{\lambda,\beta} \\ \mathcal{I}_t^{\beta,\lambda} & \mathcal{I}_t^\beta \end{pmatrix}^{-1} \begin{pmatrix} \nabla_t^\lambda \\ \nabla_t^\beta \end{pmatrix} = \mathcal{I}_t^{-1} \nabla_t \quad (32)$$

$$p_u(u_t) = |\Omega_u|^{-\frac{1}{2}} \psi^u(u_t' \Omega_u^{-1} u_t, \nu_u), \quad p_e(e_t) = |\Omega_e|^{-\frac{1}{2}} \psi^e(e_t' \Omega_e^{-1} e_t, \nu_e) \quad (33)$$

with observational density score ∇_t , associated Fisher information matrix \mathcal{I}_t^{-1} , elliptical density generators $\psi^e, \psi^u : \mathbb{R}_{\geq 0} \times \mathbb{R}_{> 0} \rightarrow \mathbb{R}_{\geq 0}$ and parameter vectors/matrices $\mu, \Phi, \omega, A_1, \dots, A_p, B_1, \dots, B_q, \Omega_u, \Omega_e, \nu_u, \nu_e$ of appropriate dimensions.

Before dealing with the main technical results of the paper, a lemma for spherically distributed random vectors will be proven first, that will be helpful in following derivations. A n -dimensional random vector x is spherically distributed if $x = rs$, where s is uniformly distributed on the $(n-1)$ -dimensional unit sphere and r is a non-negative random number that is independent of s (Fang et al. (1990)).

Lemma 1 For every $A \in \mathbb{R}^{n \times n}$ and an n -dimensional random vector x following an spherical distribution holds

$$\mathbb{E} \left(\frac{x^\top}{\|x\|} A \frac{x}{\|x\|} \middle| \|x\| \right) = \frac{1}{n} \text{tr}(A).$$

Proof. W.l.o.g. assume that $x \sim N(0, I_n)$. We compute that

$$\mathbb{E} \left(x^\top A x \right) = \mathbb{E} \left(\sum_{i,j=1}^n x_i A_{ij} x_j \right) = \sum_{i,j=1}^n A_{ij} \mathbb{E} (x_i x_j) = \sum_{i=1}^n A_{ii} \mathbb{E} (x_i^2) = \text{tr}(A)$$

The lemma is validated by observing that

$$\mathbb{E} \left(x^\top A x \right) = \mathbb{E}(\|x\|^2) \mathbb{E} \left(\frac{x^\top}{\|x\|} A \frac{x}{\|x\|} \middle| \|x\| = 1 \right)$$

and $\mathbb{E}(\|x\|^2) = \mathbb{E}(x^\top I_n x) = n$. ■

We now turn to the derivation of general formulas for the scores and information matrices for SLAPM models with elliptical distribution assumptions represented by density generator functions ψ^e and ψ^u . An explicit parameter updating scheme in the case of zero cross-information quantities

$(\mathcal{I}_t^{\lambda,\beta} = \mathcal{I}_t^{\beta,\lambda} = 0)$ will be derived in Corollary 2. Further results provide scores and information quantities for Gaussian and Student's-t SLAPM models.

Proposition 1 *The score and corresponding Fisher information matrix in the updating scheme of an elliptical SLPAM(p,q)-model are given by*

$$\nabla_t = \begin{pmatrix} \nabla_t^\lambda \\ \nabla_t^\beta \end{pmatrix} = -2 \frac{\psi_1^e}{\psi^e} \begin{pmatrix} \beta_{t-1}^\top \Omega_e^{-1} e_t \\ (\lambda_{t-1} + u_t) \otimes \Omega_e^{-1} e_t \end{pmatrix} \quad (34)$$

and

$$\begin{aligned} \mathcal{I}_t &= \begin{pmatrix} \mathcal{I}_t^\lambda & \mathcal{I}_t^{\lambda,\beta} \\ \mathcal{I}_t^{\beta,\lambda} & \mathcal{I}_t^\beta \end{pmatrix} \\ &= C_{\mathcal{I}}(\tilde{e}_t, \psi^e) \begin{pmatrix} \beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1} & (\lambda_{t-1} + u_t)^\top \otimes \beta_{t-1}^\top \Omega_e^{-1} \\ (\lambda_{t-1} + u_t) \otimes \Omega_e^{-1} \beta_{t-1} & ((\lambda_{t-1} + u_t)(\lambda_{t-1} + u_t)^\top) \otimes \Omega_e^{-1} \end{pmatrix} \end{aligned} \quad (35)$$

with

$$C_{\mathcal{I}}(\tilde{e}_t, \psi^e) = \frac{4}{N} \mathbb{E}_{t-1} \left(\|\tilde{e}_t\|^2 \left(\frac{\psi_1^e}{\psi^e} \right)^2 \right) \quad (36)$$

where $\tilde{e}_t = \Omega_e^{-1/2} e_t$ and ψ_1^e is the partial derivative with respect to the first component.

Proof. The common observational density of u_t and e_t can be derived with the given density functions. We find

$$\begin{aligned} p(e_t, u_t | \mathcal{F}_{t-1}, \theta_t) &= p(e_t | u_t, \mathcal{F}_{t-1}, \theta_t) p(u_t | \mathcal{F}_{t-1}, \theta_t) \\ &= |\Omega_e|^{-\frac{1}{2}} \psi^e \left(e_t^\top \Omega_e^{-1} e_t, \nu_e \right) |\Omega_u|^{-\frac{1}{2}} \psi^u \left(u_t^\top \Omega_u^{-1} u_t, \nu_u \right) \end{aligned}$$

and the log-likelihood

$$\begin{aligned} l_t &= \ln p(e_t, u_t | \mathcal{F}_{t-1}, \theta_t) \\ &= -\frac{1}{2} \ln |\Omega_e| - \frac{1}{2} \ln |\Omega_u| + \ln \psi^e \left(e_t^\top \Omega_e^{-1} e_t, \nu_e \right) + \ln \psi^u \left(u_t^\top \Omega_u^{-1} u_t, \nu_u \right). \end{aligned}$$

The components of the score can be computed as

$$\begin{aligned} \frac{\partial l_t}{\partial \theta_i} &= \frac{\partial}{\partial \theta_i} \ln \psi^e \left(e_t^\top \Omega_e^{-1} e_t, \nu_e \right) \\ &= \frac{\psi_1^e}{\psi^e} \frac{\partial}{\partial \theta_i} \left(e_t^\top \Omega_e^{-1} e_t \right) \\ &= 2 \frac{\psi_1^e}{\psi^e} \frac{\partial e_t^\top}{\partial \theta_i} \Omega_e^{-1} e_t \end{aligned}$$

with ψ_1^e being the first derivative of ψ with respect to its first component. The score functions of risk prices and exposures can then be obtained as follows:

$$\nabla_t^\lambda = \frac{\partial l_t}{\partial \lambda_{t-1}} = 2 \frac{\psi_1^e}{\psi^e} \frac{\partial e_t^\top}{\partial \lambda_{t-1}} \Omega_e^{-1} e_t = -2 \frac{\psi_1^e}{\psi^e} \beta_{t-1}^\top \Omega_e^{-1} e_t$$

and

$$\begin{aligned}
\nabla_t^\beta &= \frac{\partial l_t}{\partial \text{vec}(\beta_{t-1})} = 2 \frac{\psi_1^e}{\psi^e} \frac{\partial e_t^\top}{\partial \text{vec}(\beta_{t-1})} \Omega_e^{-1} e_t \\
&= 2 \frac{\psi_1^e}{\psi^e} \left(\frac{\partial}{\partial \text{vec}(\beta_{t-1})} (r_t - (\lambda_{t-1} + u_t) \beta_{t-1}) \right)^\top \Omega_e^{-1} e_t \\
&= -2 \frac{\psi_1^e}{\psi^e} \left(\frac{\partial}{\partial \text{vec}(\beta_{t-1})} (\text{vec}((\lambda_{t-1} + u_t) \beta_{t-1})) \right)^\top \Omega_e^{-1} e_t \\
&= -2 \frac{\psi_1^e}{\psi^e} \left(\frac{\partial}{\partial \text{vec}(\beta_{t-1})} (((\lambda_{t-1} + u_t)^\top \otimes I_N) \text{vec}(\beta_{t-1})) \right)^\top \Omega_e^{-1} e_t \\
&= -2 \frac{\psi_1^e}{\psi^e} ((\lambda_{t-1} + u_t) \otimes I_N) \Omega_e^{-1} e_t \\
&= -2 \frac{\psi_1^e}{\psi^e} ((\lambda_{t-1} + u_t) \otimes I_N) (1 \otimes \Omega_e^{-1} e_t) \\
&= -2 \frac{\psi_1^e}{\psi^e} ((\lambda_{t-1} + u_t) \otimes \Omega_e^{-1} e_t).
\end{aligned}$$

Define the normalized error $\tilde{e}_t = \Omega_e^{-1/2} e_t$ with $\Omega_e^{-1/2}$ being the Cholesky factor of the corresponding dispersion matrix. Remark that \tilde{e}_t is spherically distributed and therefore fulfills the conditions for applying Lemma 1. The Fisher information matrix can then be computed as

$$\begin{aligned}
(\mathcal{I}_t)_{i,j} &= \mathbb{E}_{t-1} \left(\frac{\partial l_t}{\partial \theta_i} \frac{\partial l_t^\top}{\partial \theta_j} \right) \\
&= \mathbb{E}_{t-1} \left(\left(2 \frac{\psi_1}{\psi} \right)^2 (\Omega_e^{-1} e_t)^\top \frac{\partial e_t}{\partial \theta_i} \frac{\partial e_t^\top}{\partial \theta_j} \Omega_e^{-1} e_t \right) \\
&= \mathbb{E}_{t-1} \left(\left(2 \frac{\psi_1}{\psi} \right)^2 \tilde{e}_t^\top \Omega_e^{-\frac{1}{2}} \frac{\partial e_t}{\partial \theta_i} \frac{\partial e_t^\top}{\partial \theta_j} \Omega_e^{-\frac{1}{2}} \tilde{e}_t \right) \\
&= 4 \mathbb{E}_{t-1} \left(\left\| \tilde{e}_t \right\|^2 \left(\frac{\psi_1}{\psi} \right)^2 \mathbb{E}_{t-1} \left(\frac{\tilde{e}_t^\top}{\left\| \tilde{e}_t \right\|} \Omega_e^{-\frac{1}{2}} \frac{\partial e_t}{\partial \theta_i} \frac{\partial e_t^\top}{\partial \theta_j} \Omega_e^{-\frac{1}{2}} \frac{\tilde{e}_t}{\left\| \tilde{e}_t \right\|} \right) \right) \\
&\stackrel{\text{Lemma 1}}{=} 4 \mathbb{E}_{t-1} \left(\left\| \tilde{e}_t \right\|^2 \left(\frac{\psi_1}{\psi} \right)^2 \frac{1}{N} \text{tr} \left(\Omega_e^{-\frac{1}{2}} \frac{\partial e_t}{\partial \theta_i} \frac{\partial e_t^\top}{\partial \theta_j} \Omega_e^{-\frac{1}{2}} \right) \right) \\
&= \frac{4}{N} \mathbb{E}_{t-1} \left(\left\| \tilde{e}_t \right\|^2 \left(\frac{\psi_1}{\psi} \right)^2 \right) \frac{\partial e_t^\top}{\partial \theta_i} \Omega_e^{-1} \frac{\partial e_t}{\partial \theta_j} \\
&= C_{\mathcal{I}}(\tilde{e}_t, \psi^e) \frac{\partial e_t^\top}{\partial \theta_i} \Omega_e^{-1} \frac{\partial e_t}{\partial \theta_j}
\end{aligned}$$

with $C_{\mathcal{I}}(\tilde{e}_t, \psi^e) = \frac{4}{N} \mathbb{E}_{t-1} \left(\left\| \tilde{e}_t \right\|^2 \left(\frac{\psi_1^e}{\psi^e} \right)^2 \right)$. Information quantities with respect to factor risk prices

and exposures can then be computed as follows:

$$\mathcal{I}_t^\lambda = C_{\mathcal{I}}(\tilde{e}_t, \psi^e) \beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1}$$

$$\begin{aligned} \mathcal{I}_t^\beta &= C_{\mathcal{I}}(\tilde{e}_t, \psi^e) ((\lambda_{t-1} + u_t) \otimes I_N) \Omega_e^{-1} ((\lambda_{t-1} + u_t)^\top \otimes I_N) \\ &= C_{\mathcal{I}}(\tilde{e}_t, \psi^e) ((\lambda_{t-1} + u_t) \otimes I_N) (1 \otimes \Omega_e^{-1}) ((\lambda_{t-1} + u_t)^\top \otimes I_N) \\ &= C_{\mathcal{I}}(\tilde{e}_t, \psi^e) ((\lambda_{t-1} + u_t) \otimes \Omega_e^{-1}) ((\lambda_{t-1} + u_t)^\top \otimes I_N) \\ &= C_{\mathcal{I}}(\tilde{e}_t, \psi^e) ((\lambda_{t-1} + u_t) (\lambda_{t-1} + u_t)^\top) \otimes \Omega_e^{-1} \end{aligned}$$

$$\left(\mathcal{I}_t^{\lambda, \beta} \right)^\top = \mathcal{I}_t^{\beta, \lambda} = C_{\mathcal{I}}(\tilde{e}_t, \psi^e) (\lambda_{t-1} + u_t) \otimes \Omega_e^{-1} \beta_{t-1}.$$

■

Corollary 2 *The scaled scores of an SLAPM(p, q) with characteristic distribution generator ψ^e and assuming $(\mathcal{I}_t^{\lambda, \beta})^\top = \mathcal{I}_t^{\beta, \lambda} \equiv 0$ is given by*

$$\begin{pmatrix} s_t^\lambda \\ s_t^\beta \end{pmatrix} = C(\tilde{e}_t, \psi^e) \begin{pmatrix} (\beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1})^{-1} \beta_{t-1}^\top \Omega_e^{-1} r_t - (\lambda_{t-1} + u_t) \\ (\lambda_{t-1} + u_t)^\top ((\lambda_{t-1} + u_t) (\lambda_{t-1} + u_t)^\top)^{-1} r_t - \beta_{t-1} \end{pmatrix}$$

with

$$C(\tilde{e}_t, \psi^e) = -\frac{2\psi_1^e}{\psi^e} C_{\mathcal{I}}(\tilde{e}_t, \psi^e)^{-1} = -\frac{N \frac{\psi_1^e}{\psi^e}}{2\mathbb{E}_{t-1} \left(\|\tilde{e}_t\|^2 \left(\frac{\psi_1^e}{\psi^e} \right)^2 \right)}.$$

Proof. Employing the results from Proposition 1 while assuming zero cross information quantities i.e. $\mathcal{I}_t^{\lambda, \beta} = \mathcal{I}_t^{\beta, \lambda} = 0$ we can derive the following formulas for the driving martingale difference sequences of time-varying risk prices and exposures. For λ_t we find:

$$\begin{aligned} s_t^\lambda &= (\mathcal{I}_t^\lambda)^{-1} \nabla_t^\lambda \\ &= -2 \frac{\psi_1^e}{\psi^e} C_{\mathcal{I}}(\tilde{e}_t, \psi^e)^{-1} (\beta^\top \Omega_e^{-1} \beta)^{-1} \beta^\top \Omega_e^{-1} (e_t)) \\ &= C(\tilde{e}_t, \psi^e) (\beta^\top \Omega_e^{-1} \beta)^{-1} \beta^\top \Omega_e^{-1} (r_t - \beta(\lambda_{t-1} + u_t)) \\ &= C(\tilde{e}_t, \psi^e) \left[(\beta^\top \Omega_e^{-1} \beta)^{-1} \beta^\top \Omega_e^{-1} r_t - (\lambda_{t-1} + u_t) \right]. \end{aligned} \tag{37}$$

For β_t , we analogously find:

$$\begin{aligned} s_t^\beta &= (\mathcal{I}_t^\beta)^{-1} \nabla_t^\beta \\ &= -2 \frac{\psi_1^e}{\psi^e} C_{\mathcal{I}}(\tilde{e}_t, \psi^e)^{-1} (((\lambda_{t-1} + u_t) (\lambda_{t-1} + u_t)^\top) \otimes \Omega_e^{-1})^{-1} ((\lambda_{t-1} + u_t) \otimes \Omega_e^{-1} e_t) \\ &= C(\tilde{e}_t, \psi^e) (((\lambda_{t-1} + u_t) (\lambda_{t-1} + u_t)^\top)^{-1} \otimes \Omega_e) ((\lambda_{t-1} + u_t) \otimes \Omega_e^{-1} e_t) \\ &= C(\tilde{e}_t, \psi^e) (((\lambda_{t-1} + u_t) (\lambda_{t-1} + u_t)^\top)^{-1} (\lambda_{t-1} + u_t) \otimes I_N) \text{vec}(e_t) \\ &= C(\tilde{e}_t, \psi^e) (((\lambda_{t-1} + u_t) (\lambda_{t-1} + u_t)^\top)^{-1} (\lambda_{t-1} + u_t) \otimes I_N) \text{vec}(r_t - \beta_{t-1} (\lambda_{t-1} + u_t)) \\ &= C(\tilde{e}_t, \psi^e) \left[(\lambda_{t-1} + u_t)^\top ((\lambda_{t-1} + u_t) (\lambda_{t-1} + u_t)^\top)^{-1} r_t - \beta_{t-1} \right]. \end{aligned} \tag{38}$$

■

Corollary 3 (Gaussian Residuals) *The score and the corresponding Fisher information matrix of the elliptical SLAPM(p, q)-model with Gaussian residuals are given by*

$$\nabla_t = \left(\begin{array}{c} \beta_{t-1}^\top \Omega_e^{-1} e_t \\ \text{vec}(\Omega_e^{-1} e_t (\lambda_{t-1} + u_t)^\top) \end{array} \right)$$

and

$$\mathcal{I}_t = \left(\begin{array}{cc} \beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1} & (\lambda_{t-1} + u_t)^\top \otimes \beta_{t-1}^\top \Omega_e^{-1} \\ (\lambda_{t-1} + u_t) \otimes \Omega_e^{-1} \beta_{t-1} & ((\lambda_{t-1} + u_t)(\lambda_{t-1} + u_t)^\top) \otimes \Omega_e^{-1} \end{array} \right).$$

Proof. The characteristic generator of the multivariate normal density is given by $\psi^e(x, \nu) = (2\pi)^{N/2} e^{-x/2}$. By observing that ψ^e solves the differential equation $\psi_1^e = -\frac{1}{2}\psi^e$, we find that $-2\psi_1^e/\psi^e = 1$ and

$$\begin{aligned} C_{\mathcal{I}}(\tilde{e}_t, \psi^e) &= \frac{4}{N} \mathbb{E}_{t-1} \left(\|\tilde{e}_t\|^2 \left(\frac{\psi_1^e}{\psi^e} \right)^2 \right) = \frac{4}{N} \mathbb{E}_{t-1} \left(\|\tilde{e}_t\|^2 \left(\frac{-\psi^e/2}{\psi^e} \right)^2 \right) \\ &= \frac{1}{N} \mathbb{E}_{t-1} \left(\|\tilde{e}_t\|^2 \right) = \frac{1}{N} \mathbb{E}_{t-1} \left(\tilde{e}_t^\top \tilde{e}_t \right) = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{t-1} \left(\tilde{e}_{it}^\top \tilde{e}_{it} \right) = 1 \end{aligned}$$

because $\tilde{e}_t \sim N(0, I_N)$. The assertion now follows with Proposition 1. ■

Corollary 4 (Student's t Residuals) *The score and the corresponding Fisher information matrix of the elliptical SLAPM(p, q) with residuals following a Student's t distribution are given by*

$$\nabla_t = \frac{\nu_e + N}{\nu_e + e_t^\top \Omega_e^{-1} e_t} \left(\begin{array}{c} \beta_{t-1}^\top \Omega_e^{-1} e_t \\ \text{vec}(\Omega_e^{-1} e_t (\lambda_{t-1} + u_t)^\top) \end{array} \right)$$

and

$$\mathcal{I}_t = \frac{\nu_e + N}{\nu_e + N + 2} \left(\begin{array}{cc} \beta_{t-1}^\top \Omega_e^{-1} \beta_{t-1} & (\lambda_{t-1} + u_t)^\top \otimes \beta_{t-1}^\top \Omega_e^{-1} \\ (\lambda_{t-1} + u_t) \otimes \Omega_e^{-1} \beta_{t-1} & ((\lambda_{t-1} + u_t)(\lambda_{t-1} + u_t)^\top) \otimes \Omega_e^{-1} \end{array} \right).$$

Proof. The characteristic generator of the multivariate Student's t density is given by

$$\psi(x, \nu_e) = \frac{\Gamma\left(\frac{\nu_e + N}{2}\right)}{(\nu_e \pi)^{\frac{N}{2}} \Gamma\left(\frac{\nu_e}{2}\right)} \left(1 + \frac{x}{\nu_e}\right)^{-\frac{\nu_e + N}{2}} \quad (39)$$

and can be used to compute

$$-2 \frac{\psi_1^e}{\psi^e} (e_t^\top \Omega_e^{-1} e_t, \nu_e) = -2 \frac{-\frac{\nu_e + N}{2} \left(1 + \frac{e_t^\top \Omega_e^{-1} e_t}{\nu_e}\right)^{-\frac{\nu_e + N}{2} - 1} \frac{1}{\nu_e}}{\left(1 + \frac{e_t^\top \Omega_e^{-1} e_t}{\nu_e}\right)^{-\frac{\nu_e + N}{2}}} = \frac{\nu_e + N}{\nu_e + e_t^\top \Omega_e^{-1} e_t}. \quad (40)$$

The scaling term of the information quantity can be reformulated as follows:

$$\begin{aligned}
C_{\mathcal{I}}(\tilde{e}_t, \psi^e) &= \frac{4}{N} \mathbb{E}_{t-1} \left(\|\tilde{e}_t\|^2 \left(\frac{\psi_1^e}{\psi^e} \right)^2 \right) = \frac{1}{N} \mathbb{E}_{t-1} \left(\|\tilde{e}_t\|^2 \left(\frac{\nu_e + N}{\nu_e + \|\tilde{e}_t\|^2} \right)^2 \right) \\
&= \left(\frac{\nu_e + N}{N} \right)^2 \mathbb{E}_{t-1} \left(\frac{Z}{\left(\frac{\nu_e}{N} + Z \right)^2} \right)
\end{aligned} \tag{41}$$

with $Z := \|\tilde{e}_t\|^2 / N$. Since $\|\tilde{e}_t\|^2$ being a sum of N squared t-distributed random numbers with degrees-of-freedom-parameter ν , we know that $Z \sim F(N, \nu_e)$ (see, for example, p.22 in Fang et al. (1990)). Knowing the probability density function of Z , we can compute the desired expected value:

$$\begin{aligned}
\mathbb{E}_{t-1} \left(\frac{Z}{\left(\frac{\nu_e}{N} + Z \right)^2} \right) &= \int_0^\infty \frac{z}{\left(\frac{\nu_e}{N} + z \right)^2} \frac{(N/\nu_e)^{\frac{N}{2}}}{B\left(\frac{N}{2}, \frac{\nu_e}{2}\right)} z^{\frac{N}{2}-1} \left(1 + \frac{N}{\nu_e} z \right)^{-\frac{N+\nu_e}{2}} dz \\
&= \frac{N/\nu_e}{B\left(\frac{N}{2}, \frac{\nu_e}{2}\right)} \int_0^\infty \left(\frac{N}{\nu_e} z \right)^{\frac{N}{2}} \left(1 + \frac{N}{\nu_e} z \right)^{-\frac{N+\nu_e}{2}-2} \frac{N}{\nu_e} dz \quad \left| \text{substitute with } t := \frac{N}{\nu_e} z \right. \\
&= \frac{N/\nu_e}{B\left(\frac{N}{2}, \frac{\nu_e}{2}\right)} \int_0^\infty t^{\frac{N+2}{2}-1} (1+t)^{-\frac{N+2}{2}-\frac{\nu_e+2}{2}} dt \\
&= \frac{N}{\nu_e} B\left(\frac{N}{2}, \frac{\nu_e}{2}\right)^{-1} B\left(\frac{N+2}{2}, \frac{\nu_e+2}{2}\right) \\
&= \frac{N}{\nu_e} B\left(\frac{N}{2}, \frac{\nu_e}{2}\right)^{-1} B\left(\frac{N}{2}, \frac{\nu_e+2}{2}\right) \frac{N/2}{N/2 + \nu_e/2 + 1} \\
&= \frac{N}{\nu_e} B\left(\frac{N}{2}, \frac{\nu_e}{2}\right)^{-1} B\left(\frac{N}{2}, \frac{\nu_e}{2}\right) \frac{N/2}{N/2 + \nu_e/2 + 1} \frac{\nu_e/2}{N/2 + \nu_e/2} \\
&= \frac{N^2}{(N + \nu_e + 2)(N + \nu_e)}
\end{aligned} \tag{42}$$

where we used the integral representation of the beta function $B(x, y) = \int_0^\infty t^{x-1} (1+t)^{-x-y} dt$ in the fourth equation and the identities $B(x+1, y) = B(x, y) \cdot x/(x+y)$ and $B(x, y+1) = B(x, y) \cdot y/(x+y)$ in the fifth and sixth equations respectively.

