System-wide volatility connectedness and carry trades

Katja Ida Maria Gisler*

PRELIMINARY DRAFT

April 4, 2016

Abstract

In this study, I empirically examine the system-wide volatility connectedness risk of currencies as an explanation for the risk premium of carry trade returns. Carry trade strategies exploit the forward premium puzzle by borrowing in low interest rate currencies and investing in high interest currencies without losing the generated gain to a corresponding change in exchange rates. I can show that low interest rate currencies are positively related to system-wide volatility connectedness risk. They thus serve as a hedge during unexpected high system-wide volatility connectedness episodes, typically occurring in crisis periods. In contrast, high interest rate currencies suffer from losses during these periods.

*University of St. Gallen, School of Economics and Political Science, Bodanstrasse 6, CH-9000 St. Gallen, Switzerland; katja.gisler@unisg.ch

1. Introduction

There is an extensively growing literature in international finance that tries to explain the forward premium puzzle or the violation of the uncovered interest trade parity (UIP). According to the UIP, any gain from exploiting interest rate differentials across countries should be compensated by a corresponding change in exchange rates. In other words, the UIP predicts that high interest rate currencies will depreciate. In reality, however, the exchange rates do not change such that the gain from interest rate differential is eliminated. Strategies exploiting this anomaly are called carry trade strategies. These strategies borrow in low interest rate currencies and invest in high interest rate currencies. Since low interest rate currency even tend to depreciate as opposed to appreciate, carry trade investments constitute a profitable and popular investment strategy.

The violation of the UIP is also referred to as the forward premium puzzle. The forward premium puzzle has been well documented since the 1980's, see Hansen and Hodrick (1980, 1983) and Fama (1984). The explanation of this forward premium puzzle and particularly the analysis of carry trade strategies have recently gained momentum again with the contributions by Lustig and Verdelhan (2007), Lustig et al. (2011), Burnside et al. (2006, 2009). They show that currency speculation strategies deliver substantially high Sharpe ratios comparable to those from equity markets making carry trades a profitable investment strategy. Since standard risk factor fail to rationalize the high returns to carry trade strategies, see e.g. Burnside et al. (2006), there has a large literature emerged on identifying relevant risk factors. Lustig and Verdelhan (2007), for example, provide a consumption-based CAPM explanation for the returns on carry trades. They find that high interest rate currencies typically depreciate when real U.S. consumption growth is low and vice versa for low interest rate currencies. Consequently, the risk premium on carry trade strategies can be understood as a compensation for consumption risk. In a more recent work Lustig et al. (2011) introduce two empirically motivated risk factors that explain the cross-section of carry trade returns. They propose the dollar risk representing the average currency excess return and the HML carry factor as the return to the carry trade portfolio. They show that their HML carry factor can be interpreted as a slope factor that prices the cross-section fairly well.

There have also been other risk factor proposed to explain the cross-section of carry trade returns. Brunnermeier and Pedersen (2009), for example, find that carry trades are subject to crash risk. They show that high interest rate currencies are more negatively skewed and attribute this negative skewness to sudden unwinding of carry trades typically occuring during market turmoils. Jurek (2014) and Farhi et al. (2015) confirm this finding and show that disaster risk account for a substantial amount of the carry trade risk premium in advanced countries. Related to this finding, Dobrynskaya (2014) finds evidence that high carry trade returns are a compensation for downside market risk. In another work, Menkhoff et al. (2012) introduce a aggregate volatility risk factor to the FX market similar to the one introduced by Ang et al. (2006) in the stock market. They show that high interest rate currencies are negatively related to innovations in global FX volatility. As a result, low interest rate currencies deliver positive returns in times of unexpected high volatility and thus serve as a hedge. More recently, several studies propose risk factors that use country asymmetries in explaining currency risk premia. Ready et al. (2015), for example, find that heterogeneity in commodity intensity can explain the currency risk premia and Della Corte et al. (2016) show that the spread in countries external imbalances and their propensity to issue external liabilities in foreign currency can explain the cross-section of currency returns. Related to heterogeneity in countries, Colacito et al. (2015) propose a unifying framework that can account for many currency risk factor structures proposed so far.

A recent strand of the asset pricing literature also focuses on systemic risk arising from an underlying network as a source of systematic risk. Ahern (2013), for example, finds a positive market price of centrality for assets in the stock market. He shows that the more central assets earn higher expected returns. Similarly, Herskovic (2015) finds two key network factors that matter for asset prices in the stock market, namely sparsity and concentration. Herskovic (2015) shows that sparsity as a characteristic of sectoral linkages distribution carries a positive market price. In contrast, concentration as a measure of the degree to which equilibrium output is dominated by a few large sectors carries a negative risk premium. And Billio et al. (2015) propose a modelling framework where network connections and common factors coexist. Most recently, Richmond (2016) takes the idea of Ahern (2013) to the currency market and exploits trade network centrality in the currency markets. He shows that countries that are more central in the global trade network have lower interest rates and currency risk premia.

This study aims to contribute to that literature by offering a network risk based explanation for the carry trade returns. More specifically, I propose a new systemic risk factor that is built on the network methodology introduced by Diebold and Yilmaz (2009, 2012, 2014). The underlying network of interest is constituted by the volatilities of the G10 currencies. Based on this network, a time-series of system-wide volatility connectedness is derived. This volatility connectedness can essentially be interpreted as a fear conntectedness expressed by market participants similarly to the VIX index, see Diebold and Yilmaz (2014). The volatility connectedness is typically low most of the time, but bursts during crisis periods reflecting a "bad" state of the world. In such states, shocks are propagated through the system to a substantial amount resulting in a high level of system-wide volatility connectedness. In this sense, innovations to system-wide volatility connectedness can be understood as fear risk. I subsequently examine whether this risk is priced in the cross-section of carry trade returns.

I follow Lustig and Verdelhan (2007) and Lustig et al. (2011) and sort currencies into portfolios based on their forward discount at the end of every month. The resulting carry trade strategy results in a large and significant excess return of more than 6% and almost 5% for all and only the G10 countries, respectively. I show in this paper, that these high carry trade returns can be indeed understood as compensation for connectedness or fear risk. I can empirically show that high interest rate currencies are negatively related to innovations in system-wide volatility connectedness. Interpreting innovations in system-wide volatility connectedness as fear risk, unexpected high system-wide volatility connectedness render low interest rate currencies more attractive. In other words, low interest rate currencies serve as a hedge in times of turmoils and thus display a safe heaven character, while high interest rate currencies suffer from losses.

The paper is structured as follows. First, the concept and the measurement of connectedness is introduced in section 2. In section 3, I present the data and the descriptive statistics. In section 4, the results regarding the system-wide volatility connectedness risk are provided and discussed. In section 5 robustness checks are provided and section 6 finally concludes.

2. Measuring connectedness

2.1 Approximating model and model estimation

The connectedness framework developed by Diebold and Yilmaz (2009, 2012, 2014) is used to assess the interdependencies across FX volatilities. Consider the time-series of volatility for $i = 1, 2, ...N$ currencies, each quoted against the U.S. Dollar and observed over $t = 1, 2...T$ periods. Then, the p-th order reduced form vector autoregression (VAR) for the $N \times 1$ vector of FX volatilities may be written as follows:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t, \tag{1}$$

where ϕ_i is a $N \times N$ parameter matrix and ε_t is a $N \times 1$ vector of identically and independently distributed error terms with zero mean and covariance matrix Σ. The moving average representation of this VAR model is:

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{2}$$

where the $N \times N$ coefficient matrices A_i are derived recursively as $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + ... + \phi_p A_{i-p}$ with $A_i = 0$ for $i < 0$.

In general, with an increasing number variables in the VAR, the approximating model will likely suffer form the curse of dimensionality. The parameter space hence needs to be reduced. As recently used in this context, see Fengler and Gisler (2015), Diebold and Yilmaz (2014), Demirer et al. (2015), I rely on a data-driven approach and use the least absolute shrinkage and selection operator (lasso) originally introduced by Tibshirani (1996). As a particularly appealing property, it serves simultaneously as an estimation and a variable selection technique. The lasso avoids computationally intense and exhaustive searches over the regressor space and remains feasible even in large-dimensional settings.

2.2 Variance decomposition and system-wide connectedness

There are two approaches for deriving the variance decomposition. The first approach uses the Cholesky factor orthogonalization that generates orthogonalized innovations and results in an order-dependent variance decomposition. The second approach exploits the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998) that allows for correlated, instead of orthogonalized, shocks. This in return amounts to obtaining impulse responses and variance decompositions for each variable treating each variable as the leading variable in the VAR and thus produces an order-independent variance decomposition. The order independence of the generalized variance decomposition is particularly appealing as it allows studying directional connectedness.

Following Pesaran and Shin (1998), the H-step generalized forecast error variance decomposition into variance components attributable to the different variables under consideration is given by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^T A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^T A_h \Sigma A_h^T e_i\right)}, \tag{3}$$

where Σ is the covariance matrix of the error vector ε, σ_{jj} is the variance of the error term for the jth equation and e_i is the binary selection vector whose ith entry takes the value of one and whose other entries are all zero. By construction, we have $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. Unlike orthogonolized forecast error variance decomposition, as they are for the case of the Cholesky decomposition, the sum of the contributions to the forecast-error variance is not equal to one. Diebold and Yilmaz (2012) thus propose that $\theta^g_{ij}(H)$ should be normalized such that the information in the variance decomposition matrix can directly be used for the spillover index. This yields:

$$\tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)} \,. \tag{4}$$

This expression represents approximately[1] the fraction of the H-step-ahead forecast-error variance of variable i generated by a shock to variable j. It can therefore answer the question of approximately what fraction of the H-step-ahead error variance in forecasting x_i is due to shocks to x_j. By construction, we have $\sum_{j=1}^{N} \tilde{\theta}^g_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H) = N$.

Diebold and Yilmaz (2009) define *own variance shares* and *cross variance shares* of an H-step-ahead forecast-error variance. *Own variance shares* are the fractions of the H-step-ahead forecast-error variances in forecasting variable i that are attributable to shocks to variable i, for $i = 1, \ldots, N$, while *cross variance shares* are the corresponding fractions attributable to shocks to variable j, for $j = 1, \ldots, N$, $j \neq i$. The total connectedness[2] is defined as the sum of the cross variance shares divided by the sum of all variance shares. The resulting total connectedness for the H-step-ahead forecast horizon is hence defined as:

$$C(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}^g_{ij}(H)}{N} \,. \tag{5}$$

In summary, the total connectedness that is termed *total* or *system-wide* connectedness by Diebold and Yilmaz (2012, 2014, 2015), Demirer et al. (2015), is the sum of all the off-diagonal elements of the generalized variance decomposition relative to the number of variables considered in the specific VAR at hand. It summarizes how much of the forecast-error variances can be explained by connectedness[3]. Relating this system-wide connectedness to the network literature, it can be understood as the mean of a degree

[1] The expression is not exact as it is based on the properties of the generalized variance decomposition. With Cholesky factor identification, the expression is exact.

[2] Diebold and Yilmaz (2009, 2012); Fengler and Gisler (2015) use the term *spillover* instead of *connectedness*. However, it is only the terminology that has been modified, the definition has remained unchanged. In this paper here, I adopt the new terminology and use the term *connectedness*.

[3] To reduce notational clutter, I drop the H that indicates the H-step-ahead forecast horizon.

distribution. The larger this mean degree is, the larger the network connectedness, see Diebold and Yilmaz (2014) for further details.

