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Commodity Prices and Currency Rates: An Intraday Analysis

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Abstract: We investigate the intraday relationship between two important pairs of commodities and currencies: gold/Australian dollar and oil/Canadian dollar. Gold (oil) and the Australian dollar (Canadian dollar) prices have been highly correlated over a long time period as widely reported by the news media. Using transactions data of exchange-traded funds from January 2008 to December 2009, we do not find evidence of Granger causal relations between commodity and currency asset returns. However, we find bi-directional volatility spillovers, indicating that there is information flow between markets. Thus, our results are consistent with market efficiency during short horizons such that information is efficiently incorporated into asset prices in both markets.

JEL Classification: G13, G14
Keywords: Commodity prices, Currency rates.

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1. Introduction

The Australian and Canadian dollars are among the most actively traded currencies in the foreign exchange market. As of April 2010, the Australian and Canadian dollar accounted for approximately 7.6% and 5.3%, respectively, and ranked 5th and 7th, respectively, in global foreign exchange transactions in terms of percentage shares of average daily turnover (*Triennial Central Bank Survey, 2010*). Australia and Canada are major producers and exporters of gold and oil, respectively, and their currencies exhibit a strong cross-market correlation with their corresponding commodity products. During the period 2005 to 2009, the Australian dollar was highly correlated with the price of gold (0.778), whereas the Canadian dollar had an even higher correlation with an OPEC-defined oil index (0.855; *Investors Chronicle, 2009*). By the end of 2010, the correlation between the Canadian dollar and the New York Mercantile Exchange (NYMEX) WTICrude Oil contract reached historically high levels, revealing trading opportunities to investors (*DailyFX, 2010*).

In this paper, we examine whether there are lead-lag relationships between gold and the Australian dollar as well as between oil and the Canadian dollar at intraday frequencies. Our research question is interesting for two reasons. First, the long-term correlations between gold (oil) prices and the Australian dollar (Canadian dollar) have been observed by the public and are widely reported. However, unless one asset can predict the future price of the other asset, no profit will be obtained. Thus, investigating whether potential lead-lag relationships exist is meaningful for practitioners and could aid them in making profitable investment decisions. Second, previous research has not explored the relationships between gold (oil) prices and the Australian dollar (Canadian dollar) using high frequency data. In an efficient market, any arbitrage opportunity disappears quickly. Thus, our paper contributes to the literature by further investigating commodity/currency relationships by focusing on two specific cross-asset pairs at intraday frequencies.

Australia was the third largest and is now, by far, the world's second largest gold producer as South Africa experienced a continuing decline in gold production (*BusinessDay, 2010*). Canada is among the world's top oil producers and is now the largest country to export crude oil to the U.S. (*EIA, 2010*). When an economy is closely tied with the price of its major commodity exports, its currency is known as commodity currency. Commodity currencies benefit when commodity prices rise and deteriorate as commodity prices fall. Both the Australian and Canadian dollars are commodity currencies given that, in the long run, the currencies' prices move together with the world price of gold and oil, respectively. If, at a certain time horizon, commodity prices lead the currency prices (or vice versa), substantial profits would exist for those investors who exploit such information.

Although gold (oil) and the Australian dollar (Canadian dollar) have been moving in lockstep for years, it is not clear which asset, if any, plays the leading role. For example, in the first half of 2008, oil temporarily steps ahead of the Canadian dollar (*Sweet, 2010*). Gold (oil) prices may lead the Australian dollar (Canadian dollar) because fluctuations in the commodity prices have a significant impact on the country's terms of trade, which, in turn, lead to fluctuations in that country's currency. It has also been found that gold serves as a hedge against exchange rate fluctuations (Capie, Mills and Wood, 2005). In the academic literature, exchange rate/commodity price co-movement is typically attributed to the close link between exchange rates and macroeconomic fundamentals (e.g., interest rates, money supplies, and output).

Previous studies that examine the fundamentals-to-exchange rate relationship often employ low frequency data (Chen (2004) and Chen, Rogoff, and Rossi (2010) use quarterly data and Chan, Tse, and Williams (2010) use daily data). For example, Chen et al. find that exchange rates forecast commodity prices using quarterly data. However, the leading role of exchange rates is questioned because the commodity forward markets studied by Chen et al. are not necessarily informationally efficient. Using daily futures data, Chan et al. find no causality in either direction between the commodity and currency markets.

In this study, we extend the prior literature by examining the commodity/currency relationships between gold (oil) and the Australian dollar (Canadian dollar) at intraday frequencies and between assets that are listed on the same exchange. Investigating the cross-asset lead-lag relationships using high frequency data is meaningful. As modeled in the milestone work by Kyle (1985), private information is gradually incorporated into asset prices through informed trades. With the development of globalization and improvement in the efficiency of financial markets, any temporary deviation from market efficiency could vanish during short horizons. High frequency data are necessary to describe these fast dynamics. In later sections, we explore the in-sample lead-lag relationships between gold (oil) and the Australian dollar (Canadian dollar) in returns and cross-market volatility spillover. The generalized variance decomposition and impulse response results provide additional evidence about the interaction between commodity and currency markets. Furthermore, the improvement in forecasting accuracy after adding a cross asset to the autoregressive model is examined.