Inserting (42) into (41) yields $C_{\mathcal{I}}(\tilde{e}_t, \psi^e) = \frac{\nu_e + N}{\nu_e + N + 2}$ and therefore proves the assertion in conjunction with Proposition 1. ■

Appendix B. Tables and Figures

Table 1: Simulation Results

The table shows the RMSEs of the different forecasting approaches for different numbers of assets N and time observations T computed from 1000 simulations for each cross-section. The considered forecasters are a Gaussian constant beta SLAPM(1,1) specification (SLAPM), a constant risk price specification estimated fitted with the classical approach of Fama and MacBeth (1973), and the regression-based dynamic asset pricing model of Adrian et al. (2015) (DAPM). The share of information from the correct forecaster made available to the DAPM is denoted with κ . The shaded areas indicate that the Diebold-Mariano test of the null that the SLAPM forecast is worse than or as accurate as the forecast under consideration cannot be rejected.

N/T	κ	RMSE		25/1000	50/100	50/500	50/1000	100/500	100/1000
		25/100	25/500						
SLAPM		0.5777	0.3409	0.2939	0.5643	0.3400	0.2965	0.3647	0.3189
FMB		0.6734	0.5834	0.5815	0.6860	0.5850	0.5713	0.5891	0.5577
DAPM	0	0.8271	0.6134	0.6036	0.8781	0.6232	0.6039	0.6230	0.5793
	0.1	0.8289	0.6134	0.6026	0.8714	0.6248	0.6011	0.6226	0.5776
	0.2	0.8283	0.6060	0.5916	0.8592	0.6178	0.5889	0.6145	0.5672
	0.3	0.8266	0.5868	0.5646	0.8415	0.5968	0.5621	0.5938	0.5430
	0.4	0.8270	0.5526	0.5172	0.8213	0.5570	0.5164	0.5566	0.5008
	0.5	0.8320	0.5043	0.4508	0.8045	0.4998	0.4528	0.5038	0.4412
	0.6	0.8383	0.4493	0.3763	0.7950	0.4361	0.3799	0.4443	0.3723
	0.7	0.8399	0.3988	0.3094	0.7927	0.3809	0.3121	0.3922	0.3073
	0.8	0.8342	0.3610	0.2624	0.7948	0.3440	0.2625	0.3572	0.2582
	0.9	0.8237	0.3385	0.2387	0.7986	0.3259	0.2365	0.3401	0.2306
	1	0.8119	0.3288	0.2338	0.8026	0.3214	0.2310	0.3361	0.2222

Table 2: SLAPM Estimation Results for Fama-French Three-factor Model

This table shows parameter estimates of a Gaussian constant beta SLAPM(1,1) of the FF3 model from Fama and French (1993). Test assets are 25 portfolios formed on size and book-to-market. Pricing factors are a market return on all US stocks listed on the New York stock exchange (MKT), a small-minus-big factor (SMB) and a high-minus-low factor (HML). Returns are monthly from July 1926 and ends in March 2018. Standard errors are shown in parentheses.

	MKT	SMB	HML
ω	0.0020 (0.0013)	0.0003 (0.0002)	0.0016 (0.0007)
\tilde{A}	0.1451 (0.0825)	0.0444 (0.0209)	0.0455 (0.0176)
\tilde{B}	0.5176 (0.3335)	0.8320 (0.0740)	0.5962 (0.1631)
$\bar{\lambda}$	0.0060	0.0028	0.0044

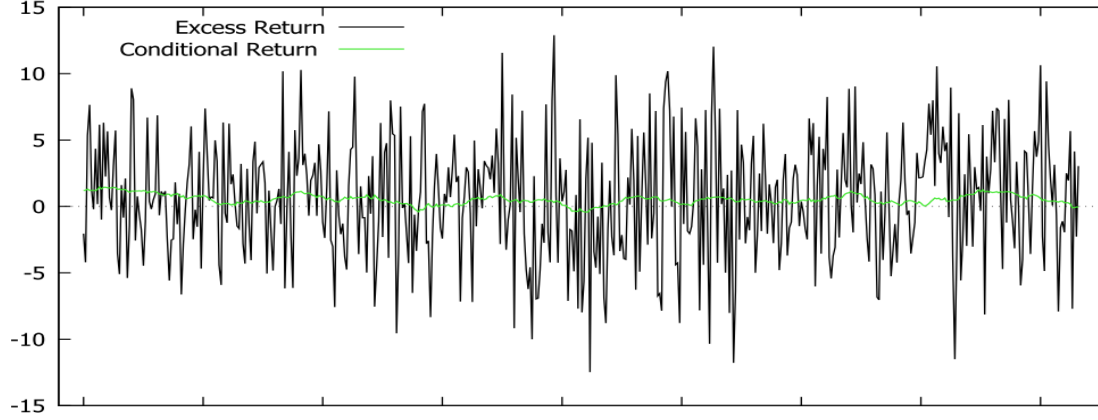
Table 3: Carry Trade Cross-Section SLAPM Estimation Results

This table shows parameter estimates of a Gaussian constant beta SLAPM(1,1) with diagonalized GAS parameter matrices fitted to a carry trade asset pricing model as studied in Lustig et al. (2011). Test assets are five currency portfolios $C1, \dots, C5$ sorted on interest differential. Pricing factors are a equally-weighted currency market return (DOL) and a high-minus-low carry trade portfolio return (HML). Returns are monthly from January 1984 to February 2017 and adjusted for transaction costs by considering bid and ask quotes. Standard errors are shown in parentheses.

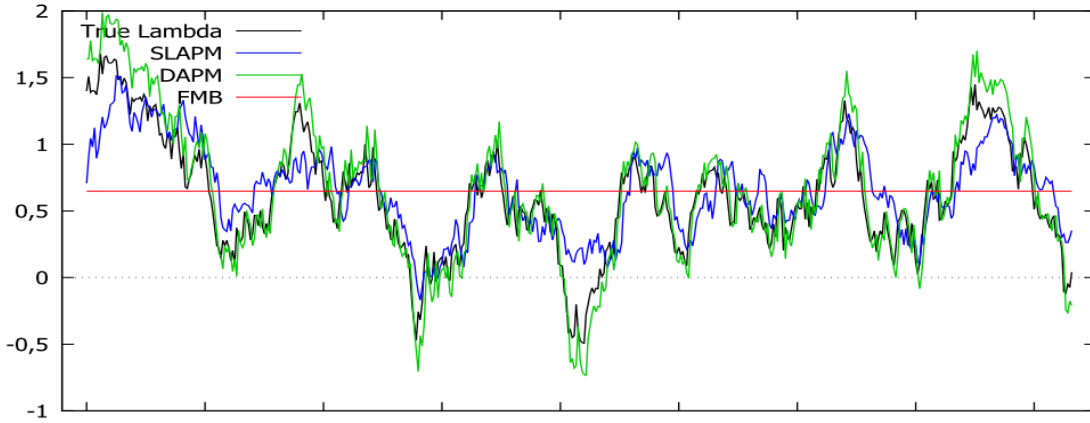
	Lambda Dynamics			Constant Betas	
	DOL	HML		DOL	HML
ω	0.0213 (0.0076)	0.1004 (0.0308)	β_{C1}	0.9959 (0.0121)	-0.4106 (0.0087)
\tilde{A}	0.3201 (0.0720)	0.3383 (0.0736)	β_{C2}	0.9751 (0.0155)	-0.1331 (0.0104)
\tilde{B}	0.5443 (0.1014)	0.5641 (0.0938)	β_{C3}	0.9646 (0.0162)	-0.0547 (0.0110)
$\bar{\lambda}$	0.1572	1.0292	β_{C4}	0.9990 (0.0181)	0.0181 (0.0122)
			β_{C5}	0.9789 (0.0204)	0.5300 (0.0170)

Figure 1: Exemplary simulated Return and Lambda

The figure shows simulated excess returns together with the conditional expectation $\beta\lambda_{t-1}$ (panel (a)) and the associated lambda series (panel (b)). The simulated cross-section consists of $N = 25$ assets and $T = 500$ observations. The considered lambda forecasters in panel (b) are a Gaussian constant beta SLAPM(1,1) specification (SLAPM), a constant risk price specification estimated fitted with the classical approach of Fama and MacBeth (1973) and the regression-based dynamic asset pricing model of Adrian et al. (2015) (DAPM) with the correct forecasting factor ($\kappa = 1$).



(a) Exemplary Simulated Return Series



(b) Exemplary Simulated Risk Price Series

Figure 2: Risk Price Dynamics in FF3.

The figure shows time-varying lambdas of market (MKT), small-minus-big factor (SMB) and high-minus-low factor (HML) factor from a fitted Gaussian constant beta SLAPM version of the FF3 model from Fama and French (1993). Test assets are 25 equity portfolios sorted on size and book-to-market. Returns are monthly from July 1926 to March 2018. Shaded areas refer to NBER recessions.

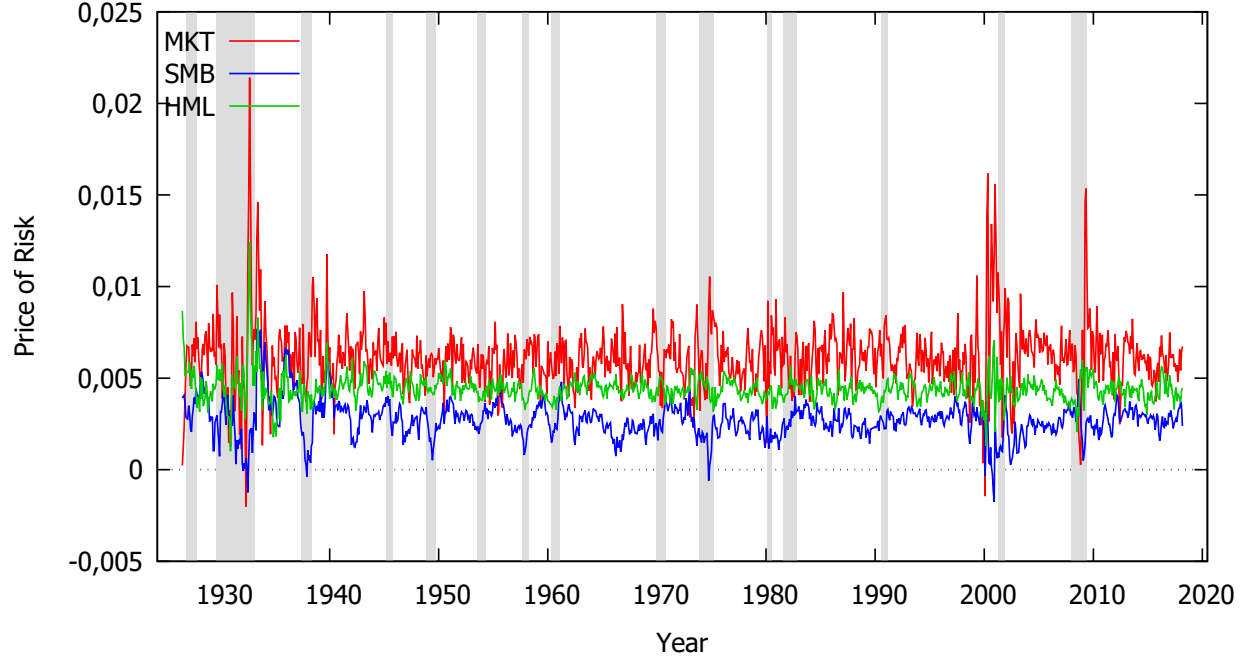
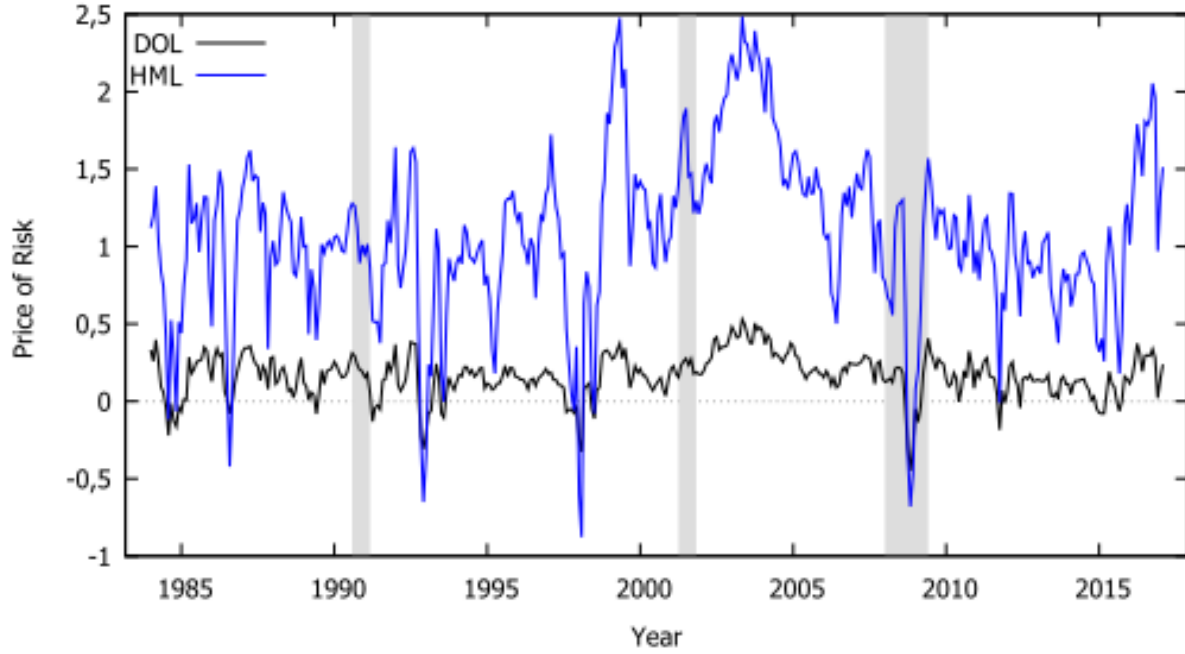


Figure 3: Risk Price Dynamics in the Carry Cross-Section.

The figure shows time-varying lambdas of the DOL (λ_t^{DOL}) as well as the HML (λ_t^{HML}) factor from a Gaussian constant betas SLAPM fitted to a five portfolio carry trade cross-section according to Lustig et al. (2011). Returns are monthly from January 1984 to February 2017 and adjusted for transaction costs by considering bid and ask quotes. Shaded areas refer to NBER recessions.



Chapter III

Risk-Premia Dynamics in Style-based Currency Investing

Abstract

This paper shows that currency risk premia in cross-sections of popular FX speculation strategies like carry, FX momentum and FX value vary over time with crucially differing patterns. Carry trade risk premia are found to be most persistent with sudden downward spikes. Premia to FX momentum are rather stable with less movement whereas FX value premia are unstable. Out-of-sample predictability can be verified for carry premia explained by changes in FX volatility and recent carry trade returns supporting that excessive carry trade returns compensate for currency crash risk as advocated by Brunnermeier et al. (2008).

Keywords: Carry Trades, Currency Risk, Exchange Rate Predictability, FX Momentum, FX Value

JEL Codes: F31, G12, G15, G17

1 Introduction

The foreign exchange (FX) market, with its turnover of 5 067 billion US dollar in 2016 (BIS (2016)) can be considered the biggest over-the-counter (OTC) market in the world. The motives for trading currencies are manifold and many different players are involved. Although it originally emerged to facilitate the exchange of goods and services by international traders, many financial players in the market today are there for different purposes including speculation and hedging. FX markets can therefore be used to exploit attractive investment opportunities like in other asset classes.

Classical currency speculation strategies are the so-called carry trades in which the investor holds a long position in currencies bearing high interest and finances this with a short position in currencies with low interest rates. But there have emerged additional speculation styles that build long and short positions in different currencies which are chosen based on currency-specific signals to generate returns. The most popular signals besides carry are FX momentum, which is the recent return value of a currency and FX value being computed via the real exchange rate. These self-financing strategies have shown promising average annual Sharpe ratios ranging from 0.923 to 1.312. However, particularly carry trades are well-known for generating considerable returns over substantial time periods but are subject to sudden recurring losses that may offset the gathered returns and possibly induces additional losses. Risk-based explanations of carry trade returns have a long tradition (Engel (1984), Fama (1984)) and have been placed in a cross-sectional perspective (Lustig et al. (2011), Menkhoff et al. (2012a), Reitz and Umlandt (2019)) more recently. Similar efforts have been made for FX momentum (Menkhoff et al. (2012b), Filippou et al. (2018)) and FX value (Asness et al. (2013), Menkhoff et al. (2017)). According to these line of research currency risk premia are compensations for higher risk exposure because high-signal currencies tend to pay off poorly in bad times (for example, in times of high volatility or during political and economic crises) whereas low-signal currencies provide a hedge.

The present paper adds a time-series perspective to the cross-sectional results in the

literature by analyzing whether and how the magnitude of currency risk premia varies over time. This could, for example, be a result of a different level of risk averseness in different states of the economy. For each of the three signals or styles carry, FX momentum and FX value I create a ranking across each currency available and allocate each of them to one of five portfolios. The first portfolio always includes the 20% of currencies with the lowest signal and the fifth portfolio includes the 20% of currencies with the highest signal. Investing in Portfolio 5 while shorting Portfolio 1 would therefore result in the associated high-minus-low (HML) strategy. I go with Lustig et al. (2011) in describing each cross-section with a set of two statistical risk factors. The first is the currency market return from investing one US-dollar in equal shares with each currency available, whereas the second factor is the HML return from the respective five-portfolio cross-section. The second factor is therefore specific to each style and its market price of risk describes the premium paid for the risk exposure from riding this strategy. The main innovation of this paper is to filter time-varying risk prices from the currency portfolio panels by treating risk prices as unobserved components, as in Umlandt (2019). Their movements are modeled with an autoregressive updating scheme relating risk price movements to cross-sectional pricing errors. In this way they tell us how much time variation in risk premia is reasonable to expect given the return data and factor structure.

Filtered risk premia show substantial time variation that is heavily heterogeneous across the three currency investing styles. In particular, carry premia show a reasonable degree of persistence and several sharp downward spikes. Their time variation can mainly be explained by recent carry gains and FX market volatility, supporting the view of Brunnermeier et al. (2008), who argue that carry trade premia compensate for the risk of currency crashes that occur once in a while. But dollar competitiveness and market liquidity also have an economically minor influence.

The results for the other two styles are mixed upon employing the alternative methods. The FX momentum premium is found to be considerably stable with only minor deviations from its unconditional risk prices. This is at least surprising when remarking

that FX momentum had, especially since 2016, an increased performance similar to carry. Whereas the upturn in carry can be explained by increased risk premia, this is not the case for momentum whose risk premium is therefore unlikely to have a crash risk interpretation. A possible explanation is that temporary high FX momentum returns are spill-overs from carry. Due to a high risk price to carry (or crash) risk, the currencies with the lowest carry exposure are those with the lowest returns (because they are considered less risky) and therefore have low momentum entering the corresponding short portfolio and generating return. Because high-carry currencies that are tending to crash are not included (or only included to a minor extent) in the long FX momentum portfolio, the momentum strategy rides the carry returns without being exposed to the crash risk. FX value premia are, on average, lower than carry premia but show less persistence, with fluctuations between approximately zero and the level of the momentum premium.

An out-of-sample forecast exercise finally shows that carry trade returns are predictable out-of-sample from cross-sectional pricing error information only, which mainly stems from the predictability in the short leg. The dynamic risk premium is unable to outperform standard benchmarks in the other two styles.

The work closest to mine is that of Byrne et al. (2017). They analyze time-varying risk premia to the carry trade with the regression-based approach of Adrian et al. (2015), employing FX volatility, a commodity market return and a funding liquidity indicator as instruments to drive the dynamics of risk prices. This work differs mainly because of the methodology employed and a broader perspective on additional FX trading strategies apart from carry. Relying solely on the method of Adrian et al. (2015) has the crucial drawback that risk price drivers have to be chosen.¹¹ This may yield inadequate estimates of risk premia series due to omitted variables. This is likely to be the case in the work of Byrne et al. (2017), where the missing contemporaneous carry performance is one of the main carry risk premium drivers. The results of the likelihood-based fil-

¹¹Besides that Umlandt (2019) provide evidence that the method of Adrian et al. (2015) has a low filtering ability for risk prices in return panels with a low cross-sectional dimension.

ter are however verified with the approach of Adrian et al. (2015), which provides reassurance with regard to the main results relating to the macro-financial drivers of currency risk premia.

Literature have also extensively the carry trade from a time-series perspective (Ranaldo and Söderlind (2010), Christiansen et al. (2011), Mancini et al. (2013), Bakshi and Panayotov (2013), Orlov (2016), Daniel et al. (2017)), connecting carry trade returns to business cycles, liquidity, commodity returns, and downside risk. My work contributes to the massive literature on the carry trade by combining both the time series view on carry trades and the literature strand analyzing average returns from a cross-sectional perspective with empirical asset pricing methods (Lustig et al. (2011), Menkhoff et al. (2012a), Mueller et al. (2017), Reitz and Umlandt (2019)). The results presented in the following can be understood as evidence of how much time series variation is in line with or expected from the cross-sectional structure of carry trades. Similarly, they are connected to the less extensive literature on FX momentum (Menkhoff et al. (2012b), Orlov (2016)) and FX value (Asness et al. (2013), Menkhoff et al. (2017)).

The content of this paper is not only of interest for academics but also highly topical for financial market professionals dealing with international investments. Results from the dynamic model provide insights into the time-varying risk structure of the three FX investing styles that provide substantial diversification benefits, such as that documented by Kroencke et al. (2014). This information might be used to hedge against the currency crashes that carry trades appear prone to but the other styles do not.

The remainder is structured as follows: Chapter 2 presents details on the currency portfolio formation, data set, and currency speculation returns. The empirical framework and estimation strategy are discussed in Chapter 3. In Chapter 4 follows the empirical analysis, including estimation results and an out-of-sample analysis. Chapter 5 provides a conclusion.

2 Currency Investing Strategies

The following analysis focuses on the three most popular style-based investment strategies in currency markets namely carry, FX momentum, and FX value¹².