3. Data and Currency Portfolios

3.1 Data

The starting point are daily spot exchange rates and 1-month forward exchange rates quoted against the U.S. dollar. This data is obtained from Barclays Bank International (BBI) and WMR/Reuters through Datastream and covers the period from 01/1987 to 06/2015. I closely follow Lustig et al. (2011) and Koijen et al. (2015) in the data generating process. That is, BBI is the default source before 01/1997 and is then replaced by WMR/Reuters. The construction of the system-wide volatility connectedness, as discussed below, is based on daily data, but the empirical analysis is carried out at the monthly frequency. My main dataset covers the same dataset as in Lustig et al. (2011). That is, I consider 39 different countries: Australia, Austria, Belgium, Canada, China Hong Kong, Czech Republic, Denmark, euro area, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Arab Emirates and the United Kingdom. As the forward series for the euro area starts in January 1999, I follow Lustig et al. (2011) and Menkhoff et al. (2012) among others and exclude the euro area countries after this date[4]. Furthermore, I also consider a subsample of countries consisting of developed countries. Contrary to most other studies, I consider a smaller subset of developed countries consisting of the G10 countries: Australia, Canada, euro area/Germany[5], Japan, New Zealand, Norway, Sweden, Switzerland and the United Kingdom. Considering the subset of the G10 currencies constitute the fair counterpart analysis to the typical

[4] I closely follow the adjustment made to the full dataset as in Lustig et al. (2011). The interested reader is referred to their paper for details

[5] Similar to the studies by Colacito et al. (2015) and Ready et al. (2015), I use Germany instead of the euro area before the introduction of the Euro in January 1999.

analysis performed in this literature as the underlying connectedness risk factor is based on the network of the G10 countries' currencies.

3.2 Currency Excess Returns and Portfolios

I follow Lustig et al. (2011) and Menkhoff et al. (2012) and denote s as the log spot rate in units of foreign currency per U.S. dollar and f as the corresponding log forward rate. The log excess return is then defined as:

$$rx_{t+1}^k = i_t^k - i_t - \Delta(s)_{t+1}^k \approx f_t^k - s_{t+1}^k \tag{6}$$

where $i_t^k - i_t$ is the (nominal) risk-free interest rate differential of the foreign country k and the domestic country. Since the interest rate parity holds closely in the data at monthly and lower frequency, see Akram et al. (2008), the following holds approximately $f_t^k - s_t^k \approx i_t^k - i_t$. This essentially implies that sorting currencies on interest rate differentials is equivalent to sorting on forward discounts. Therefore, at the end of each month, I sort currencies into portfolios based on their forward discount $f_t^k - s_t^k$,. I consider five and four portfolios for the set of all countries and the subset of the G10 countries, respectively. The log excess return for these portfolios is then determined by taking the (equally-weighted) average of the log currency excess returns in each portfolio j.

3.3 Descriptive Statistics for Portfolios

Descriptive statistics for the five and four carry trade portfolios, the DOL portfolio (average of all portfolios) and the HML portfolio (portfolio high minus portfolio low) are reported in Table 1. Panel A reports the descriptive statistics for all countries, while Panel B shows the results for the developed countries.

[Insert Table 1]

The average monthly returns increase monotonically when moving from portfolio one to five and four, respectively, and the HML portfolio. I also find the returns more negatively skewed, which is in line with the results by Brunnermeier and Pedersen (2009). Overall, the results are similar to the ones reported in Lustig et al. (2011) and Menkhoff et al. (2012).

The dollar portfolio (DOL) displays a average excess return of 1.02% for all countries and of 0.40% for the developed countries. This finding suggest that U.S. investors demand a positive risk premium for holding foreign currency although it is rather of small magnitude. This risk premium is lower as compared to the numbers found in Menkhoff et al. (2012) and Lustig et al. (2011). However, I attribute the different numbers to different sampling periods. They analyze excess returns for the period 11/1983-12/2009, while my sample covers the period from 03/1988 - 06/2015[6]. My dataset hence covers the recent sovereign debt crises that has also substantially affected the U.S. economy and as a result the USD, see also Mancini et al. (2013). Therefore, the lower risk premium might well reflect the increased riskiness of the U.S. dollar relative to other currencies.

3.4 System-wide volatility connectedness

In a first step, the system-wide volatility connectedness measure is derived from daily volatility. The volatility is estimated using a range-based estimator, see Parkinson (1980) and Alizadeh et al. (2002). More precisely, the volatility for currency k on day t is defined as:

$$\tilde{\sigma}_{k,t} = 0.361[\ln(P_{k,t}^{\max}) - \ln(P_{k,t}^{\min})]^2 \tag{7}$$

where $P_{k,t}^{\max}$ is the maximum (high) price for currency k on day t and $P_{k,t}^{\min}$ is the respective minimum price. The proposed network methodology focuses on volatility as opposed to returns for mainly two reasons. First, volatility is crisis-sensitive and connectedness becomes most apparent and relevant during crisis periods. Second, volatility tends to co-move only in crisis periods as opposed to returns that move together in crises and upswing periods.

[6]The shorter time period compared to 01/1987-06/2015 is due to the construction of the system-wide volatility connectedness risk factor as clarified in the subsequent section.

In this sense, volatility tracks investors fears, similarly to the VIX index, see Diebold and Yilmaz (2014) and Demirer et al. (2015). As a result, the system-wide volatility connectedness can be interpreted as a fear connectedness. This fear connectedness is particularly suitable to monitor and track crisis in the underlying network of interest. Consequently, the analyzed network here tracks the fear connectedness in the FX market.

Since I need a balanced dataset in order to obtain the system-wide volatility connectedness, I use a subset of currencies that provide the longest time-series possible while being fairly representative. I hence focus on the G10 currencies: Australia, Canada, euro area, Japan, New Zealand, Norway, Sweden and Switzerland. As pointed out in Colacito et al. (2015), these countries have highly developed economies and display a high degree of financial integration. However, they still provide a rich set of cross-sectional empirical differences as it involves typically funding and investment currencies. Moreover, according to the Triennial Central Bank Survey as published by the Bank of International Settlement (2015) the G10 countries' currencies account for about 90% of the global foreign exchange market turnover as of April 2013. For the G10 currencies, there are daily high and low prices available from January 1987 on[7]. For the empirical analysis at hand, I consider a VAR of order three and a predictive horizon of $H = 12$ days.[8]. In order to obtain time-varying volatility connectedness from Equation 5, I adopt the rolling window approach by Diebold and Yilmaz (2009, 2012, 2014) and Demirer et al. (2015). Based on the resulting daily volatility connectedness series, the monthly volatility connectedness is constructed similar to the volatility proxy in Menkhoff et al. (2012). That is, the monthly system-wide volatility connectedness is defined as:

$$C_t^w = \frac{1}{T_t} \sum_{\tau \in T_t} C_\tau^w$$

where T_t denotes the total number of trading days in month t, and C_τ^w is the daily volatility

[7]U.S. holidays have been dropped from the data set and the series for the euro area before January 1999 corresponds to the European currency unit that has eventually been replaced by the euro.

[8]Unreported results show, however, that the results are robust to a reasonable range of order p and predictive horizon H.

connectedness obtained for day τ and rolling window size w. The results here are reported for a rolling window size of $w = 150$ days, but the results are robust to different window sizes[9].

For the empirical analysis, I focus on monthly volatility connectedness innovations. The focus is on innovations as only the unpredictable part is perceived as risk and should hence be priced. Since volatility connectedness is a highly persistent series, I follow Korajczyka and Sadka (2008), Menkhoff et al. (2012), Asness et al. (2013) among others, and proxy volatility connectedness innovations with AR(2) residuals[10]. The volatility connectedness as well as the volatility connectedness innovations are plotted in Figure 1.

[Insert Figure 1]

The volatility connectedness in Figure 1 exhibits three episodes of increased volatility connectedness in the period 1988 to 1996. It then seems to increase from mid-1997 to early 2005, that is from 30% to 70%, and then fluctuates around 60% untill June 2015. This observation is consistent with the finding that the volatility of the foreign exchange market has been significantly higher than before the financial crisis, see Diebold and Yilmaz (2015), resulting in a higher level of system-wide volatility connectedness. Moreover, the volatility connectedness increases and spikes consistent with a number of crises, such as the recession in the early 1990s, the Tequila Peso crisis in 1994, the Asian financial crisis in 1997 or the financial crisis in 2007-2008, see (**?**, Ch. 6) for a more detailed discussion.

[9] Robustness checks have shown that the results remain qualitatively and quantitatively similar for some range of rolling window sizes. This issue will be further addressed in the robustness section.

[10] I find first differences and AR(1) residuals significantly autocorrelated with first order autocorrelations of 41% and 39%, respectively. Hence, I use AR(2) innovations. Nevertheless, as pointed out by Menkhoff et al. (2012), this procedure might induce errors-in-variables problem as it requires the full sample. To mitigate these concerns, I perform the same analysis using simple differences and obtain very similar results.

3.5 FX Volatility

For comparison reasons, I also consider the global FX volatility as introduced in Menkhoff et al. (2012). Menkhoff et al. (2012) define global FX volatility for month t as follows:

$$\sigma_t = \frac{1}{T_t} \sum_{\tau \in T} \left[\sum_{k \in K_\tau} \frac{|r_\tau^k|}{K_\tau} \right] \tag{8}$$

where K_τ corresponds to the number of available currency pairs on day τ, T_τ is the total numbers of trading days in month t and $|r_\tau^k|$ is the absolute daily log return. For the subset of the G10 countries, I consider the range-based volatility estimator as defined in Equation 7.

4. Empirical Results

4.1 Methodology

I use the traditional two-pass ordinary least squares (OLS) methodology following Fama and MacBeth (1973) to estimate the factor betas and risk prices. In the first stage, I run a time-series regression of returns on factors in order to obtain beta estimates:

$$rx_t^i = a + \beta f_t + \epsilon_t \qquad \forall i = 1, ..., N \tag{9}$$

where rx_t^i is the currency portfolio i, f_t are the considered factors, β are the factor betas, a is a constant and N is the number of currency portfolios considered. In the second stage, I run cross-sectional regressions of portfolio returns on the estimated betas from the first step at each time t:

$$rx_t^i = \beta' \lambda_t + \alpha_{it} \tag{10}$$

where λ_t is the vector of risk premia estimated at time t and α_{it} is the pricing error. In contrast to the first stage estimation, I do not include a constant in the second stage estimation ($\lambda_{0,t} = 0$). Instead I consider the DOL factor as introduced by Lustig et al. (2011). This is common procedure and motivated by the fact that the DOL factor has basically no cross-sectional relation with the currency portfolios and essentially serves as a constant, see also Burnside (2011) and Lustig et al. (2011). The market price of risk is then derived as the mean of these coefficient slopes. The corresponding standard errors are derived based on Newey and West (1987) and Shanken (1992), see Cochrane (2005) and Burnside (2011) for details.

In addition to the volatility connectedness innovations, I follow Breeden et al. (1989), Ang et al. (2006) and Menkhoff et al. (2012) and also build a factor-mimicking portfolio of volatility connectedness innovations. This procedure has the advantage to convert the non-traded factor of volatility connectedness innovations into a traded factor that allows me to examine the factor price in a straightforward way. I build the factor-mimicking portfolio by estimating the coefficient b in the following regression:

$$\Delta(C_t^w) = c + b' rx_t + u_t \tag{11}$$

where rx_t represent the currency portfolio returns and b corresponds to the weight of the currency portfolios in the factor-mimicking portfolio. The factor-mimicking portfolio's excess return is then given by $rx_t^{FM} = b' rx_t$. The average monthly excess return of the rx_t^{FM} for all countries and the subset of the G10 countries is -0.05% and -0.03%, respectively. In the following, I denote the non-traded and traded factor of system-wide volatility connectedness innovations as SVC and SVC_{FM}, respectively.