The two commodity/currency pairs (gold vs. Australian dollar, crude oil vs. Canadian dollar) are proxied by four exchange-traded funds (ETF), GLD vs. FXA and USO vs. FXC, respectively, all of which trade on the NYSE Arca. We use ETF data for several reasons. First, using ETFs that are trading on the same platform (NYSE Arca) enables us to explore the commodity/currency relationships within the same institutional environment. Second, ETFs have recently undergone rapid growth and have gained popularity among investors. ETFs enjoy liquid and reasonably efficient conditions compared with other investment options. ETFs, therefore, are relatively more accessible to a wider pool of investors than the futures markets. Third, ETFs closely track the underlying assets and can be considered a cost-effective proxy compared with other investment tools.

Using 15-minute intervals, we find that commodity/currency relationships exist contemporaneously but we do not find evidence of a Granger causal relationship in returns between gold (oil) and the Australian dollar (Canadian dollar). Only about 7-8% of the forecast error variance in one commodity (currency) asset is due to the shocks to the corresponding currency (commodity) asset from the other market, whereas the impact of one-unit shock to commodity (currency) asset on its corresponding currency (commodity) asset quickly disappears within an hour. The results are robust to the non-synchronous trading problem. However, significant volatility spillover is found at both directions, indicating the existence of inter-market information flows.

The overall results support market efficiency at intraday horizons. We continue in Section 2 with a brief review of the prior research related to commodity/currency relationships. Section 3 describes the data. Section 4 introduces the methodology of testing the in-sample lead-lag relation and out-of-sample forecast accuracy. Section 5 presents the empirical results and the robustness checking when the non-synchronous trading problem is eliminated. Section 6 concludes.

2. Background

The predictability of exchange rates from fundamentals has been extensively investigated in the literature, usually by applying various exchange rate models. Earlier literature focuses on exchange rate determination based on fundamental-based structural models. Meese and Rogoff (1983) compare the out-of-sample forecasting accuracy of various competing exchange rate models and find that the random walk model performs no worse than the other structural or time series models in the out-of-sample fit. Since then, whether exchange rates are predictable by macroeconomic fundamentals remains a puzzle and induces extensive debates.

Cheung, Chinn, and Pascual (2005) make a comprehensive comparison similar to Meese and Rogoff (1983). Cheung et al. compare the out-of-sample forecasting fit of the structural models proposed in the 1990s with the random walk model, and their results indicate that some structural models outperform the random walk model at long forecast horizons (e.g., 20 quarters). However, in their findings, there is no specific model that can consistently outperform all other competing models. Engle and West (2005) explain the exchange rate puzzle by applying a rational expectations present-value model. The asset price dynamics are found to be dominated by a random walk process as the discount factor approaches one.

Chen (2004) examines empirical exchange rate models by augmenting a fundamental based model where commodity prices are exogenous shocks. Chen finds that the commodity-augmented model largely enhances the in-sample causality of exchange rates but that out-of-sample forecasts results are more varied. Chen, Rogoff, and Rossi (2010) use quarterly commodity and currency forward data and find that exchange rates have robust forecasting power for commodity prices. Chen et al. suggest that exchange rates possess forward-looking economic information and, thus, lead the commodity prices.

However, the commodity forward contracts used in Chen et al.'s paper are not sufficiently liquid and, therefore, may not be informationally efficient. Evidence of this lack is provided in Chan, Tse, and Williams (2010) who apply highly efficient daily futures data to investigate lead-lag commodity/currency relationships. Chan et al. fail to find such relationships even at daily frequencies, which casts doubt on the possibility of commodity/currency relationships in equally liquid and efficient markets.

According to the findings of Chan et al. (2010), there is no evidence of cross-market inefficiency at daily levels given the fact that no causal relationships are found. However, whether such lead-lag relationships exist at intraday frequencies remains unexplored. Our paper provides further evidence on this issue by focusing on the gold (oil) and the Australian dollar (Canadian dollar) relationships at intraday frequencies. We provide evidence for market efficiency at short horizons by examining the return causality and volatility spillover between gold (oil) and the Australian dollar (Canadian dollar).

3. Data

Our data originate from the Trade and Quote (TAQ) database and span January

2008 to December 2009. The following ETFs all trade on NYSE Arca, and are used as proxies for the four commodity and currency assets; CurrencyShares Australian Dollar (Ticker symbol: FXA) as a proxy for the Australian dollar, CurrencyShares Canadian Dollar (FXC) as a proxy for the Canadian dollar, SPDR Gold Shares (GLD) as a proxy for gold, and the United States Oil Fund (USO) as a proxy for crude oil. All trading times are constrained to NYSE trading hours (9:30 a.m. to 4:00 p.m. EST).

CurrencyShares Australian Dollar (Ticker Symbol: FXA) and CurrencyShares Canadian Dollar (Ticker Symbol: FXC) are exchange traded funds that track the price of their corresponding currencies with the value expressed in terms of the USD. Both ETFs began trading on June 2006. The value of FXA (FXC) is based on the WM/Reuters Closing Spot at 4:00 p.m. London time each day when NYSE Arca is open for regular trading (*Prospectus, CurrencyShares Australian Dollar, CurrencyShares Canadian Dollar*).

SPDR Gold Shares (Ticker Symbol: GLD) is an ETF that tracks gold prices. Its initial pricing is based on the price of 1/10 of an ounce of gold. Each day when the NYSE Arca is open, the value of GLD is determined based on the gold price at the earlier time of 4:00 p.m. London time [1] or 12:00 p.m. EST. The gold market is most active when the trading at major OTC markets around the world (e.g., London and New York) coincides with the trading of gold futures and options on Commodity Exchange, Inc. (COMEX), which lasts for approximately four hours each New York business day (*prospectus, SPDR Gold Shares*). The other commodity ETF, United States Oil Fund (Ticker Symbol: USO), tracks the movements of light sweet crude oil. The value of the USO reflects changes in the spot price of sweet crude oil traded on the NYMEX (*prospectus, United States Oil Fund*).