2.1 Exchange Rates and Currency Portfolios

Let s_t^i be the logarithmic spot exchange rate for exchanging one US dollar to currency i in period t and let f_t^i denote the corresponding foreign country logarithmic one-month forward rate. End-of-month logarithmic excess returns from investing in foreign currency i are measured as

$$r_{t+1}^i = f_t^i - s_{t+1}^i, \quad (43)$$

which stems from market practice to realize currency payoffs from long positions in forwards. Note that the return in is equal to the return from a long-short position in foreign and home money markets under validity of the covered interest parity (CIP) condition.¹³ The set of available currencies is then sorted according to three characteristics, which results in three rankings. Each of these three rankings is then used to construct five decile portfolios.

The first five portfolios are sorted according to the interest rate differential as investigated in numerous studies (among others Brunnermeier et al. (2008), Berge et al. (2010), Lustig et al. (2011), Burnside et al. (2011), Menkhoff et al. (2012a)). We allocate each currency to one of five equally weighted portfolios sorted by their forward discounts ($f_t^i - s_t^i$). This sorting is equivalent to sorting on the interest rate differential ($i_t^i - i_t$) if CIP holds. The first portfolio (C1) therefore includes the fifth of currencies with the lowest interest rate differential to the US interest rates and the fifth portfolio (C5) the fifth of currencies with the highest interest rate differential. Shorting C1 and investing in C5 would then be a classical HML carry trade strategy.

¹²For example, Deutsche Bank offers exchange-traded funds that invest according to the considered portfolio sorts. These are listed as Global Currency Harvest Index, the DB Momentum Index and the DB Valuation Index.

¹³Among others, Akram et al. (2008) provides evidence that CIP holds on the considered frequencies. However, large deviations have been documented since the global financial crisis in 2008 (Du et al. (2018)).

The second set of five portfolios is sorted on the currencies' excess returns in the previous three months¹⁴. The first portfolio (M1) therefore includes the fifth of currencies with the lowest cumulative excess returns in the previous three months and the fifth portfolio (M5) the fifth of currencies with the highest cumulative excess returns in the previous months. A strategy going short in past losers (M1) and investing in past winners (M5) is known as HML momentum strategy. This type of currency portfolio follows an idea from the stock market literature in which momentum effects have been first documented by Jegadeesh and Titman (1993). FX momentum has been studied in Okunev and White (2003), Menkhoff et al. (2012b), Asness et al. (2013) and Filippou et al. (2018) among others.

The last five portfolios are sorted by real exchange rates. These are obtained by dividing nominal exchange rates through purchasing power parity (PPP) conversion factors provided by the OECD. Each currency is then allocated to one of five equally weighted portfolios sorted by their real exchange rate level. The first portfolio (V1) therefore includes the fifth of currencies that are most overvalued with respect to PPP and the fifth portfolio (V5) the fifth of currencies that are most undervalued with respect to PPP.¹⁵ This currency portfolio sort is studied in Asness et al. (2013) and Menkhoff et al. (2017), for example.

2.2 Currency Data

Data on spot exchange rates and one-month forward exchange rates of 48 currencies have been collected from Thomson-Reuters Datastream with the US dollar being the base currency. The following 48 countries are included: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand,

¹⁴The results of Menkhoff et al. (2012b) suggest that a three month formation period indicates currency momentum better than the previous month's return only.

¹⁵Real exchange rates are derived in terms of US dollar per unit of foreign currency and a value greater (or lesser) than one can therefore be interpreted as an overvaluation (or undervaluation) of the US dollar or a corresponding undervaluation (or overvaluation) of the foreign currency.

Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom. The panel of exchange rates covering the period from January 1984 to February 2017 is highly unbalanced with at most 38 currencies being available at the same time. The euro is included from January 1999 onward and currencies of euro-member countries are discarded in the following periods. The choice of currencies in the sample as well as the computation of currency excess returns is in line with the literature on currency risk factors, such as, for instance, Lustig et al. (2011) and Menkhoff et al. (2012a).¹⁶

2.3 Descriptive Portfolio Return Statistics

For computing portfolio returns, currencies with available excess return in $t + 1$ are ranked according to carry, FX value, or FX momentum and allocated to five quintile portfolios. For every portfolio, the equally weighted excess return for period $t + 1$ is computed by taking the average excess return of all currencies allocated to the respective portfolio. To account for transaction costs that emerge from monthly rebalancing of the currency portfolios, bid and ask quotes are considered when deriving portfolio returns as in Menkhoff et al. (2012a).

Table 12 presents descriptive statistics on the excess returns of five quintile portfolios sorted by carry, momentum and value, as well as of the corresponding HML portfolio that is an equally weighted portfolio consisting of a short position in the respective lowest quintile portfolio and a long position in the highest quintile portfolio. The mean, median, standard deviation, and Sharpe ratio are annualized.

We recognize the familiar pattern of carry trade returns that is similar to previous empirical studies (for example, Berge et al. (2010) and Burnside et al. (2011)) on carry trade returns, although we included post-financial crisis times. Monthly average returns increase monotonically from low- to high-forward-discount portfolios yielding a sub-

¹⁶In particular, some observations are deleted due to crucial deviations from CIP as well as concerns over the investability in particular currencies. This applies to South Africa (1985-2001), Hungary (2000), Indonesia (1999-2007), Philippines (1999), Taiwan (1999) and Thailand (1999).

stantial average return for the HML strategy. Returns for high-forward-discount portfolios have a higher kurtosis and are more left-skewed than the low-forward-discount portfolio representing the link between currency crashes and carry trades as proposed in Brunnermeier et al. (2008). There is no clear pattern regarding the standard deviation even though it appears to be higher for the two extreme portfolios.

Panel B shows that investing in recent winners (M5) generates positive returns on average, whereas an investment in recent losers (M1) yields negative average returns. Mean returns are again monotonically increasing with a lower spread compared to carry. Since the HML strategies of momentum and carry show similar standard deviations, the Sharpe ratio is higher for the carry trade. The most striking difference between carry and momentum HML is the missing skewness of the latter. The higher Sharpe ratio may therefore be interpreted as a compensation for the left skewness of the carry trade.

The mean of the high-value portfolio (V1) displayed in Panel C is about zero but positive average returns are granted from investing in the undervalued currency portfolio (V5). All three HML strategies generate positive excess returns on average with the Sharpe ratio being the highest for carry trades and the lowest for the value strategy.¹⁷ Figure 4 shows the cumulative log returns on the HML strategies with respect to carry, FX momentum, and FX value. All three strategies generate steady returns over the whole sample with sharp run-ups for carry and FX momentum in the first half of the 2000s and in the recent period starting around 2016. The value strategy seems to be decoupled from these developments with lower returns in general. The returns seem to be independent of economic recessions with an exception for the global financial crisis starting in 2008. Carry trade returns crash substantially whereas the value strategy returns have a clear run-up. This supports the view that all three strategies cover different dimensions of risk that are worth looking at separately. The following empirical analysis aims to shed light on the origin of the disparities in the magnitude of realized

¹⁷Menkhoff et al. (2017) show that the Sharpe ratio of currency value strategies may be increased by adjusting for macroeconomic fundamentals. I refrain from this adjustment possibility in order to keep the value portfolio returns on a monthly frequency.

returns over time as well as across strategies.

3 Methodology

The following section introduces the baseline methodology employed in the subsequent analysis to filter risk premia from the currency cross-section. The empirical model is discussed first before turning to the likelihood-based estimation strategy.

3.1 Empirical Framework

A popular explanation for positive average returns on the carry trade is that an investor takes on some risk due to the stochastic nature of the exchange rate change Δs_{t+1} ¹⁸. The typical investor dislikes risk and, consequently, demands a risk premium as compensation. Since the returns to FX momentum and FX value strategies depend on exchange rate changes they are considered risky as well and should therefore earn a risk premium. Let $rx_{1,t+1}, \dots, rx_{5,t+1}$ be the currency portfolio returns sorted by one of our characteristics. An idea now is to run a risk adjustment by assuming the existence of a stochastic discount factor (SDF) m_{t+1} that fulfils the Euler equation

$$\mathbb{E}_t(m_{t+1}rx_{i,t+1}) = 0 \quad (44)$$

for every $i \in \{1, \dots, 5\}$. In line with Lustig et al. (2011), m_t is assumed to be affine-linear in two factors. The first is a currency market average return called DOL that can be interpreted as a level factor capturing general broad currency market trends. The second is a slope factor HML^j that captures the return spread between high- and low-characteristic $j \in \{C, M, V\}$ ¹⁹ portfolios. Hence, an artificial cross-sectional factor structure derived from the cross-section itself is chosen, although there exist several economically motivated factors explaining particularly the carry trade (Menkhoff et al. (2012a), Reitz and Umlandt (2019)) and the momentum cross-section (Filippou et al.

¹⁸See, for example, Engel (1996) for a survey on risk-based explanations of the forward premium puzzle.

¹⁹HML in Lustig et al. (2011) is identical to the return in the HML carry trade.

(2018)). However, there is no economically meaningful factor that adequately explains all three cross-sections equally well. Even if there were an adequate factor for the value cross-section, employing different factors would leave it unclear whether results are driven by choosing factors that mimic potentially differing sources of risk. The two factors DOL and HML from Lustig et al. (2011) are by construction close to the first two principal components of the carry trade cross-section, together capturing over 90% of the cross-sectional variation. Since the main objective of this paper is to analyze time-varying risk premia associated with style-based currency speculation strategies, the HML return is also a reasonable choice because under correct model specifications its risk price is equal to the respective HML risk premium of interest. The convincing cross-sectional fit and the straight-forward identification of the risk premium may make up for the hindered economic interpretability of the factor. Although the results of Lustig et al. (2011) hold for carry trades we compute the respective factors for the other two currency portfolio sorts as well. They show a reasonable cross-sectional fit for their respective cross-section as well.²⁰

Stack the two cross-sectional pricing factors DOL and HML²¹ into a vector given by

$$X_t = \begin{pmatrix} DOL_t \\ HML_t \end{pmatrix} = \begin{pmatrix} |I_t|^{-1} \sum_{i \in I_t} r_t^i \\ rx_{5,t} - rx_{1,t} \end{pmatrix}. \quad (45)$$

with I_t being the index set of currencies available at time t . X_t can be interpreted as state vectors describing the state of risk in the economy affecting our portfolio returns. Its dynamics are assumed to follow a standard vector autoregressive model (VAR) of order 1:

$$X_{t+1} = c + \Phi X_t + u_{t+1} \quad (46)$$

with factor innovations $u_{t+1} = (u_{t+1}^{DOL}, u_{t+1}^{HML})^\top$, parameter vector c and matrix Φ of suitable dimensions.

²⁰Cross-sectional regressions with the DOL and HML^M and the HML^V factors respectively using the two-step estimation procedure of Fama and MacBeth (1973) report R^2 statistics of about 97%.

²¹For the sake of brevity, superscripts j indicating the investing style are omitted. The elaborations in this section hold for each style alike.

A beta representation relating (expected) returns to risk factors can be constructed as

$$rx_{i,t+1} = \beta_i^\top \lambda_t + \beta_i^\top u_{t+1} + e_{i,t+1} \quad (47)$$

with

$$\beta_i = \begin{pmatrix} \beta_i^{DOL} \\ \beta_i^{HML} \end{pmatrix} = \begin{pmatrix} Cov(r_{i,t+1}, u_{t+1}^{DOL}) / Var(u_{t+1}^{DOL}) \\ Cov(r_{i,t+1}, u_{t+1}^{HML}) / Var(u_{t+1}^{HML}) \end{pmatrix} \quad (48)$$

denoting the two-dimensional vector of risk exposures of portfolio return i to the DOL or HML risk factor and λ_t the vector of associated risk prices. Currency portfolio returns are therefore decomposed into three parts. The first part $\beta_i^\top \lambda_t$ is the conditional expected value representing the risk premium for having compensating risk exposure. This predictable part is of primary interest in this work since it carries the information of how much return can be expected from a specific currency trade in period $t + 1$. $\beta_i^\top u_{t+1}$ is an innovation part that represents the spill-over of factor innovations to the asset return according to its factor exposure β_i . This is the unpredictable return component for which the investor actually gets compensated by $\beta_i^\top \lambda_t$. The last part is an idiosyncratic innovation term e_t that is orthogonal to the factor innovation u_t .

As mentioned, the main objective is to filter the series of risk prices λ_t given the cross-section of currency returns r_t and factor time series X_t . λ_t is therefore modeled as an unobserved component following a recursive scheme given by

$$\lambda_t = \omega + As_t + B\lambda_{t-1} \quad (49)$$

with s_t being an innovation sequence we may specify as a Gaussian error term to achieve a Kalman filter. However, the likelihood-based approach from Umlandt (2019) is applied in order to abstain from introducing another source of uncertainty. This has the advantage that s_t is constructed so that we reduce movements in the error e_t that is not explained by the cross-sectional factor structure. Moreover, incorporating forecast

variables to explain risk prices dynamics is avoided for several reasons.²² First, we avoid misleading risk premia estimates due to possibly omitted variables. Second, the exchange rate predictability literature stresses the particular disconnect (Meese and Rogoff (1983)) and instability (Bacchetta and van Wincoop (2013)) in the relations between exchange rates and fundamentals that would be hard to model. Finally, an objective is to understand how much time variation would be in line with or proposed by the well researched factor structure of currency portfolio returns in the absence of external factors.

The idea in the actually employed approach is to choose s_t in such a way that the one-step ahead forecast error will be reduced by updating risk prices. This can be done by setting s_t to be the observed general least squares (GLS) error from the predictive regression (47) in period t i.e.

$$s_t = (\beta^\top \Sigma_e^{-1} \beta)^{-1} \beta^\top \Sigma_e^{-1} r_t - (\lambda_{t-1} + u_t). \quad (50)$$

with Σ_e being the covariance matrix of the idiosyncratic error term e_t . In this way, deviations from the cross-sectional factor structure are interpreted as signals bearing information about time series dynamics in risk prices. Intuitively, the updating prescribed in Equations (49) and (50) increases (or decreases) the risk prices if the local GLS error is positive (or negative) in order to reduce the local GLS error in the succeeding period in magnitude. Umlandt (2019) shows that (50) minimizes a local likelihood criterion in a Gaussian framework and, moreover, the updating direction is invariant to a specific choice of an elliptical distribution. Relying on (50) can therefore be regarded as adequate, although currency returns are fat-tailed rather than purely Gaussian.

Parameter matrices are restricted to be diagonal for the sake of parsimony. If $s_t =$

²²Estimation results from an alternative specification with risk price forecasters as proposed in Adrian et al. (2015) are presented for robustness confirming the main results.

$(s_t^{DOL}, s_t^{HML})^\top$, the updating scheme (49) can be written as system

$$\lambda_t^{DOL} = \omega^{DOL} + A^{DOL} s_t^{DOL} + B^{DOL} \lambda_{t-1}^{DOL} \quad (51)$$

$$\lambda_t^{HML} = \omega^{HML} + A^{HML} s_t^{HML} + B^{HML} \lambda_{t-1}^{HML} \quad (52)$$

with parameters $\omega = (\omega^{DOL}, \omega^{HML})^\top$, $A = \text{diag}(A^{DOL}, A^{HML})$, and $B = \text{diag}(B^{DOL}, B^{HML})$.

3.2 Estimation Strategy

The framework introduced in the previous section yields the following stacked reduced-form model to be estimated:

$$rx_{t+1} = \beta \lambda_t + \beta u_{t+1} + e_{t+1} \quad (53)$$

$$X_t = c + \Phi X_{t-1} + u_t \quad (54)$$

$$\lambda_t = \omega + A \left((\beta^\top \Sigma_e^{-1} \beta)^{-1} \beta^\top \Sigma_e^{-1} r_t - (\lambda_{t-1} + u_t) \right) + B \lambda_{t-1}. \quad (55)$$

The estimation is conducted with a (quasi) maximum likelihood estimation in two steps. The coefficients of the VAR(1) model are estimated with the standard ordinary least squares (OLS) estimator that would be the maximum likelihood estimator for the VAR in isolation when assuming Gaussian residuals. Fitted residuals \hat{u}_t are then extracted to further estimate the pricing equation. Given \hat{u}_t , a maximum likelihood estimation can be performed to achieve estimates for β, ω, A and B . When assuming Gaussian cross-sectional pricing errors $e_t \sim \mathcal{N}(0, \Sigma_e)$, the concentrated likelihood $\mathcal{L} = p(r_1, \dots, r_t | \hat{u}_t, \beta, \omega, A, B)$ can be derived and evaluated. Numerical optimization of

$$\mathcal{L} \propto - \sum_{t=1}^T e_t' \Sigma_e^{-1} e_t - T \ln \det(\Sigma_e) \quad (56)$$

with respect to β, ω, A and B yields the desired parameter estimates.

4 Empirical Results

The following subsection presents the empirical results from filtering risk premia of the three style-based cross-sections with the methodology described in the previous section. A subsequent subsection explores whether time variation in filtered risk premia can be explained by macro-financial variables. This is followed by an analysis of whether risk premia could predict style-based currency portfolio returns out-of-sample.

4.1 Estimation Results

Results from the estimation are presented in Table 5. The risk prices to the risk factors of all three investment styles show substantial variations in time as indicated by the significant coefficients in A and B. Moreover, the dynamic properties of the risk prices are quite diverse. The price of risk associated with HML^C is most persistent with an estimated B of 0.582, thus revealing that recent risk prices are more important than for the other two HML lambdas. Concerning the impact of local cross-sectional GLS errors on risk prices, it is highest for the value premium by far.

Regarding the factor exposures, we observe the typical result that DOL betas are found around unity as, for example, in Lustig et al. (2011) and Menkhoff et al. (2012a). This holds within and across cross-sections for different styles. Betas of the HML factors show a spread with negative exposure of the low-signal portfolios and positive values for the high-signal portfolios. Betas for exposures to HML^C and HML^M monotonically increase from the first to the fifth portfolios, whereas this is not the case for HML^V . This may be seen as an indicator for a weak value signal. When relying on quarterly portfolio formation, Menkhoff et al. (2017) argue that a better value signal can be acquired from an adjustment with macroeconomic fundamentals. The following analysis allows the employed monthly value signal to stay in monthly frequency. Since a reasonable spread still occurs for the value strategy and border portfolio returns are of primary interest, this appears reasonable.

Currency risk premia are the primary objects of interest because they bear the predic-

tive content of currency portfolio excess returns. The risk premium from a leveraged style-based trade can be achieved by

$$\hat{r}p_{t+1} := \hat{\mathbb{E}}_t(HML_{t+1}) = \hat{\mathbb{E}}_t(r_{t+1}^5 - r_{t+1}^1) \quad (57)$$

$$= (\hat{\beta}_5^{DOL} - \hat{\beta}_1^{DOL})\hat{\lambda}_t^{DOL} + (\hat{\beta}_5^{HML} - \hat{\beta}_1^{HML})\hat{\lambda}_t^{HML}. \quad (58)$$

The filtered risk premia to the three investment styles are visualized in Figure 5. With regard to the magnitude we see that carry trade premia vary the most by far. They show not only substantial drops in which the expected carry return even turns negative though with fast recovery but also otherwise quite persistent movements. Most of the crucial drops do not refer to recession periods (with the recent global financial crisis being an exception) but fall together with huge currency movements disconnected from macroeconomic shocks, as have been documented in carry trade returns by Brunnermeier et al. (2008). One example is the strong appreciation of the Japanese yen, a typical short-leg carry currency, in October 1998, accompanied by a huge drop in carry return expectations represented by the risk premium.

The connection to these currency crashes, however, cannot be observed for the FX momentum and value premia. In line with the parameter estimates, the momentum premium has been fairly stable over the last 30 years, whereas the value premium fluctuates within a panel from roughly zero to unity. A first takeaway from these findings is that the dynamic properties of the carry risk premium speak in favor of a crash risk interpretation. However, the sources of risk justifying FX momentum and value premia are different with economically relevant time changes in the amount of compensation convincingly evidenced for FX value only.

4.2 Explaining Factors

The analysis now tries to shed light on the relations between the risk premia associated with different FX investing styles and macro-financial variables that have been found useful in the literature to predict currency speculation returns. The variables under

consideration are described first and then employed in linear regressions to explain risk premia changes. After that, results from a similar exercise employing the direct regression-based approach of Adrian et al. (2015) simultaneously filtering risk price dynamics and estimating connections to macro-financial variables are presented for robustness.

4.2.1 Forecasting Factors

The considered explaining variables for movements in the analyzed risk premia are carry return predictors found in the literature. Predictors are employed because the risk premium is the predictable part of the return in the following period. The focus on carry stems from the fact that the predictors of carry trade returns are widely researched in contrast to the sparse literature on FX momentum predictors and almost non-existent research on the predictability of the FX value premium.

Brunnermeier et al. (2008) propose three variables possibly associated with currency crash risk that is tightly connected to the carry risk premium. First they document that gains on carry lead to a further build-up of carry trade positions as measured by an open futures position data set. A reasoning could be that if investors observe high carry trade returns, they acknowledge greater crash risk in their investment considerations and therefore demand a higher risk premium for open carry positions. This effect should be measurable when using contemporaneous leveraged carry trade returns (HML_t^C) as an explaining variable. For the FX momentum and the FX value cross-section the analogues are considered (HML_t^M and HML_t^V).

The other two variables are proxies for uncertain times in which Brunnermeier et al. (2008) find that an unwinding of carry trade positions is likely. As a measure of FX market uncertainty a global FX volatility is computed in line with Menkhoff et al. (2012a) i.e.

$$VOL_t = \frac{1}{T_t} \sum_{\tau \in T_t} \left(\frac{1}{|I_t|} \sum_{i \in I_t} |r_t^i| \right) \quad (59)$$

where r_t^i is the log-return of currency i , T_t the number of trading days, and I_t the index set of available currencies in month t . To measure the impact of uncertainty shocks, the growth rate of $VOL_t(dVOL_t)$ is considered as an explaining variable as well.²³ FX market volatility as a carry forecasting factor has also been documented in Bhansali (2007) and Bakshi and Panayotov (2013).

Besides volatility, Brunnermeier et al. (2008) suggest the TED spread (TED_t), which is computed as the three month LIBOR-based interest on US dollars and a three-month treasury bill, being associated with a sudden unwinding of carry trade positions as this measure is a representative for the funding liquidity available to investors. The data series is acquired from the Federal Reserve Bank of St. Louis.

Adrian et al. (2011) and Brunnermeier and Pedersen (2009) furthermore stress the importance of the funding conditions of financial intermediaries for risk premia. As an alternative to the TED spread, the funding conditions for financial intermediaries can be proxied by computing aggregate leverage or capital ratios from balance sheet data as in Adrian et al. (2014) or He et al. (2017). The factor from the latter consists of shocks to the aggregated capital ratio (dCr_t) of the financial intermediaries referred to as the primary dealers by the New York Fed and is also known to be a priced factor in the cross-section of carry trade returns. Whether this factor additionally explains the time series properties of speculative FX returns is investigated in the following analysis.

In addition, growth rates of the broad dollar index of the Federal Reserve Board (FRB) are considered. They measure changes in the strength of the dollar. The index is a trade-weighted average of nominal dollar exchange rates against currencies of a broad group of major US trading partners. The reason for using this factor is that a stronger dollar is suspected to increase the shadow costs of bank balance sheet capacity (see, for example, Avdjiev et al. (2016)). I refer to this factor with the abbreviation $dFRB_t$.

The last considered factor is the growth rate of the raw industrials subindex of the

²³Growth rates are computed here as fitted residuals from an AR(1)-process divided by the previous period realization.

CRB spot commodity index ($dCRB_t$). Bakshi and Panayotov (2013) provide regression evidence for carry trade predictability of this factor. A possible explanation is that typical commodity currencies (Chen and Rogoff (2003)) frequently show up in the high-yielding-interest portfolio and commodity currency exchange rate predictability from associated commodity price returns is documented in several studies (see, for example, Rossi (2013)).

