Uncovered Interest Rate Parity: A Relation to Global Trade Risk

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Abstract

The paper gives evidence of a novel pricing factor for the cross-section of carry trade returns based on trade relations between countries. In particular, we apply network theory on countries' bilateral trade to construct a measure for countries' exposure to a global trade risk. A high level of exposure to global trade risk implies that the economic activity in one country is highly dependent on the economic activity of its trade partners and on aggregate trade flow, which reflects in carry trade returns. We find empirically that low interest rate currencies are seen by investors as a hedge against global trade risk while high interest rate currencies deliver low returns when global trade risk is high. These results provide evidence on the underlying macroeconomic sources of systematic risk in currency markets.

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1 Introduction

According to the uncovered interest rate parity (UIP), if investors are risk neutral and have rational expectations, a unit of a predefined base currency can be invested domestically and converted at maturity or can be converted immediately and then invested abroad. By a statistical no-arbitrage argument, both strategies should yield on average the same amount. However, empirical observations show that on average currencies with high interest rates appreciate, even if the UIP tells us that, to compensate the investor, these currencies should depreciate on average. Deviations from UIP lead to puzzling profitable investments and to the so-called "forward premium puzzle" (Fama (1984)). The associated trading strategy is the carry trade and becomes profitable when UIP fails. It simply consists in borrowing in low interest rates currencies (funding currencies) and investing in high interest rates currencies (investment currencies).

Using a standard linear asset pricing framework, we propose a novel pricing factor that embeds countries' trade relations. Until now, the relation between macroeconomic fundamentals and foreign exchange (FX) rates has been perceived as highly unstable and empirically obscure, as suggested in Bacchetta and van Wincoop (2009) and in the survey by Fratzscher et al. (2012). Our study brings new insights on the relation between the risk-return profile of carry trade strategies and economic fundamentals risk.

In particular, exposure to global trade risk is seen as a macroeconomic source of vulnerability for countries' economic activity and productivity, impacting the exchange rates. Moreover, global trade risk can be caused by local, country-level, unexpected macroeconomic events that are spread through the demand and supply of goods and services to other countries. This assumption is based on the highly asymmetric international trade structure that limits the extent to which local shocks can cancel each-other through diversification.[1] As different episodes of economic downturn show (e.g. oil crises, financial crises), the slow-down in economic activity is propagated across countries through trade and financial channels. Given limitations on data availability for bilateral financial exposures between countries, we focus on the trade channel by using monthly bilateral trade data for a sample of 37 countries. To our knowledge, this is the first study to offer a macroeconomic explanation of the cross-sectional profits made on currency markets.

[1] Acemoglu et al. (2012) show that inter-sectoral trade networks are highly asymmetric, with non-random and non-uniform connections which allow for randomly occurring shocks to aggregate into economy-wide events instead of canceling out through diversification.

The paper contributes to the existing literature in two ways. Firstly, it introduces a novel measure for assessing countries' exposure to global trade risk based on the structure of international bilateral trade. This approach allows us to build a pricing factor that accounts for cross-border spillovers and contagion related to the real side of countries' economies. Errico and Massara (2011) offer an analysis of trade interconnectedness as a channel of cross-border transmission of shocks and use it to rank systemically important jurisdictions. They show that the trade-based ranking is similar to the one based on financial interconnectedness.[2] Compared to the previous study, which uses undirected-binary connections, we construct weighted and directed trade networks, where the weights are computed as the share of trade in the exporter's gross domestic product (GDP) (further called "normalised trade"). We evaluate the exposure of each country to global trade risk by its centrality in the network, which is measured by the principal eigenvector of the trade-based adjacency matrix.

A second contribution is the proposal of global trade risk as a novel risk factor to account for cross-sectional variation in excess returns made on currency markets. This study is in line with the existing literature on asset pricing, that sees excess returns to currency strategies as compensation for risk. For example, Menkhoff et al. (2012) show that innovations in market volatility can be seen as a state variable against which risk-averse investors wish to hedge. This means that assets with high negative return sensitivity to unexpected changes in volatility should demand higher returns in equilibrium. In this paper, we investigate a new source of risk that is based on macroeconomic fundamentals and find empirically that low interest rate currencies are seen as a hedge against global trade risk while high interest rate currencies deliver low returns when the global trade risk is high.

In the empirical analysis, we estimate a cross-sectional asset pricing model to assess the risk-return profile of excess carry trade returns. The results come from a standard stochastic discount factor approach (SDF) (Cochrane (2005)) where the global trade risk factor is built in the spirit of Fama-French risk factors. Taking the position of a U.S. investor, we first sort a set of currencies into 1-month carry trade returns according to their relative centrality. Then, we build portfolios of excess returns and compute a high minus low centrality portfolio, labeled

[2]They perform the study at sector and country level, where jurisdictions (countries) are seen as nodes in an undirected and binary network. They assume that a connection exists if total trade turnover between two jurisdictions is higher than 0.1% of each jurisdiction's GDP.

HML_{TC}. Risk factor loadings of the linear SDF are estimated using the generalized method of moments (GMM) on portfolios' Euler equations. Further, we account in the asset pricing model for four well-known risk factors, such that we avoid model misspecification: (1) the dollar risk factor which is the average excess return on all foreign currencies for a U.S. investor (referred to as DOL), (2) the carry trade potrfolio risk factor (referred to as H/L), (3) innovations in global FX volatility obtained with an autoregressive model (referred to as VOL) and (4) global FX bid-ask spread (referred to as LIQ).

Interestingly, we find that high interest rate currencies are negatively related to global trade risk while low interest rate currencies are positively related. This means that high interest rate currencies are negatively exposed to global trade risk and investors ask for a risk premium as compensation for taking on this source of risk. Additionally, we find results that confirm evidence brought by Lustig and Verdelhan (2011) regarding the relation between carry trade excess returns and the dollar risk factor. Our results also support Menkhoff et al. (2012) with respect to the role of FX volatility risk in carry trade returns. Sensitivity analysis indicates that the global trade risk factor is not related to other market-based factors.

The remainder of the paper is structured as follows. Section 2 offers a discussion of the related literature. Section 3 motivates the use of trade-based network centrality for measuring countries' exposure to global trade risk. In Section 4, we present the data and methods used to construct carry-trade returns and the global trade risk factor. Section 5 describes the methodology used for assessing the contribution of the trade-based risk factor in explaining carry-trade returns. The main results are discussed in Section 6. Finally, Section 7 concludes.

2 Related Literature

This paper is related mainly to two strands of literature. Firstly, it builds upon a growing literature investigating exchange rate puzzles using asset pricing models in the context of carry trade strategies. Starting with the work of Hansen and Hodrick (1980), Fama (1984) and Hodrick and Srivastava (1985), several papers show time series evidence of UIP failure. In general, the literature agrees to take on two different approaches. Papers that take the risk-based approach provide evidence that market, volatility and liquidity risks are priced in carry trade returns (see for instance Verdelhan (2010), Lustig et al. (2011), and Mancini et al. (2013)). Likewise, Brunnermeier et al. (2008) argue that UIP violations are a result of currency crashes risk resulting from liquidity risk. The second approach includes limited market participation in Bacchetta and van Wincoop (2010), limits to arbitrage in Mancini Griffoli and Ranaldo (2012), trade difficulties due to high transactions costs in Burnside et al. (2006), or deviations from rational expectations as described in Ilut (2012), Burnside et al. (2010) and Bacchetta et al. (2009). Lately, Lustig et al. (2011) and Menkhoff et al. (2012) show that UIP fails as well in cross-section. By sorting currencies on interest rates and building carry trade portfolios, Lustig et al. (2011) identify two risk factors; the average excess returns on carry trades for a U.S. investor, referred as the "dollar risk factor" and the return on a portfolio that goes long in high interest rate currencies and short in low interest rate currency "the carry trade risk factor". Menkhoff et al. (2012) extends the work of Lustig et al. (2011) and investigate empirical innovations in global FX volatility as another risk factor. They document that global FX volatility is a powerful pricing factor while Mancini et al. (2013) demonstrates the crucial role of liquidity risk.

Moreover, the paper is related to the literature on the role of macroeconomic fundamentals in explaining UIP failure in the scope of Farhi and Gabaix (2008), who propose a disaster-based model[3] for exchange rates valued as present value of future export productivity. Every country can be hit by a rare but extreme world disaster that affects its productivity and thus its exchange rates. Farhi and Gabaix (2008) demonstrate that rare disaster risk and country's exposure to it can explain UIP failure. Our approach considers that the relative position of a country in the world trade network embeds a country risk exposure to global trade risk that explains carry trade excess returns.

Secondly, the current study is related to a wide body of research based on complex real world networks that examines the connections between different entities, ranging from financial institutions and industries to countries, in order to account for risk flows and possible vulnerability contagion. This type of research became relevant during the last decades, given the increased globalization, international trade flows and an ever more complex and interconnected financial system. Gai et al. (2011) and Acemoglu et al. (2013) show that, because of increased concentration and complexity, modern economic systems are prone to both local and systemic shocks that

[3]Burnside et al. (2008) look at non peso and peso states and find relation between payoffs of carry trade strategies and non-peso states.

can trigger global crises. Allen and Gale (2000), Amini et al. (2012), Hale et al. (2013), Upper (2011) provide relevant theoretical and empirical research on economic and financial networks.

Finally, this paper is related to research that sheds light on the importance of economic fundamentals, in particular spillovers based on customer/supplier relations, as determinants of returns on financial markets. Buraschi and Porchia (2012) study the effects of the network structure implied by linkages among firms' earnings and show that firms that are more central in the network have lower price-divided ratios and higher expected returns. Moreover, Ahern (2013) shows that industries' exposure to systematic risk, which determines expected returns, can be caused by exogenous economic fundamentals. Ahern (2013) argues that the position of an industry in the network of inter-sectoral trade influences its exposure to system-wide volatility: sectors that are more central have greater exposure to systematic risk which implies higher average stock returns. Again, in this paper, we use as well countries' centralities in the trade-based network to evaluate their exposure to global trade risk.