4.2 Asset Pricing Tests

This section presents my main result that the system-wide volatility connectedness factor is a priced factor in explaining the cross-section of carry trade returns. Table 2 shows the results of the asset pricing tests using the five currency portfolios as test assets for all countries. Table 3 presents the same results for the subset of the G10 countries. Panel A reports the cross-sectional results, while Panel B shows the results for time-series regressions of excess returns. As factors I use DOL and the non-traded system-wide volatility connectedness innovations (SVC) or the factor-mimicking portfolio of sytem-wide volatility connectedness innovations (SVC_{FM}).

[Insert Table 2]

The primary interest is the factor risk price of the system-wide volatility connectedness innovations. Panel A in Table 2 reports a significantly negative factor price λ_{SVC} and $\lambda_{SVC_{FM}}$. That is, portfolios that covary with volatility connectedness innovations display a lower risk premium. Moreover, the risk premia for the traded factor of -0.048% is comparable to the average monthly excess return of the factor-mimicking portfolio of -0.046%. Consequently, the factor price of risk makes economically sense and is consistent with the absence of arbitrage, see Lewellen et al. (2010) and Menkhoff et al. (2012) among others. I also find a high-cross sectional fit of the volatility connectedness factor of 98%.

Considering Panel B of Table 2, I report the time-series beta for the five forward discount-sorted portfolios for both model specifications. The beta estimates are decreasing for both factors. The betas for the SVC factor is significant for 2 out of 5 portfolios, whereas they are all significant for SVC_{FM}. The rather weak significance for the factor betas found for the non-traded connectedness risk factor is not surprising. The risk factor is constructed based on the G10 network and has therefore the inherent drawback of not capturing all the information relevant to the full set of all countries, particularly not the emerging countries. The traded risk factor, SVC_{FM}, can to some extent mitigate that concern as it uses the the full set of all countries in order to build the factor-mimicking portfolio. In terms of fit, the R^2 are higher for the model specification with the traded factor. The better fit of the traded factor is not surprising either since the non-traded factor is a noisier estimate of the systemic connectedness risk by construction than its traded counterpart.

For the G10 countries the results are reported in Table 3. Similar to the set of all countries, I find a negative and highly significant and negative risk premium for the non-traded as well as the traded connectedness risk factor. Considering Panel B of Table 3 the factor beta estimates show again a monotonically decreasing pattern rationalizing the negative risk premium. In contrast to the set of all countries, the factor betas for the non-traded connectedness risk factor are all statistically significant which is also reflected in the higher t-statistics based on Shanken (1992) for the cross-sectional estimation as reported in Panel A.

[Insert Table 3]

Overall, these results show that the betas are positive for low-interest rate currencies, while they are negative for high-interest countries. Increased system-wide volatility connectedness reflects a state where global shocks are propagated to a substantial amount from one market to the other, typically occurring in crises situations. In this sense, time-varying connectedness can be interpreted as a fear index. System-wide volatility connectedness is typically low most of the time, but bursts and spikes during crises periods reflecting a "bad" state of the world, see Diebold and Yilmaz (2014), Demirer et al. (2015). Interpreting innovations to increased system-wide volatility connectedness as fear risk or unexpected increased systemic risk, these results show that investors are willing to accept lower returns on carry trade funding currencies (low interest rate currencies) in crisis or unexpected risky periods. Consequently, low-interest rate currencies are considered as a hedge for crisis periods and thus reflect a flight to safety character.

4.3 Horse races

In order to evaluate the pricing power of the system-wide volatility connectedness risk factor, I run horse races against the two most related and prominent factors as is done in Menkhoff et al. (2012). These factors are the HML_{FX} carry factor as introduced by Lustig et al. (2011) and the global volatility risk factor proposed by Menkhoff et al. (2012). I run horse races against each of these factors in a joint specification. I consider traded factors in order to allow for a fair horse race. More specifically, among the three considered factors, the system-wide volatility connectedness risk factor is i) a non-traded factor and ii) it is derived in two steps. In the first step, the volatility estimates are derived and in the second step, the connectedness measures is obtained through a rolling window VAR. Moreover, as pointed out previously, the non-traded factor SVC is based on the network constituted by the G10 currencies and thus suffers from the drawback of not capturing all the relevant network information for the set of all countries. The traded factor SVC_{FM} can to some extent reduce that drawback. It thus seems reasonable to level the playground and consider the traded counterparts in order to run a fair horse race, particularly for the full set of all countries.

4.3.1 Volatility connectedness risk factor and HML_{FX} carry risk factor

For the first horse race between HML_{FX} and the systemic volatility connectedness risk factor, I consider four different specifications. First, I include the DOL, the HML_{FX} and the non-traded SVC factor. In the second, specification I consider the same specification, but use the traded SVC_{FM} factor instead of the non-traded one. The last two specification consider orthogonalized versions of the traded factors. I obtain the orthogonalized component by running a OLS regression on the risk factor of interest and use the residuals in the joint specification. The results are reported in Table 4.

[Insert Table 4]

In Panel A of Table 4 I find that HML_{FX} and the non-traded and traded factor coexist for the set of all countries. Nevertheless, we see that the t-statistics based on the correction by Shanken (1992) is substantially lower for the non-traded factor SVC, while this is not the case for the traded factor SVC_{FM}. This finding is not too surprising though. Kan et al. (2013) show that the correction by Shanken (1992) typically has a small effect on the t-statistics of traded factors, while it might substantially impact the one for non-traded factors. The reason is that the factor betas are more precisely estimated when using the traded factors as opposed to non-traded factors resulting in a minor errors-in-variables problem. This is exactly what can be observed here.

When considering both traded factors, there might be the risk of multicollinearity since SVC_{FM} and HML_{FX} are highly correlated, i.e. -0.75. I therefore follow Menkhoff et al.

(2012) and orthogonalize either the SVC_{FM} with respect to HML_{FX} (Panel C) or vice versa (Panel D). It can be seen from Panel C that the orthogonalized component of SVC_{FM} has still a significant and negative risk premium. In contrast, in Panel D, I find that the orthogonalized HML_{FX} does not carry a significant risk premium. It might be insightful to look at the correlation of these risk factors with the principal components of the five carry trade portfolios. Lustig et al. (2011) show that their proposed factors account for roughly 88% of the variation in the carry trade returns. They find that the slope HML_{FX} factor is loading highly on the second component and essentially contains most of the cross-sectional pricing information. Looking at the correlation of SVC_{FM} with the principal components of the five carry trade portfolios, I find that SVC_{FM} loads similarly high on the second component as HML_{FX} does, while it has a substantially higher loading on the remaining three principal components. Since the last three components account for roughly 12% of the variation in the carry trade returns, it seems reasonable that the SVC_{FM} dominates HML_{FX}.

When considering the G10 countries, I find similar results. The non-traded system-wide volatility connectedness factor is dominated by HML_{FX} based on the t-statistics by Shanken (1992), while the traded counterpart coexists. Again, this is not too surprising as a non-traded factor cannot beat its own factor-mimicking portfolio, see Cochrane (2005) and Menkhoff et al. (2012). Moreover, compared to the results based on all countries, I also find the orthogonalized component of the traded SVC_{FM} to carry a significant negative risk premium. Looking again at the principal component correlations, I find a similar pattern as for the set of all countries. SVC_{FM} loads similarly on the second component as HML_{FX}, but higher on the third component.

In a nutshell, running horse races between the HML_{FX} and the traded system-wide volatility connectedness innovations, it seems fair to conclude that the traded system-wide volatility connectedness risk factor prices the cross-section of carry trades portfolio at least as well as HML_{FX} and contains some additional pricing information.

4.3.2 Volatility connectedness risk factor and volatility risk factor

In order to evaluate to what extent the system-wide volatility connectedness risk factor is different from the global volatility risk factor, I perform the same horse race but replace HML_{FX} with the corresponding volatility factor of Menkhoff et al. (2012). The results are reported in Table 5.

[Insert Table 5]

From Panel A, it can be seen that both non-traded factors carry a significant and negative risk premium when considering Newey and West (1987) robust t-statistics. However, the correction by Shanken (1992) renders VOL insignificant. Considering both traded counterparts, I find that both factors are negative and significant. Since VOL_{FM} and SVC_{FM} are also highly correlated, i.e. 0.70, I perform again the orthogonalization mechanism and report the results in Panel C and D. Similarly to the previous case, the orthogonlized component of SVC_{FM} still carries a significant and negative risk premium, while this does not hold for the orthognalized part of the volatility factor. Looking again at the correlation structure with the principal components, I find a similar pattern as for the previous case. Hence, it can be concluded that the system-wide volatility connectedness risk factor also carries additional explanatory power relative to the volatility risk factor in pricing the cross-section of carry trade portfolios based on the set of all countries.

When considering the G10 countries, I find similar results. I find both non-traded factors to be significant only when considering t-statistics based on Shanken (1992), while their traded counterparts coexist based on both t-statistics. For the results on the orthogonalized components, as reported in Panel C and D, I find similar results compared to the results reported for all countries. The orthogonalized component of the traded SVC_{FM} also carries a significant negative risk premium, while the orthogonal component of the VOL_{FM} is insignificant in the joint specification. The results thus line up with the results of the previous horse race. That is, the traded system-wide volatility connectedness risk factor also dominates the volatility factor for the subset of the G10 countries.

In summary, running horse races between the traded system-wide volatility connectedness innovations and the traded volatility factor, VOL_{FM}, we can draw the same conclusion as in the previous case. The traded system-wide volatility connectedness risk factor prices the cross-section of currency portfolio returns as well as the volatility risk factor and contains some additional information.

5. Robustness

In the robustness section, I consider several different modifications with respect to the benchmark results outlined in the main empirical results section.

5.1 Rolling window size

The derived system-wide volatility connectedness risk factor in the benchmark results is derived on a rolling window size of $w = 150$ days. I hence consider a longer and shorter window size to evaluate the sensitivity of the benchmark results. As a reminder, applying the rolling window approach essentially means introducing time-varying parameters. Hence, a longer rolling window size will result in both smoother system-wide volatility connectedness index and innovations and vice versa for a shorter rolling window size. I first discuss the results for a shorter rolling window size of $w = 100$ days and then consider the case of a rolling window size $w = 250$ days.

5.2 Shorter rolling window size: $w = 100$ days

Considering first the pricing ability of the SVC and SVC_{FM} for all countries and the G10 countries as presented in Table 6 and Table 7, respectively, it can be seen that both carry a significant and negative risk premium in both country specifications. Nevertheless, the cross-sectional R^2 for all countries and the subset of the G10 countries has slightly decreased to 93% and 98%, respectively. The factor betas still display a decreasing pattern, although the beta of the last portfolio represents a slight exception for the set of all countries.

[Insert Table 6]

[Insert Table 7]

Moreover, the results for the horse races between the traded system-wide volatility connectedness factor and HML_{FX} and the volatility factor reported in Table 8 and Table 9 show that the pricing power of the traded system-wide volatility factor decreases. That is, the orthogonalized component of both HML_{FX} and VOL_{FM} carry now a negative and significant risk premium in the joint specification with SVC_{FM} for the set of all countries. For the G10 countries, the results for the horse race between the volatility risk factor and the connectedness risk factor confirm the benchmark results. In contrast, I get different results for the horse race against the carry HML_{FX} factor. That is, the orthogonal component of SVC_{FM} no longer carries a significant negative risk premium.

[Insert Table 8]

[Insert Table 9]

Overall, the robustness check on the smaller window size confirm that the both the non-traded and the traded system-wide volatility connectedness risk factor carries a negative and significant risk premium. With regards to the horse race, I find the results to slightly worsen for the shorter rolling window. More specifically, the traded system-wide volatility connectedness risk factor on the shorter window-size coexists with the other traded factors rather than dominating them. For the subset of the G10 countries, I find the same results for the horse race against the volatility risk factor, while the results change for the horse race again the carry HML_{FX} factor. That is, the traded connectedness risk factor no longer dominates the carry HML_{FX} factor.

