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The Relationship between Currency Carry Trades and U.S. Stocks

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The Relationship between Currency Carry Trades and U.S. Stocks

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Abstract: The article examines the relationship between daily returns of currency carry trades and U.S. stocks from January 1995 through September 2010. Carry trade and stock returns are highly correlated with no Granger-causality in either direction. An EGARCH model shows that significant volatility spillovers flow from the stock market to the carry trade market, but not vice versa. The markets are more correlated in periods of high volatility. Volatilities in both markets also increase more with negative innovations than positive innovations. A sectoral analysis of the index suggests that volatilities of cyclical stocks have more impact than non-cyclical stocks on carry trades.

Keywords: Carry trades, US stocks, EGARCH

JEL Classification Codes: C22, G13

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INTRODUCTION

Currency carry trades have been a popular speculative strategy among both global investment managers and individual currency traders in recent years. Under this strategy, investors sell low interest rate currencies (funding currencies) and invest in high interest rate currencies (investment currencies). The impact of carry trades on financial markets has been reported extensively by financial news media. In particular, the carry trade and stock markets are positively related because they both reflect investors' risk appetites.

This paper examines the lead-lag relationship between currency carry trades and U.S. stocks from January 1995 through September 2010. While carry trade data are not readily available, the paper uses carry trade portfolios that hold a long position in high-yielding currencies and a short position in low-yielding currencies among 10 currencies from developed countries.

Uncovered interest rate parity (UIP) states that no profitable carrying opportunity exists since the interest differential across economies is offset by the expected change in exchange rates. Carry trades exploit the violation of UIP (or the forward premium puzzle as in Fama, 1984), speculating that high interest rate currencies will appreciate in value relative to low interest rate currencies. The carry trade does not just depend on the interest rate differential between the investment currency and the funding currency; it is also dependent on low volatility. As reported in Zurawski and D'Arcy (2009), for the period of 2003 to 2007, foreign exchange markets were relatively stable and carry trades were highly profitable, with exchange rate movements often working to enhance returns, such as the appreciation of the Australian and New Zealand dollars against the Japanese yen (Cairns, Ho, and McCauley, 2007).

The carry trade experienced a large unwinding with the turmoil that occurred in financial markets in 2008. Before the crisis, the yen was a favorable carry trade funding currency because of low Japanese interest rates. After the financial crisis broke out, investors panicked and reversed the money flows of the carry trade, which inflated the yen while depressing high-yield currency values. The unwinding of the yen carry trade overlapped a fall in the U.S. stock market. See, e.g., Cassino and Wallis (2010).

By the end of March 2009, the S&P 500 index had rebounded from a 13-year low. At the same time as the global equity market rebounded, the yen carry trade began to show a returning trend (Garnham, 2009). In the entire year of 2009, the popular yen-Australian carry trades gave an impressive return of about 40% because of the appreciation of Australian dollars against dollars and yen of 36.5% and the interest differential of 3.5%. Recently, hedge funds and major global traders extend the U.S. dollar carry-trade strategy by borrowing funds overnight in the U.S. at very low rates and reinvesting the proceeds into high-yielding currencies and global equities (Gibson, 2009; Tett and Garnham, 2010). In the second quarter of 2010, however, U.S. stocks plunged and demand for carry trades sapped as investors worried about the Greek debt crisis (Levisohn and Biggadike, 2010).

Empirical studies show that the carry trade is an important factor which causes exchange rate swings. As more investors participate in this strategy, an excess supply of the funding currency and an excess demand of the investment currency occurs. The investment currency, therefore, appreciates against the funding currency due to the imbalance of demand and supply. In contrast, carry trade unwinding spurs exchange rate swings in the opposite direction. As Brunnermeier, Nagel and Pedersen (2009) claim, sudden currency rate moves unrelated to news events can be caused by the unwinding of carry trades when speculators have funding constraints. They find that macroeconomic fundamentals determine interest rate levels while liquidity crises, such as the unexpected unwinding of carry trades, lead to currency crashes.

Funds move globally to seek high-yielding assets, causing carry trade and U.S. stock market pricing behavior to reflect risk sentiment and underlying economic fundamentals. Return volatility (or information flow as discussed in Ross, 1989) in one market is related to the other. Thus, it is important to examine the dynamic mechanism between the carry trade and U.S. stock markets. Melvin and Taylor (2009) review the global financial crisis of 2007-2009 and mention that "the volatility in currency markets followed heightened volatility in other asset classes." Because of substantial losses in bond and equity portfolios during the crisis, a deleveraging was inevitable in currency portfolios. The volatility spillover described in Melvin and Taylor has often been reported in the news media (e.g., Boyd, 2010).

Previous research on carry trades mainly attempts to tackle the UIP puzzle by relating the carry trade returns to risk premium. However, the results are not conclusive. Burnside, Eichenbaum, Kleschelski, and Rebelo (2010) find that carry trade returns are uncorrelated to standard risk factors (equity and bond returns) and argue that the positive average payoff to the carry trade reflects peso event risk (or the effects on inference caused by low-probability events). But they show that the underlying peso state features high values of the stochastic discount factor rather than large negative payoffs. Burnside (2009) reviews the evidence against risk-based and peso-problem-based explanations of carry trade returns. Brunnermeier, Nagel, and Pedersen (2009) report that currency crashes can explain the carry trade risk premium. Based on the liquidity spiral model of Brunnermeier and Pedersen (2009), Brunnermeier, Nagel, and Pedersen also document that the excess return is a premium for providing liquidity.