3 Network Centrality

The understanding of complex real world networks has recently contributed to economic and finance related research. As is the case with many real world networks, ranging from biological systems to the world-wide-web, economic networks are shown to display commonly found structures that are directly related to the fragility, resilience and efficiency of the underlying system. One of the common characteristics of such networks is the power-law (scale free) degree distribution and the small world phenomenon, which allow for the existence of hub-nodes and small average shortest path between any two nodes.

The main hypothesis of this paper is that currencies of countries most exposed to global trade risk earn higher excess returns. We define global trade risk as the aggregation of country-level shocks; this is based on the observation that downturns in the economic activity of one country can be propagated to other countries through trade and financial channels. In this paper, we focus on the trade channel, with global trade risk being caused by the aggregation of local unexpected macroeconomic events that are spread through the demand and supply of goods and services to other countries. Theoretical foundations for the limits of diversification in the context of highly asymmetric structures, as is the case for trade networks, is offered by Acemoglu et al. (2012), that show that random local shocks may lead to aggregate cascades in the presence of a sufficiently asymmetric trade network, and Gabaix (2011) who provides a microfoundation for aggregate shocks based on the existence of fat-tailed distribution of firm sizes.

The measure we propose for assessing countries' exposure to global trade risk complements the existing trade-to-GDP (or openness) ratio for countries, which is extensively used in international economics for measuring the importance of international transactions relative to domestic transactions. The openness measure is computed for each country individually, by aggregating total exports and imports of goods and services and reporting to the country's GDP. The interpretation of the openness index is the higher the index the larger the influence of trade on domestic activities. Figure 1 displays the openness measure (or the trade intensity ratio) for the U.S., China, Brazil, and the Eurozone from 1960 to 2013, evidencing a source of cross-sectional differences and diverging trends between regions as the Eurozone and China, where many countries show a high and increasing share of international trade reported to their GDP, and the U.S. and Brazil, which have rather low ratios.

However, the openness measure does not consider the details of bilateral relations between countries. In order to capture possible cross-border transmissions of economic shocks, we propose a measure of trade risk exposure that takes into account for each country also the relative openness and economic activity of their trade partners. This new measure is based on methodology coming from network analysis, where each country is seen as a node and the bilateral trade relations are seen as links. Moreover, in this study we always normalise bilateral trade by exporters' GDP, which allows us to account for the economic dynamics of the respective trading partners when assessing countries' risk exposure. By using methods coming from network analysis, we are able to better account for the international trade structure between countries and the relative importance of trading partners when assessing country-level trade risk exposures

We compute countries' trade risk exposure for each month during January 2010 to October 2014 by extracting centrality measures based on monthly bilateral trade matrices. The bilateral trade matrix can be thought of as an adjacency table, where each instance i, j is represented by the trade flow from country j (exporter) to country i (importer) divided by the GDP of country j. The way we define exposure to global trade risk is central to this paper. In particular, we use a centrality measure that is directly related to countries' exposure to random shocks that propagate through the network. Following Borgatti (2005), we select the centrality measure based on the manner in which traffic flows through a network. Given that economic shocks do not follow paths that imply a known destination, do not flow along the shortest distance, and may lead to feedback effects, where a node can be "visited" multiple times, we decide to use eigenvector centrality.

Eigenvector centrality measures the broader influence of a node in a network under the assumption that links to well connected nodes weight more than equal links to less connected nodes. The measure assigns relative scores to all the nodes in the network, depending on the importance of the neighbors to which the nodes are linked. Eigenvector centrality scores are based on the adjacency matrix and on the fact that only its principal eigenvector gives the desired centrality measure, as the scores have to be positive. Thus, the centrality score of country v in the network is given by the v-th component of the eigenvector associated with the first eigenvalue. The eigenvectors x of the adjacency matrix A are obtained as $A \cdot x = \lambda \cdot x$, where λ represents the eigenvalues of the matrix A.

Ahern (2013) explains the intuition behind eigenvector centrality from two perspectives. First, they discuss the similarity of eigenvector centrality to the Principal Component Analysis (PCA), in the sense that both computations are based on eigenvalue decomposition: the PCA uses the covariance matrix of a set of variables in order to reduce the dimensionality of the covariance to common factors while the eigenvector centrality uses the trade-based adjacency matrix to calculate each countries' contribution to the connectivity in the network. Second, eigenvector centrality is related to Markov transition matrices, whose principal eigenvector represents a stable stationary state. However, the Markov matrix interpretation is conditioned on not omitting nodes form the network and having no absorbing nodes. The normalised trade matrix could thus be considered as a Markov matrix and eigenvector centrality can be seen as the long-run proportion of time that a transitory shock is in a specific country.

4 Data and Methods

This section first describes the data for FX rates, interest rates, bilateral trade, and GDP and presents the carry trade strategy. Further, it presents in depth our proxy for international trade risk and provides an analysis of cumulative excess returns of carry trades.

4.1 Data

For the empirical analysis, we use two different types of datasets, one based on financial data and another based on trade data. Both samples cover the Eurozone[4] and the following 36 countries: Argentina, Australia, Brazil, Bulgaria, Canada, China, Croatia, Czech Republic, Denmark, Egypt, Hong-Kong, Hungary, Iceland, India, Indonesia, Israel, Japan, South Korea, Malaysia, Mexico, New Zealand, Norway, Peru, Philippines, Poland, Romania, Russia, Singapore, South Africa, Sweden, Switzerland, Thailand, Turkey, Ukraine, the United Kingdom, and the United States. For both datasets, the observation period starts in January 2010 and ends in October 2014.

We collect daily data for constructing excess returns on the currency markets and the market-based risk factors. FX rates (closing price) in direct quotations and 1-month interbank interest rates are obtained from Reuters Datastream.[5] Bid and ask FX quotes are taken from Bloomberg. As the analysis is performed at a monthly frequency, we sum up the daily excess returns and average the proxies for volatility and liquidity risks to obtain values for each month in the sample period.

Additionally, we collect monthly data for bilateral trade among the 37 countries from the UN Comtrade Database as well as annual data for country's GDP from the IMF World Economic Outlook Databases, in USD. For each month, we scale the trade data by the estimated monthly GDP of the exporter country and build export-import matrices that are further used as adjacency matrices in the network analysis.

[4]The Eurozone comprises Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain. It corresponds to the countries that were already in the Eurozone in January 2010.

[5]Owing to data availability issues, for Argentina, we use 3-month interbank rates while for Brazil, Canada, Mexico, New Zealand we employ available money market instruments (e.g. 1 month deposit rates).

4.2 Summary Statistics for Trade Data

Table I reports descriptive statistics for countries' bilateral trade, normalized with exporters' GDP, together with different centrality measures resulting from the trade-based network. The exports-to-GDP ratios have an average of 0.85% and a maximum of 143%. Their distribution shows high variance and large skewness and kurtosis, as can be also seen from the median, which is much smaller than the mean, and the 90% quantile, which is only 1.7%. This means that there are many countries that have low ratios of exports-to-GDP and only a few that have very high ratios. Most of the time, countries in south-eastern Asia (e.g. Hong Kong, Singapore, Philippines) have normalized trade that well exceeds 100%. These countries are seen as trade hubs, where trade is not necessarily based on domestic production but rather on re-exports and offshore companies.[6] Further, the descriptive statistics of centrality measures confirm the highly asymmetric trade structure. The degree centrality measures countries total normalized trade, the in-degree is related to normalized imports, the out-degree is related to normalized exports, while the eigen-centrality represents the relative importance of countries in the bilateral network. All measures have medians much smaller than their respective averages, low 90% quantiles, high kurtosis and positive skewness.

Figure 2 shows the density of the trade-based network over the period January 2010 to October 2014. The density is computed as the sum of the weights of the edges in the network, divided by the number of possible edges. In our case, the weights are given by the trade-to-GDP ratios and the network density is a measure of aggregated trade flowing among the countries in the sample. The figure shows a rather volatile density, with a marked negative trend starting in the last quarter of 2012, when the European sovereign-debt crisis was at its peak.

As explained in Section 3, we use the principal eigenvector of the bilateral trade matrix for computing countries' centrality. Figure 3 shows the histogram or the empirical distribution of log(centrality) for the countries in our sample during the period 2010-2014. The figure shows a positive skew and fat tails, confirming that the trade-based network is highly asymmetric. As Acemoglu et al. (2012) show in their paper, this means that the asymmetric structure of the trade network allows local shocks to cascade rather than cancel out. The argument behind

[6] For example, the Hong Kong Trade Development Council notes that Hong Kong plays an important role in the expanding external trade of mainland China, handling 13% of China's total trade in 2013, as well as handling an increasing volume of offshore trade and re-exports.

this observation is based on the presence of highly important countries that function either as trade-hubs, as suppliers to chains of productions in other countries, or as main markets towards which other countries export. The interconnections between countries function as a potential propagation mechanism of idiosyncratic shocks, such that the effects of local shocks do not remain confined to where they originate.

4.3 Carry Trade and Portfolios

Using the FX rates and 1-month interbank interest rates, we compute 1-month carry trades for all 36 currencies in the sample, where returns are log-returns and expressed with respect to the USD, which is chosen as the domestic currency. We focus on the excess return over UIP, from borrowing money in the domestic currency and investing in the foreign currency. The log excess return rx is given by:

$$rx_{t+1} = \Delta s_{t+1} + i_t^* - i_t, \tag{1}$$

where i^* and i are respectively the foreign and the domestic interest rates, and Δs is the change in the exchange rate over the maturity of the trade. We denote s the logarithm of the spot exchange rate quoted as the domestic currency per unit of the foreign currency.[7]

The upper panel of Figure 4 shows average cumulative returns for a U.S. investor that conducts 1-month carry trade strategies with the other 36 countries in the sample. Due to data availability of monthly exports and imports, our sample period starts at the beginning of 2010, which is often related to the start of the European sovereign-debt crisis and the end of the 2007-2009 financial crisis. We observe that this highly turbulent period negatively affects returns of the carry trade strategies. In order words, carry trade excess returns are not at all immune to financial and macroeconomic downturns conditions. The lower panel reports cumulative excess returns of the strategy against the Japanese yen, the Australian dollar, the Euro and the Singapore dollar. Japan is characterised by very low level of interest rates. This explains why cumulative returns remain negative, as for the strategy to be profitable it should be performed in the opposite direction. Figure 4 underlines as well that the returns of the strategy depend on the chosen foreign currency. Australian dollar appears to be more profitable than Singapore

[7] We will later incorporate transaction costs by using bid-ask quotes.

dollar for a U.S. investor over the period. Strategies involving the Euro do not bring profits for a U.S. investor.