In Figure 1, we plot the daily closing prices of the proxies for the two currency-commodity pairs. Over the two-year period from January 2008 to December 2009, the closing prices of FXA (FXC) and GLD (USO) mimic the pattern of each other very well.

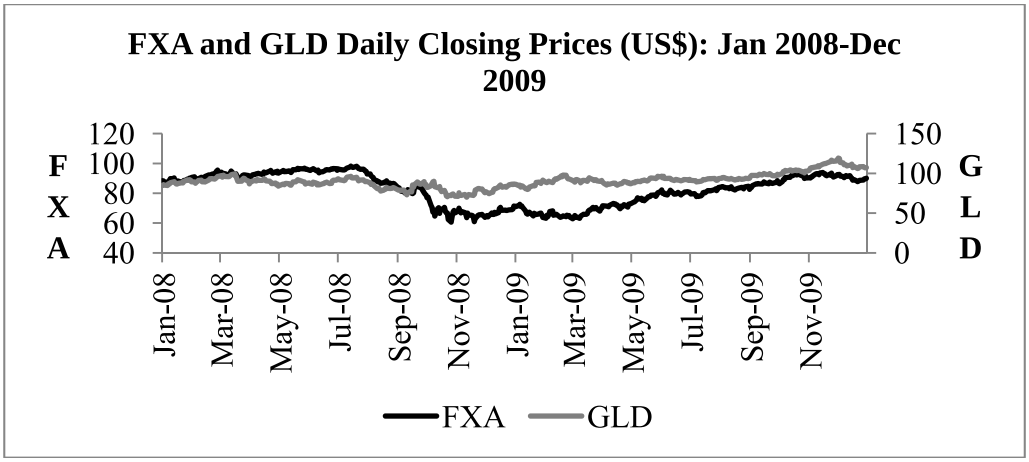
Although the four ETFs are all listed on the NYSE, they are traded in other platforms, including NASDAQ and American Stock Exchange (AMEX). The largest number of trades and trading volume take place at the NYSE Arca (about 40%) for

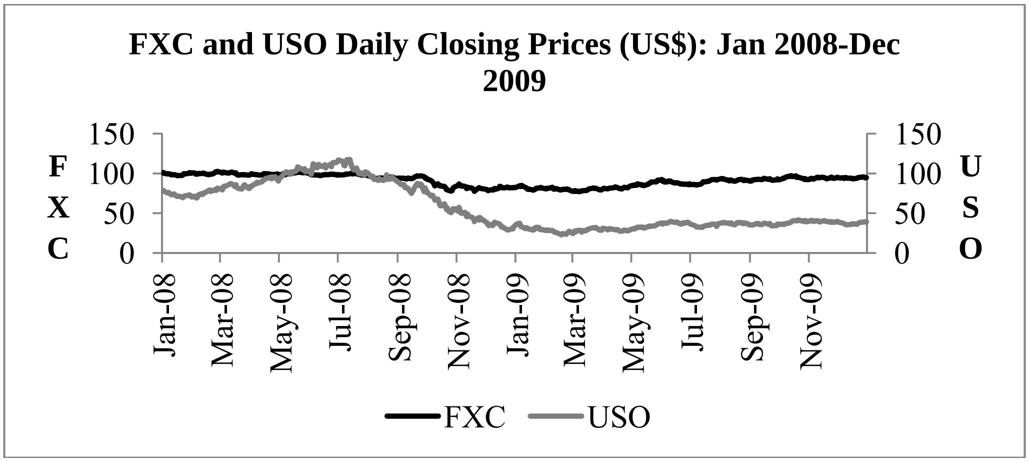
[1] The reference gold prices for a trading day are fixed twice daily during London trading hours. The gold fix starts at 10:30 a.m. and 3:00 p.m. London time. GLD is priced based on the 4:00 p.m. London fix.

each ETF, except USO (about 30%).

Figure 1

This figure plots the daily closing prices in US$ of four ETFs: FXA (proxy for Australian dollar), FXC (proxy for Canadian dollar), GLD (proxy for gold), USO (proxy for crude oil).





Intraday data are partitioned into 15-minute intervals to ensure that all securities have trades at most intervals (more than 95%). Returns for trades at each interval are calculated as the log difference between the current interval's closing price and the previous interval's closing price. Returns on the first interval are calculated as the log difference between the closing and opening prices of that interval. Commodity ETFs (GLD and USO) are more actively traded than currency ETFs (FXA and FXC) in the sample period. During January 2008 to December 2009, the daily trading volumes of these four ETFs are: GLD (15,066,093), USO (15,094,676), FXA (174,373), and

FXC (130,931). To purge the problem of non-synchronous trading, we apply the MINSPAN procedure of Harris et al. (1995) as robustness checking.

4. Methodology

In light of the findings of Chan, Tse, and Williams (2010), we examine both the in-sample Granger causality and the one-step-ahead rolling out-of-sample forecasts between commodity and currency ETFs. In particular, we focus on the intraday lead-lag relationships in returns and volatility spillover effect between GLD (USO) and FXA (FXC), which are proxies for the two cross-asset pairs: gold vs. the Australian dollar and oil vs. the Canadian dollar. Supplementary to the Granger causality tests, we examine the economic significance by forecast error variance decomposition and impulse response functions analyses.