Christiansen, Ranaldo, and Söderlind (2010) show that risk exposures of carry trade returns are regime-dependent. Moreover, about one third of the carry trade return in the high volatility period is accounted for by the exposure to standard risk factors and two thirds by the market volatility factor. See, e.g., Bacchetta and van Wincoop (2010), Lustig and Verdelhan (2007), and Verdelhan (2010) for other explanations of the UIP puzzle.[1]

Nevertheless, no previous research has explicitly examined the Granger-causal relationship between carry trades and stocks in a time series model. In this paper, unlike prior research, stock returns are not considered a risk factor. Rather, both stock returns and carry trade returns are endogenous variables in a dynamic simultaneous system that captures the intertemporal dependence between the two markets. This bidirectional interaction is important to global risk management and asset pricing.

This paper investigates this relationship by employing a vector autoregressive (VAR) model and a bivariate EGARCH-*t* model. The empirical results show that the two markets are highly correlated with no return causality in either direction. However, volatility of the US stock index (particularly, the cyclical sectors) significantly spills over to the carry trade fund, but not vice versa. This result indicates that innovations in the stock market can predict future volatility in carry trades. Both markets also exhibit asymmetric volatility effects, suggesting that bad news creates more volatility than does good news.

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[1]Bacchetta and van Wincoop (2010) point out that only a small fraction of foreign currency holdings are actively managed. Their model attributes the UIP puzzle to infrequent revisions of investor portfolio decisions. Lustig and Verdelhan (2007) find that currencies with high interest rates have high loading on consumption growth risk. The Verdelhan (2010) model also shows that when the domestic investor is more risk averse than foreign investors, the exchange rate is closely related to domestic consumption growth stocks. However, Burnside (2007) finds that the carry trade returns are uncorrelated with the consumption risk factors used in Lustig and Verdelhan.

DATA AND SUMMARY STATISTICS

The log exchange rate in units of foreign currency per US dollar is denoted by s_t. The excess return of an investment in the foreign currency financed by borrowing the U.S. dollar is given by

$$z_t = \Delta s_t - (i_{t-1} - i^*_{t-1}) \tag{1}$$

where $\Delta s_t \equiv s_t - s_{t-1}$ is the appreciation of the foreign currency, i_t is the log interest rate for the U.S. dollar, and i_t^* is the log interest rate for the foreign currency. See Brunnermeier, Nagel, and Pedersen (2009) and Christiansen, Ranaldo, and Söderlind (2010), among many others. It is a measure of exchange rate return in excess of the prediction by the uncovered interest rate parity (UIP). Burnside et al. (2010) show that the excess return of Equation (1) is the same as the forward rate bias (i.e., the difference between the forward rate at time *t* and the spot rate at time *t*+1) if the covered interest rate parity (CIP) holds.

Carry trades have been so popular that the Bloomberg Professional® makes the daily excess returns of carry trades available (Gyntelberg and Remolona, 2007). The daily excess returns are obtained from Bloomberg for the G10 currencies over the period of January 1995 through September 2010. Daily exchange rates and three-month euro-deposit rates are collected at the New York closing. The 10 currencies are U.S. dollars (USD), euros or German marks (EUR), Japanese yen (JPY), Canadian dollars (CAD), Swiss francs (CHF), British pounds (GBP), Australian dollars (AUD), New Zealand dollars (NZD), Norwegian krone (NOK), and Swedish krona (SEK).

Not surprisingly, the average daily percentage excess returns are negative for typical funding currencies with low interest rates (−0.0089 for JPY and −0.0015 for CHF) and positive for typical investment currencies with high interest rates (0.0141 for NZD and 0.0128 for AUD).

Following the carry trade strategy by Deutsche Banks's PowerShares DB G10 Currency Harvest, the carry trade portfolio is composed of a long position in the three highest-yielding currencies and a short position in the three lowest-yielding currencies out of the G10 currencies. Each currency is weighted equally. This strategy has also been used by Christiansen, Ranaldo, and Söderlind (2010). The components for the carry trade portfolios are fairly stable with JPY and CHF being the most common funding currencies and NZD and AUD being the most common investment currencies.

Like Brunnermeier, Nagel, and Pedersen (2009), the paper also considers the carry trade portfolios that include a long position in the currency with the highest interest rate and a short position in the currency with the lowest interest rate. Hereafter, the carry trade portfolios with three currencies in each of the long and short positions are denoted by CT and the portfolios with one currency in each position are denoted by CT1. The overall results of CT and CT1 are very similar and the results (available upon request) using two currencies in each position are similar to those of CT and CT1. Unless specified, the results discussed refer to CT.

The U.S. stock market is represented by the futures contract on the S&P 500 index, denoted by SP, traded on the Chicago Mercantile Exchange. Log returns are calculated from the closing prices of the most active nearby contracts (until the last five trading days of the contracts) obtained from Commodity Systems, Inc. (CSI).

Table I provides summary statistics of daily returns in percentages. The mean return of carry trade portfolios with three currencies in each of the long and short positions (CT), 0.026, is significant at the 1% level. The mean return of carry portfolios with one currency in each position (CT1) is higher, 0.030, but less statistically significant, and the mean return of S&P index futures

(SP) is much smaller, 0.014, and not significant at any conventional level. Thus, both carry trade portfolios CT and CT1 offer higher returns than the S&P 500 over the period.

It is also noted that the carry trade portfolios CT and CT1 have smaller standard deviations (0.616 and 0.997) than the U.S. stock index (1.305). By entering into long and short positions, the carry trade is expected to provide returns with low volatility. However, CT and CT1 both have negative and much smaller skewness (ie., more negative) than SP. CT, CT1, and SP have comparable kurtosis. As noted by Brunnermeier, Nagel, and Pedersen (2009), the carry trade is profitable on average with a higher Sharpe ratio but has crash risk (measured by negative skewness) and fat tails.