Further, we build six equally weighted portfolios of carry trade returns needed for the subsequent cross-section analysis. At the end of each month, excess returns of 1-month carry trades are assigned to portfolios depending on countries' interest rate difference with respect to the domestic country, in our case the U.S interest rate. The portfolios are re-balanced at the end of each month and each portfolio comprises on average six currencies. Portfolio P1 contains the six excess returns with lowest differential in interest rates and portfolio P6 the six excess returns with highest interest rates differential. Table II presents descriptive statistics by portfolio of excess returns in Panel A, and of interest rates in Panel B. As expected, average returns monotonically increase from portfolios P1 to P6. Portfolio P6 has the largest average return and contains currencies that have the highest interest rates. Information ratios (computed similarly to Sharpe ratios) are also increasing with portfolios' interest rates. Skewness is mostly negative and kurtosis points to fat tails in the excess returns' distributions. Average interest rates increase monotonically across portfolios as well as their standard deviations. A look at panels A and B signals violations of UIP present in the data. Currencies with positive interest rate differentials demonstrate also the largest average excess returns, whereas currencies with lowest interest rate differentials exhibit lowest excess returns. Data indicate positive cross-sectional correlation between interest rate differential and average excess returns.

Table III shows the transition probabilities of currencies between portfolios sorted on countries' interest rates. The probabilities represent the likelihood of currencies transitioning from one portfolio to another in one month. The values on the main diagonal, which correspond to probabilities of currencies staying in the same portfolios from one month to the other, are all higher than 80% which indicates high persistence in portfolios' composition. Moreover, when currencies do change portfolios they mostly end up in neighboring portfolios, with less than 1% probability of jumping further away over the course of one month.

4.4 A Measure for Global Trade Risk

We build the proxy for global trade risk in the spirit of the Fama-French factors (Fama and French (1992)). Their method allows us capturing global trade risk based on traded portfolios, which means that the price of the risk factor can be analysed in a natural way.

We start by sorting currencies' monthly excess returns into six quantiles based on the respective countries' centrality relative to the domestic country centrality. The six quantiles amount to equally weighted currency portfolios, referred as portfolios E1 to E6. Given that we take the position of a U.S. investor and exchange rates are expressed with respect to the U.S. dollar, we also express countries' centrality relative to the U.S. We thus subtract the centrality of the U.S. from the centrality of each country before sorting the currencies into portfolios. Next, we use the differences between the excess returns of portfolios E6 and E1 to construct the global trade risk factor. Portfolio E1 represents the average carry trade excess returns of countries that are most similar to the U.S. in terms of trade centrality, while portfolio E6 is the average carry trade excess returns of the countries that are the least similar to the U.S. However, given that the U.S. has one of the lowest trade centrality in our sample, we can also see portfolio E6 as containing countries that are much more central compared to countries in portfolio E1. Therefore, the global trade risk factor is short in portfolio E1 and long in portfolio E6, meaning that it loads on currencies that are central in the trade-based network. The global trade risk proxy is named HML_{TC}.

Table IV reports descriptive statistics for the six portfolios' monthly excess returns, sorted on countries' relative centrality, and for the HML_{TC} factor over the period 2010-2014. The average currency excess return of the lowest quantile of relative centrality is 0.31%, compared to 0.82% for the highest quantile. As the t-stats report in brackets, the difference between portfolios E6 and E1 is statistically significant at level 10%. Moreover, the augmented Dickey-Fuller test indicates that this factor is stationary.

Table V shows the transition probabilities of currencies between portfolios sorted on countries' centrality, from one month to the other. Portfolios E1 and E6, which are of interest for constructing the global trade risk factors, display very high persistence with more than 80% probability for currencies to stay in the same portfolio from one month to the other. Transition probabilities for intermediary portfolios show less persistence compared to the extremes, but the values on the main diagonal are still higher than 55%. Moreover, currencies that transit from one portfolio to another do so mostly between adjacent portfolios, with probabilities of currencies jumping further than adjacent portfolios being less than 2.6%. Table VI reports the currency composition of portfolios sorted by countries centrality relative to the U.S. (in the left panel) and portfolios sorted by interest rates differentials with respect the U.S. (in the right panel) at three points in time: January 2010, August 2011 and April 2013.

5 Cross-Sectional Pricing

In this section, we first present the risk factors commonly used in the literature and the value added of our new risk factor. Then, we discuss the estimation methods used in the paper.

5.1 Common Risk Factors

Several risk factors have been introduced in the literature to understand excess returns of carry trade strategies. Lustig et al. (2011) construct the dollar risk factor, denoted DOL, as the average of FX excess returns over all currencies in the data sample. Similar to a FX market risk factor, it corresponds to the risk taken by a domestic investor to borrow its home currency and invest in foreign currencies. They find that the dollar risk factor is important when accounting for the level of average excess returns. We include this risk factor in our analysis. The DOL factor is exhibited in the upper panel of Figure 4. We also take into account the carry trade portfolio risk factor, labeled as H/L, that is proposed in Lustig et al. (2011) and is defined as the difference between the interest-rate sorted portfolios P6 and P1.

Further, Menkhoff et al. (2012) find that innovations in global FX volatility are a strong systematic risk factor for the cross section of portfolio carry trade returns. Low interest rate currencies provide hedge against unexpected volatility changes. They also show that FX global volatility prevails over liquidity risk. To capture global FX volatility, we borrow from Menkhoff et al. (2012) and we first compute the average of absolute daily log FX returns over a month t and over all currencies K. The global FX volatility proxy in month t is computed as

$$\sigma_t^{FX} = \frac{1}{T_t} \sum_{\tau \in T_t} \left(\sum_{k \in K_\tau} \frac{|r_\tau^k|}{K_\tau} \right), \tag{2}$$

where τ corresponds to one day, T_t is the total number of days in month t, r_τ^k is the daily log return of currency k on day τ, and K_τ is the number of currencies quoted in day τ. Furthermore, we estimate an autoregressive (AR) process of order 1 on the FX volatility series σ_t^{FX} and use the innovations of the AR(1) process as a proxy for the global FX volatility risk factor. Figure 5 presents average global volatility of FX rates as well as innovations in global FX volatility, which form the VOL risk factor.

Moreover, following studies by Brunnermeier et al. (2008) and Mancini et al. (2013), we also account for the role of liquidity risk in UIP violations using bid-ask spread of FX rates (BAS). The proxy for the global FX liquidity risk is computed as

$$\psi_t^{FX} = \frac{1}{T_t} \sum_{\tau \in T_\tau} \left(\sum_{k \in K_\tau} \frac{\psi_\tau^k}{K_\tau} \right), \tag{3}$$

where ψ^k is simply the difference between the bid and ask quotes of FX spot rate for currency k. High bid-ask spread translates into less liquidity in the FX market. Figure 6 displays a time-series plot of global FX liquidity (the LIQ factor). The highest level of illiquidity appears in the beginning of the sample period, which corresponds to the end of the recent financial crisis.

Table VII reports descriptive statistics of the four risk factors cited above. As expected, average excess returns for a U.S. investors (DOL) and the H/L portfolio demonstrate high volatility, negative skewness and fat tails. AR(1) global volatility innovations (VOL) show large kurtosis but not a clear zero mean. Unit-root tests indicate that all factors except for the global liquidity risk are stationary, while the latter is stationary in first-difference. Thus, all asset pricing results obtained in the paper use LIQ as the first-difference of the global liquidity risk.

In this paper, we argue that the global trade risk factor sheds new light on understanding carry trade returns. As a preliminary investigation of the HML_{TC} factor, Table VIII presents correlations between the four risk factors, the DOL, VOL, LIQ, H/L, and our HML_{TC} factor. Global trade risk is negatively correlated with the dollar, the high minus low interest rates portfolio and the global volatility risk factors. It is positively correlated with the global liquidity risk factor. Correlations are rather low, except the largest correlation being -44% between HML_{TC} and H/L that is significant at 1% confidence level. The correlation with DOL is significant at 5% confidence level. Interestingly, liquidity risk factor has very weak correlation with the other factors.

In order to investigate into more details these results, we further analyse the sensitivity of the global trade risk factor to the other risk factors acknowledged in the literature. We thus regress the HML_{TC} factor and the excess returns of portfolios sorted on countries' centrality on a constant and the DOL, VOL, LIQ, and the H/L risk factors. Table IX presents Newey-West estimates as well as the corresponding R^2. The DOL factor has a significant and positive coefficient for all portfolios except for the HML_{TC} portfolio, where DOL is significant but negative. These results confirm previous observations stemming from the correlation table. However, as Lustig et al. (2011) point out, DOL represents the level factor and is not related to the position of countries in the network. No clear relations appear regarding loadings on VOL, LIQ and H/L; coefficient signs and statistical significance vary across the regressions. Table IX shows that the explanatory power of the common risk factors is high for portfolios E1 to E6 (R^2 is 89% on average), yet it is not related to trade centrality. The portfolio HML_{TC}, which is long in portfolio E6 and short in E1, only loads on the DOL and H/L factors but with a much smaller explanatory power (R^2 is 30%). Hence, HML_{TC} allows us to capture additional and different effects related to UIP violations compared to other market-based and the H/L risk factors.