4.1 Granger Causality in Returns and Volatility Spillovers

We use a VAR model to explore whether there is Granger causality from GLD (USO) to FXA (FXC), or vice versa. The causality relationships between commodity and currency returns are examined in the following system:

$$Cur_t = \alpha_1 + \sum_{k=1}^{4} \beta_{1k} Cur_{t-k} + \sum_{k=1}^{4} \gamma_{1k} Com_{t-k} + \varepsilon_{1t} \tag{1a}$$

$$Com_t = \alpha_2 + \sum_{k=1}^{4} \beta_{2k} Com_{t-k} + \sum_{k=1}^{4} \gamma_{2k} Cur_{t-k} + \varepsilon_{2t} \tag{1b}$$

We capture the cross-asset dynamics within a one hour period with four lags of 15-minute returns. The results are qualitatively the same if eight lags are used. In the model, Com_t and Cur_t are the 15-minute returns for commodity and currency ETFs, respectively, at time *t*. The own autoregressive components are included in equation (1) to control the explanatory power from past returns of the dependent variable. As in our sample, the commodity ETFs are GLD and USO, and the currency ETFs are FXA and FXC, respectively. Coefficients β_{1k} and β_{2k} measure the impact of an asset's return from the past hour on its current return at time *t*. Coefficients γ_{1k} and γ_{2k} measure the impact of the past returns of the cross asset. To determine whether there is Granger causality between GLD (USO) and FXA (FXC), we test the significance of cross-asset coefficients ($\gamma_{1k}$and γ_{2k}) under the following null hypothesis:

$$H_{0,a}: \ \gamma_k = 0$$

$$H_{0,b}: \ \sum_{k=1}^{4} \gamma_k = 0$$

The first null hypothesis, $H_{0,a}$, posits that all of the cross-asset coefficients are jointly equal to zero, while the second null hypothesis, $H_{0,b}$, assumes that the sum of all of the cross-asset coefficients is equal to zero.

The above VAR model is estimated using OLS with the Newey-West heteroskedasticity and autocorrelation consistent covariance matrix. The residual terms from equation (1), $\varepsilon_{1t}$and ε_{2t}, are used to examine the volatility spillover effects between currency and commodity markets. Nelson (1991) proposed the EGARCH model which considers the asymmetric volatility of asset returns. Based on Nelson's work, later empirical studies apply multivariate EGARCH models to investigate cross market volatility transmission system (e.g, Koutmos and Booth (1995) and Tse (1999)).

Following prior studies, we apply a bivairate EGARCH(1,1)-t model to examine the volatility spillover mechanism. Let Ψt−1 be the information set at $t-1$, σ_{1t}^2 and σ_{2t}^2 the conditional variance. Suppose that the residual terms, $\varepsilon_{1t}$and ε_{2t}, follow a conditional Student-t distribution with v degrees of freedom. The model is specified as:

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

$$\ln(\sigma_{1t}^2) = \omega_1 + \alpha_1 W_{1,t-1} + k_1 W_{2,t-1} + \beta_1 \ln(\sigma_{1,t-1}^2) \tag{3a}$$

$$\ln(\sigma_{2t}^2) = \omega_2 + \alpha_2 W_{2,t-1} + k_2 W_{1,t-1} + \beta_2 \ln\left(\sigma_{2,t-1}^2\right), \tag{3b}$$

$$W_{it} = |z_{it}| - E[|z_{it}|] + \delta_i z_{it}, \quad z_{it} = \varepsilon_{it}/\sigma_{it} \ , i = 1 \ or \ 2 \tag{4}$$

$$E[|z_{it}|] = \sqrt{2/\pi}\left[\Gamma(v-1)/2\right]\Gamma(v/2) \tag{5}$$

$$\sigma_{12,t} = \rho_0 \sigma_{1t} \sigma_{2t} \tag{6}$$

Equations (2) to (6) are jointly estimated by maximizing the log-likelihood function with the BHHH algorithm:

$$L(K) = \sum_{t=1}^{T} \ln\{l_t(K)\} \tag{7}$$

where

$$l_t(K) = \frac{\Gamma[(2+v)/2]}{\Gamma(v/2)[\pi(v-2)]}|\Omega_t|^{-1/2}[1+\frac{1}{v-2}\varepsilon_t'\Omega_t^{-1}\varepsilon_t]^{-(1+v/2)} \quad (8)$$

and K is the parameter vector of the model.

Coefficients k_1 and k_2 in equation (3) describe the volatility spillover between the currency and commodity markets. In particular, k_1 describes volatility spillover from GLD (USO) to FXA (FXC), while k_2 describes the volatility spillover from FXA (FXC) to GLD (USO).In the same equation, the coefficient of $\alpha_1(\alpha_2)$ and $\beta_1(\beta_2)$ reflects the market-specific volatility autocorrelations. The asymmetric volatility is captured by coefficient δ_i in equation (4). A negative $\delta_i$indicates the existence of asymmetric volatility in the corresponding market, that is, bad news (negative returns) has larger impact on volatility than good news (positive returns). The coefficient of ρ_0 in equation (6) describes the constant conditional correlation between commodity and currency markets.

4.2 Innovation Accounting Analysis

As noted in Sims (1980), VAR systems such as equation (1) tend to suffer from oscillating estimated coefficients on the successive lag terms. Thus, the economic interpretation based on such non-smooth coefficients tends to be misleading. Such problems can be avoided by transforming the VAR system to a vector moving average (VMA) system.