Panel B of Table I indicates that the U.S. stock market is significantly correlated with the carry trade, 0.440 with CT and 0.347 with CT1. The two carry trade portfolios are also highly correlated with a coefficient of 0.796. The carry trade and U.S. stock markets are correlated because they both reflect investors' risk appetites. As described by many news articles, high risk appetites induce investors to invest in both markets, and low risk appetites result in selling stocks and unwinding carry trades. Both the carry trade and U.S. stock portfolios plunged in the most downward month of October 2008.

A shock to one market may signal economic news or a change in risk appetite that is relevant to the other market. The King and Wadhwani (1990) model shows that investors infer information from price changes in other markets, resulting in contagion in financial markets. In particular, financial crises cause panic among investors and lead to carry trade unwinding. Deterioration in the U.S. equity market will also aggravate carry trade unwinding. Such interactions between the carry trade and the U.S. market lead to the highly correlated pricing behavior of the carry trade and stock markets.

Contagion effects during periods of high volatility have been reported by more recent papers. Baele (2005) finds evidence for contagion from the U.S. market to a number of European equity markets during periods of high world market volatility. Bekaert, Harvey, and Ng (2005) define contagion as correlation over what one would expect from economic fundamentals. They find contagion during the East-Asian crisis, but not during the Mexican crisis in the late 1990s. However, Forbes and Rigobon (2002) point out that contagion cannot be tested by directly comparing correlations between stable and crisis periods because correlations are higher during volatile periods even under the null of no contagion. Using a heteroskedasticity-adjusted simple-correlation analysis, Chiang, Jeon, and Li (2007) find evidence of contagion effects during the Asian financial crisis, a finding that refutes the ‘‘no contagion’’ conclusion reached by Forbes and Rigobon. Baele and Inghelbrecht (2010) further show that the specification of the global and regional market exposure is an important issue in any test for contagion.

Longstaff (2010) discusses other channels (such as liquidity and risk premium) by which contagion effects can be propagated through different markets. Using data for the ABX subprime indexes, he finds strong evidence of contagion in the financial markets through liquidity and risk-premium channels. Results of the carry trade returns reported in Brunnermeier, Nagel, and Pedersen (2009) provide support for the theoretical liquidity spirals model in Brunnermeier and Pedersen (2009). The Brunnermeier and Pedersen model suggests that speculators' capital is a driver of market liquidity and risk premiums. Market liquidity, accordingly, can suddenly dry up and has commonality across securities, such as carry trade and stock markets.

Finding a contemporaneous relationship, the next section investigates the direction of potential mean and volatility spillovers between the two markets. A better understanding of the causality relationship between carry trades and stock movements is important in global risk management and asset pricing.

GRANGER CAUSALITY IN RETURNS AND VOLATILITIES

The daily causality relationship in returns between the carry trade and the U.S. stock markets is examined by a vector autoregressive (VAR) model:

$$\Delta CT_t = a_1 + \sum_{j=1}^{5} c_{1j}\Delta CT_{t-j} + \sum_{j=1}^{5} f_{1j}\Delta SP_{t-j} + \varepsilon_{1t} \tag{2a}$$

$$\Delta SP_t = a_2 + \sum_{j=1}^{5} c_{2j}\Delta CT_{t-j} + \sum_{j=1}^{5} f_{2j}\Delta SP_{t-j} + \varepsilon_{2t} \tag{2b}$$

The VAR model is estimated using OLS with the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix. The coefficients f_{1j} in (2a) describe the causality from the stock market to the carry trade market; c_{2j} in (2b) describe the causality from the carry trade market to the stock market. For coefficient testing, two restriction tests are employed on the cross-market coefficients, f_{1j} and c_{2j}, in the VAR as follows:

$H_{o,1} : f_{1j} = 0$ for all $j = 1, ..., 5$

$H_{o,2} : \Sigma_j f_{1j} = 0$

The first test assumes that all cross-market coefficients are jointly equal to zero. The second test assumes that the sum of all the coefficients is equal to zero.

The VAR model is modified by separating the effects of lagged positive and negative returns:

$$\Delta CT_t = a_1 + \sum_{j=1}^{5} c_{1j}\max[0,\ \Delta CT_{t-j}] + \sum_{j=1}^{5} d_{1j}\min[0,\ \Delta CT_{t-j}] + \sum_{j=1}^{5} f_{1j}\max[0,\ \Delta SP_{t-j}] + \sum_{j=1}^{5} g_{1j}\min[0,\ \Delta SP_{t-j}] + \varepsilon_{1t} \tag{3a}$$

$$\Delta SP_t = a_2 + \sum_{j=1}^{5} c_{2j}\max[0,\ \Delta CT_{t-j}] + \sum_{j=1}^{5} d_{2j}\min[0,\ \Delta CT_{t-j}] + \sum_{j=1}^{5} f_{2j}\max[0,\ \Delta SP_{t-j}] + \sum_{j=1}^{5} g_{2j}\min[0,\ \Delta SP_{t-j}] + \varepsilon_{2t} \tag{3b}$$

This modification is motivated by the results of Chordia, Roll, and Subrahmanyam (2002). They find that although past S&P 500 returns have no predictive power of current returns, the signed lagged returns, $\max[0, \text{return}_{t-j}]$ and $\min[0, \text{return}_{t-j}]$, do. In particular, a positive return tends to be followed by a continuation and a negative return tends to be reversed. They emphasize that these surprising results deserve mention and further discussion (p.125). The coefficients f_{1j} and g_{1j} in (3a) describe the causality from the positive and negative stock returns, respectively, to the carry trade returns; c_{2j} and d_{2j} in (3b) describe the causality in the reverse direction.