5.2 Estimation Methods

The estimation method is similar to the one in Lustig et al. (2011) and in Menkhoff et al. (2012). We follow a standard stochastic discount factor (SDF) approach and we consider a linear pricing kernel m_t. The assumption of absence of arbitrage opportunities allows us to verify the Euler equation for all six portfolios sorted on interest rates. Hence, carry trade excess returns of each portfolio Pi satisfy

$$\mathbb{E}(m_t rx_t^i) = 0, \tag{4}$$

where the stochastic discount factor is defined as $m_t = 1 - b'(h_t - \mu_h)$, with b being the vector of factor loadings, h the vector of risk factors and μ the vector of associated factor means.

As linear models for the discount factor are equivalent to beta pricing models, we know that expected excess returns of each portfolio Pi equal the product of factor prices λ and risk quantities β (Cochrane (2005)). We thus have

$$\mathbb{E}(rx^i) = \lambda' \beta_i. \tag{5}$$

Factor prices λ are given by $\lambda = \Sigma_{h,h} b$, where Σ is the covariance matrix of the factors. We estimate SDF factor loadings b as well as means μ_h and the variance covariance matrix $\Sigma_{h,h}$ of the risk factors via the GMM estimation procedure. No instruments are introduced in the GMM estimation. Heteroskedasticity and autocorrelation consistent (HAC) weighting matrix with Newey-West optimal lags is used. Factor prices λ are thus computed with GMM estimates of b from equations 4.

In addition, we adopt the Fama-MacBeth (FMB) two-stage procedure for directly estimating factor prices λ in equation 5, which is well-documented in Cochrane (2005). The first stage consists in time-series regressions of portfolio carry trade excess returns on the pricing factors and collecting the factor betas. The loadings on the risk factors (βs) for the carry trade portfolios are obtained with Newey-West estimations. The second stage involves running cross-sectional regressions of portfolio returns on their respective factor betas at each time period. All standard errors are Newey-West adjusted and estimates of factor prices λ are obtained by averaging second-stage coefficients over time.

6 Empirical Results

This section exposes the estimation results of different asset pricing model specifications. The first part gives results for the global trade risk factor. In the second part, we additionally account for other common risk factors used in the literature.

6.1 Global Trade Risk Pricing Results

Table X reports estimates of the pricing kernel m_t obtained from GMM and Fama-MacBeth (FMB) estimations of equations 4. The pricing kernel is built on the dollar and the global trade risk factors, further referred as the benchmark specification, and has the following form:

$$m_t = 1 - b_{DOL}(DOL_t - \mu_{DOL}) - b_{HML_{TC}}(HML_{TC,t} - \mu_{HML_{TC}}), \tag{6}$$

where the means and covariance matrix of risk factors are estimated together with SDF parameters in the GMM procedure.

In particular, Panel A of Table X shows estimates of SDF factor loadings b and implied factor prices λs obtained by GMM estimation. The estimate of $b_{HML_{TC}}$ is statistically significant, meaning that the global trade factor helps to price carry trade returns given the dollar factor. Along with the GMM procedure, we estimate as well means μ_h and the variance covariance matrix $\Sigma_{h,h}$ of the risk factors. Estimates of λs follow from the product of the covariance matrix of the risk factors and the estimates of the factor loadings. Panel B shows Fama-MacBeth estimates of the factor prices λs.

The two estimation procedures lead to similar conclusions regarding our risk factor. Global trade price risk $\lambda_{HLM_{TC}}$ is negative and highly significant. Portfolios that co-move positively with this factor demand a lower premium while portfolios that co-move negatively ask for a higher risk premium. Concerning the risk price of the dollar risk factor, both estimation procedures yield similar results regarding the positive sign but not the statistical significance.

The risk factor estimates of βs for the carry trade portfolios are obtained with Newey-West time-series regressions of carry trade excess returns on risk factors. Table XI reports results of average currency excess returns of portfolios P1 to P6 on a constant (α), the dollar risk factor (DOL) and global trade intensity risk (HML_{TC}). Estimates of $\beta_{HML_{TC}}$ are statistically significant for five out of the six portfolios and roughly monotonically decreasing across portfolios. Global trade risk loadings are positive for currencies with low interest rates and negative for currencies with high interest rates. Therefore, investors demand a higher risk premium for investment currencies. These currencies are more subject to global trade risk while currencies with low interest rates provide a hedge against this risk. Portfolios' factor loadings for the dollar risk factor are all strongly statistically significant, positive and around a value of 1. These results on the dollar risk factor are very in line with Lustig et al. (2011) and Menkhoff et al. (2012).

Figure 7 shows the relation between the exposure of currency portfolios to the global trade risk factor (factor betas) and their interest rate differential. We can see that the relation is roughly monotonically decreasing, with low-interest rate countries displaying a large positive exposure to the global trade risk factor while high-interest rate countries display a negative exposure. This is expected, given that the factor price of $\lambda_{HML_{TC}}$ is negative. Hence, investors ask for higher excess returns as compensation for accepting exposure to unexpected global trade risk.

6.2 Accounting for Other Risk Factors

In this section, we add global volatility innovations (VOL), aggregate liquidity risk in first-difference (LIQ) and the high minus low interest rate portfolio (or carry trade portfolio (H/L)) as common risk factors of excess returns over UIP. Hence, when we consider altogether the above-mentioned risk factors, the pricing kernel is:

$$\begin{aligned} m_t &= 1 - b_{DOL}(DOL_t - \mu_{DOL}) - b_{HML_{TC}}(HML_{TC,t} - \mu_{HML_{TC}}) \\ &\quad - b_{VOL}(VOL_t - \mu_{VOL}) - b_{LIQ}(LIQ_t - \mu_{LIQ}) - b_{H/L}(H/L_t - \mu_{H/L}). \end{aligned} \tag{7}$$

Table XII reports GMM estimates of the pricing kernel m_t when the other common risk factors are introduced. Different specifications can be found in the different panels. Generally, all loadings b of the pricing kernel have statistically significant estimates. This implies that all selected factors help to price carry trade returns given the other factors. In addition, the risk price $\lambda_{HML_{TC}}$ is in most specifications statistically significant and has a high magnitude.

Interestingly, when we add the global volatility risk factor to the benchmark specification (see Panel A), we obtain a significant and negative estimate for λ_{VOL}, whose value is very close to the one reported in Menkhoff et al. (2012).[8] The risk price of the global trade risk factor remains negative and statistically significant, supporting the results displayed in Table X. Moreover, the $\lambda_{HML_{TC}}$ has the highest magnitude. Hansen's test χ^2_{HJ} does not reveal over-identification issues. In Panel B, we add global liquidity risk to the benchmark specification. The loading of the pricing kernel on liquidity risk factor is negative and highly significant while the loadings for the benchmark factors keep their significance but change sign. Thus, all three pricing factors help to price carry trade excess returns. In Panel C, we include the carry trade risk factor in the benchmark model. We observe that both $\lambda_{H/L}$ and $\lambda_{HML_{TC}}$ risk prices are positive and statistically significant, while the λ_{DOL} risk price is not. Even so, once the carry trade portfolio risk factor is introduced the dollar risk factor still demonstrates statistical relevance as a pricing factor. Panels D and E bring similar observations. However, when all risk factors are considered in Panel E, we reject the null that the over-identifying restrictions are valid at 10% confidence level.

[8] Indeed, they report an estimate of -0.07 while we obtain -0.075 for λ_{VOL}.

For comparison purposes, Table XIII displays Fama-MacBeth estimates of the factor prices λ for the asset pricing specifications considered in Table XII. While the results for the dollar and global trade risk factors confirm in most cases the GMM ones in terms of statistical significance and sign, the results for the liquidity risk and volatility risk factors show discrepancies. Interestingly, the Fama-MacBeth estimations deliver factor prices that are strongly consistent across the five specifications, with the global trade risk factor having a negative price while the dollar, liquidity and carry trade risk factors having a positive price in all estimations. We would therefore expect currencies that deliver high excess returns (portfolios P5 and P6) to load negatively on the global trade risk factor and positively on the liquidity and carry trade risk factors. Moreover, $\lambda_{HML_{TC}}$, λ_{LIQ}, and $\lambda_{H/L}$ generally have high statistical significance while the λ_{DOL} risk price is not significant in any of the specifications.

Table XIV reports results for time-series regressions of each portfolio excess returns on the dollar, the global trade risk and the global volatility risk factors. Portfolio's loadings of the dollar risk factor are all positive and highly significant, as in the benchmark model. Funding currencies exhibit a positive exposure to the global trade risk factor and investment currencies prove to be negatively exposed to this risk. Exposure to the global risk factor is statistically significant for five out six portfolios. The factor loadings for the global volatility risk factor generally increase monotonically, passing from negative for the portfolios containing low interest rate currencies to positive for high interest rate currencies but is not statistically significant on average.

Table XV shows estimation results for Newey-West regressions of portfolios' excess returns on the dollar, the global trade and the liquidity risk factors. Portfolios' loadings on the dollar factor are all positive and highly significant. As expected, the loadings for the global trade risk factor show a roughly decreasing trend from low interest rate to high interest rate portfolios. Combined with a negative risk price, this means that high interest rate currencies with a negative exposure to trade risk demand a higher risk premia while low interest rate currencies that comove positively with the factor are seen as a hedge and demand lower risk premia. The aggregate liquidity factor, which is considered in first-difference, has no significant loadings and its sign shows no trend across portfolios. These observations support the ones resulting from every previous specifications, including the benchmark model.

Table XVI displays estimates for time-series regressions of each portfolio excess returns on the dollar, the global trade risk and the carry trade risk factors. Again, in this model specification, the dollar risk factor is positive and statistically significant. All portfolios are statistically exposed to the global trade risk factor except portfolio P2 and P5. Although, as shown in Table XIII, the global trade risk risk price is statistically significant, there is no clear relation between exposures to this risk and interest rate currencies. The loadings on portfolios for the carry trade portfolio risk indicates that low interest rate currencies are negatively correlated with this risk while high interest rate currencies co-move positively, together with a positive risk price $\lambda_{H/L}$ shown in Table XIII. Again, the global trade risk and the carry trade risk factors are the two factors that are the most closely related. While the carry trade portfolio is obtained by going long in high interest rate currencies and short in low interest rate currencies, the global trade risk goes long in the most central currencies and short in less central currencies. All these results highlight the importance of a relation between trade centrality risk and interest rates.