Suppose the matrix form of our VAR system is expressed as:

$$X_t = C + \sum_{k=1}^{4} \Phi_k X_{t-k} + \varepsilon_t$$

Through recursive substitution, the VMA representation is obtained as:

$$X_t = \mu + \sum_{k=0}^{\infty} A_k e_{t-k}$$

In the VMA model, the return matrix (X_t) is expressed in terms of current and past period shocks (e_{t-k}). In the moving average representation, the estimated coefficients associated with residual terms are smooth and can be used to trace the time paths of the asset return’s responses to the innovations in the system.

As long as the coefficients on cross-asset terms in the VAR are non-zero, the traditional impulse response functions vary with different orderings. The generalized impulse response method proposed by Pesaran and Shin (1998), however, is unique and immune to the ordering of variables in the VAR system. The variance decomposition of the forecast error can also be derived based on the generalized impulse response functions. In later sections, we apply the generalized method to examine the forecast error variance decomposition and the system's responses to asset returns shock.

4.3 Out-of-sample Forecast Accuracy

Based on the in-sample Granger causality test and the innovation accounting analysis, we further explore whether including cross-asset returns will improve the out-of-sample forecast accuracy of a single-asset autoregressive (benchmark) model. The forecasting accuracy of the cross-asset augmented model and an autoregressive (benchmark) model are compared as follows.

Cross-asset forecasting in returns from commodity to currency:

$$Cur_t = \alpha_1 + \sum_{k=1}^{4} \beta_{1k} Cur_{t-k} + \sum_{k=1}^{4} \gamma_{1k} Com_{t-k} + \varepsilon_{1t} \tag{1a}$$

$$Cur_t = a_1 + \sum_{k=1}^{4} b_{1k} Cur_{t-k} + \epsilon_{1,t} \tag{9a}$$

Cross-asset forecasting in returns from currency to commodity:

$$Com_t = \alpha_2 + \sum_{k=1}^{4} \beta_{2k} Com_{t-k} + \sum_{k=1}^{4} \gamma_{2k} Cur_{t-k} + \varepsilon_{2t} \tag{1b}$$

$$Com_t = a_2 + \sum_{k=1}^{4} b_{2k} Com_{t-k} + \epsilon_{2t} \tag{9b}$$

Equation (1) is the cross-asset augmented model, while equation (9) is the benchmark (autoregressive) model. The forecasting accuracy between equations (1) and (9) is compared by applying a one-step-ahead rolling out of sample forecasting approach. Based on an initial estimation with the first half of the sample data, a one-step-ahead, out-of-sample forecast is computed. The forecasting process continues with a moving sample window. The root mean square error (RMSE), which is used to measure the forecasting accuracy of each model, is calculated based on the forecast results. We then use the percentage difference of the RMSE between equations (1) and (9) to determine whether forecasting accuracy in the benchmark model has been improved by including the past returns from a cross asset. The percentage difference of the RMSE is calculated as:

$$\frac{RMSE_{(1a)} - RMSE_{(9a)}}{RMSE_{(9a)}} \quad and \quad \frac{RMSE_{(1b)} - RMSE_{(9b)}}{RMSE_{(9b)}}$$

As indicated by the formula, the percentage difference of the RMSE describes the increase in forecasting error (or the decrease in forecasting accuracy) of the benchmark model after including a cross asset. If the number is negative, then the cross-asset augmented model provides superior forecasts compared to the original benchmark model.

5. Empirical Results

5.1 Correlations

Table 1 reports the autocorrelation and the cross-correlation of the four ETFs (FXA, FXC, GLD, and USO) at 15-minute intervals. We include four lags to capture the dynamics within an hour. Panel A in Table 1 reports the autocorrelation coefficients. The correlation between each ETF and its own lagged returns from lag one to lag four are reported. Except for the crude oil ETF (USO), all other ETFs are significantly auto-correlated at lag one with low magnitude. USO does not exhibit any significant autocorrelation during a one hour period. For the currency ETFs (FXA and FXC), the current period returns are also significantly correlated with the returns at lag four.

Panel B reports the contemporaneous correlation and the cross-asset correlations in returns from different periods. GLD (USO) and FXA (FXC) are significantly and contemporaneously correlated at approximately 0.2 to 0.3. Moreover, the lagged returns of GLD (USO) are significantly correlated with the current returns of FXA (FXC). However, no such relation is found in the reverse direction. The significant cross-correlation between currency ETF returns and lagged commodity ETF returns seems to indicate a potential lead-lag relation between these two asset pairs. The magnitude of these correlation coefficients, however, is relatively low (less than 0.1) for both pairs.

Table 1
Autocorrelation and Cross Correlation at 15-minute Intervals

The table reports Pearson correlation coefficients of autocorrelation and cross-correlation for each ETF (FXA, FXC, GLD, USO) at 15-minute intervals for the period January 2008 to December 2009. **significant at the 1% level.