5.3 Longer rolling window size: $w = 250$ days

Considering the pricing ability for the longer rolling window size presented in Table 10 and Table 11, the risk premium for the traded and non traded system-wide volatility connectedness risk factor is again significant and negative for both set of all and the subset of the G10 countries. Moreover, the cross-sectional has decreased down to 87% for all countries and to 79% for the G10 country specification. Moreover, also the factor betas display a decreasing pattern although the decreasing pattern for the set of all countries is no longer monotonic.

[Insert Table 10]

[Insert Table 11]

Turning to the horse race results as presented in Table 12 and Table 13, I find the same results as for the benchmark case for the set of all countries although the orthogonalized component of traded system-wide volatility factor is significant only for the t-statistics by Shanken (1992). For the subset of the G10 countries, the results of the horse races change. More specifically, the results change to the extent that the orthogonalized traded system-wide volatility factor for the G10 countries is no longer significant. Hence, the results based on the longer window size shows that the results worsen in the sense that the traded connectedness risk factor contains the same information as the other factors for the subset of the G10 countries, while it still contains additional explanatory power for the set of all countries.

[Insert Table 12]

[Insert Table 13]

In summary, the results based on the longer and shorter rolling window size confirm the results based on the benchmark results to the extent that the system-wide volatility connectedness risk factor carries a significant and negative risk premium. Considering the horse races, I find the results to worsen to the extent that the traded system-wide volatility connectedness risk factor prices the cross-section of the currency portfolios at least as well as HML_{FX} and VOL_{FM} instead of dominating them.

The results from the robustness section show that the system-wide connectedness risk factor is sensitive to the rolling window size, particularly when it comes to the horse races. A too short as well as a too long window size, i.e. too quickly or too slowly changing parameters, will impact the pricing power of the connectedness risk factor with respect to HML_{FX} and VOL_{FM}. However, the main conclusion still remains intact. That is, the system-wide volatility connectedness risk factor i) carries a significant and negative risk premium and ii) it prices the cross-section of carry trade returns at least as well as the prominent and related factors HML_{FX} and VOL_{FM}.

5.4 Developed currencies

I perform to same analysis as above but this time I consider the commonly analyze set of 15 developed currencies: Australia, Belgium, Canada, Denmark, euro area, France, Germany, Italy, Japan Netherlands, New Zealand, Norway, Sweden, Switzerland and the United Kingdom. I again sort the currencies into five portfolios based on their lagged forward discount. The descriptive statistics are provided in Table 14.

[Insert Table 14]

As can be seen from Table 14, a similar pattern as in Table 1 can be found. That is, average excess returns increase from portfolio 1 to 5 albeit not monotonically and the spread between the high and low portfolio is highly significant.

Considering the results from the asset pricing test analysis in Table 15, I find a significant and negative risk premium for both the non-traded and traded system-wide volatility connectedness risk factor as expected. Nevertheless, the cross-sectional fit of 78% is lower as in the other two benchmark specifications. Moreover, Panel B in Table 15 documents the same monotonic decreasing pattern for the factor beta estimates. Therefore, the results for the developed countries confirm the conclusion from the results for the set of all countries and the subset of the G10 countries as discussed previously.

[Insert Table 15]

I also perform the same horse race exercise as in subsection 4.3. The results are reported in Table 16 and Table 17.

[Insert Table 16]

[Insert Table 17]

From these results, we can see that the traded connectedness-risk factor contains the same information as the other two factors. Hence, the results are weaker for the subset of the developed countries when considering the horse races.

5.5 Beta-sorted portfolios

If system-wide volatility connectedness risk is a priced factor, sorting currencies according to their exposure to system-wide volatility connectedness risk should yield a cross-section of portfolios with a significant spread, see also Lustig et al. (2011), Menkhoff et al. (2012) or Dobrynskaya (2014).

I hence sort the currencies at the end of every month into five portfolios based on their past system-wide volatility connectedness risk beta. The betas are estimated in a rolling window of 36 months and I rebalance the portfolios every month. I hence adopt the same sorting scheme as in Lustig et al. (2011). Since the system-wide connectedness is based on the G10 currencies it has by construction the drawback of not capturing all the information of all countries, particularly not for the emerging markets. Therefore, instead of sorting on the non-traded system-wide connectedness factor, SVC, I perform the beta-sorting on its traded counterpart, SVC_{FM}. The traded system-wide volatility connectedness risk factor can to some extent reduce the inherent drawback of the SVC as it uses the full set of all countries in order to obtain the factor mimicking portfolio. Nevertheless, I also report the beta-sorting scheme as in Dobrynskaya (2014) or Herskovic (2015) for the G10 countries. Descriptive statistics for portfolio excess returns are shown in Table 18. The system-wide connectedness risk factor is obtained based on the benchmark rolling window size of $w = 150$ days.

[Insert Table 18]

I first consider the results for the set of G10 countries. Panel C reports the results obtained from the beta sorting scheme as outlined in Lustig et al. (2011) for the traded factor, SVC_{FM}, while Panel D shows the results obtained form the beta sorting scheme as in Dobrynskaya (2014) for the non-traded factor, SVC. As can be seen from these results, I obtain a significant spread for both sorting schemes and a decreasing pattern for the average excess returns. However, this decreasing pattern is only monotonic for the results reported in Panel D. Moreover, for the results reported in Panel D I find a monotonic increasing skewness from portfolio one to portfolio four and HML. This skewness pattern is similar to the one obtained from the sorting on lagged forward discount as reported in Table 1 indicating that sorting on volatility connectedness risk is similar to sorting on lagged forward discount.

In contrast, from Panel A one can see that no such monotonic pattern is obtained for the portfolios based on the full set of all countries although it does generate the expected difference between portfolio one and portfolio five. Nevertheless, this spread is i) not that large and ii) not significant. It thus seems that the factor-mimicking portfolio SVC_{FM} cannot fully correct for the previously discussed drawback of the SVC factor. Yet, unreported results for sorting on the HML_{FX} factor reveal a very similar, non conclusive pattern to sorting on SVC_{FM}. Hence, to some extent, the results might also be attributed to the particular sample period, that is 04/1993 to 06/2015, since Lustig et al. (2011) find a decreasing pattern and a significant spread for the period of 12/1986 to 12/2009 for the same sorting scheme. For the subset of the developed countries as reported in Panel B, I find a monotonically decreasing pattern and a significant return. In summary, the beta-sorting shows that the connectedness risk factor matters for understanding the cross-section of currency excess returns.

6. Conclusion

In this study, I empirically examine the system-wide volatility connectedness risk of currencies as an explanation for the risk premium of carry trade returns. Carry trade strategies exploit the failure of the uncovered interest rate parity (UIP). That is, they generate a positive return by exploiting the interest rate differential between low and high interest rate currencies. This positive return is not eliminated by a corresponding change in exchange rates as predicted by UIP.

I rely on the new network methodology introduced by Diebold and Yilmaz (2009, 2012, 2014, 2015) that allows me to measure interdependencies across FX markets. I adopt a rolling-window approach in order to obtain time-varying system-wide volatility connectedness. This time-varying system-wide volatility connectedness measure can be understood as a fear conntectedness as pointed out by Diebold and Yilmaz (2014, 2015). The system-wide volatility connectedness is usually low most of the time, but increases substantially during crisis periods. Such bursts or cyclical system-wide volatility connectedness typcially reflects a "bad" state of the world where shocks are propagated to a substantial amount through the system. Consequently, innovations to system-wide volatility connectedness can be understood as fear risk. I can empirically show that carry trade returns are significantly and negatively related to system-wide volatility connectedness risk. In a horse race against two related factors, i.e. the carry factor by Lustig et al. (2011) and the volatility risk of Menkhoff et al. (2012), I can show that the traded system-wide volatility connectedness does price the cross-section of carry trade returns at least as well as these two factors.

Nevertheless, the empirical approach adopted here remains agnostic as to how connectedness arises. It rather takes it as given and aims to measure it as well as possible, see Diebold and Yilmaz (2015). In this sense, it remains consistent with a variety of underlying causal structures and essentially represents a reduced-form empirical framework capturing different sources of connectedness risk. It is thus related to many currency risk factor structures proposed so far in the literature, for example, Colacito et al. (2015), Della Corte et al. (2016), Richmond (2016). For future work, it will be particularly interesting to exploit the different channels through which connectedness arises and relate it to the connectedness measure as presented here in this paper.

Graphics

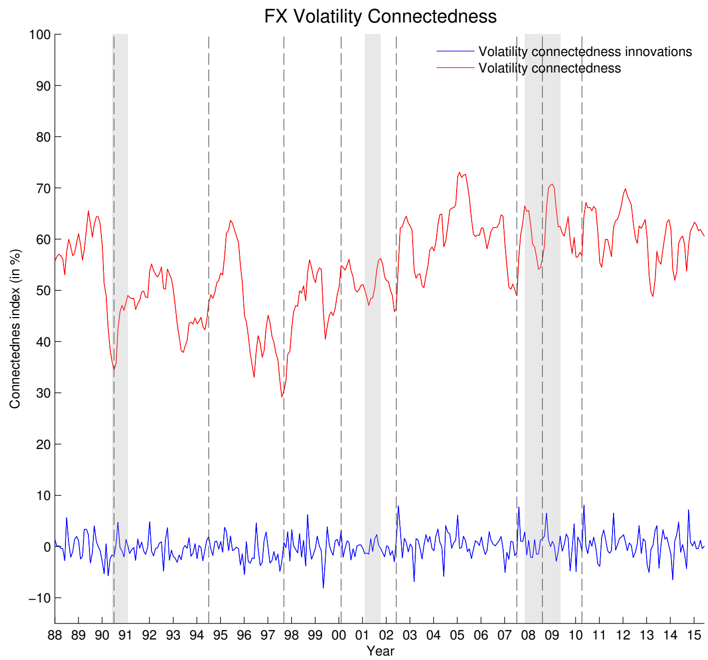

Figure 1: **Volatility connectedness and volatility connectedness innovations.** The figure shows the monthly volatility connectedness and the innovations in volatility connectedness for a rolling window size of $w = 150$ days.

Tables

Panel A: All countries

Portfolio	1	2	3	4	5	DOL	HML
Mean	-2.56	-0.42	1.67	2.62	3.79	1.02	6.35
	-1.84	-0.3	1.05	1.57	1.78	0.71	3.39
Std	6.97	6.48	7.5	8.07	9.79	6.73	8.62
Skewness	-0.09	-0.35	-0.14	-0.67	-0.96	-0.58	-0.75
Kurtosis	4.31	4.91	3.95	5.25	6.74	4.36	4.63
SR	-0.37	-0.07	0.22	0.32	0.39	0.15	0.74

Panel B: G10 countries

Portfolio	1	2	3	4	DOL	HML
Mean	-2.00	-1.23	2.14	2.71	0.40	4.70
	-1.11	-0.67	1.18	1.18	0.24	2.29
Std	9.07	8.51	8.89	10.49	7.89	9.84
Skewness	0.25	-0.08	-0.42	-0.58	-0.26	-0.83
Kurtosis	3.96	3.32	5.35	5.04	3.77	4.84
SR	-0.22	-0.14	0.24	0.26	0.05	0.48

The table reports the mean returns, standard deviation (both annualized), skewness and kurtosis of currency portfolios sorted on $f_{t-1} - s_{t-1}$ (forward discounts). Also the annualized Sharpe Ratios (SR) and AC(1), first-order autocorrelation coefficient are reported. Numbers in parentheses show the Newey and West (1987) HAC t-statistics. Returns are monthly and the sample period is March 1988 to June 2015.