7 Conclusion

This paper proposes a novel pricing factor for explaining the cross-section of carry trade returns arising from the failure of the uncovered interest rate parity. The pricing factors suggested in the existent literature, such as volatility and liquidity risk factors, are FX market-based risks. In contrast, we focus on the role of macroeconomic fundamentals in explaining the UIP failure together with the relative position of countries in a world trade network to embed their exposure to global trade risk.

In particular, centrality measure results from network theory in order to assess countries' exposure to global trade risk while accounting for possible cross-border spillovers of local shocks to the real side of countries' economies. A higher level of exposure implies that the economic activity in one country is highly dependent on the economic activity of its trade partners and the aggregate trade flow.

Using the Fama and French (1992) methodology to construct a traded risk factor that captures the global trade risk, we build a risk factor by taking the carry trade returns difference between excess returns of last minus the first quantiles of countries' centrality. By means of a standard asset pricing approach, we test the pricing power of the global trade-based risk factor alongside other risk factors.

Interestingly, we offer evidence that cross-sectional variation in carry trade excess returns can be partially explained by countries exposure to global trade risk arising from the structure of international trade flows. Results show that high interest rate currencies are negatively related to global trade risk while low interest rate currencies are positively related. This means that high interest rate currencies are negatively exposed to this risk and investors ask for a risk premium as compensation for taking it. Sensitivity analysis indicates that the global trade risk factor is not related to other market-based factors and proves to be a significant source of risk.

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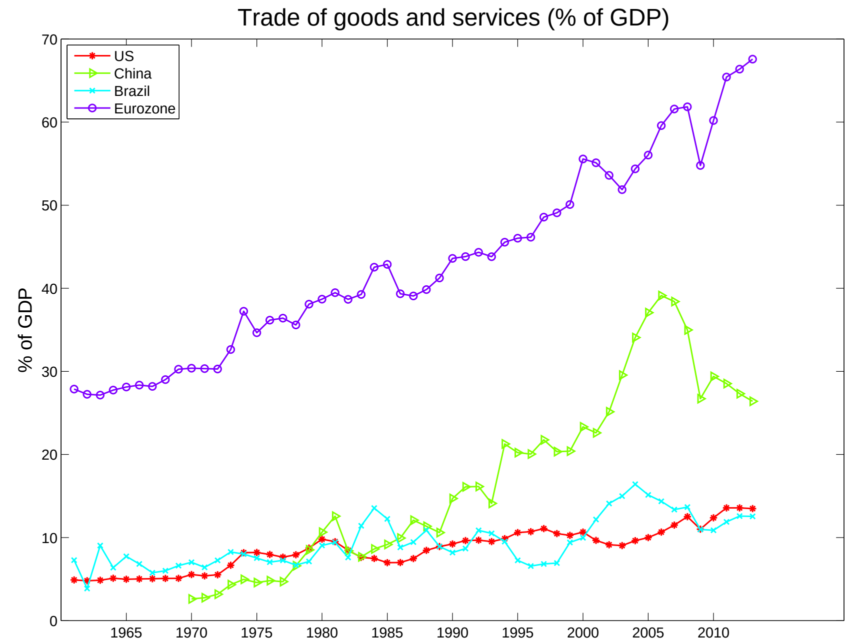

Figure 1: The figure shows the evolution over the period 1960 to 2013 of total trade of goods and services as percentage of GDP (known as openness) for a selection of four countries.

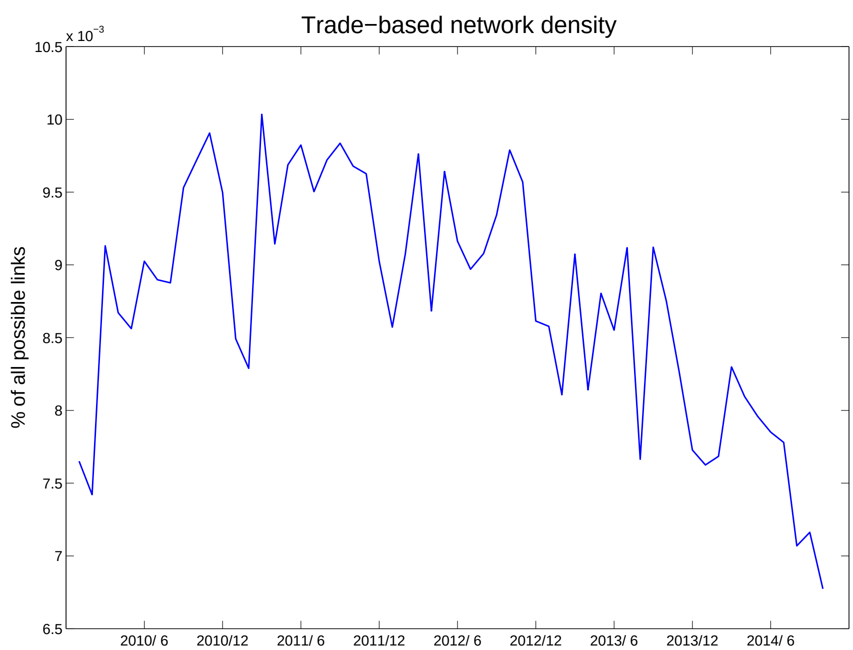

Figure 2: The figure shows the density of the trade-based network over the period January 2010 to October 2014. The density is computed as the sum of the weights of the edges in the network, divided by the number of possible edges.

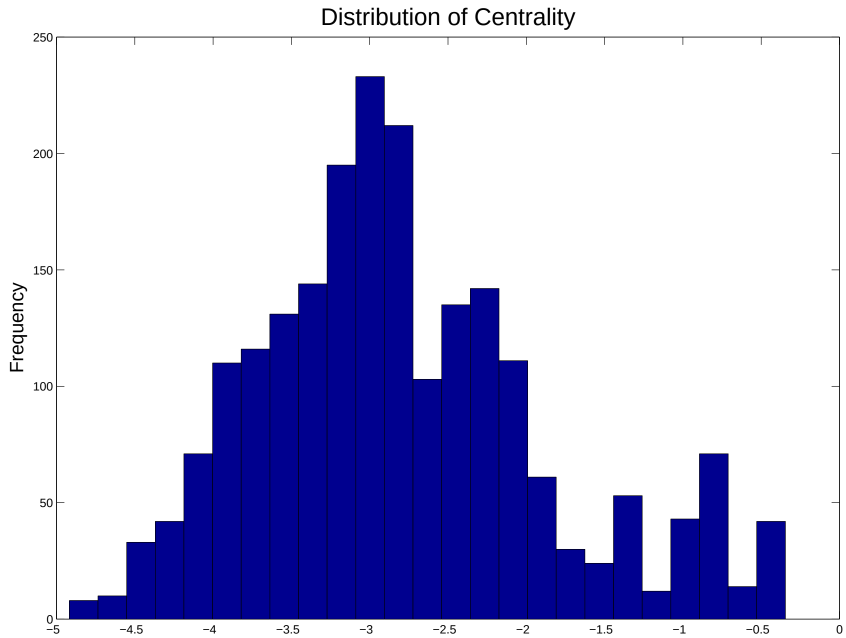

Figure 3: The figure shows the histogram of log(centrality) for 37 countries during the period 2010-2014. Countries' centrality is computed as the principal eigenvector of the bilateral trade matrix.

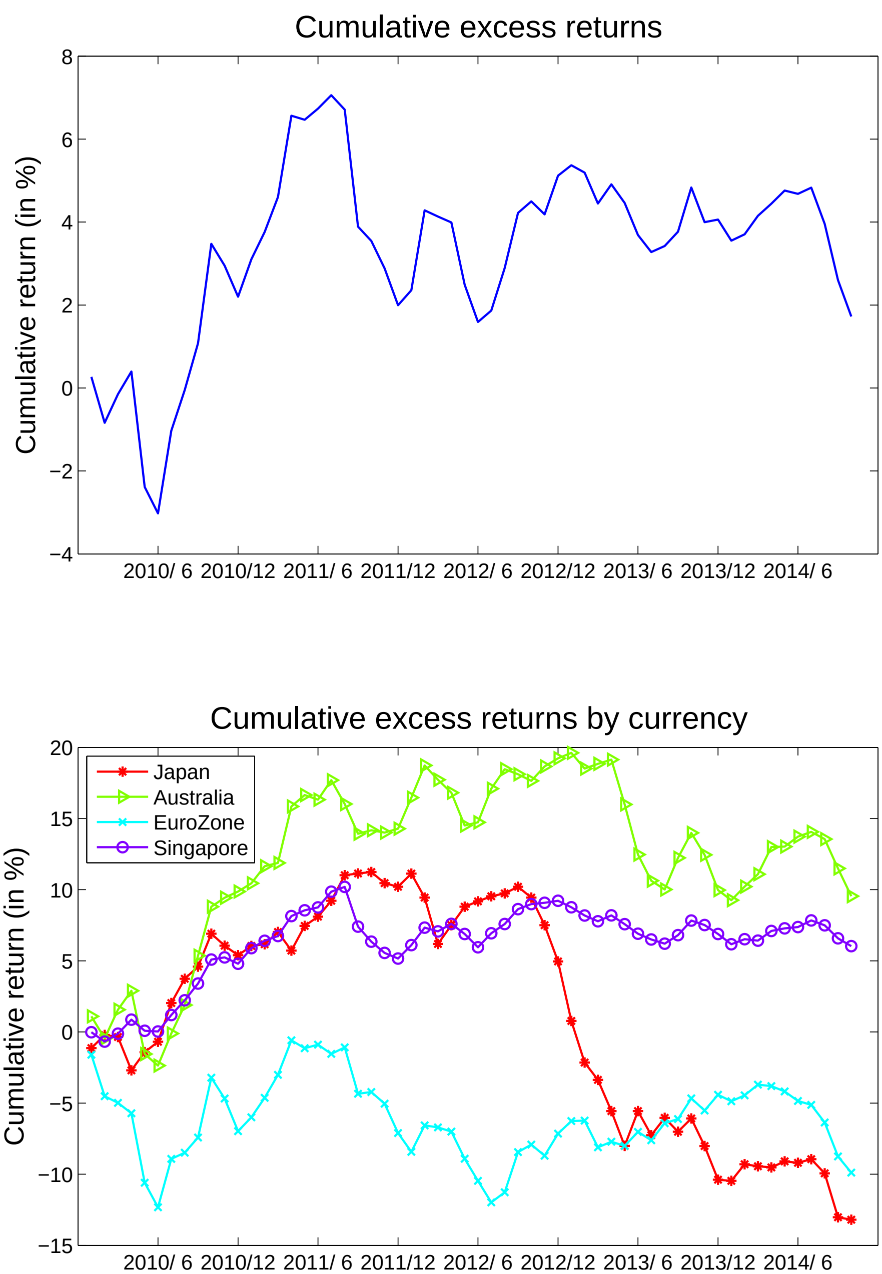

Figure 4: The upper panel of this figure shows average cumulative log excess returns of 36 currencies over the period January 2010 to October 2014 for a U.S. investor who borrows in his home currency and invests in foreign ones. The lower panel of the figure shows cumulative excess returns for a selection of four countries over the same period.