Panel A. Autocorrelation $\rho(CUR_t, CUR_{t-k}), \rho(COM_t, COM_{t-k})$

Lag(k)	FXA	FXC	GLD	USO
1	-0.0467**	-0.0630**	-0.0428**	0.0048
2	-0.0046	0.0105	0.0401**	0.0055
3	-0.0081	0.0012	0.0124	-0.0033
4	-0.0278**	0.0235**	0.0148	-0.0045

Panel B. Cross Correlation $\rho(CUR_t, COM_{t-k})$

Lag(k)	$\rho(FXA_t, GLD_{t-k})$	$\rho(FXC_t, USO_{t-k})$
-4	0.0146	0.0108
-3	-0.0099	0.0087
-2	0.0010	0.0045
-1	0.0052	0.0037
0	0.2586**	0.2815**
1	0.0584**	0.0684**
2	0.0111	0.0482**
3	0.0261**	0.0053
4	0.0080	0.0085

5.2 Variance Ratios

Variance ratios provide greater insight into the source of the volatility in asset returns. Daytime returns (R_D_t) are defined as the log difference between the closing and opening prices on day t, and overnight returns (R_N_t) are estimated as the log difference between the opening price on day t and the closing price on day $t-1$.

$$R\_D_t = \log(Close_t) - \log(Open_t)$$

$$R\_N_t = \log(Open_t) - \log(Close_{t-1})$$

The daytime to overnight variance ratios are calculated as the ratio of daytime return variance divided by overnight return variance and are reported in Table 2. We apply Bartlett's test for homogenous variance to check the null hypothesis that daytime variance is not different from overnight variance. When the variance ratio is significantly greater than one, there are more innovations during the day than overnight, and vice versa.

Table 2
Variance Ratios

The table reports the daytime to overnight variance ratios (VR) and the test statistics of Bartlett's test of homogeneous variances (χ^2) for the sample period January 2008 to December 2009. Daily and overnight average returns are calculated as:
$R\_D_t = \log(Close_t) - \log\,(Open_t)$,$R\_N_t = \log(Open_t) - \log\,(Close_{t-1})$
*significant at the 5% level.

	VR	χ^2
FXA	0.653	19.99*
FXC	1.009	0.01
GLD	1.349	9.59*
USO	1.615	24.20*
SPY	2.508	85.42*

During the non-trading hours of the U.S. market, the innovations such as macroeconomic news and interest rate changes are active in the Australia market. Thus, the variance ratio of FXA is significantly lower than one (VR=0.653). In contrast, Canada has overlapping trading hours when the U.S. market is open and, thus, has more innovation during the daytime compared with the FXA. As reported in Table 2, the variance ratio of the FXC is close to one (VR=1.009). The variance ratio of commodity ETFs, GLD and USO, are both significantly greater than one (i.e., 1.349 and 1.615, respectively), indicating that the variance in commodity assets returns are largely influenced by innovation generated during the trading hours of the U.S. market. For comparison, the SPDR S&P 500 (SPY) has a variance ratio of 2.508, indicating that the U.S. stock market is much more volatile during the day than overnight.

Information is more likely to be generated during the open hours of the market (French and Roll (1986)). Fleming, Kirby, and Ostdiek (2006) examine the trading to non-trading period variance ratios in weather-sensitive markets where the public information flow evolves around the clock. They found that the variance ratio in weather-sensitive markets lies between the variance ratio in the stock market and the variance ratio in the currency market. In the foreign exchange markets, exchange rates are found to exhibit significant responses to news released during business hours. For example, the announcement of U.S. macroeconomic news has significant effect on the returns and the volatility of the dollar-Mark and dollar-Yen exchange rates during the short term (Pearce and Solakoglu, 2007). The volatility of DEM/$ responses symmetrically to the macroeconomic news announcements from Germany and the U.S. (Chang and Taylor, 2003). Consistent with previous research, the variance ratios of the ETFs in our sample indicate that more information is generated when the market is open, and the release of public information has a significant impact on the volatility of corresponding assets. Moreover, the daytime volatility of commodity ETFs is reinforced by the information flow from the futures market during the overlapping trading hours when the COMEX and the NYMEX are open during the day.

5.3 Granger Causality in Returns and Volatility Spillovers

Panel A of Table 3 reports the p-values of coefficient restriction tests of Granger causality in returns between two currency/commodity ETF pairs, FXA vs. GLD and FXC vs. USO. The sum of estimated cross-asset coefficients is also reported. Including open and close dummy variables for the first and the last 30-minute of each trading day in the VAR models does not change the results qualitatively.

Table 3
Granger Causality in Returns

The table reports the p-values and estimated coefficients from the following test:
Granger causality in returns:

$$Cur_t = \alpha_1 + \sum_{k=1}^{4} \beta_{1k} Cur_{t-k} + \sum_{k=1}^{4} \gamma_{1k} Com_{t-k} + \varepsilon_{1t} \quad (1a)$$

$$Com_t = \alpha_2 + \sum_{k=1}^{4} \beta_{2k} Com_{t-k} + \sum_{k=1}^{4} \gamma_{2k} Cur_{t-k} + \varepsilon_{2t} \quad (1b)$$

Hypothesis testing:

$$H_{0,a}: \ \gamma_k = 0 \quad H_{0,b}: \ \sum_{k=1}^{4} \gamma_k = 0$$

	p-value		*Coefficients*
	$H_{0,a}$	$H_{0,b}$	$\sum_{k=1}^{4} \gamma_k$
Panel A. 15-minute Intervals			
GLD causes FXA	0.000	0.000	0.115
FXA causes GLD	0.322	0.910	-0.005
USO causes FXC	0.000	0.000	0.047
FXC causes USO	0.661	0.185	0.124
Panel B. MINSPAN			
GLD causes FXA	0.000	0.000	0.090
FXA causes GLD	0.025	0.002	0.036
USO causes FXC	0.000	0.000	0.034
FXC causes USO	0.048	0.157	0.046

The null hypotheses, $H_{0,a}$ and $H_{0,b}$, are rejected at 1% for commodity augmented currency models, while the currency augmented commodity models have insignificant p-values for both tests. In addition to the statistical significance as indicated by the p-values, the sum of the coefficients ($\sum_{k=1}^{4} \gamma_k$) describe the magnitude of the economic impact from the cross asset. For the first cross-market asset pair (FXA and GLD), the impact from the lagged returns of GLD is greater than the reverse situation. The second pair (FXC and USO), however, indicates a larger economic impact of FXCs lagged returns on USO, which is inconsistent with the statistical implications from the p-values. Thus, the p-values and the estimated coefficients do not provide a conclusive result for the inter-market causality in returns for the asset pair USO and FXC.