4.2.2 Risk Premia Regression Results

Table 6 reveals that changes in carry trade risk premia can be explained by several sources due to regression-based evidence. Whereas recent FX volatility, the TED spread, and growth in the broad dollar index are found to have a significantly negative impact, a significantly positive impact can be observed by lagged carry trade returns and shocks to FX volatility. Coefficients relating to shocks to financial intermediaries' balance sheet capacity and the commodity index are not significantly different from zero. The economically most relevant explaining factors of risk premia movements appear to be the FX market volatility variables as well as recent carry trade returns, as emphasized in Figure 7(a). The results fit the concept advocated in Brunnermeier et al. (2008) that macroeconomic factors may explain differences in interest rates, but speculative currency crash risk and funding constraints explain returns to carry by pushing exchange rates away from their uncovered interest parity (UIP) level. The investors' high engagements in carry trading increase the probability of a sudden collective unwinding of carry trade positions and its adverse magnitude on exchange rate changes are unfavorable for carry positions that are still open. This causes investors to demand a higher risk premium following high carry trade realizations. Moreover, low carry trade profits may induce smooth carry trade unwinds that lower the crash risk. Otherwise, huge unwinds of carry trades, as are frequently observed in high volatility states, push down carry return expectations as reflected in low lambdas.

Concerning premia for the other two investment styles, FX volatility seems to be unimportant in sharp contrast to what can be observed in carry. But again, the economi-

cally most relevant impact stems from recent returns to the respective strategy. The expected returns are higher when observing current high realized returns supporting a speculative view with a much lower economic magnitude.

Striking are the differing effects of changes in dollar competitiveness to risk premia associated with the three investment styles. For carry and FX momentum, the coefficient is significantly negative, in line with the observation that a strong dollar is associated with less cross-border dollar lending according to the risk-taking channel (Borio and Zhu (2012), Bruno and Shin (2015)). Tighter financial conditions seem to induce an unwinding of open speculative positions that are usually leveraged and therefore lower expected returns. However, the FX value premium reacts in a significantly positive way to a strengthening US dollar. This may be devoted to the lower volume of value transactions in the FX markets in such a way that the risk-taking channel is less effective but may also be attributed to the traditional trade channel of exchange rate adjustments. If the domestic currency devalues with respect to the dollar, the export prices rise, inducing a rising domestic price level as well. Because long positions in FX value strategies bet on PPP reinforcement, adjusting price levels are expected to be followed by higher convergence rates in PPP and therefore higher returns.

Findings for the other forecasting variables are also mixed. Coefficients to the funding liquidity measures TED_t and dCr_t are positive, if significant at all. The commodity factor $dCRB_t$ has a negative impact on the value premium with 1%-significance but seem to have no impact on the momentum or carry premium.

4.2.3 Direct Regression-based Estimation

Instead of filtering risk premia from the panel data set of portfolio returns and regressing them on explaining variables afterwards, the approach of Adrian et al. (2015) allows for directly modeling risk prices as affine-linear functions of forecasting factors and estimating them with a three-step regression procedure. The approach has been conducted for the study on time-varying carry risk premia in Byrne et al. (2017). The following analysis extends the analysis to FX momentum and FX value portfolios and

the carry cross-section to a longer sample period. It additionally considers a richer set of forecasting factors.²⁴

Decompose the state vector in (3.2) into X_{1t} that are pricing factors only, X_{2t} that are pricing and forecasting factor and X_{3t} that are pure forecasting factors, such that $X_t = (X_{1t}^\top, X_{2t}^\top, X_{3t}^\top)^\top$. Let us collect the cross-sectional pricing factors with $C_t = (X_{1t}^\top, X_{2t}^\top)^\top$ and forecasting factors with $F_t = (X_{2t}^\top, X_{3t}^\top)^\top$. As pricing factors, we use the same factors as before and as forecasting factors the considered explaining variables for the time variation in risk premia introduced in the previous section i.e.

$$X_{1,t} = DOL_t, \quad X_{2,t} = HML_t^j, \quad X_{3,t} = \begin{pmatrix} VOL_t \\ dVOL_t \\ dCr_t \\ TED_t \\ dFRB_t \\ dCRB_t \end{pmatrix} \quad (60)$$

with $j \in \{C, M, V\}$. The model equations (53) to (55) are now adjusted so that

$$rx_{t+1} = \beta\lambda_t + \beta\tilde{u}_{t+1} + e_{t+1} \quad (61)$$

$$X_t = c + \Phi X_{t-1} + u_t \quad (62)$$

$$\lambda_t = \lambda_0 + \Lambda_1 F_t \quad (63)$$

with \tilde{u}_{t+1} being the first two components of u_{t+1} associated with the cross-sectional pricing factors. The structure of this dynamic asset pricing model (DAPM) specification is similar to the ones employed earlier. The difference is that time-varying risk prices are not related to contemporaneous cross-sectional pricing errors but to forecasting factors that are directly incorporated to explain the dynamics.

The parameters of this section's DAPM is conducted with the three-step regression

²⁴Byrne et al. (2017) employ a specification with a six-portfolio cross-section, the same set of risk factors DOL and HML, and a total of three forecasting factors VOL, TED, and dCRB. The sample period is November 1983 to December 2013.

approach of Adrian et al. (2015). First, the VAR parameters in (62) are estimated via OLS and used to extract the risk factor innovations \hat{u}_{t+1} . The beta representation (61) can be interpreted as a seemingly unrelated regressions (SUR) model of the form $rx_{t+1} = A_0 + A_1 F_t + \beta \tilde{u}_{t+1} + e_{t+1}$ that is fitted in a second step and that yields parameter estimates of $A_0 = \beta \lambda_0$, $A_1 = \beta \Lambda_1$ and β . In a final step, λ_0 and Λ_1 are inferred by regressing A_0 and A_1 respectively on β . Adrian et al. (2015) show that estimates from this procedure are consistent and asymptotically normal. Standard errors are robust with respect to heteroscedasticity in pricing errors.

Table 9 shows the estimation results of the dynamic regression-based framework. With regard to the carry premium associated with the HML^C risk factor, the relevance of currency market volatility as a risk premium driver is less clear-cut than in the case of likelihood filtered risk premia and as documented by Byrne et al. (2017). The coefficient measuring the impact of FX volatility on the HML risk price is of the same magnitude as above but insignificant.²⁵ However, the positive impact of shocks to FX volatility is still significant. The significantly positive impact of contemporaneous carry returns (HML^C) is reconciled in the DAPM as well. The negative relation to the TED spread, as also observed in Byrne et al. (2017), appears robust. Dollar competitiveness appears robust although the magnitude of the $dFRB_t$ coefficient is considerably larger. The explaining patterns for the risk premia associated with HML^M and HML^V observed in the previous section cannot be verified with the direct estimation approach. Only the coefficient with respect to HML^V preserves its sign and statistical significance. However, this result is not too surprising when considering the constant or unsystematic patterns of FX momentum and FX value premia respectively.

The results for the risk price dynamics associated with DOL risk grant some additional insights. The first is that the DOL risk price is negatively affected by changes in the capital ratio of financial intermediaries (dCr_t). The finding is robustly observed in all three cross-sections and in line with the findings of Adrian et al. (2011) who note that

²⁵The insignificance is also robust with respect to choosing alternative subsets of forecast variables. Discrepancies with Byrne et al. (2017) may still be explained by an altering sample period.

balance sheet variables amplify the volatility of foreign exchange risk premia. General exchange rate risk is therefore compensated with a higher risk premium in times of tightening funding constraints ($dCr_t < 0$). The effect is not visible in the three slope risk premia, thus supporting the view that intermediary balance sheet conditions affect the magnitude currency risk premia irrespective of carry, momentum, or value of the respective currency. A second insight from the dollar risk premium is that the risk price is positively affected by shocks to the commodity price index ($dCRB_t$). The finding is again robustly observed in all three cross-sections. This indicates that commodity currencies being exposed to commodity market developments are quite evenly allocated into the different portfolios. This together with the observation that the commodity variable could not forecast carry returns in-sample as found in the previous section is at odds with results in Bakshi and Panayotov (2013). They find in-sample as well as out-of-sample carry trade return predictability from the CRB return. An explanation could be the differing choices of bilateral rates used for carry trading. Whereas the present analysis employs up to a total of 48 currencies available to the investor, Bakshi and Panayotov (2013) restrict themselves to the G10 currencies in which the typical high-yielding currencies are the Australian dollar and the New Zealand dollar. These are the typical commodity currencies among the developed economies. However, a substantial number of commodity currencies can be identified within developing countries. If these (together with the developed commodity currencies) show no clear pattern regarding their interest differential, the premium would be earned evenly via the DOL risk factor and not the slope factor due to carry.

As a sharply condensed baseline of the present section on explaining factors, one could conclude that risk premia to value, FX momentum, and FX value are time-varying and predictable to some degree in-sample. Whereas movements in carry premia can be mainly explained by recent carry gains and FX market volatility (growth), no such conclusion can be robustly achieved with regard to premia for the other two signals.

4.3 Out-of-sample Analysis

It is still questionable whether the observed in-sample dynamics of risk premia also provide out-of-sample predictability of currency portfolio returns. The out-of-sample analysis in following predicts HML returns to the different investing styles on a rolling window of $T_0 = 240$ observations or roughly 20 years. The evaluation period therefore starts in 2004 with a total of $T - T_0 = 182$ forecast evaluations until February 2019. The forecast implied by the dynamic framework from the previous section is the one-period-ahead risk premium forecast

$$\widehat{r}p_{t|t+1} = (\hat{\beta}_5^{DOL} - \hat{\beta}_1^{DOL})\hat{\lambda}_t^{DOL} + (\hat{\beta}_5^{HML} - \hat{\beta}_1^{HML})\hat{\lambda}_t^{HML} \quad (64)$$

and it is compared to two benchmarks.

4.3.1 Forecast Benchmarks

The first benchmark is a random walk forecast where the underlying exchange rates are assumed to follow random walks with drifts in such a way that the HML forecast is given by the empirical mean of the returns on the window i.e.

$$\widehat{HML}_{t|t+1}^j = \frac{1}{T_0} \sum_{s=0}^{T_0-1} HML_{t-s}^j. \quad (65)$$

Besides the random walk benchmark that has been proven to be a tough one particularly in exchange rate predictability (Meese and Rogoff (1983), Rossi (2013)), an asset pricing model with constant risk prices is considered as the second benchmark. In this way, it can be clarified whether possible predictability really comes from risk price dynamics or by incorporating cross-sectional information from the middle portfolios that is not exploited in the random walk forecast. The second benchmark forecast therefore comes from a model as the one outlined in the previous section but with constant

lambdas such that the one period ahead HML forecast is given by

$$\widehat{HML}_{t|t+1}^j = (\hat{\beta}_5^{DOL} - \hat{\beta}_1^{DOL})\hat{\lambda}^{DOL} + (\hat{\beta}_5^{HML} - \hat{\beta}_1^{HML})\hat{\lambda}^{HML}. \quad (66)$$

The parameters for this model are estimated with the three-step approach developed by Adrian et al. (2015) with the omitted forecasting factor ($\Lambda_1 = 0$). The regression-based approach is chosen to have a benchmark that is close to the classical estimation approach of Fama and MacBeth (1973) without skipping the factor dynamics in (3.2).²⁶ As a result, the benchmark is tougher and a superior predictability simply because of explicitly modeling a time-varying factor mean can be ruled out.

4.3.2 Forecast Evaluation Methods

HML portfolio return forecasts are evaluated using three methods. The first one is the difference of the root means squared forecast error between the dynamic model and the repective benchmark i.e.

$$\Delta RMSE^j = \sqrt{\frac{\sum_{t=T_0}^{T-1} (HML_{t+1}^j - \widehat{HML}_{t|t+1}^j)^2}{T - T_0}} - \sqrt{\frac{\sum_{t=T_0}^{T-1} (HML_{t+1}^j - \hat{r}p_{t|t+1}^j)^2}{T - T_0}} \quad (67)$$

as employed in Welch and Goyal (2008). The dynamic forecast therefore improves on the benchmark with respect to lower forecast errors if $\Delta RMSE^j$ is positive.

The second statistic computed is the out-of-sample R^2 proposed in Campbell and Thompson (2008) computed as

$$R_{OOS}^2 = 1 - \frac{\sum_{t=T_0}^{T-1} (HML_{t+1}^j - \hat{r}p_{t|t+1}^j)^2}{\sum_{t=T_0}^{T-1} (HML_{t+1}^j - \widehat{HML}_{t|t+1}^j)^2} \quad (68)$$

which is positive if the dynamic forecast has a lower mean squared error. The third evaluation criterion is a Diebold and Mariano (1995) test with an alternative hypothesis

²⁶Adrian et al. (2015) argue that the classical estimator of Fama and MacBeth (1973) is nested in their approach with constant risk prices ($\Lambda_1 = 0$) and zero autoregressive coefficients in the factor VAR model ($\Phi = 0$).

that the dynamic forecasts is more adequate than the benchmark forecast in terms of mean squared errors.

4.3.3 Out-of-Sample Results

The results from the out-of-sample exercise are reported in Table 10. They primarily show that risk premia dynamics which are found in-sample do not necessarily translate into out-of-sample return predictability. An important exception would be the returns on the leveraged carry trade HML^C and the low-interest-currency portfolio C1 a can be seen in Panel A of Table 10. The dynamic risk price model can outperform both benchmarks, the random walk model as well as the constant lambda asset pricing model. The predictability is therefore likely to stem from allowing risk prices to vary over time. Since HML^C is a combination of the low- and high-interest-portfolios, one can argue that the predictability of HML^C mainly stems from the superior forecast ability of low-interest-currency returns. These low interest currencies are mostly typical safe-haven currencies like the Swiss franc and the Japanese yen that tend to appreciate (or depreciate) in adverse (or favorable) states of the world economy due to Ranaldo and Söderlind (2010). Figure 7 shows the cumulative differences in the sum of squared (forecast) errors (SSE) between the constant lambda benchmark forecast and the dynamic forecast. An increase (or decrease) of the cumulative SSE therefore indicates superior (or inferior) forecast adequacy in the respective time period. This way we have the opportunity to identify not only the predictable lag of the carry trade return but additionally can investigate in which time periods time-varying risk premia are important for out-of-sample forecasting.

The first panel of Figure 7 illustrates the predictive ability due to time-varying lambda for the leveraged carry trade. It shows that time variation in risk prices has been particularly important in the global financial crisis with a huge cumulative SSE difference after the Lehman collapse stemming from the predictability of the high interest portfolio. However, apart from this financial crisis effect, superior predictability of the C5 portfolio return due to incorporating lambda dynamics cannot be supported. In line

with these results, the carry panel reveals that the predictability mainly stems from the short leg (C1) and particularly from the recent period starting in 2016. Furthermore, the dynamic lambda high-interest portfolio return forecaster seems to be outperformed by the benchmark in this respective period. The forecast accuracy of the HML^C seems to be unaffected by the development in the high-carry portfolio and appears to be particularly accurate as opposed to the benchmark following 2016. This finding supports the view that prices for risk associated with carry, which according to the previous literature and supported by in-sample insights from this work, are mainly devoted to currency crash risk that is mirrored in the returns to safe-haven currencies. This risk, despite the otherwise favorable economic circumstances, has increased in recent years and is a crucial driver of the time-varying magnitude of carry trade returns.

A similar pattern regarding the increased short leg carry trade predictability starting in 2016 can be found for the leveraged FX momentum strategy as well when looking on Figure 8(b). However, the effect is quantitatively smaller and the dynamic lambda specification tended to be outperformed by the benchmark before 2016. This fits the observation that safe-haven currencies that are usually low-carry currencies have been experiencing a strong negative momentum in their returns.

Still puzzling are the recent extreme profits in leveraged carry and FX momentum strategies but the much lower risk premia for the latter. The evidence from the out-of-sample analysis supports the view that FX momentum returns stem from carry spillovers. Returns from carry trades can be explained with an increased risk premium that produces particular low returns for low-interest-rate currencies because of the negative exposure to the HML^C risk factor. These currencies will therefore be allocated to the short leg of the leveraged FX momentum portfolio. The resulting exposure of the leveraged FX momentum portfolio to the risks associated with carry will not enter the momentum premium because high carry currencies may not predominantly enter the high FX momentum portfolio. In this way, FX momentum returns could earn a carry or crash risk premium without the model indicating this.

As expected from the statistical predictability results the cumulative SSE difference of

the value style portfolios do not crucially diverge away from zero, favoring neither the dynamic model nor the benchmark with respect to forecast accuracy.

5 Conclusions

Risk dynamics differ substantially across different investment styles in currency trading. Expected returns to the carry trade can be understood as compensations for currency crash risk. The amount of compensation paid is higher following periods of high realized carry returns. In this way, the time series findings of Brunnermeier et al. (2008) fit the risk price dynamics implied by the cross-sectional factor structure proposed by Lustig et al. (2011). Moreover, the expected carry returns decrease sharply in times of high FX market volatility in which, as documented by Rinaldo and Söderlind (2010), positions are shifted into safe-haven currencies that tend to appreciate in response and finally incur losses in the short legs of carry trade positions. This points to a dual role of FX market volatility for being simultaneously a priced factor in the cross-section (Menkhoff et al. (2012a)) and a carry return predictor.

Risk premia in momentum portfolio returns are, in contrast, very stable, whereas the value premium is found to fluctuate roughly within the band from zero to the unconditional momentum risk price.

Low-interest currencies have been experiencing a strongly negative momentum due to large carry risk prices recently. This could be a compensation for the increased crash risk to which carry trades are prone. However, these returns have been realizing in the momentum strategy as well, but they can not be attributed to a risk premium due to the momentum factor. A question that cannot be answered within the scope of this paper is whether investing in FX momentum instead of carry offers an opportunity to achieve carry-like profits without being exposed to crash risk as the FX momentum returns. This could be thought of because FX momentum has not previously been affected by large unwinding in speculative positions and currency crashes. Or it could be that a structural break, possibly due to the increased popularity of FX momentum

trades, caused FX momentum returns to be exposed to currency crash risk and that the employed model cannot identify this due to limited data availability.

Appendix A. Tables and Figures

Table 4: Descriptive Statistics of Portfolio Returns

This table shows descriptive statistics on the excess returns of five quintile portfolios sorted by carry, momentum, and value, as well as of the corresponding HML portfolio that is an equally weighted portfolio consisting of a short position in the respective lowest quintile portfolio and a long position in the highest quintile portfolio. Returns are monthly and adjusted for transaction costs. The mean, median, standard deviation, and Sharpe ratio are annualized. The time span is from January 1984 to February 2019.

Portfolio	1	2	3	4	5	HML
<i>Panel A: Carry</i>						
Mean	-5.844	0.032	2.366	2.225	7.115	12.959
Median	-3.636	0.803	3.072	3.294	10.944	16.172
Std Deviation	8.684	7.095	7.843	8.221	10.286	9.874
Skewness	-0.071	-0.234	-0.265	-0.643	-0.877	-0.745
Kurtosis	3.970	3.953	4.205	5.123	5.477	4.966
Sharpe Ratio	-0.673	0.005	0.302	0.271	0.692	1.312
<i>Panel B: Momentum</i>						
Mean	-4.438	-0.958	1.002	2.274	5.964	10.402
Median	-1.988	1.841	0.391	2.663	6.815	9.876
Std Deviation	9.977	8.519	8.196	8.183	8.551	10.019
Skewness	-0.387	-0.883	-0.028	-0.102	-0.204	0.015
Kurtosis	5.694	6.756	4.574	4.287	4.802	4.536
Sharpe Ratio	-0.445	-0.112	0.122	0.278	0.697	1.038
<i>Panel C: Value</i>						
Mean	-0.273	2.082	1.761	2.924	4.639	4.912
Median	-0.262	1.792	3.899	5.481	4.765	3.872
Std Deviation	9.605	9.073	8.568	10.367	9.026	5.324
Skewness	-0.257	-0.059	-0.661	-0.625	-0.231	0.509
Kurtosis	3.811	3.198	7.014	5.123	4.268	4.759
Sharpe Ratio	-0.028	0.229	0.206	0.282	0.514	0.923

Table 5: Parameter Estimation Results

This table shows the maximum likelihood estimation results of the beta pricing equation $rx_{t+1} = \beta\lambda_t + \beta u_{t+1} + e_{t+1}$ and the risk price updating scheme $\lambda_t = \omega + As_t + B\lambda_{t-1}$ where $s_t = (\beta^\top \Sigma_e^{-1} \beta)^{-1} \beta^\top \Sigma_e^{-1} r_t - (\lambda_t + u_t)$ is the local cross-sectional GLS pricing error. Portfolios have been sorted on carry, momentum and value. Returns are monthly and adjusted for transaction costs. Standard errors are derived from the numerically computed inverse Fisher information matrix. The time span is from January 1984 to February 2019.