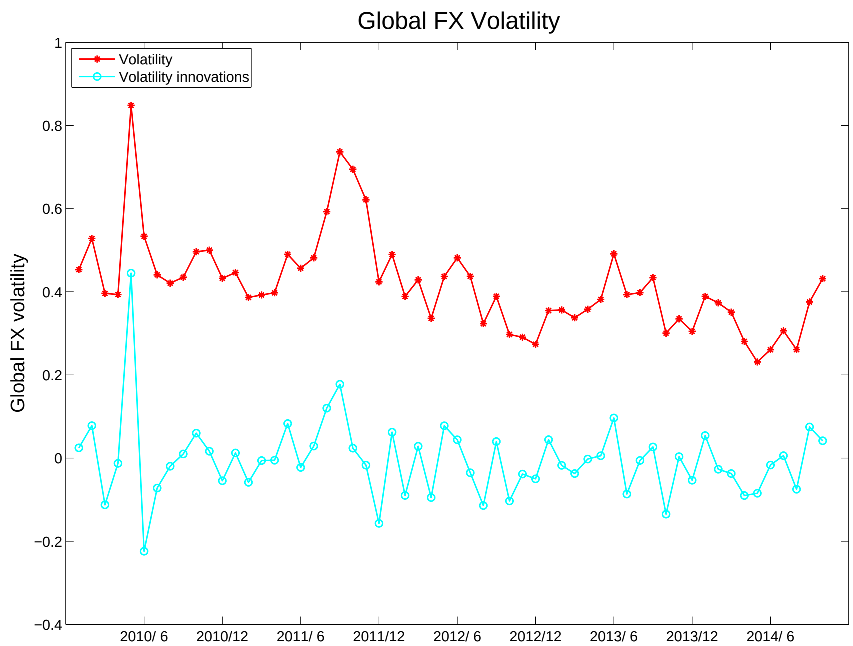

Figure 5: This figure shows a time-series plot of global volatility in the FX market for a U.S. investor (upper red line) and the volatility-based risk factor (lower blue line) during the period January 2010 to October 2014. The factor is AR(1) innovations of the FX volatility.

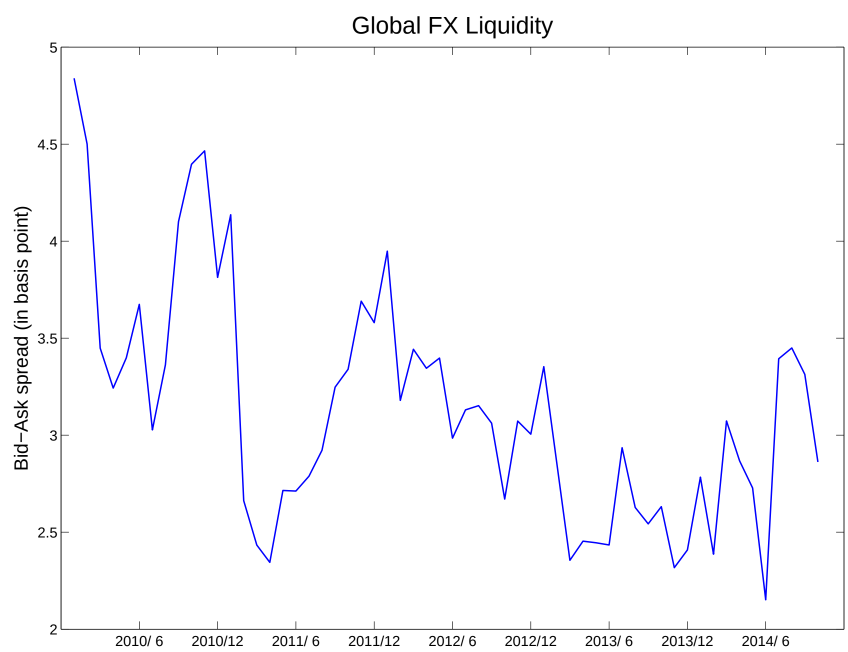

Figure 6: This figure shows a measure of liquidity risk during the period from January 2010 to October 2014. The factor is computed as the average over the 36 currencies bid-ask spreads.

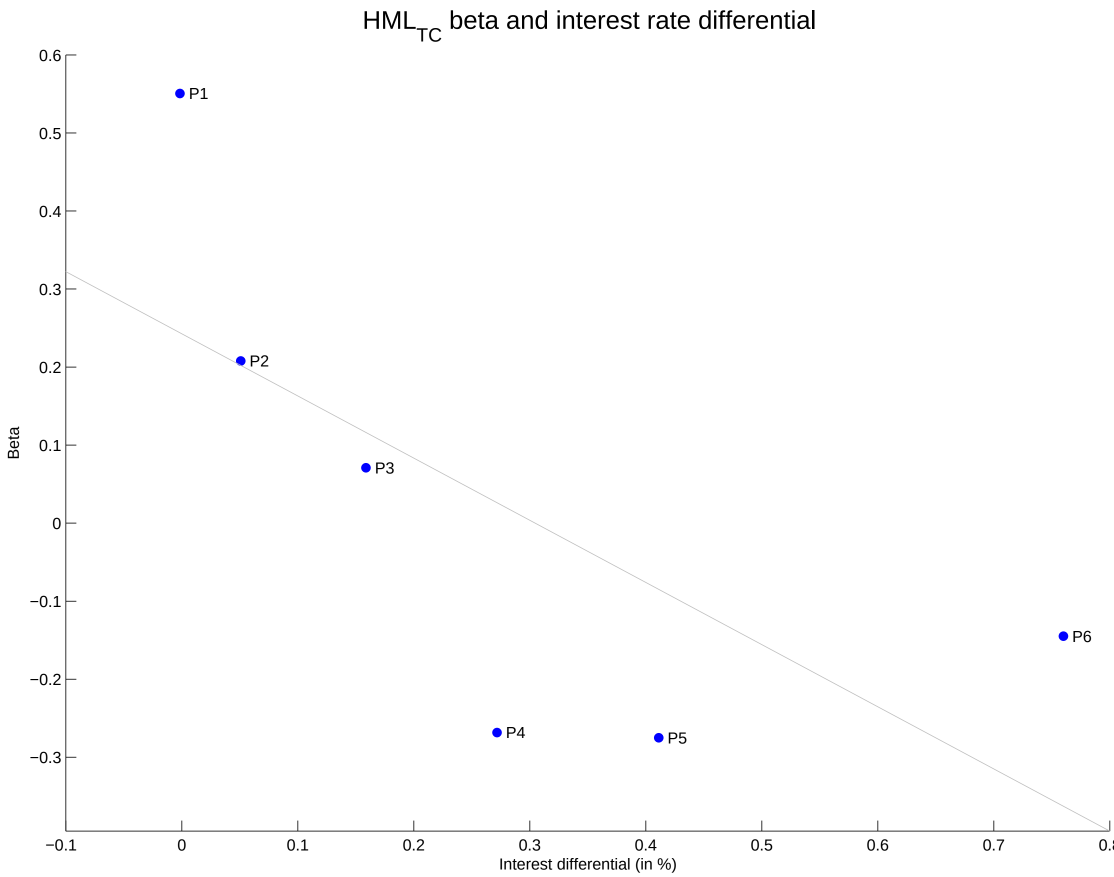

Figure 7: The figure shows the relationship between the exposure of currency portfolios to the global trade risk factor and their interest rate differential. The sample period is January 2010 to October 2014 and we add a least-squares line to fit the scatter plot.

Table I: Descriptive statistics for normalized trade and trade-based centrality measures

	Exports-to-GDP	Eigen-centr.	Degree	In-degree	Out-degree
Mean	0.850	0.101	0.583	0.291	0.291
Std. dev.	3.651	0.130	0.607	0.571	0.259
Min	0.000	0.000	0.000	0.000	0.000
Max	142.968	0.761	3.829	3.664	1.679
10% quantile	0.007	0.020	0.161	0.023	0.084
50% quantile	0.126	0.054	0.396	0.120	0.219
90% quantile	1.703	0.254	1.362	0.487	0.690
Skewness	16.620	2.700	2.857	3.858	2.204
Kurtosis	411.962	10.360	12.225	18.385	8.128

The table reports descriptive statistics for countries' bilateral trade (normalized with exporters' GDP) together with different centrality measures resulting from the trade-based network. The degree centrality measures countries' total trade, the in-degree is related to normalized imports, the out-degree is related to normalized exports, while the eigen-centrality represents the relative importance of countries in the bilateral network. We report means, standard deviations, minima, maxima, skewness, kurtosis, and the 10%, 50% and 90% quantiles.