The unautocorrelated residuals, ε_{1t} and ε_{2t}, from the VAR model are used to investigate the spillovers of conditional volatility shocks between the two markets. As pointed out by Ross (1989), the variance of price changes is related directly to the rate of information flow. Substantial attention has been focused on how news from one market affects the volatility process of another market using the GARCH model. Volatility spillovers based on the GARCH model are first introduced and named "meteor showers" in foreign exchange markets by Engle, Ito, and Lin (1990). They name the usual market-specific volatility autocorrelations "heat waves." Significant empirical studies in volatility spillovers include Hamao, Masulis, and Ng (1990) and Lin, Engle, and Ito (1994) in international stock markets and Chan, Chan, and Karolyi (1991) in index futures markets. See also, e.g., Booth, Chowdhury, Martikainen, and Tse (1997) and Melvin and Melvin (2003).

Several empirical studies, e.g., Koutmos and Booth (1995) and Tse (1999), of volatility spillovers based on the Nelson (1991) EGARCH model also include the stylized fact that stock volatility tends to rise when the previous return innovation is negative. Two major explanations for this asymmetric volatility are the leverage effect and the volatility feedback effect. The leverage effect by Black (1976) and Christie (1982) suggests that a firm's stock volatility changes due to changes in its financial leverage. With a negative realized return the firm value declines, making the equity riskier and increasing its volatility. The volatility feedback effect by Pindyck (1984) and French, Schwert, and Stambaugh (1987) argues that an anticipated increase in volatility raises the required return on equities, thereby causing an immediate stock price decline. See also Bekaert and Wu (2000) and Wu (2001). However, Avramov, Chordia, and Goyal (2006) provide evidence against these two explanations and they show that selling trading activity governs the asymmetric volatility effect in daily stock returns.

The following bivariate EGARCH(1,1)-*t* model is used to examine the volatility spillover mechanism:

$$\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})' | \Psi_{t-1} \sim Student\text{-}t(0, \Omega_t, \nu), \quad \Omega_t = \begin{pmatrix} \sigma_{1t}^2 & \sigma_{12,t} \\ \sigma_{12,t} & \sigma_{2t}^2 \end{pmatrix} \tag{4}$$

$$\ln(\sigma_{1t}^2) = \omega_1 + \alpha_1 W_{1,t-1} + k_1 W_{2,t-1} + \beta_1 \ln(\sigma_{1,t-1}^2) \tag{5a}$$

$$\ln(\sigma_{2t}^2) = \omega_2 + \alpha_2 W_{2,t-1} + k_2 W_{1,t-1} + \beta_2 \ln(\sigma_{2,t-1}^2), \tag{5b}$$

$$W_{it} = |z_{it}| - E[|z_{it}|] + \delta_i z_{it}, \quad z_{it} = \varepsilon_{it}/\sigma_{it}, \; i = 1 \text{ or } 2 \tag{6}$$

$$E[|z_{it}|] = \sqrt{2/\pi}[\Gamma(\nu - 1)/2]\Gamma(\nu/2) \tag{7}$$

$$\sigma_{12,t} = (\rho_0 + \rho_1 HV_{t-1})\sigma_{1t}\sigma_{2t} \tag{8}$$

where Ψ_{t-1} is the information set at $t-1$. Eqs. (4) to (8) are jointly estimated by maximizing the log-likelihood function with the BHHH algorithm:

$$L(\mathrm{K}) = \sum_{t=1}^{T} \ln\{l_t(\mathrm{K})\} \tag{9}$$

where

$$l_t(\mathrm{K}) = \frac{\Gamma[(2+\nu)/2]}{\Gamma(\nu/2)[\pi(\nu-2)]} |\Omega_t|^{-1/2} [1 + \frac{1}{\nu-2} \varepsilon_t' \Omega_t^{-1} \varepsilon_t]^{-(1+\nu/2)} \tag{10}$$

and K is the parameter vector of the model.[2]

The coefficients of particular interest are k_1 and k_2 in Equation (5) that describe volatility spillover between the two markets. Specifically, k_1 describes volatility spillovers from the U.S. stock market (SP) to the carry trade market (CT) while k_2 reflects volatility spillovers from the carry trade

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[2]Estimating the VAR and the EGARCH models in two steps is asymptotically equivalent to a joint estimation of the two models because the OLS estimators used in the VAR are unbiased and consistent in the presence of GARCH effects. See, e.g., Lin, Engle, and Ito (1994).

market to the U.S. stock market. The coefficients of α_i and β_i depict the market-specific volatility autocorrelations.

To account for excess kurtosis, the residual errors follow a conditional Student-*t* distribution with *v* degrees of freedom (Bollerslev, 1987). Susmel and Engle (1994), Tse (1998), and others, point out the importance of using *t*-distribution for more efficient estimation than normal distribution. Asymmetric volatility is captured by the δ_i coefficients in (6). A negative δ_i indicates that negative return shocks or bad news will increase volatility more than positive return shocks or good news.

The coefficient ρ_o in (8) represents the constant conditional correlation between markets. The coefficient ρ_1 describes the observations that financial markets are more correlated in periods of high volatility (Longin and Solnik, 1995). HV_{t-1} is a dummy variable that equals one if the estimated conditional variance of SP, σ_{2t}^2, is greater than its (exogenous) unconditional variance and 0 otherwise. Accordingly, ρ_o and ρ_1 should both be positive.