Table 1: Descriptive Statistics

Table 2: Cross-setional Asset Pricing Results: Volatility Connectedness Risk

Panel A: Factor prices - all countries

	Non-traded SVC						Traded SVC				
	DOL	SVC	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2		DOL	SVC_{FM}	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2
λ	0.09	-0.04	0.88	0.30	0.98	λ	0.09	-0.05	0.88	0.89	0.98
NW	0.73	-4.00	0.83	0.96		NW	0.73	-4.03	0.83	0.83	
SH	0.8	-2.42				SH	0.8	-4.35			

Panel B: Factor betas - all countries

	Non-traded SVC					Traded SVC			
	α	DOL	SVC	R^2		α	DOL	SVC_{FM}	R^2
1	-0.28	0.86	7.97		1	-0.01	0.95	6.15	
	-4.19	15.59	3.03	0.69		-0.51	59.66	47.68	0.97
2	-0.1	0.8	2.67		2	-0.01	0.83	2.06	
	-1.82	13.29	1.12	0.69		-0.19	16.68	4.13	0.73
3	0.05	1.02	-1.14		3	0.01	1.00	-0.88	
	1.03	23.88	-0.61	0.84		0.24	26.01	-2.38	0.84
4	0.12	1.09	-4.56		4	-0.03	1.04	-3.53	
	2.25	24.28	-2.02	0.84		-0.77	38.17	-13.1	0.91
5	0.21	1.23	-4.94		5	0.04	1.17	-3.81	
	2.25	16.42	-1.44	0.72		0.45	17.38	-7.80	0.77

The table reports factor prices and factor betas for a rolling window size of $w = 150$ days. The test assets are excess returns to five and four carry trade portfolios based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows the factor risk prices λ obtained by FMB cross-sectional regression. I do not use a constant in the second-stage FMB regression. Robust t-statistics based on Shanken (1992) are reported in paranthesis. I also report the cross-sectional R^2. Panel B shows the factor betas for time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL) and the non-traded volatility connectedness innovations (SVC) or the factor-mimicking portfolio for of volatility connectedness innovations (SVC_{FM}). HAC standard errors (Newey-West adjusted with optimal lag selection according to Andrews (1991)) are reported. The sample period is from March 1988 to June 2015 and the returns are not transaction cost adjusted.

Table 3: Cross-setional Asset Pricing Results: Volatility Connectedness Risk

Panel A: Factor prices - G10 countries

	Non-traded SVC						Traded SVC				
	DOL	SVC	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2		DOL	SVC_{FM}	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2
λ	0.03	-0.02	0.15	0.07	0.99	λ	0.03	-0.03	0.15	0.13	0.99
NW	0.24	-3.05	0.93	0.96		NW	0.24	-2.98	0.93	0.94	
SH	0.26	-2.26				SH	0.26	-3.01			

Panel B: Factor betas - G10 countries

	Non-traded SVC					Traded SVC			
	α	DOL	SVC	R^2		α	DOL	SVC_{FM}	R^2
1	-0.2	0.9	9.33		1	0.01	1.01	6.44	
	-2.1	14.49	2.17	0.62		0.15	31.52	13.39	0.82
2	-0.13	0.93	5.56		2	-0.01	1.00	0.93	
	-2.08	19.02	1.84	0.74		-0.19	32.49	8.54	0.82
3	0.14	1.00	-5.78		3	0.02	0.93	-3.99	
	2.5	22.62	-1.98	0.79		0.33	38.87	-11.48	0.87
4	0.18	1.17	-9.10		4	-0.02	1.06	-6.29	
	2.28	20.7	-2.43	0.78		-0.34	49.5	-20.57	0.93

The table reports factor prices and factor betas for a rolling window size of $w = 150$ days. The test assets are excess returns to five and four carry trade portfolios based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows the factor risk prices λ obtained by FMB cross-sectional regression. I do not use a constant in the second-stage FMB regression. Robust t-statistics based on Newey and West (1987) and Shanken (1992) are reported in parentheses. I also report the cross-sectional R^2. Panel B shows the factor betas for time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL) and the non-traded volatility connectedness innovations (SVC) or the factor-mimicking portfolio for of volatility connectedness innovations (SVC_{FM}). HAC standard errors (Newey-West adjusted with optimal lag selection according to Andrews (1991)) are reported. The sample period is from March 1988 to June 2015 and the returns are not transaction cost adjusted.

Table 4: Cross-setional Asset Pricing Results: Volatility Connectedness Risk and HML_{FX}

All countries

Panel A: SVC and HML_{FX}					Panel B: SVC_{FM} and HML_{FX}				
	DOL	HML_{FX}	SVC	R^2		DOL	HML_{FX}	SVC_{FM}	R^2
λ	0.09	0.52	-0.03	0.99	λ	0.09	0.52	-0.05	0.99
NW	0.72	3.31	-2.64		NW	0.72	3.31	-4.36	
SH	0.80	3.67	-1.69		SH	0.8	3.75	-4.51	

Panel C: HML_{FX} and SVC_{FM} (orth.)					Panel D: HML_{FX} (orth.) and SVC_{FM}				
	DOL	HML_{FX}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$HML_{FX}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.09	0.52	-0.02	0.99	λ	0.09	0.05	-0.05	0.99
NW	0.72	3.31	-2.59		NW	0.72	0.45	-4.36	
SH	0.80	3.75	-2.66		SH	0.8	0.51	-4.51	

G10 countries

Panel A: SVC and HML_{FX}					Panel B: SVC_{FM} and HML_{FX}				
	DOL	HML_{FX}	SVC	R^2		DOL	HML_{FX}	SVC_{FM}	R^2
λ	0.03	0.39	-0.03	0.999	λ	0.03	0.39	-0.08	0.999
NW	0.24	2.36	-2.06		NW	0.24	2.36	-3.17	
SH	0.27	2.50	-1.30		SH	0.27	2.51	-3.10	

Panel C: HML_{FX} and SVC_{FM} (orth.)					Panel D: HML_{FX} (orth.) and SVC_{FM}				
	DOL	HML_{FX}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$HML_{FX}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.03	0.39	-0.01	0.999	λ	0.03	-0.03	-0.03	0.999
NW	0.24	2.36	-2.01		NW	0.24	-0.32	-3.17	
SH	0.27	2.51	-1.83		SH	0.27	-0.32	-3.10	

The table reports the factor prices for models where I jointly include the DOL factor, HML_{FX}, and different variants of volatility connectedness innovations (SVC and SVC_{FM}) based on a rolling window size of $w = 150$ days. Test assets are the excess returns to the five and four carry trade based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows results for volatility connectedness innovations (SVC), Panel B for the factor-mimicking portfolio of volatility connectedness innovations (SVC_{FM}), Panel C for the factor-mimicking portfolio orthogonalized with respect to HML_{FX} , denoted as $SVC_{FM}^{\text{orth.}}$, and Panel D for the factor-mimicking portfolio for volatility connectedness innovations and HML_{FX} orthogonalized with respect to volatility, denoted as $HML_{FX}^{\text{orth.}}$. The sample period is March 1988 to June 2015.

Table 5: Cross-setional Asset Pricing Results: Volatility Connectedness Risk and Volatility Risk

All countries

Panel A: SVC and VOL					Panel B: SVC_{FM} and VOL_{FM}				
	DOL	VOL	SVC	R^2		DOL	VOL_{FM}	SVC_{FM}	R^2
λ	0.09	-0.04	-0.03	0.99	λ	0.09	-0.09	-0.05	0.99
NW	0.72	-2.17	-2.85		NW	0.72	-2.94	-4.29	
SH	0.80	-1.60	-1.78		SH	0.80	-3.39	-4.47	

Panel C: VOL_{FM} and SVC_{FM} (orth.)					Panel D: VOL_{FM} (orth.) and SVC_{FM}				
	DOL	VOL_{FM}	$SVC_{FM}^{\mathbf{orth.}}$	R^2		DOL	$VOL_{FM}^{\mathbf{orth.}}$	SVC_{FM}	R^2
λ	0.09	-0.09	-0.02	0.99	λ	0.09	-0.05	-0.01	0.99
NW	0.72	-2.94	-2.97		NW	0.72	-0.30	-4.29	
SH	0.80	-3.39	-3.09		SH	0.80	-0.35	-4.47	

G10 countries

Panel A: SVC and VOL					Panel B: SVC_{FM} and VOL_{FM}				
	DOL	VOL	SVC	R^2		DOL	VOL_{FM}	SVC_{FM}	R^2
λ	0.03	-0.03	-0.02	0.997	λ	0.03	-0.07	-0.03	0.997
NW	0.24	-1.80	-2.01		NW	0.24	-2.19	-3.14	
SH	0.26	-1.39	-1.32		SH	0.26	-2.40	-3.09	

Panel C: VOL_{FM} and SVC_{FM} (orth.)					Panel D: VOL_{FM} (orth.) and SVC_{FM}				
	DOL	VOL_{FM}	$SVC_{FM}^{\mathbf{orth.}}$	R^2		DOL	$VOL_{FM}^{\mathbf{orth.}}$	SVC_{FM}	R^2
λ	0.03	-0.07	-0.01	0.997	λ	0.03	0.01	-0.03	0.997
NW	0.24	-2.19	-1.96		NW	0.24	0.37	-3.14	
SH	0.26	-2.40	-1.99		SH	0.26	0.41	-3.09	

The table reports the factor prices for models where I jointly include the DOL factor, the non-traded and traded volatility risk factor of Menkhoff et al. (2012), denoted as VOL and VOL_{FM}, and the corresponding counterparts of volatility connectedness innovations (SVC and SVC_{FM}) based on a rolling window size of $w = 150$ days. Test assets are the excess returns to the five and four carry trade based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows results for non-traded factors of volatility innovations (VOL) and volatility connectedness innovations (SVC), Panel B for the factor-mimicking portfolio of volatility innovations VOL_{FM} and volatility connectedness innovations (SVC_{FM}), Panel C for the factor-mimicking portfolio orthogonalized with respect to VOL_{FM} , denoted as $SVC_{FM}^{\text{orth.}}$, and Panel D for the factor-mimicking portfolio for volatility connectedness innovations and VOL_{FM} orthogonalized with respect to volatility, denoted as $VOL_{FM}^{\text{orth.}}$. The sample period is March 1988 to June 2015.

Table 6: Cross-setional Asset Pricing Results: Volatility Connectedness Risk

Panel A: Factor prices - all countries

	Non-traded SVC					Traded SVC					
	DOL	SVC	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2		DOL	SVC_{FM}	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2
λ	0.09	-0.06	1.36	0.40	0.93	λ	0.09	-0.12	1.36	1.74	0.93
NW	0.74	-4.27	0.71	0.94		NW	0.74	-4.03	0.71	0.63	
SH	0.81	-2.07				SH	0.82	-4.14			

Panel B: Factor betas - all countries

	Non-traded SVC					Traded SVC			
	α	DOL	SVC	R^2		α	DOL	SVC_{FM}	R^2
1	-0.28	0.85	4.58		1	-0.04	0.73	6.82	
	-4.17	15.06	2.15	0.69		-1.11	23.92	20.18	0.92
2	-0.1	0.80	2.13		2	0.01	0.74	3.17	
	-1.82	13.18	1.17	0.69		0.18	14.16	5.5	0.75
3	0.05	1.02	-1.91		3	-0.05	1.07	-2.84	
	1.02	23.96	-1.11	0.84		-0.91	29.39	-6.23	0.87
4	0.12	1.10	-2.59		4	-0.01	1.17	-3.86	
	2.24	24	-1.46	0.84		-0.28	44.13	-10.14	0.89
5	0.21	1.23	-2.21		5	0.09	1.29	-3.29	
	2.25	16.2	-0.80	0.71		0.96	18.15	-5.02	0.74

The table reports factor prices and factor betas for a rolling window size of $w = 100$ days. The test assets are excess returns to five and four carry trade portfolios based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows the factor risk prices λ obtained by FMB cross-sectional regression. I do not use a constant in the second-stage FMB regression. Robust t-statistics based on Shanken (1992) are reported in paranthesis. I also report the cross-sectional R^2. Panel B shows the factor betas for time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL) and the non-traded volatility connectedness innovations (SVC) or the factor-mimicking portfolio for of volatility connectedness innovations (SVC_{FM}). HAC standard errors (Newey-West adjusted with optimal lag selection according to Andrews (1991)) are reported. The sample period is from March 1988 to June 2015 and the returns are not transaction cost adjusted.