To check whether the above results are affected by the non-synchronous trading problem, we employ the MINSPAN procedure initiated by Harris et al. (1995). The main logic of MINSPAN is to find the trade pairs that have the minimum time span among the price series. Booth, Lin, Martikainen and Tse (2002) use the MINSPAN approach to match the prices from a downstairs market with prices from an upstairs market. In particular, for any price in the second market, they search forward and backward in the first market to find matched prices and retain the one that occurs the closest in time to the second market's trade. We find the matched prices from the commodity market to form pairs with the prices from the currency market. Trade pairs are formed sequentially until all of the prices in the currency market have been matched with a minimum time span price from the commodity market.

The number of matched trade pairs is 153,754 for (GLD, FXA) and 132,000 for (USO, FXC). The average time span between the commodity and currency price is approximately 2 seconds. The percentage of times when each security arrives earlier is very close. For example, for the pair (FXA, GLD), the probability that either price arrives early is approximately 20%. Thus, the security price pairs obtained by the MINSPAN procedure can be considered free from the non-synchronous trading problem.

The log return series from the MINSPAN procedure are then obtained and used to test for Granger causality across assets. As reported in Panel B of Table 3, after controlling for non-synchronous trading between commodity and currency, we find similar results in the causality relation for return series.

The test results of volatility spillovers based on the bivariate EGARCH-t model are reported in Table 4. The main finding is that there is bidirectional volatility spillover between commodity and currency markets. For both asset pairs, k_1 and k_2 are significant at 1% level, showing that innovations in GLD (USO) spill over to FXA (FXC), and vice versa. The existence of bi-directional spillovers indicates information flow between the commodity and the currency ETFs. The market-specific volatility autocorrelations, as represented by the coefficients of α_i and β_i are significantly positive in both the currency and commodity markets. Additionally, all four of these ETFs exhibit asymmetric volatility, as shown by the negative $\delta_i's$, although the coefficients on GLD and FXC are not statistically significant. Even though volatility spills from one asset to the other, the direction of price movement is still unknown. The significant results of volatility spillovers, therefore, do not necessarily refute market efficiency.

Table 4
Volatility Spillovers: 15-minute Intervals

The table reports the estimation results of the following bivariate EGARCH-*t* Model:

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

$$\ln(\sigma_{1t}^2) = \omega_1 + \alpha_1 W_{1,t-1} + k_1 W_{2,t-1} + \beta_1 \ln(\sigma_{1,t-1}^2) \qquad (3a)$$

$$\ln(\sigma_{2t}^2) = \omega_2 + \alpha_2 W_{2,t-1} + k_2 W_{1,t-1} + \beta_2 \ln\left(\sigma_{2,t-1}^2\right), \qquad (3b)$$

$$W_{it} = |z_{it}| - E[|z_{it}|] + \delta_i z_{it}, \quad z_{it} = \varepsilon_{it}/\sigma_{it}, \; i = 1 \; or \; 2 \qquad (4)$$

$$E[|z_{it}|] = \sqrt{2/\pi}\left[\Gamma(v-1)/2\right]\Gamma(v/2) \qquad (5)$$

$$\sigma_{12,t} = \rho_0 \sigma_{1t} \sigma_{2t} \qquad (6)$$

wherek_1 (k_2) describes the volatility spillover from commodity (currency) to currency (commodity). $\delta_i$describes asymmetric volatility.**significant at the 1% level.

	Currency		Commodity	
	Coef	*t*-stat	Coef	*t*-stat
Panel A: FXA vs. GLD				
ω	-0.018**	-4.99	-0.024**	-5.83
α	0.095**	17.78	0.115**	17.56
β	0.997**	1853.39	0.995**	1159.94
δ	-0.141**	-3.38	-0.012	-0.31
k	0.051**	8.11	0.038**	6.08
	Coef		*t*-stat	
ρ_0	0.334**		36.34	
ν	4.351**		37.34	
Panel B: FXC vs. USO				
ω	-0.015**	-4.32	-0.006**	-3.03
α	0.081**	13.62	0.047**	10.34
β	0.997**	1590.50	0.999**	2645.12
δ	-0.050	-1.02	-0.216**	-3.37
k	0.020**	3.78	0.032**	6.57
	Coef		*t*-stat	
ρ_0	0.297**		30.34	
ν	4.338**		33.18	

5.4 Innovation Accounting Analysis

The economic interpretation based on the Granger causality test could be misleading because the estimated coefficients on lag terms tend to be non-smooth (Sims, 1980). A better way to describe the economic interrelationships between asset returns is to analyze variance decomposition, which depicts the magnitude of forecast errors in one asset that can be explained by its corresponding cross asset. The impulse response functions, which represent the response of the system to one standard deviation unit shock, track the persistence of the impact of the innovations from one asset on all of the assets in the system. We apply the generalized impulse response technique proposed by Pesaran and Shin (1998) in the following analysis.