Note that the conditional volatility processes are estimated using only information observable at time $t-1$. More specifically, both endogenous variables of the carry trade and stock returns are treated symmetrically by including for each variable a volatility equation explaining its evolution based on the lags of its own and the other variable. In contrast, Christiansen, Ranaldo, and Söderlind (2010) model stock and bond returns as exogenous risk factors. Accordingly, they examine the exposure of carry trades to the *current* and *lagged* stock and bond returns. They find that the exposure to stock returns is larger during volatile periods with one third of the carry trade return being explained by the risk factors and two thirds by the market volatility factor.

Empirical Results on the S&P 500 Index

The return causality between carry trades and U.S. stocks using unsigned lagged returns and signed lagged returns are reported in Tables II and III, respectively. Both restriction tests in the two tables show that the carry trade and U.S. stock returns do not have a significant lead-lag impact on each other. Nor are own-market lagged returns capable of predicting current returns in both markets. The results using 5 lags in the VAR model are qualitatively the same as using 10 lags. Adding a dummy variable (to allow the tendency of stocks to produce lower returns on Mondays than other days of the week) that equals one for Mondays and days after holidays, and zero otherwise, does not change the results either. Therefore, carry trade returns cannot predict future stock returns, and vice versa. While linear return causality does not exist in either direction, nonlinear models for complex dynamics warrant future research.

Panel A of Table IV reports that the volatility spillover coefficients between CT and SP, k_1 = 0.023 (t-stat. = 2.84) and $k_2 = -0.005$ (t-stat.=−0.42). Results using CT1 in Pane B are similar: k_1 = 0.026 (t-stat. = 2.82) and k_2 = 0.000 (t-stat.= 0.03). This indicates that significant volatility spillover flows from the stock market to the carry trade market, while no significant volatility spillover flows from the other direction. Based on the logics of Engle, Ito, Lin (1990) and Lin, Engle, and Ito (1994), when information flows from the stock market to the carry trade market, investors with heterogeneous interpretations on the information revise their prior beliefs and start trading.[3] Financial integration has also made different markets more prone to the spillover effects (e.g., Baele, 2005; Bekaert, Harvey, and Ng, 2005; Baele and Inghelbrecht 2010). Brunnermeier and

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[3]Hogan and Melvin (1994) report that the volatility spillovers in foreign exchange markets are related to the degree of heterogeneity of expectations about the U.S. trade balance announcement.

Pedersen (2009) and Longstaff (2010) offer an alternative explanation to the information channel that the spillovers can be propagated through liquidity and risk-premium channels.

As expected, the coefficients of α and β are positive and significant in both markets. Two additional results are given by the volatility equations. First, both δ_1 and δ_2 are significantly negative, −0.196 (*t*-stat.=−2.77) and −0.952 (*t*-stat.=−6.52), showing that there exists asymmetric volatility in both the carry trade and U.S. stock markets. Negative information (bad news that results in a negative return) leads to more volatility than positive information (good news) does. Secondly, ρ_o and ρ_1 of the conditional correlation coefficients are 0.223 (*t*-stat.=10.78) and 0.184 (*t*-stat.=5.82), respectively, indicating a higher correlation during periods of high market volatility.[4] The diagnostic checks (available upon request) of the EGARCH model on the standardized residuals, $z_{it} = \varepsilon_{it}/\sigma_{it}$ show that the residuals and the squared residuals are both generally unautocorrelated. The estimated model, therefore, reasonably fits the data.

In summary, the mean causality results provide evidence that returns in neither market predict future returns in the other. However, there is significant volatility spillover from the U.S. stock market to the carry trade market, but not in the reverse direction. This suggests that new information disseminates in the stock market first, and then spills over to the carry trade market. The spillover results can also be explained by the fact that the volatilities of both carry trades and stocks are driven by the same factors and these factors are more closely associated with the stock

[4]Some previous studies (e.g., Ang and Chen, 2002) suggest that financial markets are also more correlated during downside moves. Like Longin and Solnik (1995), adding a dummy variable that equals one if the stock return shock is negative does not change our results and the dummy variable is not significant.

innovations.[5] Moreover, the stock market may be more sensitive to market illiquidity and funding constraints than the carry trade market. The empirical results also show that asymmetric volatility exists in both markets. Specifically, bad news induces more volatility than good news in both the carry trade and U.S. stock markets.

In recent years, carry trades have become so prevalent that the market has created tradable benchmarks for them. One readily available carry trade index, DBV, is an exchange-traded fund traded on the NYSE Arca, an all-electronic U.S. trading platform. DBV tracks the changes of the Deutsche Bank PowerShares DB G10 Currency Harvest Index. This currency index is designed to reflect the returns from investing in long currency futures for the three highest-yielding currencies and in short currency futures for the three lowest-yielding currencies out of the G10 currencies. The PowerShares currency fund began trading on September 18, 2006. See *PowerShares DB G10 Currency Harvest Fund, Prospectus,* Deutsche Bank (2009), for detailed descriptions. The DBV index fund invests in liquid nearby futures contracts trading on the Chicago Mercantile Exchange (CME). The DBV and other ETF data used in the following section are collected from Bloomberg.

The relationship between DBV and SP is examined starting from October of 2006, the first entire trading month of DBV. The results are summarized as follows. The DBV and SP returns are highly correlated with a coefficient of 0.698, but causality does not exist in either direction.[6] The

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[5]See the volatility spillovers from large firms to small firms reported in Conrad, Gultekin, and Kaul (1991).