Table 7: Cross-setional Asset Pricing Results: Volatility Connectedness Risk

Panel A: Factor prices - G10 countries

	Non-traded SVC				
	DOL	SVC	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2
λ	0.03	-0.04	0.37	0.13	0.98
NW	0.24	-3.02	0.83	0.94	
SH	0.27	-1.83			

	Traded SVC				
	DOL	SVC_{FM}	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2
λ	0.03	-0.02	0.37	0.33	0.98
NW	0.24	-2.92	0.83	0.85	
SH	0.27	-2.85			

Panel B: Factor betas - G10 countries

	Non-traded SVC			
	α	DOL	SVC	R^2
1	-0.2	0.9	5.47	
	-2.09	13.76	1.55	0.62
2	-0.13	0.93	2.4	
	-2.08	18.35	1.06	0.74
3	0.14	1	-3.53	
	2.49	21.98	-1.62	0.79
4	0.18	1.17	-4.34	
	2.27	19.85	-1.39	0.78

	Traded SVC			
	α	DOL	SVC_{FM}	R^2
1	0.03	0.77	10.36	
	0.54	22.92	16.97	0.87
2	-0.04	0.87	4.54	
	-0.56	22.42	6.34	0.79
3		1.09	-6.69	
	-0.02	50.99	-15.38	0.9
4	0.01	1.28-8.20		
	0.13	53.56	-16.23	0.9

The table reports factor prices and factor betas for a rolling window size of $w = 100$ days. The test assets are excess returns to five and four carry trade portfolios based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows the factor risk prices λ obtained by FMB cross-sectional regression. I do not use a constant in the second-stage FMB regression. Robust t-statistics based on Newey and West (1987) and Shanken (1992) are reported in parentheses. I also report the cross-sectional R^2. Panel B shows the factor betas for time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL) and the non-traded volatility connectedness innovations (SVC) or the factor-mimicking portfolio for of volatility connectedness innovations (SVC_{FM}). HAC standard errors (Newey-West adjusted with optimal lag selection according to Andrews (1991)) are reported. The sample period is from March 1988 to June 2015 and the returns are not transaction cost adjusted.

Table 8: Cross-setional Asset Pricing Results: Volatility Connectedness Risk and HML_{FM}

All countries

	Panel A: SVC and HML_{FM}				Panel B: SVC_{FM} and HML_{FX}				
	DOL	HML_{FM}	SVC	R^2		DOL	HML_{FM}	SVC_{FM}	R^2
λ	0.08	0.52	-0.04	0.997	λ	0.08	0.52	-0.03	0.997
NW	0.71	3.31	-2.65		NW	0.71	3.31	-4.01	
SH	0.79	3.66	-1.63		SH	0.79	3.74	-3.98	

	Panel C: SVC_{FM} (orth.) and HML_{FM}				Panel D: SVC_{FM} and HML_{FM} (orth.)				
	DOL	HML_{FM}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$HML_{FM}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.08	0.52	-0.02	0.997	λ	0.08	0.24	-0.03	0.997
NW	0.71	3.31	-2.42		NW	0.71	1.72	-4.01	
SH	0.79	3.74	-2.50		SH	0.79	2.01	-3.98	

G10 countries

	Panel A: SVC and HML_{FM}				Panel B: SVC_{FM} and HML_{FX}				
	DOL	HML_{FM}	SVC	R^2		DOL	HML_{FM}	SVC_{FM}	R^2
λ	0.03	0.39	-0.05	0.99	λ	0.03	0.39	-0.02	0.99
NW	0.25	2.30	-2.11		NW	0.25	2.30	-3.08	
SH	0.27	2.45	-1.01		SH	0.27	2.47	-2.95	

	Panel C: SVC_{FM} (orth.) and HML_{FM}				Panel D: SVC_{FM} and HML_{FM} (orth.)				
	DOL	HML_{FM}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$HML_{FM}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.03	0.39	-0.01	0.99	λ	0.03	0.03	-0.02	0.99
NW	0.25	2.30	-1.58		NW	0.25	0.27	-3.08	
SH	0.27	2.47	-1.63		SH	0.27	0.31	-2.95	

The table reports the factor prices for models where I jointly include the DOL factor, HML_{FX}, and different variants of volatility connectedness innovations (SVC and SVC_{FM}) based on a rolling window size of $w = 100$ days. Test assets are the excess returns to the five and four carry trade based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows results for volatility connectedness innovations (SVC), Panel B for the factor-mimicking portfolio of volatility connectedness innovations (SVC_{FM}), Panel C for the factor-mimicking portfolio orthogonalized with respect to HML_{FX} , denoted as $SVC_{FM}^{\text{orth.}}$, and Panel D for the factor-mimicking portfolio for volatility connectedness innovations and HML_{FX} orthogonalized with respect to volatility, denoted as $HML_{FX}^{\text{orth.}}$. The sample period is March 1988 to June 2015.

Table 9: Cross-setional Asset Pricing Results: Volatility Connectedness Risk and Volatility Risk

All countries

Panel A: SVC and VOL_{FM}					Panel B: SVC_{FM} and VOL_{FM}				
	DOL	VOL	SVC	R^2		DOL	VOL_{FM}	SVC_{FM}	R^2
λ	0.09	-0.05	-0.04	1	λ	0.09	-0.08	-0.11	1
NW	0.72	-3.19	-2.95		NW	0.72	-2.93	-4.01	
SH	0.79	-2.21	-1.73		SH	0.79	-3.37	-4.00	
Panel C: VOL_{FM} (orth.) and SVC_{FM}					**Panel D: VOL_{FM} and SVC_{FM} (orth.)**				
	DOL	VOL_{FM}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$VOL_{FM}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.09	-0.09	-0.03	1	λ	0.09	-0.05	-0.03	1
NW	0.72	-2.93	-3.09		NW	0.72	-1.91	-4.01	
SH	0.79	-3.37	-3.15		SH	0.79	-2.24	-4.00	

G10 countries

Panel A: SVC and VOL_{FM}					Panel B: SVC_{FM} and VOL_{FM}				
	DOL	VOL	SVC	R^2		DOL	VOL_{FM}	SVC_{FM}	R^2
λ	0.03	-0.04	-0.05	0.99	λ	0.03	-0.07	-0.02	0.99
NW	0.24	-2.4	-1.97		NW	0.24	-2.21	-3.07	
SH	0.27	-1.35	-0.90		SH	0.27	-2.42	-2.96	
Panel C: SVC_{FM} (orth.) and VOL_{FM}					**Panel D: SVC_{FM} and VOL_{FM} (orth.)**				
	DOL	VOL_{FM}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$VOL_{FM}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.03	-0.07	-0.01	0.99	λ	0.03	-0.02	-0.01	0.99
NW	0.24	-2.21	-1.70		NW	0.24	-0.50	-3.07	
SH	0.27	-2.42	-1.81		SH	0.27	-0.60	-2.96	

The table reports the factor prices for models where I jointly include the DOL factor, the non-traded and traded volatility risk factor of Menkhoff et al. (2012), denoted as VOL and VOL_{FM} , and the corresponding counterparts of volatility connectedness innovations (SVC and SVC_{FM}) based on a rolling window size of $w = 100$ days. Test assets are the excess returns to the five and four carry trade based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows results for non-traded factors of volatility innovations (VOL) and volatility connectedness innovations (SVC), Panel B for the factor-mimicking portfolio of volatility innovations VOL_{FM} and volatility connectedness innovations (SVC_{FM}), Panel C for the factor-mimicking portfolio orthogonalized with respect to VOL_{FM} , denoted as $SVC_{FM}^{\text{orth.}}$, and Panel D for the factor-mimicking portfolio for volatility connectedness innovations and VOL_{FM} orthogonalized with respect to volatility, denoted as $VOL_{FM}^{\text{orth.}}$. The sample period is March 1988 to June 2015.

Table 10: Cross-setional Asset Pricing Results: Volatility Connectedness Risk

Panel A: Factor prices - all countries

	Non-traded SVC						Traded SVC				
	DOL	SVC	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2		DOL	SVC_{FM}	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2
λ	0.08	-0.03	7.16	1.77	0.87	λ	0.08	-0.03	7.16	7.74	0.87
NW	0.71	-3.64	0.07	0.62		NW	0.71	-3.65	0.07	0.05	
SH	0.79	-1.81				SH	0.79	-3.91			

Panel B: Factor betas - all countries

	Non-traded SVC					Traded SVC			
	α	DOL	SVC	R^2		α	DOL	SVC_{FM}	R^2
1	-0.29	0.86	6.30		1	-0.13	0.99	6.27	
	-4.13	15	1.26	0.68		-2.32	26.01	12.14	0.82
2	-0.1	0.8	7.24		2	0.08	0.95	7.20	
	-1.83	13.25	2.21	0.7		2.22	39.44	22.12	0.91
3	0.05	1.02	-2.24		3	0.00	0.97	-2.23	
	1.04	23.86	-0.6	0.84		-0.05	26.7	-3.62	0.85
4	0.13	1.1	-3.35		4	0.04	1.03	-3.33	
	2.25	23.81	-1.02	0.84		0.74	29.04	-5.36	0.87
5	0.21	1.23	-7.96		5	0.01	1.06	-7.92	
	2.25	16.17	-1.25	0.72		0.19	20.33	-7.95	0.83

The table reports factor prices and factor betas for a rolling window size of $w = 250$ days. The test assets are excess returns to five carry trade portfolios based on set of all countries. Panel A shows the factor risk prices λ obtained by FMB cross-sectional regression. I do not use a constant in the second-stage FMB regression. Robust t-statistics based on Shanken (1992) are reported in paranthesis. I also report the cross-sectional R^2. Panel B shows the factor betas for time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL) and the non-traded volatility connectedness innovations (SVC) or the factor-mimicking portfolio for of volatility connectedness innovations (SVC_{FM}). HAC standard errors (Newey-West adjusted with optimal lag selection according to Andrews (1991)) are reported. The sample period is from March 1988 to June 2015 and the returns are not transaction cost adjusted.