Table II: Descriptive statistics of excess returns for portfolios sorted by interest rates

	P1	P2	P3	P4	P5	P6
Panel A: Excess returns						
Mean	-0.469	-0.401	-0.032	0.628	1.034	1.113
Std. dev.	3.589	4.632	3.637	4.387	4.447	3.082
Min	-3.117	-3.964	-3.110	-5.206	-3.285	-2.005
Max	2.743	3.236	2.189	2.294	3.751	1.875
Skewness	-0.137	-0.084	-0.321	-1.234	0.053	-0.025
Kurtosis	3.689	3.685	3.531	6.861	4.062	2.520
Information ratio	-0.131	-0.087	-0.009	0.143	0.233	0.361
Panel B: Interest rates						
Mean	-0.019	0.610	1.905	3.261	4.935	9.121
Std. dev.	0.027	0.118	0.165	0.155	0.155	0.414
Min	-0.024	0.007	0.075	0.192	0.338	0.559
Max	0.012	0.121	0.237	0.351	0.519	1.024

The table reports annualized descriptive statistics; means, standard deviations, minimum, maximum, skewness and kurtosis of excess returns of carry trade strategies sorted by interest rates. Portfolio P1 contains excess returns of carry trade for countries with lowest interest rates, whereas portoflio P6 is composed of excess returns currencies with highest interest rates. Returns are in log, expressed in USD. Sample period is January 2010 to October 2014.

Table III: Transition probabilities between portfolios sorted on interest rates

	P1	P2	P3	P4	P5	P6	Pr(Up)	Pr(Down)
P1	92.615	7.077	0.308	0.000	0.000	0.000	0.000	7.385
P2	6.433	85.965	6.725	0.292	0.292	0.292	6.433	7.602
P3	0.301	7.229	83.133	9.036	0.301	0.000	7.530	9.337
P4	0.000	0.000	8.772	81.287	9.064	0.877	8.772	9.942
P5	0.000	0.000	0.292	9.064	81.871	8.772	9.357	8.772
P6	0.000	0.271	0.000	0.542	7.859	91.328	8.672	0.000

This table shows the transition probabilities of currencies between portfolios sorted on countries' interest rates. The probabilities represent the likelihood of currencies transitioning from one portfolio to another in one month.

Table IV: Descriptive statistics for portfolios sorted by centrality

	E1	E2	E3	E4	E5	E6	HML_{TC}
Mean	0.315	-0.041	0.329	1.111	-0.488	0.820	0.505
	[0.642]	[-0.088]	[0.630]	[2.081]	[-0.744]	[2.098]	[1.759]
Std. dev.	3.734	3.596	3.979	4.067	4.998	2.976	2.186
Min	-2.989	-3.440	-3.129	-2.588	-4.868	-2.137	-1.366
Max	2.216	1.823	2.647	3.390	3.176	1.631	1.825
Skewness	-0.413	-0.630	-0.338	0.236	-0.389	-0.381	0.323
Kurtosis	3.284	3.884	3.590	3.671	4.739	2.974	3.622
Sharpe ratio	0.084	-0.012	0.083	0.273	-0.098	0.275	0.231

The table reports annualized descriptive statistics; means, standard deviations, minimum, maximum, skewness and kurtosis of excess returns sorted by centrality. Centrality is again relative to United States' position in the network. Portfolio E1 contains excess returns of a set of countries that are the most similar to the U.S. while portfolio E6 is composed of excess returns of countries that are less similar to the home country. HML_{TC} is the excess returns difference between portfolio E6 and portfolio E1. Statistical significance of means is reported by t-statistics in brackets. The sample period is January 2010 to October 2014.

Table V: Transition probabilities between portfolios sorted on centrality

	E1	E2	E3	E4	E5	E6	Pr(Up)	Pr(Down)
E1	83.626	13.743	1.754	0.877	0.000	0.000	0.000	16.374
E2	13.450	64.327	19.298	2.047	0.877	0.000	13.450	22.222
E3	1.462	18.713	54.971	22.807	1.754	0.292	20.175	24.854
E4	0.585	2.632	21.345	56.725	17.544	1.170	24.561	18.713
E5	0.877	0.585	2.047	16.082	72.515	7.895	19.591	7.895
E6	0.000	0.000	0.585	1.462	7.310	90.643	9.357	0.000

This table shows the transition probabilities of currencies between portfolios sorted on countries' centrality. The probabilities represents the likelihood of currencies transitioning from one portfolio to another in one month.

Table VI: Composition of portfolios sorted by centrality and by interest rates

	sorted by relative centrality			sorted by interest rates		
	2010/ 1	2011/ 8	2013/ 4	2010/ 1	2011/ 8	2013/ 4
Portfolio P1	New Zealand	Argentina	Argentina	Hong-Kong	Switzerland	Switzerland
	Turkey	Turkey	Philippines	Switzerland	Japan	Denmark
	Ukraine	Brazil	Egypt	Canada	Hong-Kong	Eurozone
	Canada	Croatia	Brazil	Japan	South Africa	Japan
	Egypt	New Zealand	Turkey	South Africa	United-Kingdom	Czech Republic
	Argentina	Canada	Canada	Sweden	Croatia	South Africa
Portfolio P2	Russia	Egypt	New Zealand	United-Kingdom	Czech Republic	Hong-Kong
	Croatia	United-Kingdom	Croatia	Eurozone	Canada	Bulgaria
	United-Kingdom	Eurozone	India	Israel	Eurozone	United-Kingdom
	Eurozone	Singapore	South Korea	Philippines	Denmark	Poland
	Brazil	Peru	China	Thailand	Bulgaria	Croatia
	Philippines	Russia	Australia	Denmark	Sweden	Canada
Portfolio P3	South Korea	South Korea	Japan	Czech Republic	Norway	Sweden
	Singapore	Philippines	Eurozone	China	Peru	Peru
	Iceland	Sweden	United-Kingdom	Croatia	Mexico	Israel
	India	Iceland	Israel	Peru	Thailand	Norway
	Romania	Romania	Singapore	Mexico	Israel	Malaysia
	Peru	Denmark	Peru	Malaysia	Malaysia	Thailand
Portfolio P4	Sweden	Ukraine	Norway	Bulgaria	Poland	Australia
	Denmark	India	Sweden	Norway	Singapore	Mexico
	Australia	Bulgaria	Iceland	Romania	Iceland	Brazil
	Bulgaria	Israel	Denmark	India	Philippines	Romania
	Japan	Japan	Russia	Australia	Russia	Philippines
	Israel	Norway	Hong-Kong	New Zealand	New Zealand	China
Portfolio P5	Czech Republic	Australia	Poland	Poland	Romania	New Zealand
	Norway	Switzerland	Ukraine	Hungary	Australia	Indonesia
	Switzerland	Czech Republic	Switzerland	Indonesia	South Korea	South Korea
	Hungary	China	Romania	Turkey	Ukraine	Ukraine
	Malaysia	Hungary	Malaysia	Brazil	Hungary	Hungary
	China	Poland	Bulgaria	South Korea	Indonesia	Turkey
Portfolio P6	Poland	Indonesia	Indonesia	Singapore	China	Russia
	Indonesia	Malaysia	Hungary	Egypt	Brazil	Iceland
	Thailand	Thailand	Czech Republic	Iceland	Turkey	Singapore
	Hong-Kong	Mexico	Thailand	Russia	India	India
	Mexico	Hong-Kong	Mexico	Argentina	Egypt	Egypt
	South Africa	South Africa	South Africa	Ukraine	Argentina	Argentina

The table reports the currency composition of portfolios sorted by countries' centrality relative to the U.S. (in the left panel) and portfolios sorted by interest rates differentials with respect the U.S. (in the right panel) at three points in time: January 2010, August 2011 and April 2013.

Table VII: Descriptive statistics for risk factors

	DOL	VOL	LIQ	H/L
Mean	0.357	-0.017	0.376	1.582
Std. dev.	3.467	0.316	0.021	2.868
Min	-2.820	-0.147	0.022	-2.974
Max	2.396	0.444	0.048	1.340
Skewness	-0.270	2.092	0.774	-1.140
Kurtosis	4.036	11.245	3.232	5.063

The table reports annualized descriptive statistics; means, standard deviations, minimum, maximum, skewness and kurtosis of the mentionned measures of risk: the dollar risk factor (DOL), global FX volatility innovations (VOL), the liquidity risk factor (LIQ) and the high minus low interest rates portfolio (H/L). Sample period is January 2010 to October 2014.

Table VIII: Risk factors correlation matrix

	DOL	VOL	LIQ	H/L	HML_{TC}
DOL	1.000	-0.035	0.098	-0.099	-0.282**
VOL	-0.035	1.000	0.010	0.158	-0.138
LIQ	0.098	0.010	1.000	-0.046	0.187
H/L	-0.099	0.158	-0.046	1.000	-0.444***
HML_{TC}	-0.282**	-0.138	0.187	-0.444***	1.000

The table reports correlation matrix of the risk factors, namely, the dollar risk factor (DOL), global FX volatility innovations (VOL), liquidity risk factor (LIQ), high minus low interest rates portfolio (H/L), and the global trade intensity factor (HML_{TC}). Correlations are computed over the whole sample period, thus from January 2010 up to October 2014. Statistical significance at the 10%, 5% and 1% level is indicated by *, **, and ***.