[6]The Johansen test statistics indicate that the closing prices of DBV and SP are not cointegrated. The sector ETF prices used in the next section are not cointegrated with the carry trade portfolios either. Cointegration and correlation are different statistical concepts (Baillie et al., 2002). The high correlation suggests that the two markets move together because of correlated information, while non-cointegration indicates that the error correction process does not exist between the two prices.

volatility spillovers from SP to DBV are significant with the volatility-spillover coefficient k_1=0.100 (t=4.30); the spillovers from DBV to SP represented by k_2 are insignificant. The results are similar if the carry trade portfolios, CT and CT1, are used: k_1 = 0.087 (t=3.91) for CT and k_1 = 0.086 (t=3.12) for CT1, and k_2 is insignificant for both portfolios. Therefore, the significant results of the one-directional volatility spillovers from the stock market to the carry trade market are similar whether the DBV fund or the carry trade portfolios are used. The results also show that these spillovers spanning a period of the recent financial crisis are more significant than the results of the entire sample.

Empirical Results on S&P 500 Sectors

Are the significant volatility spillovers to the carry trade market derived from the cyclical or non-cyclical sectors? Examining this issue provides more insights on the dynamics between the carry trade and U.S. stock markets. The S&P classifies stocks into nine sectors and Sector SPDRs are the ETFs of the sector indexes: materials (ticker symbol, XLB), energy (XLE), financial (XLF), industrial (XLI), technology (XLK), consumer staples (XLP), utilities (XLU), health care (XLV), and consumer discretionary (XLY). The first trading day of the Sector SPDRs is December 22, 1998; thus, the following sectoral analysis starts from January 1999. All the sector ETFs are traded on the NYSE Arca.

Table V shows that the nine sectors have very different volatilities measured by standard deviations, ranging from 1.07 (consumer staples) to 2.23 (financial). Nevertheless, all the sectors are highly correlated with carry trades with a narrower range of 0.333 (health care) to 0.476 (energy). Results of the S&P index futures returns (with a standard deviation of 1.38 and a correlation of 0.509) are also included for comparison purpose. Like the S&P 500 index, all the sectors do not Granger-cause the returns on carry trades, and no causality exists in the reverse direction. Results are not reported but are available on request.

Results of the volatility spillovers based on the bivariate EGARCH model are summarized in Table VI. All the sectors significantly volatility-spillover to the carry trade market, except utilities and health care. The results are also broadly consistent with the notion that the cyclical sectors (such as materials and industrial with the highest coefficients $k_1 = 0.053$ and 0.041 and both are significant) have larger impact than non-cyclical sectors (utilities and health care with the smallest and insignificant coefficients $k_1 = 0.021$ and 0.022) on the carry trade market. The coefficient k_1 for the S&P 500 index futures is 0.028, significant, and close to the sectors' median coefficient. Results in the reverse direction are also similar to those of the S&P index. Volatility of carry trade returns does not spill over to any sector. Therefore, carry trade investors should pay more attention to the volatility of cyclical stocks.

The results of the conditional correlations are comparable to the stock index futures results. The constant conditional correlation ρ_o is significantly positive for all sectors. The coefficient that captures the increased correlation because of large volatility, ρ_1, is also positive for all sectors, although it is not significant in technology and health care.

CONCLUSIONS

Although the news media have widely reported that carry trades and stock movements are closely related, little research has explicitly examined the lead-lag relationship between these markets in mean and volatility. This paper investigates this relationship between the carry trade market and the U.S. stock market for the period of January1995 through September 2010. The carry trade portfolios are created by investing in high interest rate currencies while selling low interest rate currencies. The stock market is represented by the S&P 500 Index futures.

The two markets are significantly correlated. Mean causality results indicate that a change in carry trade returns does not have a significant impact on future stock returns, nor are stock returns capable of predicting future carry trade returns. However, the volatility spillover analysis from the EGARCH model provides evidence of significant volatility spillover from stock returns to carry trade returns, but not vice versa. Moreover, both the carry trade and stock markets show asymmetric volatility, which means that negative innovations in either market increase volatility more than positive innovations. The two markets are also more correlated in periods of high volatility.

The results of volatility spillovers suggest that the stock market reflects information before the carry trade market. Nevertheless, these results do not necessarily imply informational inefficiency of carry trades. The results are also consistent with the fact that the volatilities of both carry trades and stocks are driven by the same factors and that these factors are more closely associated with the volatility innovations to stocks. Moreover, the stock market may be more sensitive to illiquidity and funding constraints than the carry trade market. From the analysis of the nine S&P sectors, the significant volatility spillover to the carry trade market is mainly driven by cyclical stocks.

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Table I
Summary Statistics of Daily Returns
January 1995 - September 2010

	ΔCT_t		$\Delta CT1_t$		ΔSP_t	
Panel A: Daily Returns						
	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
Mean	0.026	0.009	0.030	0.055	0.014	0.502
Standard Deviation	0.616		0.997		1.305	
Skewness	−0.573	0.000	−0.724	0.000	−0.067	0.084
Kurtosis (excess)	9.255	0.000	9.318	0.000	9.650	0.000
Panel B: Correlation Coefficients						
ΔCT_t	1.000					
$\Delta CT1_t$	0.796		1.000			
ΔSP_t	0.440		0.347		1.000	

Note. The carry trade portfolios with three currencies in each of the long and short positions are denoted by CT and the portfolios with one currency in each position are denoted by CT1. The S&P index futures contract is denoted by SP. All the returns are close-close daily returns.