Table 11: Cross-setional Asset Pricing Results: Volatility Connectedness Risk

Panel A: Factor prices - G10 countries

	Non-traded SVC						Traded SVC				
	DOL	SVC	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2		DOL	SVC_{FM}	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2
λ	0.04	-0.02	4.67	1.61	0.79	λ	0.04	-0.02	4.67	3.78	0.79
NW	0.25	-2.6	0.10	0.45		NW	0.25	-2.45	0.10	0.15	
SH	0.28	-1.72				SH	0.28	-2.61			

Panel B: Factor betas - G10 countries

	Non-traded SVC					Traded SVC			
	α	DOL	SVC	R^2		α	DOL	SVC_{FM}	R^2
1	-0.2	0.9	13.41		1	0.02	1.12	12.63	
	-2.11	14.26	1.59	0.62		0.61	92.71	50.88	0.97
2	-0.13	0.93	0.35		2	-0.13	0.93	0.33	
	-2.09	18.32	0.09	0.74		-1.90	18.02	0.43	0.74
3	0.14	1.00	-3.79		3	0.08	0.94	-3.57	
	2.49	22.06	-0.72	0.79		1.49	24.54	-5.67	0.82
4	0.19	1.17	-9.97		4	0.03	1.01	-9.39	
	2.28	20	-1.58	0.78		0.63	44.79	-20.5	0.93

The table reports factor prices and factor betas for a rolling window size of $w = 250$ days. The test assets are excess returns to four carry trade portfolios based on the subset of the G10 countries. Panel A shows the factor risk prices λ obtained by FMB cross-sectional regression. I do not use a constant in the second-stage FMB regression. Robust t-statistics based on Shanken (1992) are reported in paranthesis. I also report the cross-sectional R^2. Panel B shows the factor betas for time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL) and the non-traded volatility connectedness innovations (SVC) or the factor-mimicking portfolio for of volatility connectedness innovations (SVC_{FM}). HAC standard errors (Newey-West adjusted with optimal lag selection according to Andrews (1991)) are reported. The sample period is from March 1988 to June 2015 and the returns are not transaction cost adjusted.

Table 12: Cross-setional Asset Pricing Results: Volatility Connectedness Risk and HML_{FX}

All countries

Panel A: SVC and HML_{FX}					Panel B: SVC_{FM} and HML_{FX}				
	DOL	HML_{FX}	SVC	R^2		DOL	HML_{FX}	SVC_{FM}	R^2
λ	0.08	0.49	-0.02	0.90	λ	0.08	0.49	-0.03	0.90
NW	0.71	3.05	-1.71		NW	0.71	3.05	-3.72	
SH	0.79	3.45	-1.15		SH	0.79	3.51	-3.77	

Panel C: SVC_{FM} (orth.) and HML_{FX}					Panel D: SVC_{FM} and HML_{FX} (orth.)				
	DOL	HML_{FX}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$HML_{FX}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.08	0.49	-0.01	0.90	λ	0.08	0.09	-0.03	0.90
NW	0.71	3.05	-1.64		NW	0.71	0.86	-3.72	
SH	0.79	3.51	-1.71		SH	0.79	1.01	-3.77	

G10 countries

Panel A: SVC and HML_{FX}					Panel B: SVC_{FM} and HML_{FX}				
	DOL	HML_{FX}	SVC	R^2		DOL	HML_{FX}	SVC_{FM}	R^2
λ	0.03	0.43	0.03	0.84	λ	0.03	0.43	-0.02	0.84
NW	0.24	2.59	0.63		NW	0.24	2.59	-2.44	
SH	0.27	2.63	0.27		SH	0.27	2.73	-2.59	

Panel C: HML_{FX} and SVC_{FM} (orth.)					Panel D: HML_{FX} (orth.) and SVC_{FM}				
	DOL	HML_{FX}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$HML_{FX}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.03	0.43	0.001	0.84	λ	0.03	0.03	-0.02	0.84
NW	0.24	2.59	0.65		NW	0.24	1.06	-2.44	
SH	0.27	2.73	0.69		SH	0.27	1.11	-2.59	

The table reports the factor prices for models where I jointly include the DOL factor, HML_{FX}, and different variants of volatility connectedness innovations (SVC and SVC_{FM}) based on a rolling window size of $w = 250$ days. Test assets are the excess returns to the five and four carry trade based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows results for volatility connectedness innovations (SVC), Panel B for the factor-mimicking portfolio of volatility connectedness innovations (SVC_{FM}), Panel C for the factor-mimicking portfolio orthogonalized with respect to HML_{FX} , denoted as $SVC_{FM}^{\text{orth.}}$, and Panel D for the factor-mimicking portfolio for volatility connectedness innovations and HML_{FX} orthogonalized with respect to volatility, denoted as $HML_{FX}^{\text{orth.}}$. The sample period is March 1988 to June 2015.

Table 13: Cross-setional Asset Pricing Results: Volatility Connectedness Risk and Volatility Risk

All countries

Panel A: SVC and VOL					Panel B: SVC_{FM} and VOL_{FM}				
	DOL	VOL	SVC	R^2		DOL	VOL_{FM}	SVC_{FM}	R^2
λ	0.08	-0.05	-0.02	0.92	λ	0.08	-0.07	-0.03	0.92
NW	0.71	-3.09	-2.25		NW	0.71	-2.55	-3.6	
SH	0.79	-2.28	-1.43		SH	0.79	-3.03	-3.67	

Panel C: VOL_{FM} and SVC_{FM} (orth.)					Panel D: VOL_{FM} (orth.) and SVC_{FM}				
	DOL	VOL_{FM}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$VOL_{FM}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.08	-0.08	-0.01	0.92	λ	0.08	-0.02	-0.03	0.92
NW	0.71	-2.55	-2.16		NW	0.71	-0.79	-3.6	
SH	0.79	-3.03	-2.24		SH	0.79	-0.95	-3.67	

G10 countries

Panel A: SVC and VOL					Panel B: SVC_{FM} and VOL_{FM}				
	DOL	VOL	SVC	R^2		DOL	VOL_{FM}	SVC_{FM}	R^2
λ	0.04	-0.02	0.07	0.93	λ	0.04	-0.07	-0.02	0.93
NW	0.26	-1.05	1.55		NW	0.26	-2.27	-2.26	
SH	0.29	-0.23	0.27		SH	0.29	-2.47	-2.45	

Panel C: VOL_{FM} and SVC_{FM} (orth.)					Panel D: VOL_{FM} (orth.) and SVC_{FM}				
	DOL	VOL_{FM}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$VOL_{FM}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.04	-0.07	-0.0003	0.93	λ	0.04	-0.002	-0.02	0.93
NW	0.26	-2.27	-0.16		NW	0.26	-0.41	-2.26	
SH	0.29	-2.47	-0.16		SH	0.29	-0.40	-2.45	

The table reports the factor prices for models where I jointly include the DOL factor, the non-traded and traded volatility risk factor of Menkhoff et al. (2012), denoted as VOL and VOL_{FM} , and the corresponding counterparts of volatility connectedness innovations (SVC and SVC_{FM}) based on a rolling window size of $w = 250$ days. Test assets are the excess returns to the five and four carry trade based on the set of all countries and the subset of the G10 countries, respectively. Panel A shows results for non-traded factors of volatility innovations (VOL) and volatility connectedness innovations (SVC), Panel B for the factor-mimicking portfolio of volatility innovations VOL_{FM} and volatility connectedness innovations (SVC_{FM}), Panel C for the factor-mimicking portfolio orthogonalized with respect to VOL_{FM} , denoted as $SVC_{FM}^{\text{orth.}}$, and Panel D for the factor-mimicking portfolio for volatility connectedness innovations and VOL_{FM} orthogonalized with respect to volatility, denoted as $VOL_{FM}^{\text{orth.}}$. The sample period is March 1988 to June 2015.

Panel A: Developed countries

Portfolio	1	2	3	4	5	DOL	HML
Mean	-2.00	-1.51	1.57	1.13	3.65	0.57	5.65
	-1.10	-0.74	0.81	0.57	1.56	0.32	2.67
Std	9.21	8.99	9.22	9.71	11.01	8.34	10.29
Skewness	0.21	-0.11	-0.27	-0.65	-0.46	-0.33	-0.64
Kurtosis	3.92	3.8	4.07	5.85	4.9	3.91	4.24
SR	-0.22	-0.17	0.17	0.12	0.33	0.07	0.55

The table reports the mean returns, standard deviation (both annualized), skewness and kurtosis of currency portfolios sorted on $f_{t-1} - s_{t-1}$ (forward discounts). Also the annualized Sharpe Ratios (SR) and AC(1), first-order autocorrelation coefficient are reported. Numbers in parentheses show the Newey and West (1987) HAC t-statistics. Returns are monthly and the sample period is March 1988 to June 2015.

Table 14: Descriptive Statistics: Developed countries

Table 15: Cross-setional Asset Pricing Results: Volatility Connectedness Risk

Panel A: Factor prices - developed countries

	Non-traded SVC					Traded SVC					
	DOL	SVC	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2		DOL	SVC_{FM}	$\chi^2_{\mathbf{NW}}$	$\chi^2_{\mathbf{SH}}$	R^2
λ	0.05	-0.02	9.04	5.09	0.78	λ	0.05	-0.03	9.04	8.43	0.78
NW	0.34	-2.73	0.03	0.17		NW	0.34	-2.73	0.03	0.04	
SH	0.38	-2.18				SH	0.38	-2.83			

Panel B: Factor betas - developed countries

	Non-traded SVC					Traded SVC			
	α	DOL	SVC	R^2		α	DOL	SVC_{FM}	R^2
1	-0.21	0.87	10.26		1	-0.03	0.98	6.70	
	-2.17	14.25	2.36	0.62		-0.52	35.74	16.87	0.84
2	-0.17	0.93	5.62		2	-0.07	0.99	3.67	
	-2.38	15.95	1.87	0.74		-1.16	27.6	7.15	0.81
3	0.08	1.03	0.43		3	0.09	1.04	0.28	
	1.52	31.82	0.17	0.87		1.61	34.34	0.63	0.87
4	0.04	1.04	-8.27		4	-0.1	0.95	-5.40	
	0.65	21.88	-2.74	0.81		-2.62	45.52	-24.46	0.94
5	0.25	1.13	-8.04		5	0.11	1.05	-5.25	
	2.79	18.79	-1.89	0.74		1.73	30.2	-12.2	0.84

The table reports factor prices and factor betas for a rolling window size $w = 150$ days. The test assets are excess returns to five carry trade portfolios based on the subset of developed countries. Panel A shows the factor risk prices λ obtained by FMB cross-sectional regression. I do not use a constant in the second-stage FMB regression. Robust t-statistics based on Shanken (1992) are reported in paranthesis. I also report the cross-sectional R^2. Panel B shows the factor betas for time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL) and the non-traded volatility connectedness innovations (SVC) or the factor-mimicking portfolio for of volatility connectedness innovations (SVC_{FM}). HAC standard errors (Newey-West adjusted with optimal lag selection according to Andrews (1991)) are reported. The sample period is from March 1988 to June 2015 and the returns are not transaction cost adjusted.

Table 16: Cross-setional Asset Pricing Results: volatility connectedness risk and HML_{FX}

Developed countries

Panel A: SCV and HML_{FX}

	DOL	HML_{FX}	SVC	R^2
λ	0.05	0.46	-0.01	0.83
NW	0.33	2.66	-0.68	
SH	0.37	2.83	-0.61	

Panel B: SVC_{FM} and HML_{FX}

	DOL	HML_{FX}	SVC_{FM}	R^2
λ	0.05	0.46	-0.02	0.83
NW	0.33	2.66	-2.59	
SH	0.37	2.83	-2.61	

Panel C: SVC_{FM} (orth.) and HML_{FX}

	DOL	HML_{FX}	$SVC_{FM}^{\textbf{orth.}}$	R^2
λ	0.05	0.46	-0.004	0.83
NW	0.33	2.66	-0.62	
SH	0.37	2.83	-0.58	

Panel D: SVC_{FM} and HML_{FX} (orth.)