Table IX: Factors sensitivity by centrality

	DOL	VOL	LIQ	H/L	α	R^2
E1	0.800***	-0.334	9.428**	-0.622***	-0.276**	0.900
	(0.055)	(0.316)	(5.447)	(0.067)	(0.161)	
E2	1.236***	-0.441**	-16.534***	-0.267***	0.482***	0.918
	(0.063)	(0.217)	(5.522)	(0.055)	(0.179)	
E3	1.000***	0.000	-11.496***	0.057	0.320**	0.904
	(0.067)	(0.304)	(4.303)	(0.051)	(0.152)	
E4	1.169***	0.041	-0.090	0.175**	-0.003	0.834
	(0.123)	(0.806)	(6.937)	(0.090)	(0.221)	
E5	1.217***	0.775**	8.816	0.228***	-0.255	0.901
	(0.050)	(0.412)	(5.582)	(0.065)	(0.158)	
E6	0.800***	-0.334	9.428**	0.378***	-0.276**	0.864
	(0.055)	(0.316)	(5.447)	(0.067)	(0.161)	
HML_{TC}	-0.220***	1.387**	-8.276	-0.348***	0.356	0.300
	(0.069)	(0.793)	(8.235)	(0.052)	(0.328)	

The table shows results of Newey-West time-series regressions of excess returns for portfolios E1 to E6 on a constant (α), the dollar risk factor (DOL), the global FX volatility innovations, the global average bid-ask spread (LIQ) and the high minus low interest rates portfolio (H/L). In parentheses are Newey-West standard errors with 10 lags. Portfolios are excess returns of carry trade strategies. Excess returns are sorted by centrality to form six portfolios. HML_{TC} is the porfolio that goes long in portfolio E6 ans short in portfolio E1. Statistical significance at the 10%, 5% and 1% level is indicated by *,**, and ***. Reported R-squared are adjusted R-squared.

Table X: Factor prices

	DOL	HML_{TC}	χ^2_{HJ}
	Panel A: GMM		
b	-0.068***	-0.689***	6.320
	(0.011)	(0.035)	(0.176)
λ	0.045***	-0.094***	
	(0.009)	(0.005)	
	Panel B: FMB		
λ	0.025	-0.171***	
	(0.017)	(0.019)	

The table presents cross-sectional pricing results for portfolios P1 to P6 Euler equations. Considered risk factors are the dollar risk factor (DOL) and global trade intensity factor (HML_{TC}). Panel A reports estimates of SFD parameters b and corresponding factor risk prices λ obtained with GMM estimations. We do not use instruments except a constant. Heteroskedasticity and autocorrelation consistent (HAC) weighting matrix with Newey-West optimal lags is used. Robust standard errors are in parentheses. Panel B reports results for a standard FMB two-step regression to estimate λ. We employ a first-step time-series regressions for each of the 6 portfolios, followed by a second-step, that consists in regressing excess returns on in-sample estimates of betas. In parentheses are Newey-West standard errors of lag 10. Statistical significance at the 10%, 5% and 1% level is indicated by *, **, and ***. χ^2_{HJ} is the Hansen's J test for overidentifying restriction. Below χ^2_{HJ} in parentheses are p-values. The sample period is from January 2010 to October 2014.

Table XI: Factor betas

	DOL	HML_{TC}	α	R^2
P1	0.938***	0.519***	-0.089	0.751
	(0.054)	(0.134)	(0.070)	
P2	1.291***	0.185**	-0.080	0.890
	(0.057)	(0.088)	(0.076)	
P3	1.010***	0.066	-0.035	0.903
	(0.081)	(0.052)	(0.051)	
P4	1.109***	-0.256***	0.030	0.842
	(0.128)	(0.088)	(0.051)	
P5	1.161***	-0.237***	0.062	0.889
	(0.046)	(0.073)	(0.044)	
P6	0.737***	-0.153**	0.077	0.740
	(0.085)	(0.080)	(0.085)	

The table reports results of time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL), and global trade risk (HML_{TC}). Newey-West with 10 lags standard errors are reported in parentheses. The sample period is from January 2010 to October 2014. Statistical significance at the 10%, 5% and 1% level is indicated by *, **, and ***. Reported R-squared are adjusted R-squared.

Table XII: Factor prices (GMM)

	DOL	HML_{TC}	VOL	LIQ	H/L	χ^2_{HJ}
			Panel A			
b	0.054***	-0.674***	-8.773***			4.601
	(0.007)	(0.056)	(0.188)			(0.203)
λ	0.017**	-0.133***	-0.075***			
	(0.009)	(0.008)	(0.002)			
			Panel B			
b	-0.020***	0.027***		-47.372***		4.005
	(0.003)	(0.006)		(3.085)		(0.261)
λ	-0.002	0.009***		-0.010***		
	(0.002)	(0.001)		(0.001)		
			Panel C			
b	0.892***	1.330***			3.196***	4.079
	(0.049)	(0.063)			(0.192)	(0.253)
λ	0.038	0.053**			0.241***	
	(0.039)	(0.023)			(0.028)	
			Panel D			
b	-0.004	-0.132***	-3.374***	-78.995***		6.432
	(0.003)	(0.023)	(0.162)	(4.439)		(0.040)
λ	0.002	-0.030***	-0.020***	-0.005***		
	(0.004)	(0.003)	(0.001)	(0.000)		
			Panel E			
b	0.126***	0.252***	-4.417***	-91.389***	0.169***	2.763
	(0.022)	(0.055)	(0.408)	(8.103)	(0.028)	(0.097)
λ	0.001	-0.007	-0.021***	-0.003***	-0.008	
	(0.015)	(0.006)	(0.002)	(0.000)	(0.007)	

The table presents cross-sectional pricing results for portfolios P1 to P6 Euler equations for five different model specifications. Estimates of SDF parameters b and corresponding factor risk prices λ obtained with GMM estimations. We do not use instruments except a constant. Heteroskedasticity and autocorrelation consistent (HAC) weighting matrix with Newey-West optimal lags is used. Robust standard errors are in parentheses. Statistical significance at the 10%, 5% and 1% level is indicated by *, **, and ***. χ^2_{HJ} is the Hansen's J test for overidentifying restriction. Below χ^2_{HJ} in parentheses are p-values. The sample period is from January 2010 to October 2014.

Table XIII: Factor prices (FMB)

	(1)	(2)	(3)	(4)	(5)
DOL	0.025	0.025	0.025	0.025	0.025
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
HML_{TC}	-0.171***	-0.182***	-0.053**	-0.149***	-0.033
	(0.023)	(0.020)	(0.031)	(0.025)	(0.040)
VOL	-0.005			0.007	0.021**
	(0.008)			(0.009)	(0.010)
LIQ		0.003***		0.003***	0.002***
		(0.001)		(0.001)	(0.001)
H/L			0.143***		0.143***
			(0.015)		(0.014)

The table presents cross-sectional pricing results using Fama MacBeth estimation for five different model specifications. Newey-West standard errors are presented in parentheses. Statistical significance at the 10%, 5% and 1% level is indicated by *, **, and ***. The sample period is from January 2010 to October 2014.

Table XIV: Factor betas

	DOL	HML_{TC}	VOL	α	R^2
P1	0.952***	0.550***	-0.939	-0.092	0.753
	(0.057)	(0.143)	(0.674)	(0.072)	
P2	1.301***	0.208**	-0.677**	-0.082	0.890
	(0.060)	(0.090)	(0.394)	(0.072)	
P3	1.012***	0.071	-0.136	-0.036	0.902
	(0.081)	(0.052)	(0.301)	(0.050)	
P4	1.104***	-0.268***	0.383	0.031	0.840
	(0.117)	(0.084)	(0.739)	(0.051)	
P5	1.145***	-0.275***	1.118**	0.065	0.893
	(0.047)	(0.079)	(0.468)	(0.040)	
P6	0.740***	-0.145**	-0.235	0.077	0.736
	(0.084)	(0.085)	(0.534)	(0.086)	

The table reports results of time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL), the global trade risk (HML_{TC}) and global FX volatility innovations (VOL). Newey-West with 10 lags standard errors are reported in parentheses. The sample period is from January 2010 to October 2014. Statistical significance at the 10%, 5% and 1% level is indicated by *, **, and ***. Reported R-squared are adjusted R-squared.

Table XV: Factor betas

	DOL	HML_{TC}	LIQ	α	R^2
P1	0.938***	0.518***	0.425	-0.087	0.746
	(0.054)	(0.135)	(8.173)	(0.073)	
P2	1.293***	0.178**	4.030	-0.072	0.889
	(0.055)	(0.088)	(15.384)	(0.068)	
P3	1.009***	0.063	-2.937	-0.034	0.902
	(0.079)	(0.052)	(6.577)	(0.052)	
P4	1.106***	-0.255***	-9.477	0.026	0.840
	(0.125)	(0.087)	(10.047)	(0.055)	
P5	1.161***	-0.232***	0.248	0.057	0.887
	(0.047)	(0.074)	(7.454)	(0.042)	
P6	0.741***	-0.147**	10.622	0.075	0.738
	(0.084)	(0.085)	(7.192)	(0.084)	

The table reports results of time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL), global trade risk (HML_{TC}) and gloabl liquidity risk factor (LIQ). Newey-West with 10 lags standard errors are reported in parentheses. The sample period is from January 2010 to October 2014. Statistical significance at the 10%, 5% and 1% level is indicated by *, **, and ***. Reported R-squared are adjusted R-squared.

Table XVI: Factor betas

	DOL	HML_{TC}	H/L	α	R^2
P1	0.826***	0.144**	-0.558***	0.004	0.903
	(0.059)	(0.061)	(0.077)	(0.051)	
P2	1.233***	-0.007	-0.286***	-0.032	0.913
	(0.057)	(0.055)	(0.064)	(0.058)	
P3	1.028***	0.127***	0.090	-0.050	0.905
	(0.072)	(0.044)	(0.056)	(0.047)	
P4	1.131***	-0.183***	0.109	0.012	0.843
	(0.124)	(0.046)	(0.088)	(0.048)	
P5	1.201***	-0.105	0.197**	0.029	0.900
	(0.059)	(0.091)	(0.088)	(0.054)	
P6	0.826***	0.144**	0.442***	0.004	0.869
	(0.059)	(0.061)	(0.077)	(0.051)	

The table reports results of time-series regressions of excess returns on a constant (α), the dollar risk factor (DOL), global trade risk (HML_{TC}) and the carry trade risk factor (H/L). Newey-West with 10 lags standard errors are reported in parentheses. The sample period is from January 2010 to October 2014. Statistical significance at the 10%, 5% and 1% level is indicated by *, **, and ***. Reported R-squared are adjusted R-squared.