Table II
Granger Causality in Returns
January 1995 - September 2010

$$\Delta CT_t = a_1 + \sum_{j=1}^{5} c_{1j}\Delta CT_{t-j} + \sum_{j=1}^{5} f_{1j}\Delta SP_{t-j} + \boldsymbol{\varepsilon}_{1t}$$

$$\Delta SP_t = a_2 + \sum_{j=1}^{5} c_{2j}\Delta CT_{t-j} + \sum_{j=1}^{5} f_{2j}\Delta SP_{t-j} + \boldsymbol{\varepsilon}_{2t}$$

	ΔCT_t		ΔSP_t	
	Statistic	p-value	Statistic	p-value
Panel A: CT				
	$\chi^2(5)$		$\chi^2(5)$	
H_o: $c_{ij} = 0$ for all j	2.73	0.742	6.84	0.232
H_o: $f_{ij} = 0$ for all j	5.73	0.333	9.61	0.087
	t		t	
H_o: $\sum_j c_{ij} = 0$	−1.57	0.117	−1.04	0.297
H_o: $\sum_j f_{ij} = 0$	0.12	0.890	−2.01	0.043
Panel B: CT1				
	$\chi^2(5)$		$\chi^2(5)$	
H_o: $c_{ij} = 0$ for all j	1.19	0.946	3.94	0.557
H_o: $f_{ij} = 0$ for all j	2.11	0.833	10.67	0.058
	t		t	
H_o: $\sum_j c_{ij} = 0$	−0.45	0.655	−1.09	0.274
H_o: $\sum_j f_{ij} = 0$	−0.57	0.568	−2.07	0.038

Note. The coefficients f_{1j} in the first equation describe the causality from the stock market to the carry trade market; c_{2j} in the second equation describe the causality from the carry trade market to the stock market.

Table III
Granger Causality in Positive and Negative Returns
January 1995 - September 2010

$$\Delta CT_t = a_1 + \sum_{j=1}^{5} c_{1j}\max[0,\ \Delta CT_{t-j}] + \sum_{j=1}^{5} d_{1j}\min[0,\ \Delta CT_{t-j}] + \sum_{j=1}^{5} f_{1j}\max[0,\ \Delta SP_{t-j}] + \sum_{j=1}^{5} g_{1j}\min[0,\ \Delta SP_{t-j}] + \varepsilon_{1t}$$

$$\Delta SP_t = a_2 + \sum_{j=1}^{5} c_{2j}\max[0,\ \Delta CT_{t-j}] + \sum_{j=1}^{5} d_{2j}\min[0,\ \Delta CT_{t-j}] + \sum_{j=1}^{5} f_{2j}\max[0,\ \Delta SP_{t-j}] + \sum_{j=1}^{5} g_{2j}\min[0,\ \Delta SP_{t-j}] + \varepsilon_{2t}$$

	ΔCT_t		ΔSP_t	
	Statistic	*p*-value	Statistic	*p*-value
Panel A: CT				
	$\chi^2(5)$		$\chi^2(5)$	
H_o: $c_{ij} = 0$ for all j	6.93	0.226	11.01	0.052
H_o: $d_{ij} = 0$ for all j	2.46	0.782	3.30	0.653
H_o: $f_{ij} = 0$ for all j	4.22	0.518	5.57	0.350
H_o: $g_{ij} = 0$ for all j	2.13	0.831	6.13	0.294
	t		t	
H_o: $\sum_j c_{ij} = 0$	−1.78	0.075	−1.28	0.198
H_o: $\sum_j d_{ij} = 0$	−0.82	0.410	−0.37	0.708
H_o: $\sum_j f_{ij} = 0$	−0.36	0.722	−1.14	0.254
H_o: $\sum_j g_{ij} = 0$	0.46	0.643	−1.82	0.069
Panel B: CT1				
	$\chi^2(5)$		$\chi^2(5)$	
H_o: $c_{ij} = 0$ for all j	2.08	0.838	7.55	0.183
H_o: $d_{ij} = 0$ for all j	1.34	0.930	4.34	0.502
H_o: $f_{ij} = 0$ for all j	7.37	0.194	3.93	0.559
H_o: $g_{ij} = 0$ for all j	6.39	0.270	7.85	0.164
	t		t	
H_o: $\sum_j c_{ij} = 0$	−0.58	0.561	−1.67	0.094
H_o: $\sum_j d_{ij} = 0$	−0.46	0.642	−0.51	0.610
H_o: $\sum_j f_{ij} = 0$	−1.34	0.180	−1.15	0.250
H_o: $\sum_j g_{ij} = 0$	0.60	0.549	−1.84	0.066

Note. The VAR model is modified by separating the effects of lagged positive and negative returns. The coefficients f_{1j} and g_{1j} in the first equation describe the causality from the positive and negative stock returns, respectively, to the carry trade returns; c_{2j} and d_{2j} in the second equation describe the causality in the reverse direction.