	DOL	$HML_{FX}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.05	0.12	-0.03	0.83
NW	0.33	1.24	-2.59	
SH	0.37	1.22	-2.61	

The table reports the factor prices for models where I jointly include the DOL factor, HML_{FX}, and different variants of volatility connectedness innovations (SVC and SVC_{FM}) based on a rolling window size of $w = 150$ days. Test assets are the excess returns to the five carry trade based on the subset of the 15 developed countries. Panel A shows results for volatility connectedness innovations (SVC), Panel B for the factor-mimicking portfolio of volatility connectedness innovations (SVC_{FM}), Panel C for the factor-mimicking portfolio orthogonalized with respect to HML_{FX} , denoted as $SVC_{FM}^{\text{orth.}}$, and Panel D for the factor-mimicking portfolio for volatility connectedness innovations and HML_{FX} orthogonalized with respect to volatility, denoted as $HML_{FX}^{\text{orth.}}$. The sample period is March 1988 to June 2015.

Table 17: Cross-setional Asset Pricing Results: volatility connectedness risk and volatility risk

Developed countries

Panel A: SCV and VOL					Panel B: SVC_{FM} and VOL_{FM}				
	DOL	VOL	SVC	R^2		DOL	VOL_{FM}	SVC_{FM}	R^2
λ	0.05	-0.04	-0.01	0.80	λ	0.05	-0.05	-0.03	0.80
NW	0.34	-1.52	-0.81		NW	0.34	-2.33	-2.66	
SH	0.37	-1.4	-0.72		SH	0.37	-2.56	-2.71	

Panel C: SVC_{FM} (orth.) and VOL_{FM}					Panel D: SVC_{FM} and VOL_{FM} (orth.)				
	DOL	VOL_{FM}	$SVC_{FM}^{\textbf{orth.}}$	R^2		DOL	$VOL_{FM}^{\textbf{orth.}}$	SVC_{FM}	R^2
λ	0.05	-0.05	-0.01	0.80	λ	0.05	-0.01	-0.03	0.80
NW	0.34	-2.33	-0.94		NW	0.34	-0.45	-2.66	
SH	0.37	-2.56	-1.06		SH	0.37	-0.54	-2.71	

The table reports the factor prices for models where I jointly include the DOL factor, the non-traded and traded volatility risk factor of Menkhoff et al. (2012), denoted as VOL and VOL_{FM} , and the corresponding counterparts of volatility connectedness innovations (SVC and SVC_{FM}) base on a rolling window size of 150 days. Test assets are the excess returns to the five carry trade based on the subset of the 15 developed countries. Panel A shows results for non-traded factors of volatility innovations (VOL) and volatility connectedness innovations (SVC), Panel B for the factor-mimicking portfolio of volatility innovations VOL_{FM} and volatility connectedness innovations (SVC_{FM}), Panel C for the factor-mimicking portfolio orthogonalized with respect to VOL_{FM} , denoted as $SVC_{FM}^{\text{orth.}}$, and Panel D for the factor-mimicking portfolio for volatility connectedness innovations and VOL_{FM} orthogonalized with respect to volatility, denoted as $VOL_{FM}^{\text{orth.}}$. The sample period is March 1988 to June 2015.

Panel A: All countries

Portfolio	1	2	3	4	5	DOL	HML
Mean	2.16	0.6	0.38	1.43	-0.46	0.82	-2.62
	1.01	0.32	0.22	0.92	-0.28	0.54	-1.44
Std	9.64	8.27	7.62	6.44	6.55	6.47	9.52
Skewness	-0.90	-0.32	-0.75	-0.23	0.1	-0.63	0.96
Kurtosis	7.15	5.42	5.53	4.88	3.79	5.17	6.02
SR	0.22	0.07	0.05	0.22	-0.07	0.13	-0.28

Panel B: developed countries

Portfolio	1	2	3	4	5	DOL	HML
Mean	2.84	1.49	0.49	-0.05	-1.16	0.72	-4.00
	1.08	0.67	0.21	-0.02	-0.61	0.37	-1.79
Std	10.68	9.58	9.41	9.33	8.23	8.06	10.12
Skewness	-0.34	-0.55	-0.41	-0.11	0.35	-0.27	0.93
Kurtosis	6.06	5.29	3.91	4.23	3.48	4.17	7.29
SR	0.27	0.16	0.05	-0.01	-0.14	0.09	-0.39

Panel C: G10 countries

Portfolio	1	2	3	4	DOL	HML
Mean	3.29	0.63	-0.6	-0.36	0.74	-3.65
	1.21	0.3	-0.25	-0.2	0.36	-1.72
Std	11.12	9.69	9.18	8.04	8.15	10
Skewness	-0.57	-0.3	-0.41	0.4	-0.33	0.74
Kurtosis	6.07	5.18	3.83	3.43	4.60	4.90
SR	0.30	0.06	-0.06	-0.05	0.09	-0.37

Panel D: G10 countries v2

Portfolio	1	2	3	4	DOL	HML
Mean	2.56	1.19	0.05	-0.63	0.79	-3.19
	1.02	0.52	0.03	-0.33	0.4	-1.75
Std	10.42	9.8	9.04	7.88	8.09	8.51
Skewness	-0.58	-0.22	-0.15	0.17	-0.3	0.42
Kurtosis	7.39	3.2	4.95	3.23	4.48	5.02
SR	0.25	0.12	0.01	-0.08	0.1	-0.38

The table reports the mean returns, standard deviation (both annualized), skewness and kurtosis of currency portfolios sorted on past betas. Panel A, B and C report results based on the beta sorting scheme as in Lustig et al. (2011) using the traded factor SVC_{FM}, while Panel D repots the results based on the beta sorting scheme as in Dobrynskaya (2014) using the non-traded factor SVC. The system-wide volatility connectedness risk factors are obtained based on a rolling window size of $w = 150$ days Also the annualized Sharpe Ratios (SR) is reported. Numbers in parentheses show the Newey and West (1987) HAC t-statistics. Returns are monthly and the sample period is April 1993 to June 2015.

Table 18: Descriptive Statistics for beta sorted portfolios

References

Ahern, K. 2013. Network Centrality and the Cross Section of Stock Returns. Tech. rep., Universiy of Southern California.

Akram, Q. F., D. Rime, and L. Sarno. 2008. Arbitrage in the Foreign Exchange Market: Turning on the Microscope. *Journal of International Economics* 76:237–253.

Alizadeh, S., M. W. Brandt, and F. X. Diebold. 2002. Range-based estimation of stochastic volatility models. *Journal of Finance* 57:1047–1092.

Andrews, D. W. K. 1991. Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation. *Econometrica* 59:817–858.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61:259–299.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and Momentum Everywhere. *Journal of Finance* 68:929–985.

Bank of International Settlement. 2015. Foreign exchange turnover in April 2013: preliminary global results. Tech. rep., Triennial Central Bank Survey.

Billio, M., M. Caporin, R. Panzica, and L. Pelizzon. 2015. Network Connectivity and Systematic Risk. Tech. rep., University Ca Foscari Venezia.

Breeden, D. T., R. G. Michael, and R. Litzenberger. 1989. Empirical tests of the consumption-oriented CAPM. *Journal of Finance* 44:231–262.

Brunnermeier, M., and L. H. Pedersen. 2009. Market liquidity and funding liquidity. *Review of Financial Studies* 22:2201–2238.

Burnside, C. 2011. The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk: Comment. *American Economic Review* 101:34563476.

Burnside, C., M. Eichenbaum, I. Kleshchelski, and S. Rebelo. 2006. The returns to currency speculation. Tech. rep., NBER Working Paper No. 12489.

Burnside, C., M. Eichenbaum, and S. Rebelo. 2009. Understanding the forward premium puzzle: A microstructure approach. *American Economic Journal: Macroeconomics* 1:127–154.

Cochrane, J. H. 2005. *Asset Pricing*. NJ: Princeton University Press.

Colacito, R., M. M. Croce, F. Gavazzoni, and R. Ready. 2015. Currency Risk Factors in a Recursive Multi-Country Economy. Tech. rep., INSEAD Working Paper Series.

Della Corte, P., S. J. Riddiough, and L. Sarno. 2016. Currency Premia and Global Imbalances. *Review of Financial Studies* forthcoming.

Demirer, M., F. X. Diebold, L. Liu, and K. Yilmaz. 2015. Estimating blobal bank network connectedness. Tech. rep., University of Pennsylvania.

Diebold, F. X., and K. Yilmaz. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal* 119:158–171.

Diebold, F. X., and K. Yilmaz. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28:57–66.

Diebold, F. X., and K. Yilmaz. 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics* 182:119–134.

Diebold, F. X., and K. Yilmaz. 2015. *Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring*. Oxford University Press.

Dobrynskaya, V. 2014. Downside Market Risk of Carry Trades. *Review of Finance* 24:1–29.

Fama, E. F. 1984. Forward and spot exchange rates. *Journal of Monetary Economics* 14:319–338.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return and equilibrium: Empirical tests,. *Journal of Political Economy* 81:607–636.

Farhi, E., S. P. Fraiberger, X. Gabaix, R. Ranciere, and A. Verdelhan. 2015. Crash risk and currency markets. Tech. rep., NYU Working Paper No. FIN-09-007.

Fengler, M. R., and K. I. M. Gisler. 2015. A variance spillover analysis without covariances: What do we miss? *Journal of International Money and Finance* 51:174–195.

Hansen, L. P., and R. J. Hodrick. 1980. Forward exchange rates as optimal predic- tors of future spot rates: An econometric analysis. *Journal of Political Economy* 88:829–853.

Hansen, L. P., and R. J. Hodrick. 1983. Risk-averse speculation in the forward foreign exchange market: An econometric analysis of linear models. In *Exchange Rates and International Macroeconomics*. University of Chicago Press, Chicago.

Herskovic, B. 2015. Networks in Production: Asset Pricing Implications. Tech. rep., UCLA Anderson School of Management.

Jurek, J. 2014. Crash-neutral currency carry trades. *Journal of Financial Economics* 113:325–347.

Kan, R., C. Robotti, and J. Shanken. 2013. Pricing Model Performance and the Two-Pass Cross-Sectional Regression Methodology. *Journal of Finance* 68:2617–2649.

Koijen, R. S. J., T. J. Moskowitz, L. H. Pedersen, and E. B. Vrugt. 2015. Carry. Tech. rep., Fama-Miller Working Paper.

Koop, G., M. H. Pesaran, and S. M. Potter. 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74:119–147.

Korajczyka, R. A., and R. Sadka. 2008. Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics* 87:45–72.

Lewellen, J. W., S. Nagel, and J. Shanken. 2010. A skeptical appraisal of asset pricing tests. *Journal of Financial Economics* 96:175–194.

Lustig, H., N. L. Roussanov, and A. Verdelhan. 2011. Common risk factors in currency markets. *Review of Financial Studies* 24:3731–3777.

Lustig, H., and A. Verdelhan. 2007. The cross-section of foreign currency risk premia and consumption growth risk. *American Economic Review* 97:89–117.

Mancini, L., A. Ranaldo, and J. Wrampelmeyer. 2013. Liquidity in the foreign exchange market: measurement, commonality, and risk premiums. *Journal of Finance* 68:1805–1841.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf. 2012. Carry trades and global foreign exchange volatility. *Journal of Finance* 67:681–718.

Newey, W. K., and K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–708.

Parkinson, M. 1980. The extreme value method for estimating the variance of the rate of return. *Journal of Business* 53:61–65.

Pesaran, M. H., and Y. Shin. 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58:17–29.

Ready, R. C., N. L. Roussanov, and C. Ward. 2015. Commodity Trade and the Carry Trade: A Tale of Two Countries. Tech. rep., NBER Working Paper No. w19371.

Richmond, R. J. 2016. Trade Network Centrality and Currency Risk Premia. Tech. rep., University of California, Los Angeles (UCLA), Anderson School of Management.

Shanken, J. 1992. On the estimation of beta-pricing models. *Review of Financial Studies* 5:1–33.

Tibshirani, R. 1996. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society Series B* 58:267–288.