	Carry		FX Momentum		FX Value	
	DOL	HML	DOL	HML	DOL	HML
ω	0.061	0.488	0.036	0.700	0.050	0.304
s.e.	0.006	0.083	0.006	0.081	0.007	0.019
A	0.524	0.603	0.394	0.457	0.316	1.015
s.e.	0.077	0.089	0.007	0.053	0.020	0.059
B	0.456	0.582	0.457	0.222	0.808	0.239
s.e.	0.080	0.064	0.013	0.084	0.019	0.016
β_1	1.031	-0.404	0.988	-0.529	1.112	-0.437
s.e.	0.012	0.013	0.005	0.015	0.012	0.018
β_2	0.847	-0.111	0.936	-0.103	1.059	-0.033
s.e.	0.013	0.013	0.006	0.007	0.020	0.021
β_3	0.926	-0.032	0.969	0.089	0.927	0.005
s.e.	0.013	0.009	0.006	0.004	0.013	0.001
β_4	0.959	0.019	0.986	0.142	1.203	-0.047
s.e.	0.009	0.009	0.011	0.006	0.017	0.022
β_5	1.011	0.453	0.982	0.440	1.152	0.454
s.e.	0.009	0.015	0.005	0.003	0.022	0.004
LL	-917.482		-417.275		-1269.708	
MAPE	0.722		0.763		0.831	

Table 6: Carry Premium Regressions

This table shows results from regressing the filtered carry trade risk premium on explaining variables. These are the contemporaneous high-minus-low carry trade return (HML), foreign exchange volatility (VOL), foreign exchange volatility growth (dVOL), shocks to the aggregate capital ratio of FED primary dealers (dCr), the TED spread (TED), growth rates of the broad dollar index of the Federal Reserve Board (dFRB) and the growth rate of the raw industrials subindex of the CRB spot commodity index (dCRB). Newey-West standard errors are shown in parentheses. The time span varies within the period from January 1984 to February 2019 due to data availability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HML	0.135*** (0.010)	0.125*** (0.010)	0.131*** (0.010)	0.130*** (0.010)	0.132*** (0.010)	0.131*** (0.011)	0.131*** (0.010)
VOL		-0.648*** (0.228)	-1.416*** (0.312)	-1.401*** (0.303)	-1.456*** (0.316)	-1.408*** (0.299)	-1.344*** (0.282)
dVOL			1.542*** (0.395)	1.532*** (0.367)	1.688*** (0.435)	1.780*** (0.414)	1.796*** (0.395)
dCr				-0.050 (0.369)	-0.012 (0.377)	-0.120 (0.322)	-0.204 (0.312)
TED					-0.080** (0.036)	-0.090** (0.038)	-0.081** (0.039)
dFRB						-5.414*** (1.807)	-4.429** (1.865)
dCRB							1.524* (0.917)
Constant	0.900*** (0.024)	1.167*** (0.089)	1.464*** (0.120)	1.456*** (0.116)	1.521*** (0.123)	1.518*** (0.118)	1.484*** (0.113)
Observations	422	422	422	419	395	395	395
R ²	0.457	0.477	0.508	0.503	0.527	0.541	0.545
Adjusted R ²	0.455	0.475	0.505	0.498	0.521	0.534	0.537

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 7: FX Momentum Premium Regressions

This table shows results from regressing the filtered FX momentum risk premium on explaining variables. These are the contemporaneous high-minus-low FX momentum return (HML), foreign exchange volatility (VOL), foreign exchange volatility growth (dVOL), shocks to the aggregate capital ratio of FED primary dealers (dCr), the TED spread (TED), growth rates of the broad dollar index of the Federal Reserve Board (dFRB) and the growth rate of the raw industrials subindex of the CRB spot commodity index (dCRB). Newey-West standard errors are shown in parentheses. The time span varies within the period from January 1984 to February 2019 due to data availability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HML	0.018*** (0.002)	0.018*** (0.002)	0.018*** (0.002)	0.018*** (0.002)	0.018*** (0.002)	0.019*** (0.002)	0.019*** (0.002)
VOL		0.005 (0.030)	-0.030 (0.063)	-0.028 (0.068)	-0.007 (0.076)	0.003 (0.078)	0.0004 (0.078)
dVOL			0.067 (0.111)	0.078 (0.117)	0.086 (0.135)	0.106 (0.132)	0.105 (0.132)
dCr				0.068 (0.090)	0.040 (0.097)	0.019 (0.099)	0.023 (0.101)
TED					-0.017 (0.011)	-0.019* (0.011)	-0.019* (0.011)
dFRB						-1.051*** (0.316)	-1.094*** (0.348)
dCRB							-0.069 (0.232)
Constant	0.851*** (0.004)	0.849*** (0.013)	0.863*** (0.025)	0.861*** (0.027)	0.863*** (0.030)	0.861*** (0.031)	0.863*** (0.032)
Observations	422	422	422	419	395	395	395
R ²	0.230	0.230	0.232	0.229	0.239	0.253	0.253
Adjusted R ²	0.228	0.226	0.226	0.222	0.229	0.241	0.240

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 8: FX Value Premium Regressions

This table shows results from regressing the filtered FX value risk premium on explaining variables. These are the contemporaneous high-minus-low FX value return (HML), foreign exchange volatility (VOL), foreign exchange volatility growth (dVOL), shocks to the aggregate capital ratio of FED primary dealers (dCr), the TED spread (TED), growth rates of the broad dollar index of the Federal Reserve Board (dFRB) and the growth rate of the raw industrials subindex of the CRB spot commodity index (dCRB). Standard errors are shown in parentheses. The time span varies within the period from January 1984 to February 2019 due to data availability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HML	0.125*** (0.005)	0.124*** (0.005)	0.124*** (0.005)	0.126*** (0.005)	0.129*** (0.005)	0.119*** (0.003)	0.117*** (0.003)
VOL		0.122* (0.074)	0.081 (0.074)	0.084 (0.075)	0.121 (0.074)	0.065 (0.042)	0.040 (0.042)
dVOL			0.078 (0.099)	0.085 (0.100)	0.013 (0.114)	-0.114 (0.091)	-0.120 (0.095)
dCr				0.013 (0.120)	0.015 (0.122)	0.160** (0.080)	0.195** (0.078)
TED					0.008 (0.022)	0.019** (0.008)	0.016** (0.008)
dFRB						6.851*** (0.407)	6.483*** (0.420)
dCRB							-0.624*** (0.234)
Constant	0.342*** (0.006)	0.294*** (0.027)	0.310*** (0.029)	0.307*** (0.029)	0.287*** (0.032)	0.295*** (0.017)	0.309*** (0.017)
Observations	422	422	422	419	395	395	395
R ²	0.619	0.623	0.623	0.637	0.653	0.764	0.767
Adjusted R ²	0.618	0.621	0.621	0.634	0.648	0.760	0.763

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 9: DAPM Results

This table shows results from estimating a dynamic asset pricing model according to Adrian et al. (2015) where the risk price dynamics are given by $\lambda_t = \lambda_0 + \Lambda_1 F_t$. Considered forecasting factors F_t are the contemporaneous high-minus-low carry trade return (HML), foreign exchange volatility (VOL), foreign exchange volatility growth (dVOL), shocks to the aggregate capital ratio of FED primary dealers (dCr), the TED spread (TED), growth rates of the broad dollar index of the Federal Reserve Board (dFRB) and the growth rate of the raw industrials subindex of the CRB spot commodity index (dCRB). Standard errors are shown in parentheses. The time span varies within the period from January 1984 to February 2019 due to data availability.

	λ_0	HML^j	VOL	dVOL	dCr	TED	dFRB	dCRB
<i>Panel A: Carry</i>								
DOL	-0.237 (0.465)	0.028 (0.038)	1.249 (1.156)	-2.297 (1.624)	-6.371*** (1.576)	-0.269 (0.243)	-8.926 (8.519)	10.780*** (4.018)
HML^C	1.734*** (0.632)	0.301*** (0.052)	-1.402 (1.570)	4.872** (2.213)	-1.102 (2.147)	-0.682** (0.330)	-34.658*** (11.605)	-0.474 (5.473)
<i>Panel B: FX Momentum</i>								
DOL	-0.163 (0.459)	-0.045 (0.035)	1.184 (1.152)	-2.489 (1.598)	-6.252*** (1.567)	-0.302 (0.242)	-8.568 (8.514)	10.113** (4.039)
HML^M	2.400*** (0.667)	0.062 (0.051)	-4.434*** (1.671)	6.017** (2.326)	3.813* (2.273)	0.181 (0.351)	9.196 (12.365)	-8.612 (5.848)
<i>Panel C: FX Value</i>								
DOL	-0.222 (0.459)	0.089 (0.068)	1.412 (1.161)	-2.799* (1.618)	-6.117*** (1.591)	-0.298 (0.243)	-8.625 (8.701)	11.412*** (4.085)
HML^V	-0.081 (0.361)	0.210*** (0.053)	1.075 (0.914)	-1.306 (1.262)	-1.215 (1.244)	-0.074 (0.190)	-1.628 (6.815)	-1.178 (3.191)

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 10: Out-of-Sample Predictability

This table shows results from a forecasting exercise with a rolling window of 240 observations. Forecasts are computed for 182 time periods. Relative forecast performance of the dynamic model from Section 3 is evaluated with respect to a random walk benchmark as well as a constant lambda benchmark that assumes constant risk prices over time. $\Delta RMSE$ is the difference between the root mean squared forecasting errors of the dynamic and the benchmark model. $OOS-R^2$ is the out-of-sample R^2 of Campbell and Thompson (2008). DM p-value refers to a Diebold and Mariano (1995) test with an alternative hypothesis that the benchmark model has an inferior predicting accuracy. The time span is from January 1984 to February 2019.

Portfolio	1	2	3	4	5	HML
<i>Panel A: Carry</i>						
Random Walk Benchmark						
$\Delta RMSE$	0.057	-0.010	-0.011	-0.002	0.018	0.189
$OOS-R^2$	0.053	-0.010	-0.009	-0.002	0.013	0.146
DM p-value	0.012	0.697	0.633	0.523	0.400	0.006
Constant λ Benchmark						
$\Delta RMSE$	0.072	-0.012	-0.012	-0.001	0.019	0.191
$OOS-R^2$	0.066	-0.013	-0.011	-0.001	0.014	0.148
DM p-value	0.003	0.742	0.668	0.514	0.395	0.006
<i>Panel B: FX Momentum</i>						
Random Walk Benchmark						
$\Delta RMSE$	0.023	0.006	-0.011	0.007	0.004	-0.002
$OOS-R^2$	0.016	0.005	-0.011	0.006	0.003	-0.002
DM p-value	0.317	0.412	0.682	0.400	0.424	0.527
Constant λ Benchmark						
$\Delta RMSE$	0.005	0.014	-0.005	0.009	-0.018	-0.005
$OOS-R^2$	0.004	0.013	-0.004	0.009	-0.015	-0.004
DM p-value	0.449	0.305	0.576	0.362	0.827	0.562
<i>Panel C: FX Value</i>						
Random Walk Benchmark						
$\Delta RMSE$	-0.009	-0.017	-0.005	0.006	-0.030	0.009
$OOS-R^2$	-0.007	-0.015	-0.004	0.004	-0.028	0.012
DM p-value	0.639	0.778	0.596	0.399	0.891	0.269
Constant λ Benchmark						
$\Delta RMSE$	-0.007	-0.016	-0.004	0.004	-0.029	0.008
$OOS-R^2$	-0.006	-0.014	-0.003	0.002	-0.028	0.010
DM p-value	0.607	0.759	0.585	0.413	0.879	0.310

Figure 4: Cumulative Log Returns to HML Strategies

The figure shows cumulative log excess returns to the HML portfolio strategies sorted on carry, FX momentum and FX value. The sample period is January 1984 to February 2019. Shaded areas refer to NBER recessions.

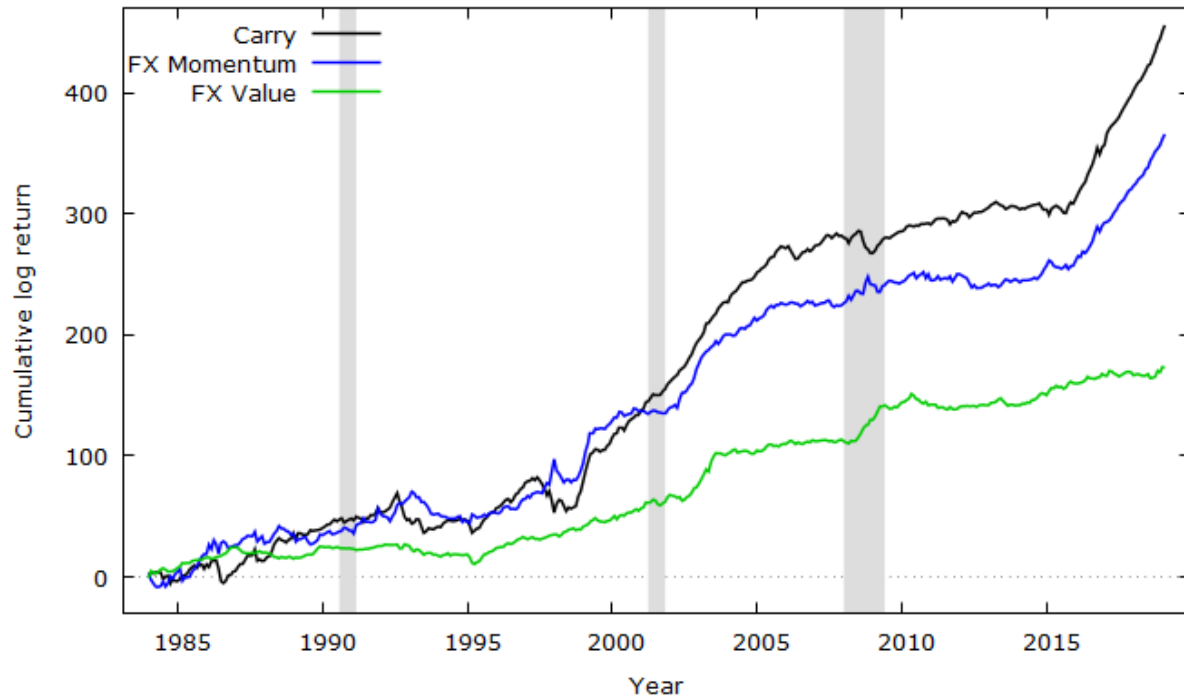


Figure 5: Risk Premia to HML Strategies

The figure shows risk premia to the HML portfolio strategies returns sorted on carry, FX momentum and FX value. Risk premia are computed as $\hat{r}_{p_{t+1}} = (\hat{\beta}_5^{DOL} - \hat{\beta}_1^{DOL})\hat{\lambda}_t^{DOL} + (\hat{\beta}_5^{HML} - \hat{\beta}_1^{HML})\hat{\lambda}_t^{HML}$. The sample period is January 1984 to February 2019. Shaded areas refer to NBER recessions.

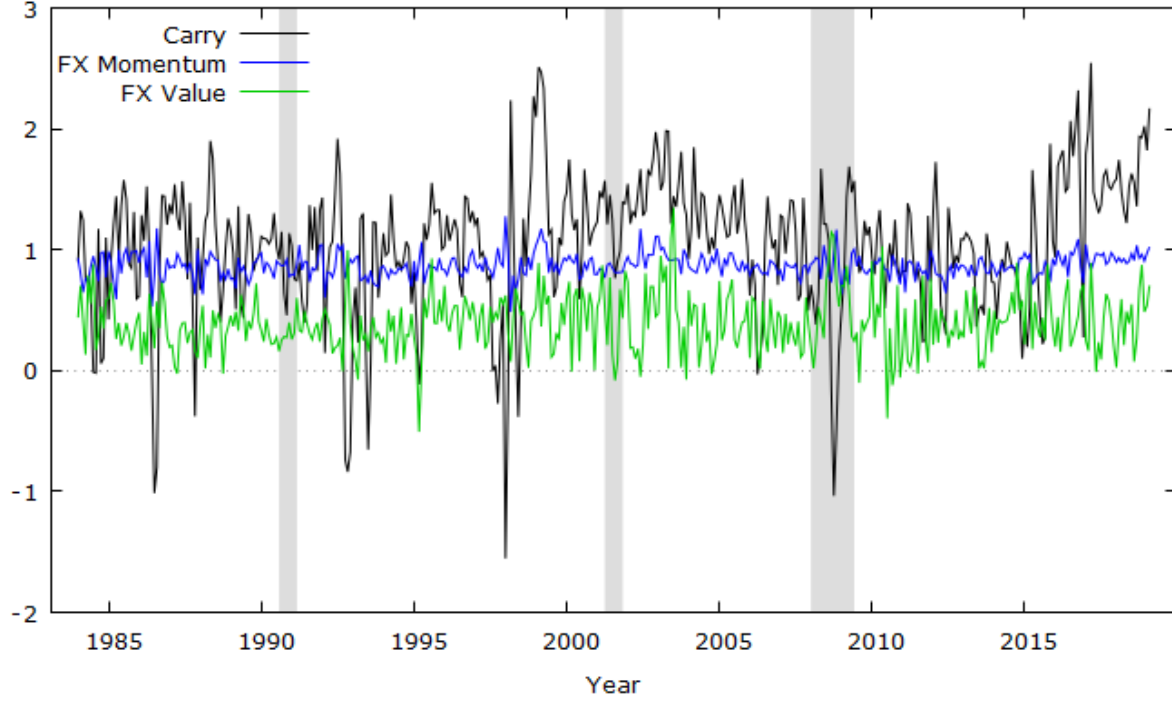
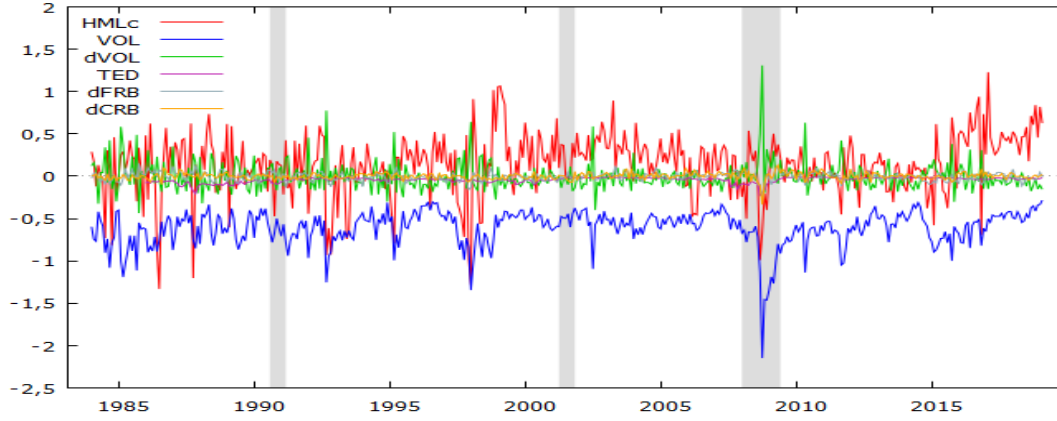
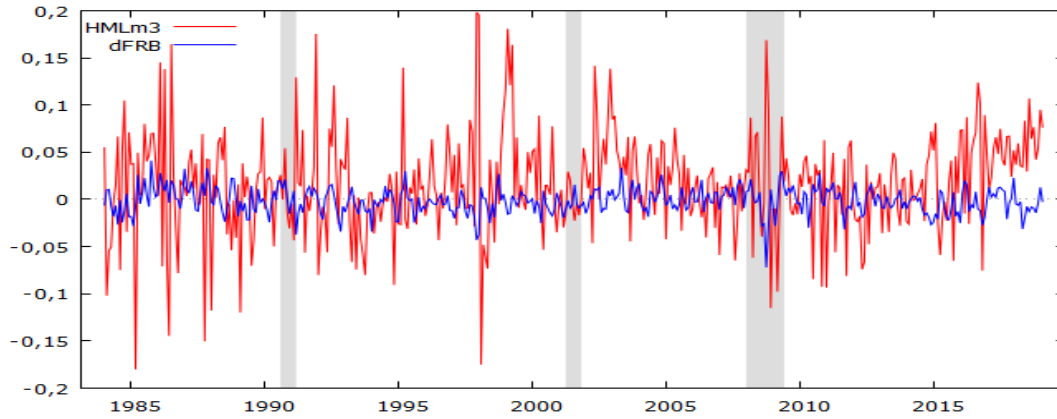


Figure 6: Contribution of Explaining Factors

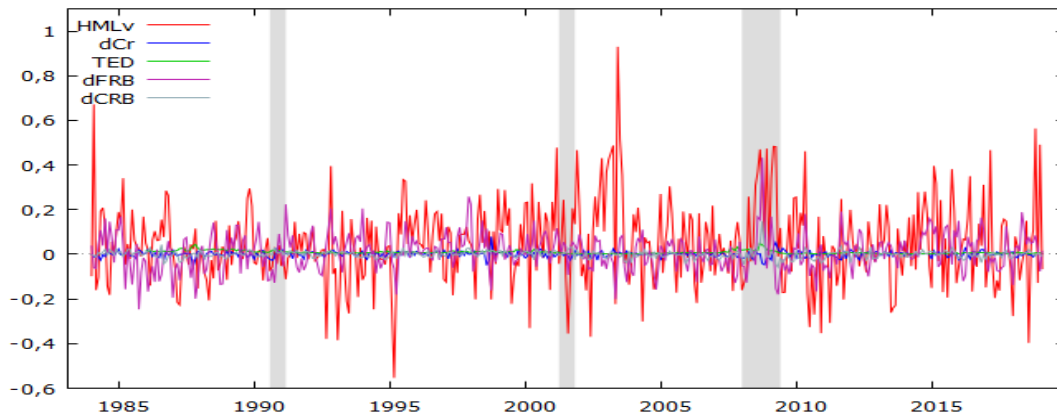
The figure shows the contribution of significant explaining factors for the HML risk premium of carry, FX momentum and FX value respectively. Plotted series are explaining factor time series times the respective estimated coefficient. Only series with significant coefficient are plotted.



(a) Carry



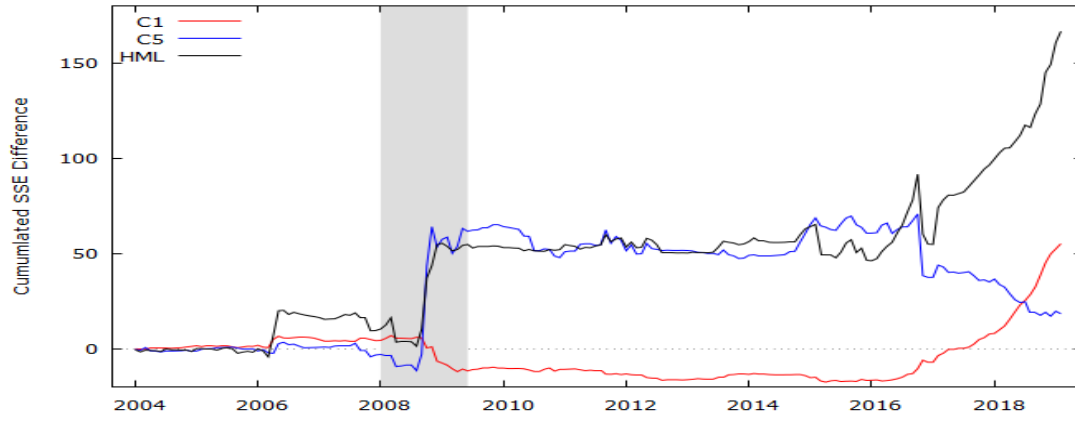
(b) FX Momentum



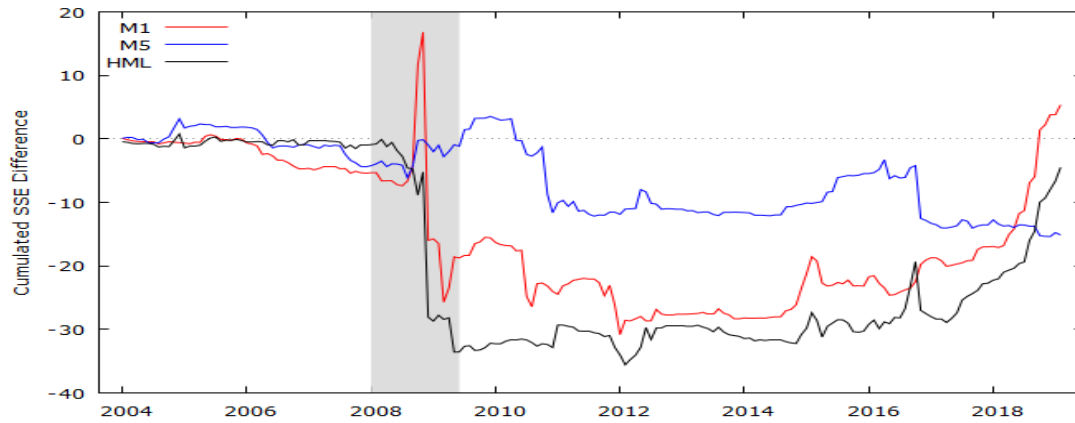
(c) FX Value

Figure 7: Cumulative SSE Differences

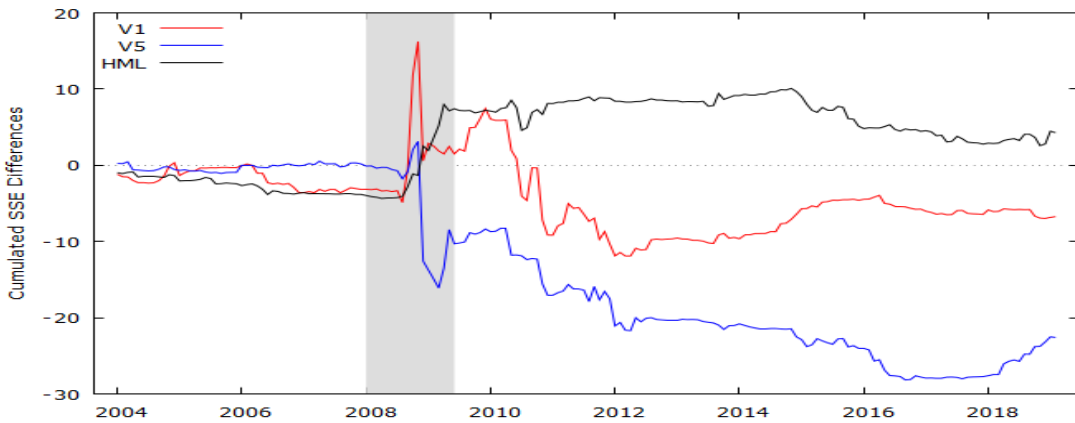
The figures show the cumulative differences in sum of squared (forecast) errors (SSE) between the constant lambda benchmark forecast and dynamic forecast for returns of portfolios sorted on carry (Panel (a)), FX momentum (Panel (b)) and FX value (Panel (c)). Plotted are the cumulative SSE differences for each the low-signal portfolios (C1, M1, V1), the high-signal portfolios (C5, M5, V5) and the high-minus-low portfolios (HML).