Table IV
Volatility Spillovers: Estimation of Bivariate EGARCH-*t* Model
January 1995 - September 2010

$$\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})' | \Psi_{t-1} \sim Student\text{-}t(0, \Omega_t, \nu), \quad \Omega_t = \begin{pmatrix} \sigma_{1t}^2 & \sigma_{12,t} \\ \sigma_{12,t} & \sigma_{2t}^2 \end{pmatrix}$$

$$\ln(\sigma_{1t}^2) = \omega_1 + \alpha_1 W_{1,t-1} + k_1 W_{2,t-1} + \beta_1 \ln(\sigma_{1,t-1}^2)$$

$$\ln(\sigma_{2t}^2) = \omega_2 + \alpha_2 W_{2,t-1} + k_2 W_{1,t-1} + \beta_2 \ln(\sigma_{2,t-1}^2),$$

$$W_{it} = |z_{it}| - E[|z_{it}|] + \delta_i z_{it}, \quad z_{it} = \varepsilon_{it}/\sigma_{it}, \; i = 1 \text{ or } 2$$

$$E[|z_{it}|] = \sqrt{2/\pi}[\Gamma(\nu-1)/2]\Gamma(\nu/2)$$

$$\sigma_{12,t} = (\rho_0 + \rho_1 HV_{t-1})\sigma_{1t}\sigma_{2t}$$

	ΔCT_t				ΔSP_t	
	Coef	*t*-stat			Coef	*t*-stat
Panel A: CT						
ω	−0.084**	−7.50			−0.031**	−5.02
α	0.143**	8.57			0.118**	7.85
β	0.975**	223.44			0.979**	381.80
δ	−0.196**	−2.77			−0.952**	−6.52
k	0.023**	2.84			−0.005	−0.42
			Coef	*t*-stat		
ρ_o			0.223**	10.78		
ρ_1			0.184**	5.82		
ν			7.533**	12.84		
Panel B: CT1						
ω	−0.070**	−7.73			−0.034**	−5.05
α	0.166**	9.30			0.123**	7.62
β	0.963**	158.83			0.977**	344.53
δ	−0.275**	−3.81			−0.942**	−6.33
k	0.026**	2.82			0.000	0.03
			Coef	*t*-stat		
ρ_o			0.136**	6.25		
ρ_1			0.142**	4.08		
ν			7.479**	13.21		

Note. The coefficients of particular interests are k_1 and k_2 in the conditional variance equations. k_1 describes volatility spillovers from the U.S. stock market to the carry trade market while k_2 reflects volatility spillovers from the carry trade market to the U.S. stock market. Asymmetric volatility is captured by the δ_i coefficients. The coefficient ρ_1 describes the observations that financial markets are more correlated in periods of high volatility. HV_{t-1} is a dummy variable that equals one if the estimated conditional variance of SP is greater than its unconditional variance and 0 otherwise. *significant at the 5% level. **significant at the 1% level.

Table V
Sector Indexes
January 1999 - September 2010

Sector	Ticker Symbol	Standard Deviation	Correlation with	
			CT	CT1
Materials	XLB	1.71	0.468	0.390
Energy	XLE	1.91	0.476	0.409
Financial	XLF	2.23	0.445	0.390
Industrial	XLI	1.47	0.464	0.378
Technology	XLK	1.91	0.350	0.255
Consumer Staples	XLP	1.07	0.339	0.298
Utilities	XLU	1.34	0.379	0.319
Health Care	XLV	1.25	0.333	0.269
Consumer Discretionary	XLY	1.61	0.422	0.344
S&P 500	SP	1.38	0.509	0.417

Note. The S&P classifies stocks into nine sectors and Sector SPDRs are the exchange-traded funds of the sector indexes. The first trading day of the Sector SPDRs is December 22, 1998.

Table VI
Summary Results of Volatility Spillovers: Sector Indexes
January 1999 - September 2010

	Volatility Spillover Coefficients				Conditional Correlation Coefficients			
	k_1		k_2		ρ_o		ρ_1	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Panel A: CT								
Materials	0.053**	3.68	0.005	0.34	0.224**	9.29	0.242**	6.94
Energy	0.040**	2.91	−0.008	−0.51	0.241**	10.71	0.220**	6.22
Financial	0.036**	3.33	0.017	1.29	0.223**	9.80	0.192**	4.88
Industrial	0.041**	3.44	−0.005	−0.34	0.238**	9.71	0.177**	4.94
Technology	0.023*	2.10	−0.011	−0.86	0.288**	12.54	0.042	1.06
Consumer Staples	0.024*	2.42	0.003	0.25	0.190**	7.69	0.087**	2.22
Utilities	0.021	1.60	0.017	0.99	0.193**	8.22	0.127**	3.13
Health Care	0.022	1.93	−0.015	−1.04	0.230**	9.73	0.011	0.27
Consumer Discret.	0.032**	3.32	−0.012	−1.07	0.229**	9.30	0.124**	3.40
S&P 500	0.028**	3.26	−0.007	−0.50	0.274**	11.90	0.177**	5.12
Panel B: CT1								
Materials	0.060**	3.96	0.015	1.03	0.141**	5.63	0.242**	6.36
Energy	0.040**	2.60	−0.009	−0.63	0.206**	9.03	0.172**	4.61
Financial	0.039**	3.42	0.017	1.27	0.103**	4.30	0.293**	7.22
Industrial	0.045**	3.51	−0.004	−0.25	0.140**	5.51	0.207**	5.37
Technology	0.021	1.73	−0.002	−0.18	0.225**	9.39	0.158**	3.83
Consumer Staples	0.020	1.94	0.008	0.69	0.157**	6.15	0.053	1.30
Utilities	0.022*	2.22	−0.001	−0.04	0.156**	6.49	0.074	1.76
Health Care	0.027*	2.16	−0.015	−1.08	0.190**	7.78	−0.056	−1.29
Consumer Discret.	0.028**	2.56	−0.001	−0.16	0.118**	4.54	0.151**	3.88
S&P 500	0.028**	3.09	−0.008	−0.58	0.177**	7.26	0.157**	4.13

Note. The table summarizes the results of the volatility spillovers based on the bivariate EGARCH model. *significant at the 5% level. **significant at the 1% level.