(a) Carry



(b) FX Momentum



(c) FX Value

Chapter IV

Foreign Exchange Dealer Asset Pricing

Coauthored by Stefan Reitz

Abstract

We show that excess returns to the carry trade can be interpreted as compensation for foreign exchange dealers' capital risk. Given that the top market makers in foreign exchange are at the heart of the market's information aggregation process we also suggest that it is their marginal value of wealth which prices foreign currencies. Consistent with this hypothesis the empirical results show that shocks to the equity capital ratios of the top three foreign exchange dealers have explanatory power for the cross-sectional variation in expected currency market returns, while those of the average dealer provide no substantial additional information.

Keywords: Carry Trades, Intermediary Asset Pricing, FX Dealers, Currency Risk

JEL Codes: F31, G12, G15

1 Introduction

The foreign exchange (FX) market with a turnover of 5,067 billion US dollar in 2016 (BIS 2016) can be considered as the biggest over-the-counter (OTC) market in the world, where a set of specialized dealers provide FX liquidity for a large variety of customers and trade heavily among each other. Particularly large foreign exchange dealers may be perceived as internationally-active financial intermediaries potentially being marginal for pricing FX assets. This is supported by the fact that they are at the core of the FX dealing process, face low transaction costs, and make use of complex investment strategies as well as extensive data resources. These properties nicely fit the underlying assumptions of consumption-based asset pricing models regarding the sophisticated representative investor and his optimizing behavior. Thus, it is the marginal value of wealth of large FX dealers which may propagate a stochastic discount factor instead of the marginal value of wealth of the representative household. Regarding the intermediaries' specific metric for asset pricing information in general recent empirical contributions stress the importance of balance sheet variables for explaining the cross-section of excess returns in a number of asset classes (He et al. 2017; Adrian et al. 2014).²⁷

This paper provides a detailed analysis of the role of FX dealers' balance sheet constraints for currency pricing. Our empirical results show that their aggregated capital ratio explains remarkable well as a priced risk factor in a variety of currency portfolio cross-section. The key insight, however, arises from ranking data we collected from the EuroMoney FX survey. In fact, balance sheet information of the reported biggest three FX dealers by market share is sufficient to describe the cross-sectional variation of currency portfolio returns. Factor horse races reveal that this factor outperforms the factor calculated from the broader set of financial intermediaries listed as the New York Fed's primary dealers as used in He et al. (2017).

From a theoretical perspective, the results nicely fit the specific two-tier over-the-

²⁷Note that banking regulation, which impacts dealers' balance sheets has been shown to significantly constrain their position taking in FX markets (Du et al. 2018).

counter structure of foreign exchange markets. The first tier consists of a dealer-to-customer trading segment, where dealers trade foreign exchange with their clients such as importers, exporters, and international investors. The second tier refers to an dealer-to-dealer trading segment confined to FX dealers operating among themselves (Lyons 1995). The information dissemination is assumed to start with customers reacting to macro news by submitting orders to their FX dealers. The excess of all buying and selling orders from customers of a given dealer is then transferred to the dealer-to-dealer segment of foreign exchange (Lyons 1997).²⁸ This market structure suggests that information aggregation may be time consuming (Evans and Lyons 2005; Love and Payne 2008). More importantly, however, the market structure implies that the size of the dealer matters for FX pricing as large dealers represent a substantial fraction of the overall order flow. In addition, large dealers typically dominate the dealer-to-dealer trading thereby also attracting a major share of other dealers' order flow. The predictions for dealers' balance sheet measures are straightforward. The average (periphery) dealer is able to hand over her exposure from FX trading to major (core) dealers functioning as the ultimate liquidity providers (Moore et al. 2016). Moreover, core dealers tend to take risks on their balance sheets from their FX business instead of engaging in the hot potato. This is suggested by survey evidence discussed in Moore et al. (2016) and confirmed by Hasbrouck and Levich (2019) using CLS settlement data. To quote from Moore et al. (2016): *'The top-tier dealer banks that intermediate the lions share of customer flows have maintained their position as large flow internalisers, price-makers and liquidity providers.'* If balance sheet effects of FX trading is neutralized for periphery dealers, but not for core dealers, then capital ratios of core dealers should contain most of the information relevant for FX pricing, while those of periphery dealers are less likely to be informative. Our empirical results provide support for this hypothesis showing that excess returns in currency markets can reasonably be explained by the

²⁸More recently, Malamud and Schrimpf (2018) develop a general equilibrium model with FX dealers being marginal investors in international financial markets. The consideration of market frictions such as dealers' market power in dealer-to-customer trading helps to explain the role of the US dollar as a safe haven currency and the recently observed departures from covered interest parity.

financial wealth of the three most active FX dealers who are the relevant marginal dealers, while the additional explanatory power from including more peripheral dealers' capital ratios is negligible.

Aside from providing insights into the pricing ability of top-tier dealers for currency portfolio returns, we extend the analysis by performing empirical asset pricing tests separately on cross-sections sorted by carry, momentum and value. In particular, our intermediary asset pricing models show a remarkably good fit for carry trade portfolios. This points towards a risk-based explanation of carry trade returns related to balance-sheet conditions of main FX dealers. Currencies trading at a high forward discount tend to pay off poorly when the capital ratio decreases and balance sheet constraints are tightening. In contrast, the negative beta of currencies with a forward premium suggests that these provide a hedge for times of a decreasing capital ratio. With respect to other portfolio sorts, however, little pricing ability of the intermediary factors is found to explain value portfolios and almost none for currency portfolios sorted on exchange rate momentum implying that these portfolios seem to exert little impact on core FX dealers' balance sheets. The missing evidence fits the recent literature on currency risk factors reporting that factors which matter for carry trade pricing are less successful in explaining currency momentum returns Menkhoff et al. (2012b).

Our findings contribute to several strands in the finance as well as economics literature. Recent contributions in macro-financial modeling point to the importance of balance sheet variables of financial intermediaries for asset returns. He and Krishnamurthy (2013) as well as Brunnermeier and Sannikov (2014) propose models in which financial intermediaries face equity constraints affecting risk premia when binding. Examples of models taking leverage constraints into consideration are Brunnermeier and Pedersen (2009) as well as Adrian and Boyarchenko (2012). Extending a banking economy with financial frictions to a two-country model, Maggiori (2017) analyzes the role of intermediaries for international risk sharing. More closely related to our set up is Malamud and Schrimpf (2018) who provide a fully micro-founded general equilibrium model in which top FX dealers are the relevant marginal investors.

The predictions of the above discussed intermediary asset pricing theories concerning the price of risk associated with intermediaries' balance sheets differ substantially. Whereas theories that favor intermediaries net worth as state variable find intermediary equity to be procyclical, theories emphasizing the role of leverage predict procyclical intermediary leverage implying countercyclical net worth behavior. Our empirical results favor pro-cyclical intermediary equity in foreign exchange risk premia.

In the empirical intermediary asset pricing literature, Adrian et al. (2014) find that a factor model with innovations to broker-dealer leverage being the only factor is able to prize stock and bond portfolios with a remarkable R^2 of about 77% outperforming standard multi-factor models. Adrian et al. (2016) extend this result to a dynamic framework allowing risk prices to be driven by lagged intermediary balance sheet variables as proposed by the theoretical contributions discussed above. He et al. (2017) generalizes the work of Adrian et al. (2014) to various asset classes using shocks to financial intermediary capital ratios and find significant explanatory power for cross-sectional variation in excess returns. Their capital ratio factor which is also used in our work is found to be pro-cyclical and would therefore imply the corresponding leverage to be counter-cyclical. This is in contrast to the positive price of leverage risk observed in Adrian et al. (2014) as well as Adrian et al. (2016).

With respect to our application to FX markets it is important to note that intermediaries' balance sheet factors matter most for those asset markets, which are highly intermediated (Haddad and Muir 2018). However, direct empirical evidence from FX markets is relatively scarce. Adrian et al. (2011) provide evidence that balance sheet variables have an impact on the price of market risk in foreign exchange. Closest to our analysis is He et al. (2017) who demonstrate that capital ratio innovations from a broad set of the Federal Reserve's primary dealers are a priced risk factor in many asset classes. Although the authors also provide results for the cross-section of currency portfolio returns sorted on carry and momentum, the main purpose of their paper is to show the universal pricing power of balance sheet factors for a maximum variety of assets. However, our empirical evidence from FX markets suggests that primary

dealers are not a homogeneous group of intermediaries equally important on every asset market. Instead, considering the specific OTC nature of FX trading as outline above, we show that capital ratio innovations of the three largest dealers are sufficient to describe excess FX returns.

Our work is further related to the recent research agenda on covered interest parity (CIP) deviations, that are mainly devoted to changes in banking regulation (Du et al. 2018, Borio et al. 2016, Avdjiev et al. 2016). Du et al. (2018) argue that post-crisis balance sheet regulations constrain financial intermediaries resulting in an inelastic supply of currency hedging and therefore leave arbitrage opportunities due to CIP deviations unexploited. Aside from regulatory issues funding liquidity premia, which differ across currency areas may be key to understand CIP deviations. In fact, Rime et al. (2019) report substantial differences in USD funding costs implying that only very few intermediaries are able to gain significant arbitrage profits. Moreover, Andersen et al. (2019) emphasize the role of funding value adjustments covered in quoted dealer prices due to debt overhang costs to their shareholders. They argue that the dealer's credit spread must be exceeded by the cross-currency basis to make them benefit from arbitraging CIP deviations.

Another important strand of the literature focuses on risk factors in the cross-section of currency returns. For instance, Lustig et al. (2011) find that this cross-section can be largely explained by only two principal components, where the first one can be interpreted as a currency market return²⁹ and the second factor can be identified as a slope factor that is closely related to a high-minus-low carry trade return.³⁰ The use of linear factor models with the dollar risk factor and a second slope factor gained popularity in subsequent literature focusing on currency market risks. Menkhoff et al. (2012a) propose a measure of global FX volatility as alternative slope factor that has a significantly negative price of risk. Mueller et al. (2017) show another way to extract

²⁹Typically called 'dollar risk factor' as it is computed as the return from investing on dollar into an equally weighted portfolio of all currencies available.

³⁰In the classical high-minus-low carry trade strategy the investor buys the portfolio of currencies with the highest interest rates and finances this purchase with a short position in the lowest interest rate currency portfolio.

information from currency moments by observing that the cross-sectional dispersion of FX correlations widens in market downturns. A factor measuring the dispersion of FX correlations is found to serve well as a slope factor for pricing currency portfolios. Lettau et al. (2014) stresses the role of downside risk to explain the cross-section of carry trade returns. Further risk factors in currency returns that have been investigated are currency momentum (Menkhoff et al. 2012b; Asness et al. 2013) and illiquidity (Mancini et al. 2013; Karnaukh et al. 2015). A common feature of most factors studied so far is that they are specific to the currency market and exert only little pricing power in other asset classes. Conversely, typical risk factors from stock markets for example only have very limited pricing power for currency returns (Burnside (2012)). We particularly contribute to this literature by investigating FX dealer balance sheet factors as an alternative slope factor that carries an intuitive economic interpretation. The ability of the factor to explain excess returns on FX markets is surprising given that in contrast to many competitor slope factors it is calculated from exogenous sources and not from the time series of FX returns themselves.

The paper is organized as follows. Section 2 briefly outlines the idea of the risk-based explanation of excess returns in currency markets and the connection to intermediary asset pricing. Section 3 discusses our data set, the construction of our top FX dealer factors and explains how currency portfolios are constructed. In Section 5 we present our empirical results. Section 6 finally concludes.

2 Currency Returns and Intermediary Asset Pricing

Throughout the paper we think of an financial intermediary with an accounting framework based on US dollars.³¹ The continuously compounded return of investing one dollar in a foreign currency from periods t until $t+1$ via a FX forward contract can be

³¹The assumption is clearly satisfied for US intermediaries. However we mostly consider internationally-acting financial institutions that are also likely to base decisions on US-dollar-denoted payoffs.

derived as

$$rx_{t+1}^i \approx f_{t,t+1}^i - s_{t+1}^i, \quad (69)$$

where s_t^i denotes the logarithmic spot exchange rate for exchanging one US dollar to currency i in period t and $f_{t,t+1}^i$ is the corresponding logarithmic forward rate. In a simple two-period consumption-based asset pricing model where the representative investor maximizes an utility function $U(c_t, c_{t+1}) = u(c_t) + \beta u(c_{t+1})$, and faces a consumption stream c_t, c_{t+1} , the first order condition would imply that

$$0 = \mathbb{E} \left(\beta \frac{u'(c_{t+1})}{u'(c_t)} rx_{t+1} \right), \quad (70)$$

where the price on the left-hand-side is zero because the investment strategy generating the return in (69) is self-financing. Hence the stochastic discount factor (SDF) $m_{t+1} = \beta u'(C_{t+1})/u'(C_t)$ that determines the price of the asset depends on the investor's marginal value of wealth. If we interpret the consumption-based model from the point of view of a financial intermediary, it is reasonable to suspect that the marginal value of wealth depends on the intermediaries wealth level that in turn depends on aggregate wealth of the economy as well as the composition of the intermediaries balance sheet. Most financial intermediary theories therefore would justify to assume the SDF being an affine-linear function of aggregate wealth in the economy W_t and a proxy for the wealth of the intermediary sector I_t , or more precisely $m_t = 1 - b^W(W_t - \bar{W}) - b^I(I_t - \bar{I})$ with \bar{W} and \bar{I} being the respective means. Such an pricing kernel would then yield the following linear representation for the expected excess return:

$$\mathbb{E}_t(rx_{t+1}) = b^W \mathbb{E}_t(rx_{t+1}(W_{t+1} - \bar{W})) + b^I \mathbb{E}_t(rx_{t+1}(I_{t+1} - \bar{I})) \quad (71)$$

$$= b^W Cov_t(rx_{t+1}, W_{t+1}) + b^I Cov_t(rx_{t+1}, I_{t+1}) \quad (72)$$

$$= \beta_t^W \lambda_t^W + \beta_t^I \lambda_t^I \quad (73)$$

with $\beta_t^W = Cov_t(rx_{t+1}, W_{t+1})/Var_t(C_{t+1})$, $\beta_t^I = Cov_t(rx_{t+1}, I_{t+1})/Var_t(C_{t+1})$ denoting the vector of risk exposures of the asset to the corresponding factor and λ_t^W, λ_t^I being the associated prices of risk.

Lustig et al. (2011) find that the cross-section of currency returns can be explained by two principal components and therefore favor a two-factor asset pricing model as in (73). The first one can be identified as a constant factor that is highly correlated to the excess return of an equally weighted portfolio consisting of each currency available. We refer to this factor as Dollar factor and denote it with DOL_t . It can be interpreted as an analogue to market return in the stock pricing literature since it gives information about how much return an investor gets for investing in the whole currency market. This interpretation falls in line with the aggregated wealth factor W frequently found in the intermediary asset pricing literature. The second factor can be identified as a slope factor. Lustig et al. (2011) hence propose the "high minus low"-factor HML_t that is the return of the classical carry trade strategy in which the investor buys the portfolio with the highest interest rates and finances this purchase with a short position in the lowest interest rate portfolio. This second factor rationalized from intermediary asset pricing would be the intermediary wealth factor I . If W really captures the same variation in asset prices as DOL we would expect the same to hold for HML and I . In terms of equation (73) we therefore arrive at expectations derived from

$$\mathbb{E}_t(rx_{t+1}) = \beta_t^{DOL} \lambda_t^{DOL} + \beta_t^I \lambda_t^I, \quad (74)$$

where β_t^{DOL} denotes the risk exposure to the Dollar factor and λ_t^{DOL} the associated price of risk.

3 Data

The following sections discuss the construction of FX dealer risk factors and currency portfolios for estimation of the FX intermediary asset pricing framework introduced above.

3.1 Intermediary Capital Ratio Factors

To empirically test the proposed model we apply a risk factor approximating the financial wealth of marginal traders identified by their market share of overall turnover in foreign exchange. As outlined in the introduction the top three FX dealers are assumed to be closest to the core dealers in FX markets acting as ultimate liquidity providers for customers and average dealers.³² Moreover, as suggested by Moore et al. (2016) and Hasbrouck and Levich (2019) only the top-tier dealers are expected to also warehouse FX inventory risks in their balance sheets, while the average dealer hands over her balance sheet exposure to core dealers.

To capture the market share of FX dealers we rely on data reported in the Euromoney FX survey. The survey is published every year in the Euromoney magazine since 1979.³³ In about the first four months of a year respondents are asked to name their top 20 foreign exchange dealers by volume and the volume they traded with each dealer. This information allows to construct a ranking of the biggest dealers and to estimate their respective market share. As shown in Table 11, a total of 39 financial institutions entered the top ten at least once in the period between 1984 and 2017. Increasingly fierce competition in the market triggered mergers and acquisitions implying that a number of the listed dealers no longer exist. In addition, most of the dealers and in particular the top three are large international banks, among which Citibank, UBS, and Deutsche Bank as well as precursors of JP Morgan Chase (Chase Manhattan, Chemical) played or still play an important role.

³²We also used top-five and top-ten dealers as a robustness check. The empirical results documented in section 4.5 remain qualitatively unchanged.

³³The survey has been usually published together with some accompanying articles in the May issue.

The increasing importance of core FX dealers can be observed from the estimated market shares displayed in Figure 8.³⁴ Whereas the biggest three intermediaries maintain a combined share of below 20% in the 1980s, they reach a peak of over 40% market share in 2008. In general, Figure 8 confirms that foreign exchange trading became much more concentrated over time.³⁵ Aside from pure market share the grouping of dealers is also backed by the correlation of capital ratios among core dealers and between core dealers and periphery dealers. Particularly in the 2000s the correlation of capital ratios is higher than 90% between Barclays, Citigroup, Deutsche Bank, HSBC, RBS, but substantially lower towards dealers like Lehman Brothers or RBC.³⁶ Reflecting the internationalization of the intermediation business we also observe an overall increasing correlation of capital ratios over time.

Following He et al. (2017) we use balance sheet data on market equity and book debt of FX dealers' holding companies from CRSP/Compustat as well as Datastream. The authors' decision to use balance sheet data of holding companies is driven by the potential importance of intermediaries' internal capital markets. Profit and loss agreements within the financial conglomerates most likely lead to mitigation of shocks to the broker-dealer subsidiary, but show up in the holding company. Conversely, stress situations might be considered where funding for FX exposure of the subsidiary is impaired due to large negative shocks experienced by the holding company. Thus, the aggregate capital ratio of institution i at period t is computed as

$$\eta_{i,t} = \frac{MarketEquity_{i,t}}{(MarketEquity_{i,t} + BookDebt_{i,t})}. \quad (75)$$

To get the market equity we multiply the share price of the stock market where the holding is located with the number of common shares outstanding. The reason for using the market value of equity is that it better reflects whether the intermediary

³⁴The Euromoney survey articles from 1991 to 1995 do not provide estimates of individual market shares and are therefore linearly interpolated in the figure.

³⁵A more detailed picture on FX market concentration can be found in BIS (2010).

³⁶An important exception is the capital ratio of UBS with a correlation coefficient of around 70% to most of its top-tier competitor dealers.

is in financial distress. Due to a lack of availability, book values of debt are used to proxy the corresponding market value. Book debt is computed as total assets minus total common equity of the considered institution. Data for US institutions is obtained from CRSP and from Datastream for all other origins, respectively. Since book debt is available only at a quarterly frequency we use the monthly observation of market equity together with the most recently available quarterly observation of book debt. To be consistent with previous work on carry trade risk premia the empirical analysis is based on monthly frequency, however, the results are qualitatively similar when using quarterly data.

We compute the average capital ratio of the core FX dealers in each month by computing a weighted mean of the three FX dealers' capital ratios that possess the biggest market share in foreign exchange trading. These top three FX dealers are identified with the ranking in Table 11 constructed from the Euromoney survey discussed above and the corresponding market shares are used as weights. Since the Euromoney survey appears yearly, the covered dealers and weights are adjusted yearly while the average capital ratio is computed on a monthly basis.³⁷ Weighting by market share is in line with our idea that core dealers' balance sheets contain the relevant information for asset pricing in the FX market.³⁸ We also compute the accumulated capital ratio according to HKM as the average of all holding companies weighted by market capitalization associated with institutions from the New York Fed's primary dealers list. This represents the broadest dealer group incorporating a large number of periphery dealers and allows to compare our results to those of the existing literature. Conversely, every holding company we identify as top FX dealer is simultaneously associated with a New York Fed primary dealer. Hence, our FX dealer factor is also included in HKM.³⁹

Figure 9 shows the resulting capital ratios for the core FX dealers as well as the capital ratio derived due to HKM. While the overall development of the two series is quite

³⁷Missing market shares are linearly interpolated in the period from 1991 to 1995.

³⁸Note, however, that alternative weightings in equal shares or by market capitalization do not affect the qualitative results of our following analysis.

³⁹The construction of the periphery dealers' balance sheet factor is discussed below.

similar, core FX dealers seem to be equipped with slightly less equity (relative to total assets) most of the time in comparison to the average of all holdings of the New York Fed's primary dealers. Percentage shocks to capital ratios are derived by calculating standardized residuals from fitted AR(1) processes. We denote the time series of shocks to the core FX dealer average capital ratio by $FXcore$ and shocks regarding the broad set of dealers as HKM . As already indicated by the above correlations between single dealers we observe a relatively low correlation coefficient between $FXcore$ and HKM of 0.62. This is surprising given the fact that HKM does contain the capital ratio innovations of the core dealers.

3.2 Exchange Rates and Currency Portfolios

We collected data on spot exchange rates and one-month forward exchange rates of 48 currencies from Thomson-Reuters Datastream with the US dollar being the base currency.⁴⁰ The following 48 countries are included: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom. The panel of exchange rates covering the period from January 1984 to February 2017 is highly unbalanced with at most 38 currencies being available at the same time. We include the Euro from January 1999 onward and discard currencies of euro-member currencies in following periods.⁴¹

The choice of currencies in the sample as well as the currency excess returns as computed in eq. (69) is in line with the literature on currency risk factors as, for instance, Lustig et al. (2011) and Menkhoff et al. (2012a). From the panel of exchange rates

⁴⁰We additionally performed our empirical exercise with the British Pound as well as the Japanese Yen as base currency. The results do not differ qualitatively.

⁴¹The introduction of the euro is taken as a cause to provide sub-sample estimates using data ranging from 1999 to 2017.

we build a cross-section of 15 currency portfolios sorted on three different variables. In each period t we sort the currencies with available excess return in $t + 1$ on a pre-defined variable and allocate them into five quintile portfolios. For every portfolio we then compute the equally weighted excess return for period $t + 1$ by taking the average of all currencies allocated to the respective portfolio. To account for transaction costs that emerge from monthly rebalancing the currency portfolios we perform a bid-ask-spread adjustment as in Menkhoff et al. (2012a).

The first five portfolios are sorted on the forward discount as studied in Lustig et al. (2011). We allocate each currency to one of five equally-weighted portfolios sorted by their forward discounts $(f_t^i - s_t^i)$.⁴² The first portfolio (C1) therefore includes the fifth of currencies with the lowest interest rate differential to the US interest rates and the fifth portfolio (C5) the fifth of currencies with the highest interest rate differential. Shorting C1 and investing in C5 would then be a classical high-minus-low carry trade strategy.

The second set of five portfolios is sorted on the currencies' excess returns over the previous three months.⁴³ The first portfolio (M1) therefore includes the fifth of currencies with the lowest excess returns in the previous three months and the fifth portfolio (M5) the fifth of currencies with the highest excess returns in the previous three months. A strategy going short in past losers (M1) and invests in past winners (M5) is known as momentum strategy. This type of currency portfolios is studied in Menkhoff et al. (2012b).

We sort the last five portfolios by real exchange rates. The latter are calculated by dividing nominal exchange rates by purchasing power parity (PPP) conversion factors provided by the OECD. We then allocate each currency to one of five equally-weighted portfolios sorted by their real exchange rate level. The first portfolio (V1) therefore includes the fifth of currencies that are most overvalued with respect to PPP and the

⁴²This sorting is equivalent to sorting on the interest rate differential if CIP holds.

⁴³The construction of momentum portfolios based on the returns over the past three months instead of just one month follows Menkhoff et al. (2012b) and is intended to lower the otherwise high portfolio turnover. Note, however, that the results do not change qualitatively when considering one-month returns.

fifth portfolio (V5) the fifth of currencies that are most undervalued with respect to PPP.⁴⁴ This currency portfolio sort is studied in Menkhoff et al. (2017).

Merging these three types of portfolio sorts helps to overcome problems of low degrees of freedom in the cross-section since they capture different dimensions of currency risk premia. Note that all covered types of portfolio sorts are commonly used in FX markets.⁴⁵

Table 12 shows descriptive statistics of the fifteen portfolio return series and the corresponding HML strategy return. We recognize the familiar pattern of carry trade returns that is similar to previous empirical studies (for example Berge et al. (2010) and Burnside et al. (2011)) on carry trade returns although we included post-financial crisis times. Monthly average returns and kurtosis increase monotonically from low to high forward discount portfolios whereas the skewness becomes more negative. There is no clear pattern regarding the standard deviation. Panel B shows that investing on recent winners (M5) generates positive returns on average whereas an investment in recent losers currencies yields negative average returns. However, the increase in mean return is unlike carry trades not monotonically increasing. The mean of the high value portfolio (V1) displayed in Panel C is about zero, but positive average returns are granted from investing in the undervalued currency portfolio (V5). All three HML strategies generate positive excess returns on average with Sharpe ratio highest for carry trades and lowest for the value strategy.⁴⁶

⁴⁴We derive real exchange rates in terms of US dollar per unit of foreign currency and a value greater (smaller) one can therefore be interpreted as an overvaluation (undervaluation) of the US dollar or a corresponding undervaluation (overvaluation) of the foreign currency.

⁴⁵For example Deutsche Bank offers exchange traded funds that invest according to the considered portfolio sorts as the Global Currency Harvest, the DB Momentum index and the DB valuation index.

⁴⁶Menkhoff et al. (2017) show that the Sharpe ratio of currency value strategies may be increased by adjusting for macroeconomic fundamentals. We refrain from this adjustment possibility for keeping our value portfolio returns on a monthly frequency.

4 Empirical Analysis

The following sections present the empirical results establishing a superior pricing power of the FXcore factor with respect to a factor covering the wealth of the financial intermediary sector in general. Asset pricing tests concerned as main results follow in the next subsection. Afterwards, further subsections enhance the analysis and provide further robustness.

4.1 Asset Pricing Tests

We begin to investigate the pricing ability of the capital ratio factors by conducting traditional asset pricing tests. Following Burnside (2011) a GMM framework is employed that reproduces traditional two-step estimates as in the spirit of Fama and MacBeth (1973). The first set of moment conditions relates the (expected) returns of each portfolio to the dollar risk factor DOL and the intermediary risk factor I via its corresponding risk exposures β_i^{DOL} and β_i^I . These correspond to the time series regressions in Fama and MacBeth (1973) and are in our model given by

$$\mathbb{E}(rx_t^i - c_i - \beta_i^{DOL}DOL_t - \beta_i^I I_t) = 0, \quad i = 1, \dots, N \quad (76)$$

of excess returns rx_t^i for each portfolio i on the dollar factor of Lustig et al. (2011) to capture long-run trends and the capital ratio risk factor I being either HKM or $FXcore$. The cross-sectional pricing equation (74) is imposed with the moment condition

$$\mathbb{E}(rx_t^i - \lambda^{DOL}\beta_i^{DOL} - \lambda^I\beta_i^I) = 0, \quad i = 1, \dots, N \quad (77)$$

where λ^{DOL} and λ^I denote the risk prices of interest to be estimated. The set of moment conditions is then completed by including orthogonality conditions given by:

$$\mathbb{E}((rx_t^i - c_i - \beta_i^{DOL}DOL_t - \beta_i^I I_t) DOL_t) = 0, \quad i = 1, \dots, N \quad (78)$$

$$\mathbb{E}((rx_t^i - c_i - \beta_i^{DOL}DOL_t - \beta_i^I I_t) I_t) = 0, \quad i = 1, \dots, N. \quad (79)$$

The GMM estimator based on conditions (76) to (79) recovers estimates that could also be achieved by estimating the linear regression models corresponding to (76) and (77) as already mentioned above. However, the associated GMM standard errors of the risk price estimates account for uncertainty from pre-estimating betas. To account for heteroscedastic and autocorrelated pricing errors, we compute the long-run covariance matrix of the GMM errors with the heteroscedasticity and autocorrelation consistent (HAC) covariance estimator of Newey and West (1987) with a Bartlett kernel as proposed in Andrews (1991). The following subsections discuss the results of the time series and the cross-sectional conditions, respectively.

4.1.1 Time-Series Results

As indicated in the data section we provide empirical results using two different time periods. The first period covers the full sample between 1984 and 2017, while the second period ranges from 1999 to 2017 to account for the introduction of the euro and the strong market concentration in FX trading observed in the 2000s.⁴⁷ For both samples GMM estimates reveal highly significant betas for the dollar factor in a range between 0.9 and 1.2 (with a few outliers exceeding 1.2) confirming the results documented in Lustig et al. (2011).⁴⁸ The estimated capital ratio risk exposures are collected in Table 13.

Starting with the five carry trade portfolios we find that beta is monotonically increasing from a negative value for C1 (low interest rate currency) to a positive value for C5 (high interest rate currency). The latter value constitutes a relatively high risk exposure with respect to intermediaries' capital ratio. High interest rate currencies tend to pay off poorly during bad times when the capital ratio decreases and balance sheet constraints are tightening. Instead, the negative sign of the C1 basket beta reveals a hedging capacity of the low interest rate currencies in times of intermediaries' balance

⁴⁷Considering the period starting in 1999 additionally provides some technical robustness since we circumvent interpolating missing market shares for the factor weighting.

⁴⁸We refrain from reporting the betas for the sake of parsimony, however, the estimates are available from the authors upon request.

sheet distress. This is in line with the view that at least part of the risk premium to the carry trade can be interpreted as a compensation for high exposure to risk associated with intermediaries balance sheet capacity. The spread between high and low interest portfolio exposure shrinks when specializing the capital ratio factor from a broad set of financial institutions (HKM) to the top three FX dealers (FXcore), but remains statistically significant. The overall results are similar in the more recent sample, however, the differences in estimated exposures are less pronounced. Remarkably, the statistical significance of the exposure of HKM to the high interest portfolio C5 weakens, while the exposure of the core dealer factor (FXcore) remains highly significant. This may point towards an increased relevance of core dealers' balance sheet capacity in recent times as may be expected from the massive increase in market concentration shown in Figure 8.

Estimated exposures of momentum portfolios towards the capital ratio risk factor show no remarkable patterns in either of the considered samples. Betas are generally insignificant except for a negative exposure of the past winners portfolio ($M4$) in the full sample. The missing evidence fits the recent literature on currency risk factors reporting that factors which matter for carry trade pricing are less successful in explaining currency momentum returns (Menkhoff et al. (2012b)). A distinguished risk factor for explaining momentum returns may arise from political risk as argued by Filippou et al. (2018).

Regarding the exposure of value portfolios to the HKM factor we observe that the overvalued-currencies portfolio V1 has a significantly negative beta whereas moderately undervalued currency portfolios V3 & V4 show significantly positive betas. This observation may stem from the fact that the latter portfolio includes a number of emerging market currencies, which, in times of a global financial downturn, experience substantial capital outflows due to massive cutbacks of balance sheet exposure in industrialized countries. This is in line with Menkhoff et al. (2017) showing that a weak real exchange rate is contemporaneously associated with a high currency risk premium. In such a situation a portfolio of overvalued currencies, typically from industrialized

countries, tends to provide a hedge.⁴⁹ With regard to the top FX dealer factors we see that the associated exposures are statistically significant in the moderately overvalued and undervalued currency portfolio V2 and V4, respectively. In contrast, the extreme over- and undervalued portfolios seem to be unrelated to the core FX dealers' business.

4.1.2 Cross-Sectional Results

We now address the question as to whether the balance sheet factors of FX dealers are able to explain excess returns of FX assets. For this purpose we refer to Table 14 showing the GMM results of for the cross-sectional moment conditions in (77). As a preliminary result the table reports a positive but insignificant dollar factor risk price, which is in line with other asset pricing studies of currency portfolios (Lustig et al. (2011), Menkhoff et al. (2012a)).

In contrast, we find that both intermediary capital ratio factors are statistically significant when investigated separately. This holds for the full (columns 1 and 2) sample as well as for the more recent period starting in 1999 (column 4 and 5). The exposure of an FX asset to dealer's financial conditions and in particular to those of the core dealers can therefore be seen as a source of risk that needs to be compensated by a premium. The magnitude of the FXcore risk price is more than twice as high as the HKM risk price possibly resulting from the lower magnitude of FXcore betas. This implies that the intermediary risk premium $\beta_i^I \lambda^I$ is roughly the same if measured by FXcore of HKM. However in the recent sample we also see doubled risk price for FXcore although exposures of the high carry portfolio (C5) with respect to the intermediary factors are roughly equal resulting in a higher premium for the FXcore exposure.

The cross-sectional fits of the models lend support for the hypothesis that only core dealers are relevant for FX pricing. The R^2 of the model using FXcore (48%) substantially exceeds the model using the broader set of broker dealers (38%). When considering both factors in a joint model as reported in the third and sixth column the

⁴⁹The highly undervalued currencies portfolio V5 is statistically insignificant in the most of the cases across samples.

HMK factor turns insignificant. From the adjusted R^2 s it can additionally be inferred that the inclusion of the HKM factor does not help to explain variations in the FX test asset returns. This strongly suggests that an FX-specific balance sheet factor as constructed above outperforms a general balance sheet factor as applied in He et al. (2017). In line with the two-tier market structure all useful information contained in dealer balance sheets is provided by a few core dealers warehousing the risk of market making. Having a look on the cross-sectional fit in the sample starting in 1999 that covers periods affected by a strong market concentration we see that the R^2 of the FX-core model remains at the given level, but the R^2 of the model including HKM drops significantly. Again, the inclusion of more balance sheet information from intermediaries with lower market shares in foreign exchange therefore adds more irrelevant noise than additional information explaining currency return cross-sections. This may be interpreted as support for the idea that the specialization of intermediaries matters and we have a currency market SDF that is widely distinct from SDF's of other asset classes.

4.2 Individual Portfolio Cross-Sections

This section gives a more detailed analysis of the cross-sectional fit of the FX intermediary model in individual currency portfolio cross-sections sorted each on carry, momentum or value only. Figure 10 showing the cross-sectional pricing errors for asset pricing models with capital ratio innovations of core FX dealers as a risk factor reveals a strong discrepancy between the cross-sectional fit of different portfolio sorts when included in the same cross-section. Whereas the cross-section of carry trades seem to be well-described by the intermediary model, the relation for momentum portfolios is almost reversed.

Running cross-sectional asset pricing tests for portfolios separately sorted on carry, momentum and value provides us with the opportunity to investigate the differences in the cross-sectional fit further. Moreover we can directly compare our results reported in Table 15 with those of the existing literature that mainly focuses on carry trade

cross-sections.

The first column of Table 15 shows the results for the five portfolios sorted on carry as it is analyzed in much of the finance literature on carry trades (see, for instance, Lustig et al. (2011) and Menkhoff et al. (2012a)). The risk price of the intermediary balance sheet risk factor is significantly positive. Considering the signs of the risk exposures we can conjecture that excess returns from the carry trade may be interpreted as a compensation for balance sheet risk. High forward discount currencies tend to pay off badly when the capital ratio decreases and balance sheet constraints are tightening. In contrast, currencies with a forward premium tend to providing a hedge for times of a decreasing capital ratio. The model prices the cross-section of carry trade returns with an R^2 of over 90%. This is remarkable in the sense that the capital ratio risk factor, in contrast to most of the existing competitors in the literature, which also show ability to price carry trades, is not derived from the time series of currency returns itself.⁵⁰ In the more recent sample starting in 1999 the *FXcore* factor shows a similar cross-sectional fit. We can therefore conjecture that in the recent period of financial market stress the balance sheets of the top three FX dealers is still important for pricing carry trades. For the momentum sorted cross-section in the second column we find no significant estimates of the risk prices at all. The results indicate that FX dealers seem to prevent momentum portfolios to exert an impact on their balance sheets. Moreover, we also refer to the observation in the literature that factors explaining the cross-section of carry trade returns are also unable to price currency momentum returns and vice versa as explored in Filippou et al. (2018).

The third column shows the results for value sorted portfolios where the balance sheet risk prices are found to be positive and significant for the recent sample starting from 1999. The cross-sectional relation is estimated with reasonable levels of R^2 . We therefore find that variations in intermediaries' balance sheet capacity can simultaneously explain returns to currency portfolios based carry and value, which capture largely

⁵⁰For example, Menkhoff et al. (2012a) report a cross-sectional fit of $R^2 = 90\%$ using FX volatility as a priced risk factor.

unrelated risk premia as argued by Menkhoff et al. (2017).

4.3 Individual Currencies

In this section we provide a more detailed analysis of the capital ratio risk factors in explaining FX assets' excess returns using individual exchange rate time series instead of portfolios. We compute returns from investing one US dollar in a single foreign currency and regress them on the *DOL* and the *FXcore* intermediary factor. Table 16 shows the corresponding results from regressing individual currency returns on the two risk factors DOL and FXcore. We find that typical funding currencies in carry trades like the Swiss franc and Japanese yen have a strikingly-strong negative exposure to capital ratio innovations whereas investment currencies as the Norwegian krone and the Mexican peso show significantly positive betas. This is reflected in the intermediary factor's success in explaining the spread between high and low carry trade portfolios. In addition, currencies of emerging market economies, in our sample particularly the South African rand and the Mexican peso, have positive exposures to balance sheet innovations. These currencies typically show up in the undervalued currency portfolios V4 and V5. In the overvalued portfolio V1 we find primarily the Swiss Franc, Norwegian and Danish krone that have differing significant signs in exposure to our factor. With regard to the momentum strategy, however, we do not have typical winner and loser currencies, but currencies that frequently switch from the long to the short portfolio. These are G10 currencies that either have a positive or negative significant time-series exposure to intermediary balance sheet innovations and can therefore not explain spreads in momentum strategies.

In summary, portfolio sorts based on the carry trade fit the exposures of bilateral exchange rates best. Typical carry currencies additionally enter under- or overvalued currency baskets quite often, explaining the satisfactory cross-sectional fit of our model with respect to value portfolios.

4.4 Other Asset Classes

One of the major contributions of differentiating between core and periphery dealers is to show that balance sheet information from the cross section of dealers are not equally important for FX asset pricing. Ideally, we would like to perform similar exercises for core dealers in other asset classes, too. Since data on dealers' market shares are unavailable for a sufficient period of time or not available at all, however, we follow a different strategy. Since entering the group of core dealers may be perceived as a substantial irreversible investment a given financial institution will consider only a few asset markets for its dealer business. Under these circumstances, relevant balance sheet information is concentrated on the core FX dealers only for currency markets and not necessarily for other asset classes. Thus, we may test whether the *FXcore* factor also exhibits superior pricing power in other asset classes compared to a broad group of broker dealers such as *HKM*. In particular, the portfolio cross-section from He et al. (2017) is used to run horse races between *HKM* and *FXcore*.⁵¹ The results presented in Table 17 indicate that in contrast to FX markets, the *FXcore* factor remains statistically insignificant in other asset markets. Only the *HKM* factor produces a significant price of risk in case of credit default swaps.

The results generally support the idea of differing pricing powers of balance sheet factors across intermediaries. Although we have mostly information from global banks in our core dealer factor, it is unable to outperform a balance sheet factor derived from a broader group of intermediaries in all other asset classes. This supports the idea of a specific FX pricing factor, although it cannot be ruled out that the top FX dealer are simultaneously important competitors in other classes, too.

⁵¹Returns are quarterly and collected from pre-existing studies: Fama and French (1993) 25 size and value sorted portfolios for equity, ten portfolios sorted on yield spreads from Nozawa (2017) together with ten maturity-sorted government bond portfolios for US bonds, six sovereign bond portfolios from Borri and Verdelhan (2012), 18 index option portfolios from Constantinides et al. (2013), 20 CDS portfolios sorted by spreads using individual name 5-year contracts with returns defined in accordance with Palhares (2013) and 23 commodity portfolios derived with returns to commodity futures from the Commodities Research Bureau as used in Yang (2013).

4.5 Top-Ten and Top-Five FX Dealers

The heterogeneity hypothesis of FX dealers put forward in the preceding analysis showed that capital ratios of core dealers are informative. Using the largest three dealers was driven by the idea to only include those dealers who receive substantial incoming order flow from periphery dealers and warehouse risks from FX trading in their balance sheets, but this is clearly an arbitrary choice. In fact, the changing degree of competition in the market over time suggests that more dealers might be relevant for FX pricing. Thus, for a further robustness check we additionally compute the *FXcore* factor using the top-ten as well as top-five dealers. We will call the alternative factors *FXcore5* and *FXcore10*, respectively. Due to limited availability of balance sheet data for some intermediaries included in the top ten in the 80s and 90s, we report regression results only for the more recent sample.

Table 18 shows the cross-sectional results from horse races between the four intermediary factors considered. Although *FXcore5* and *FXcore10* are found to price the currency cross-section, we generally observe that *FXcore* outperforms the two alternative factors. This indicates that including balance sheet information from additional top FX dealers besides the top three does not improve the asset pricing performance of the FX dealer model. Moreover a general decline in the pricing ability can be observed as the *FXcore5* pulls the *FXcore10* factor insignificant in a separate horse race. Taken together, the results of this robustness check lend support to the importance of dealer heterogeneity in OTC markets.

This supports our view that the relevant marginal dealers in foreign exchange whose balance sheet conditions should determine the pricing kernel are the core dealers with the highest market share whereas the periphery dealers do not provide any additional useful information for pricing.

5 Conclusions

Since at least the seminal contribution by Brunnermeier and Pedersen (2009) financial intermediaries' balance sheets are playing an increasingly important role in describing asset price dynamics, because of their ability to reflect current funding conditions of key players in the market. This implies that broker dealers' balance sheet factors should matter more for highly intermediated asset than for assets that households are willing to hold directly (Haddad and Muir 2018). Given that the foreign exchange market is by far the largest venue for intermediated over-the-counter transactions, FX dealers' balance sheets may be a promising candidate to understand currency excess returns. Indeed, our empirical results confirm that FX dealers' capital ratios perform remarkably well, particularly when it comes to explaining excess return to the carry trade. The key insight of this paper, however, arises from the relaxation of the assumption that FX dealers' balance sheets are equally informative. Considering the specific two-tier over-the-counter structure of foreign exchange markets, where new information contained in customer order flow is aggregated to eventually arrive at the inter-dealer market, the core market makers' balance sheets are expected to be most informative. Our empirical results provide strong support for this heterogeneity hypothesis showing that excess returns in currency markets are superiorly explained by the financial wealth of the three most active dealers rendering only them as the relevant marginal investors.

Appendix A. Tables and Figures

Table 11: Top FX Dealer

This table shows the ranks of financial intermediaries in the Euromoney Forex Survey. Boxes indicate whether the intermediary in the given year was ranked within the top ten (light gray), five (medium gray) or three (dark gray) FX dealers by market share.

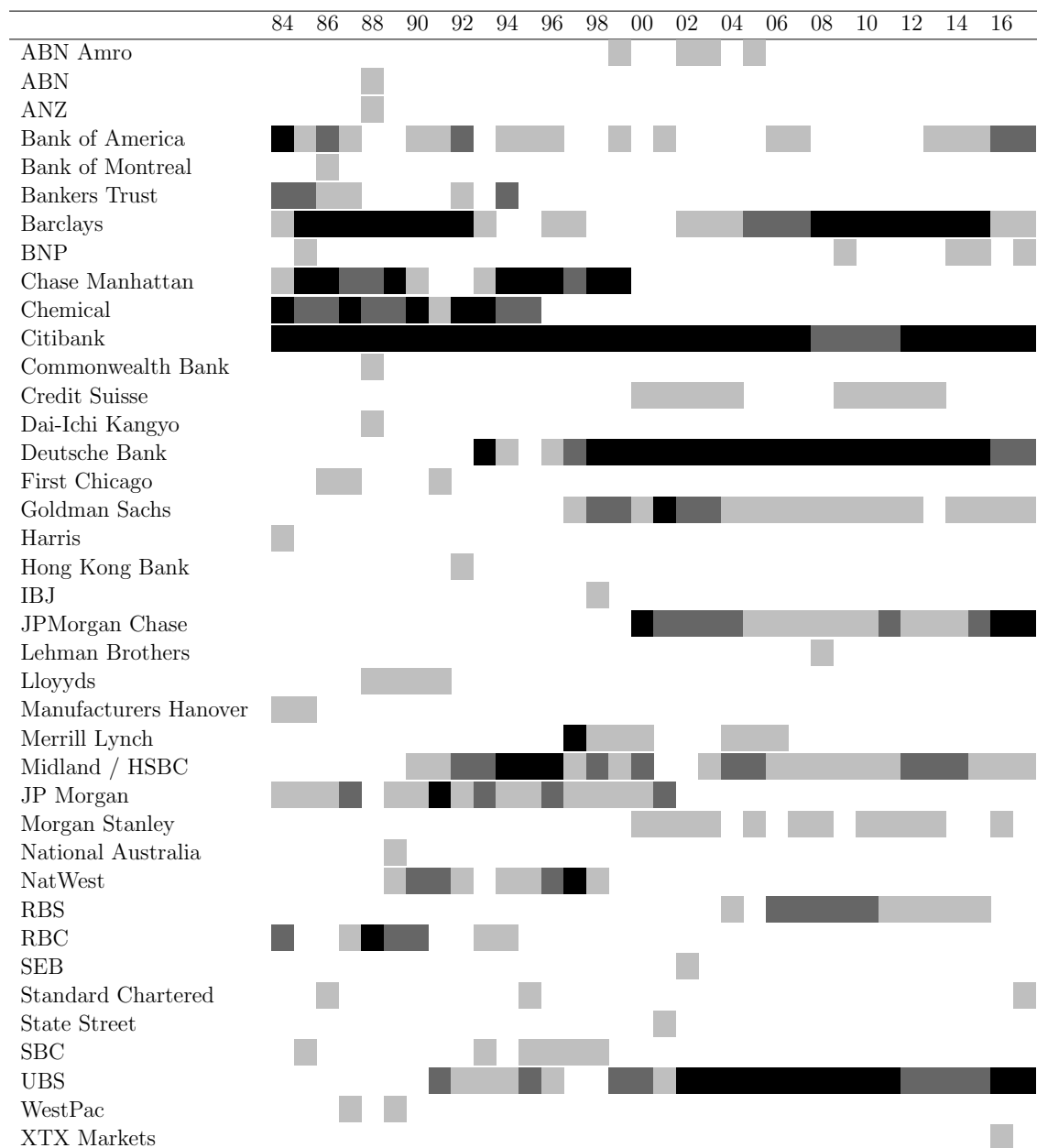


Table 12: Descriptive Statistics of Portfolio Returns

This table shows descriptive statistics on log excess returns of five quintile portfolios sorted by carry, momentum and value as well as of the corresponding HML portfolio that is an equally weighted portfolio consisting of a short position in the respective lowest quintile portfolio (1) and a long position in the highest quintile portfolio (5). Returns are monthly from January 1984 to February 2017 and adjusted for transaction costs.

Portfolios	1	2	3	4	5	HML
<i>Panel A: Carry</i>						
Mean	-0.303	0.0004	0.205	0.197	0.618	0.921
Median	-0.196	0.058	0.268	0.279	0.932	1.181
Std.dev.	2.437	2.087	2.309	2.416	3.030	2.841
Skewness	-0.113	-0.230	-0.281	-0.652	-0.886	-0.713
Kurtosis	1.282	0.805	1.037	1.970	2.280	1.943
Sharpe	-0.124	0.0002	0.089	0.082	0.204	0.324
<i>Panel B: Momentum</i>						
Mean	-0.202	-0.090	0.088	0.211	0.535	0.737
Median	-0.078	0.144	0.048	0.229	0.607	0.686
Std.dev.	2.848	2.519	2.407	2.409	2.507	2.914
Skewness	-0.470	-0.854	-0.030	-0.121	-0.237	0.101
Kurtosis	3.061	3.378	1.428	1.125	1.693	1.539
Sharpe	-0.071	-0.036	0.037	0.088	0.213	0.253
<i>Panel C: Value</i>						
Mean	-0.009	0.178	0.149	0.250	0.408	0.417
Median	-0.014	0.136	0.351	0.448	0.393	0.327
Std.dev.	2.825	2.664	2.522	3.017	2.640	1.510
Skewness	-0.274	-0.061	-0.666	-0.637	-0.238	0.489
Kurtosis	0.674	0.092	3.747	2.121	1.168	1.801
Sharpe	-0.003	0.067	0.059	0.083	0.154	0.276

Table 13: Capital Ratio Exposures

This table reports estimated capital ratio risk exposures β_i^I and R^2 from two-factor asset pricing models with including the dollar risk factor DOL and a intermediary risk factor I. The latter is derived as averaged capital ratio from dealers covered in the FED primary dealer list as in He et al. (2017) (HKM) or from top three FX dealers (FXcore) identified with the Euromoney FX survey. Parameters are estimated with first-stage GMM approach and Newey-West standard errors are shown in parentheses. R^2 's are achieved from corresponding time series regressions. Test assets are 15 currency portfolios sorted on carry (C1-C5), momentum (M1-M5) and value (V1-V5).

	01/1984 - 02/2017				01/1999 - 02/2017			
	FXcore		HKM		FXcore		HKM	
	β^I	R^2	β^I	R^2	β^I	R^2	β^I	R^2
C1	-2.593*** (0.791)	0.696	-4.252*** (1.072)	0.698	-2.666** (1.106)	0.638	-4.990*** (1.647)	0.642
C2	-1.143** (0.516)	0.774	-1.300* (0.703)	0.773	-1.287** (0.573)	0.849	-0.508 (0.889)	0.845
C3	0.961* (0.524)	0.844	1.139 (0.807)	0.843	0.651 (0.517)	0.886	1.088 (0.924)	0.886
C4	0.549 (0.459)	0.851	1.006 (0.681)	0.851	0.488 (0.609)	0.886	1.794* (1.070)	0.888
C5	2.227** (0.876)	0.668	3.406** (1.417)	0.668	2.814** (1.127)	0.686	2.616 (2.006)	0.677
M1	0.941 (0.932)	0.611	0.860 (1.447)	0.610	0.761 (1.249)	0.693	0.099 (2.010)	0.692
M2	0.034 (0.676)	0.766	0.810 (1.316)	0.766	0.432 (0.860)	0.785	2.051 (2.146)	0.788
M3	-0.445 (0.787)	0.803	0.151 (0.872)	0.803	-1.213 (1.239)	0.796	0.930 (1.116)	0.793
M4	-1.148** (0.544)	0.806	-1.842** (0.922)	0.807	-0.670 (0.627)	0.813	-1.770 (1.232)	0.814
M5	0.515 (0.847)	0.626	-0.296 (1.479)	0.626	0.385 (1.015)	0.639	-1.379 (1.975)	0.640
V1	-0.448 (0.591)	0.849	-2.104** (0.958)	0.852	-0.596 (0.893)	0.844	-3.233** (1.617)	0.849
V2	-0.931* (0.537)	0.806	-0.514 (1.085)	0.805	-1.512*** (0.571)	0.809	-0.045 (1.306)	0.805
V3	1.175 (0.887)	0.668	4.375*** (1.018)	0.679	0.220 (1.235)	0.804	2.867 (1.762)	0.809
V4	2.380*** (0.707)	0.782	4.677*** (1.111)	0.786	2.678*** (0.824)	0.841	5.441*** (1.384)	0.845
V5	-0.218 (0.560)	0.816	-2.373*** (0.877)	0.820	1.473 (1.011)	0.759	1.688 (1.816)	0.756

*p<0.1; **p<0.05; ***p<0.01

Table 14: Cross-Sectional Asset Pricing Tests (Carry, Momentum & Value Portfolios)

The table reports price of risk first-stage GMM estimates λ^{DOL} and λ^I from the cross-sectional moment condition $\mathbb{E}(rx_{t+1}) = \beta^{DOL}\lambda^{DOL} + \beta^I\lambda^I$. The asset pricing model comprises a dollar risk factor DOL and an intermediary risk factor I. The latter is derived as averaged capital ratio from dealers covered in the FED primary dealer list as in He et al. (2017) (HKM) or from top three FX dealers (FXcore) identified with the Euromoney FX survey. GMM standard errors are obtained by the Newey and West (1987) approach with Bartlett kernel according to Andrews (1991) and are shown in parentheses. R^2 's are achieved from corresponding cross-sectional regressions. Test assets are 15 currency portfolios sorted on carry (C1-C5), momentum (M1-M5) and value (V1-V5).

	01/1984 - 02/2017			01/1999 - 02/2017		
	(1)	(2)	(3)	(4)	(5)	(6)
DOL	0.130 (0.140)	0.136 (0.140)	0.131 (0.084)	0.096 (0.186)	0.098 (0.188)	0.104 (0.101)
FXcore	0.097*** (0.036)		0.140** (0.059)	0.146*** (0.054)		0.152** (0.061)
HKM		0.035** 0.016	0.024 (0.046)		0.053*** (0.016)	0.040 (0.055)
R^2	0.479	0.380	0.522	0.462	0.261	0.478
Adj. R^2	0.399	0.285	0.402	0.380	0.147	0.348

*p<0.1; **p<0.05; ***p<0.01

Table 15: Cross-Sectional Asset Pricing Tests (Individual Portfolio Cross-Sections)

The table reports price of risk first-stage GMM estimates λ^{DOL} and λ^{FXcore} from the cross-sectional moment condition $\mathbb{E}(rx_{t+1}) = \beta^{DOL}\lambda^{DOL} + \beta^{FXcore}\lambda^{FXcore}$. The asset pricing model comprises a dollar risk factor DOL and an intermediary risk factor that is derived as the averaged capital ratio from top three FX dealers (FXcore) identified with the Euromoney FX survey. GMM standard errors are obtained by the Newey and West (1987) approach with Bartlett kernel according to Andrews (1991) and are shown in parentheses. R^2 's are achieved from corresponding cross-sectional regressions. Test assets are separated in three cross-sections consisting of 5 currency portfolios each sorted on carry, momentum or value.

	01/1984 - 02/2017			01/1999 - 02/2017		
	Carry	Momentum	Value	Carry	Momentum	Value
DOL	0.144 (0.136)	0.096 (0.133)	0.163 (0.130)	0.123 (0.174)	0.078 (0.175)	0.107 (0.162)
FXcore	0.167*** (0.054)	-0.070 (0.075)	0.019 (0.036)	0.222*** (0.081)	-0.036 (0.077)	0.074** (0.034)
R^2	0.959	0.160	0.668	0.939	0.053	0.572
Adj. R^2	0.932	-0.400	0.447	0.898	-0.579	0.286

*p<0.1; **p<0.05; ***p<0.01

Table 16: Bilateral Currencies Time-series Regressions

This table reports the results from separately estimating regression equations $rx_t^i = c_i + \beta_i^{DOL} DOL_t + \beta_i^{FXcore} FXcore_t + u_t^i$ for every series of returns from investing one dollar in a foreign currency. DOL is the return from investing one dollar into an equally-weighted portfolio of all currencies available. FXcore is the AR(1)-innovation from the market-share-weighted capital ratio of top three FX dealers. Newey-West standard errors are shown in parentheses. The sample spans the time period from January 1999 to February 2017.

	c	β^{DOL}	β^{FXcore}	R^2		c	β^{DOL}	β^{FXcore}	R^2
GBP	-0.190* (0.111)	0.860*** (0.093)	-0.136 (1.694)	0.434	ZAR	0.701* 0.424	1.696*** 0.163	2.732 3.551	0.364
CHF	-0.168 (0.138)	1.242*** (0.093)	-5.803*** (1.474)	0.614	SGD	-0.081 0.074	0.689*** 0.050	-0.953 0.817	0.667
JPY	-0.280 (0.199)	0.456*** (0.156)	-6.737*** (2.491)	0.131	HUF	0.027 0.154	1.766*** 0.105	-0.690 2.943	0.709
CAD	0.001 (0.106)	0.859*** (0.066)	4.128*** (1.161)	0.489	IDR	1.740*** 0.655	1.143*** 0.180	2.168 3.090	0.153
AUD	0.084 (0.131)	1.570*** (0.074)	0.203 (1.265)	0.716	KWD	0.001 0.033	0.227*** 0.031	-1.439*** 0.414	0.396
NZD	0.144 (0.155)	1.568*** (0.096)	-1.102 (2.099)	0.621	MYR	0.925** 0.368	0.928*** 0.107	-0.809 1.885	0.194
SEK	-0.254*** (0.097)	1.435*** (0.063)	1.464 (1.118)	0.761	MXN	0.109 0.181	0.747*** 0.129	6.173*** 2.124	0.339
NOK	-0.107 (0.108)	1.350*** (0.104)	2.945** (1.837)	0.707	PHP	0.095 0.118	0.450*** 0.056	0.797 1.122	0.234
DKK	-0.246** (0.104)	1.325*** (0.052)	-2.596* (1.332)	0.777	SAR	0.011 0.008	-0.001 0.002	0.122** 0.057	0.012
EUR	-0.259** (0.106)	1.334*** (0.052)	-2.650* (1.353)	0.776	TWD	-0.136 0.086	0.459*** 0.038	0.405 0.807	0.425
HKD	-0.028*** (0.010)	0.013** (0.007)	-0.018 (0.128)	0.036	THB	0.074 0.117	0.488*** 0.057	0.669 1.211	0.276

*p<0.1; **p<0.05; ***p<0.01

Table 17: Factor Horse Races in Alternative Asset Classes

This table reports GMM estimation results of intermediary asset pricing models including a market factor (Market), the capital ratio factor from He et al. (2017) (HKM), and the top three FX dealer capital ratio factor (FXcore) for cross-sections from different asset classes. GMM standard errors are obtained by the Newey and West (1987) approach with Bartlett kernel according to Andrews (1991) and are shown in parentheses. R^2 's are achieved from corresponding cross-sectional regressions. Test assets are from several cross-sections of different asset classes as used in He et al. (2017). The frequency is quarterly and the sample period varies within 01/1984 to 12/2012 depending on the data availability.

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.
Market	0.019 (0.021)	-0.039 (0.257)	0.003 (0.052)	0.012 (0.044)	0.008 (0.018)	0.011 (0.061)
FXcore	-0.030 (0.291)	0.474 (1.192)	0.116 (0.097)	0.320 (0.915)	0.013 (0.035)	0.017 (0.199)
HKM	0.057 (0.080)	0.248 (0.595)	0.068 (0.058)	0.196 (0.359)	0.066** (0.027)	0.057 (0.110)
R^2	0.934	0.729	0.963	0.992	0.632	0.132
Adj. R^2	0.925	0.682	0.927	0.990	0.566	0.002
Assets	25	20	6	18	20	23
Quarters	116	112	65	103	47	105

*p<0.1; **p<0.05; ***p<0.01

Table 18: Alternative Factor Horse Races

This table reports results of horse races between different intermediary asset pricing model estimated with GMM. The asset pricing models comprises a dollar risk factor DOL and two intermediary risk factors. The latter are derived as averaged capital ratios from dealers covered in the FED primary dealer list as in He et al. (2017) (HKM) or from top ten (FXcore10), top five (FXcore5), or top three FX dealers (FXcore) identified with the Euromoney FX survey. GMM standard errors are obtained by the Newey and West (1987) approach with Bartlett kernel according to Andrews (1991) and are shown in parentheses. R^2 's are achieved from corresponding cross-sectional regressions. Portfolios are sorted on carry (C1-C5), momentum (M1-M5) and value (V1-V5). The sample spans the period from January 1999 to February 2017.

	(1)	(2)	(3)	(4)	(5)
DOL	0.120 (0.197)	0.104 (0.202)	0.088 (0.197)	0.098 (0.196)	0.100 (0.198)
FXcore	0.133** (0.052)	0.142** (0.066)			
FXcore5	0.042 (0.046)		0.107** (0.051)	0.098** (0.049)	
FXcore10		0.015 (0.036)	0.068 (0.042)		0.065* (0.034)
HKM				0.050** (0.024)	0.054** (0.023)
R^2	0.606	0.732	0.317	0.291	0.267
Adj. R^2	0.508	0.665	0.146	0.114	0.084

*p<0.1; **p<0.05; ***p<0.01

Figure 8: Market Shares

The plot shows estimated market shares of top 20, 10, 5 and 3 FX dealers based on the Euromoney Survey. The sample period is 1979 to 2017 with interpolated shares from 1991 to 1995.

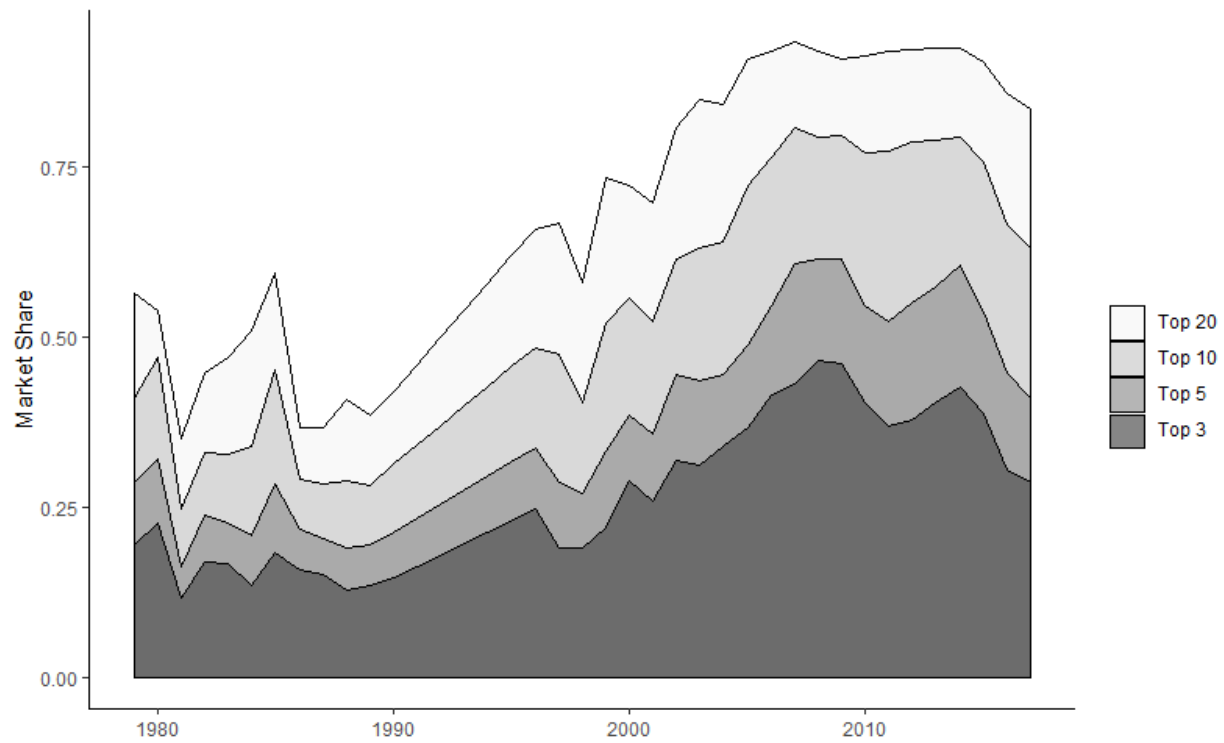


Figure 9: Capital Ratios and Growth Rates

The upper plot shows average capital ratios of all New York Fed primary dealers as computed in He et al. (2017) as well as of the top three foreign exchange dealers by market share according to the Euromoney FX survey weighted. The middle and bottom plot show growth rates of the both capital ratio series derived from AR(1)-innovations.

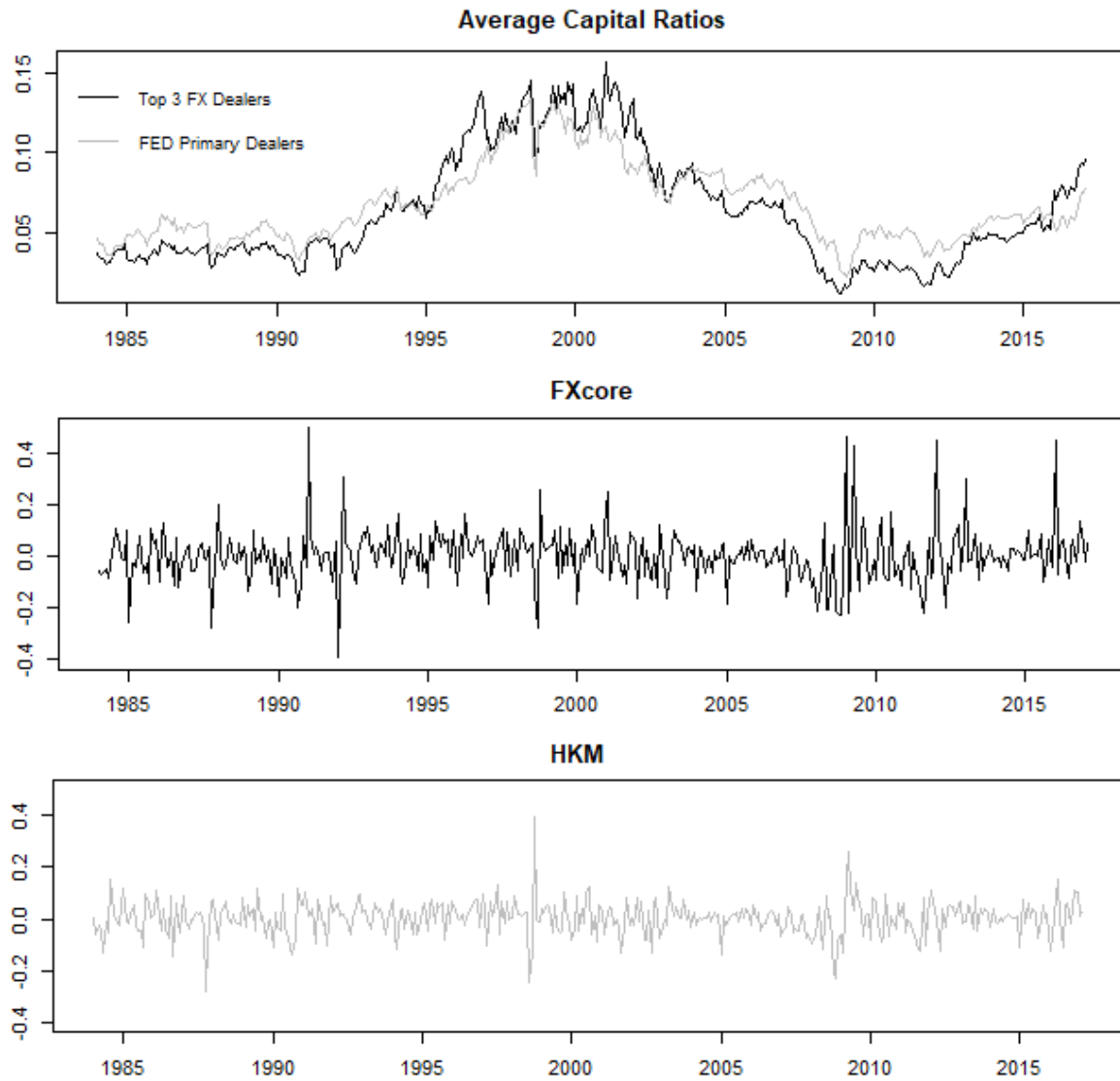
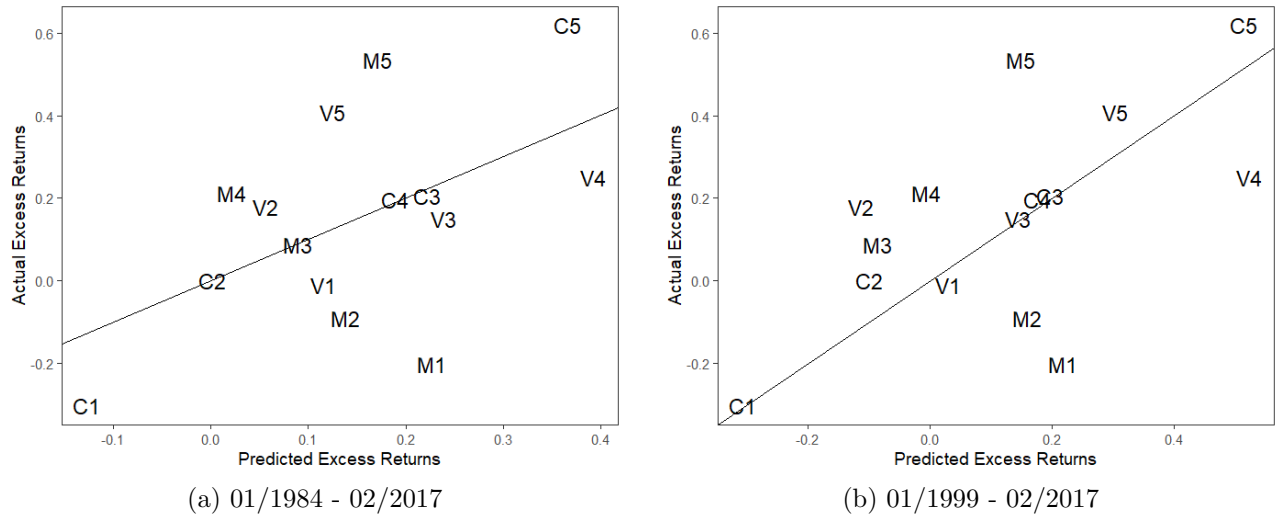


Figure 10: Pricing Errors

The figure shows cross-sectional pricing errors for asset pricing models with the dollar return (DOL) and capital ratio innovations of top three FX dealers (FXcore) as risk factors.



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Erklärung zur Koautorenschaft des vierten Kapitels:

Wir erklären hiermit, dass an dem Papier "Foreign Exchange Dealer Asset Pricing" beide Koautoren einen wesentlichen Beitrag gemäß der DFG-Richtlinien "Sicherung guter wissenschaftlicher Praxis" geleistet haben. Spezieller lassen sich die Beiträge wie folgt zuordnen:

Stefan Reitz

- Konzeption der empirischen Analyse und Auswertung der Befunde (zu ~50%).
- Verfassen des Papieres (zu ~50%). Besonderer Anteil an den Abschnitten 1. und 6.

Dennis Umlandt

- Zusammentragen der Devisenmarktdaten und Berechnung der analysierten Portfoliorenditen.
- Zusammentragen der Survey-Informationen aus Euromoney-Artikeln und Konstruktion der Dealer-Faktoren.
- Durchführung der Berechnungen für die empirische Analyse.
- Konzeption der empirischen Analyse und Auswertung der Befunde (zu ~50%).
- Verfassen des Papieres (zu ~50%). Besonderer Anteil an den Abschnitten 2. und 3.

Kiel, den 18.12.2019

Erklärung zum selbständigen Verfassen der Arbeit:

Ich erkläre hiermit, dass ich meine Doktorarbeit "Essays in Empirical Dynamic Asset Pricing: Methods and Applications in Foreign Exchange" selbstständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautor maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Beiträge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

Kiel, den 18.12.2019