The generalized forecast error variance decomposition of four assets is reported in Table 5. By design, the decomposition numbers from the generalized method add up to more than 100%. Thus, for interpretation purposes, the numbers reported in Table 5 are normalized to a 100% scale. The associated plots of the generalized variance decomposition and the impulse response functions are reported in Figures 2 and 3, respectively.

Table 5
Generalized Variance Decompositions

The table reports the generalized forecast error variance decomposition at ten period horizons. Each entry represents the percentage of forecast error variance of the asset explained by innovations in itself and another asset. Numbers are normalized to a 100% scale.

Market Explained	By Innovations in		Market Explained	By Innovations in	
	FXA	GLD		FXC	USO
FXA	93.19%	6.81%	FXC	92.00%	8.00%
	FXA	GLD		FXC	USO
GLD	6.47%	93.53%	USO	7.45%	92.55%

The variance decomposition in forecast error measures the proportion of an asset's forecast uncertainty that can be explained by its own shock and by the shock to the other asset in the system. For the FXC and USO return pair, forecast errors due to the shocks to cross asset are at a minor and comparable level (7% to 8%). Even for the FXA and GLD return pair, where we previously found a commodity to currency causality with the Granger causality test, only a small proportion (fewer than 7%) of the forecast errors can be explained by each other. Thus, cross assets play a minor role in explaining the forecast error variance.

Figure 2
Generalized Variance Decompositions

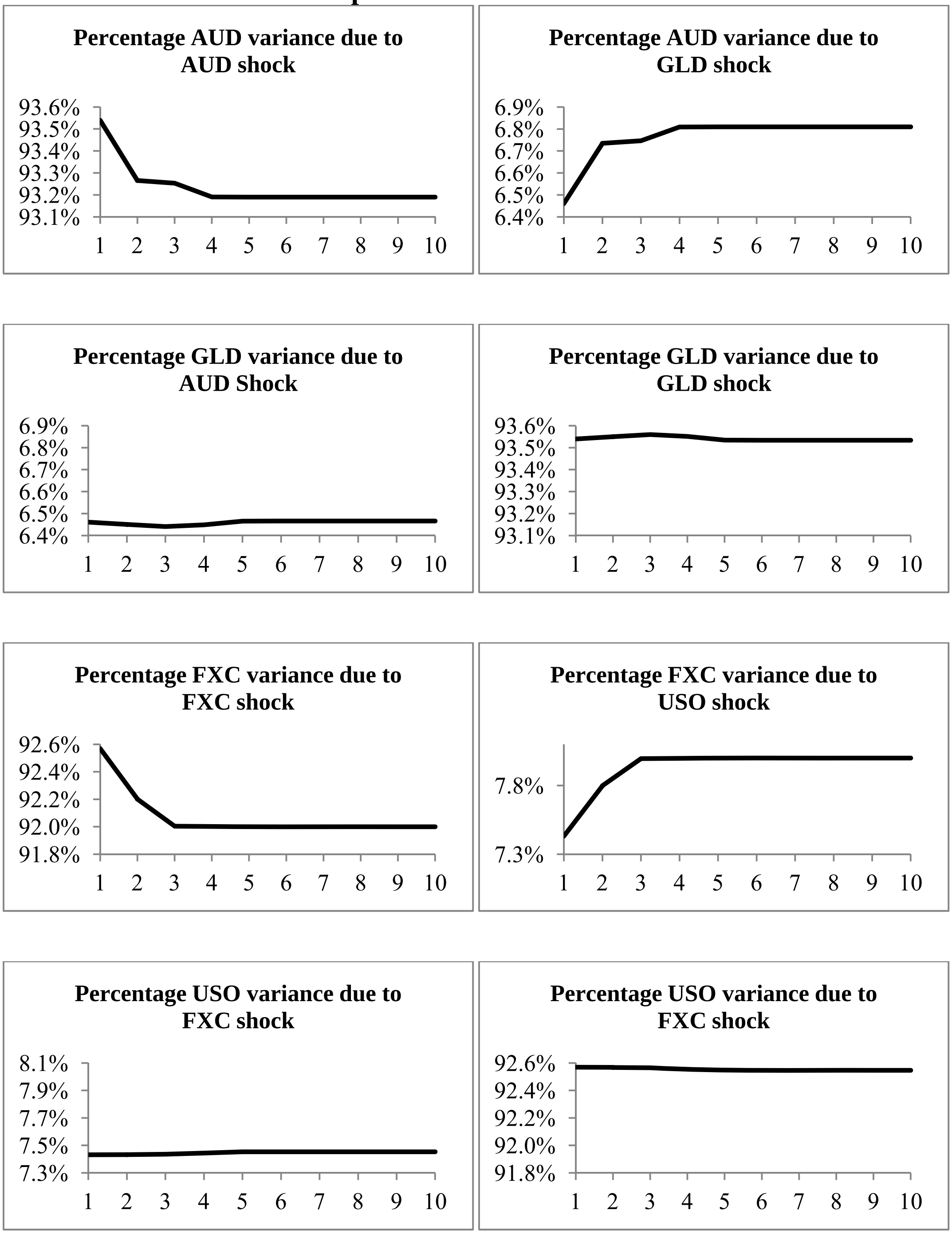
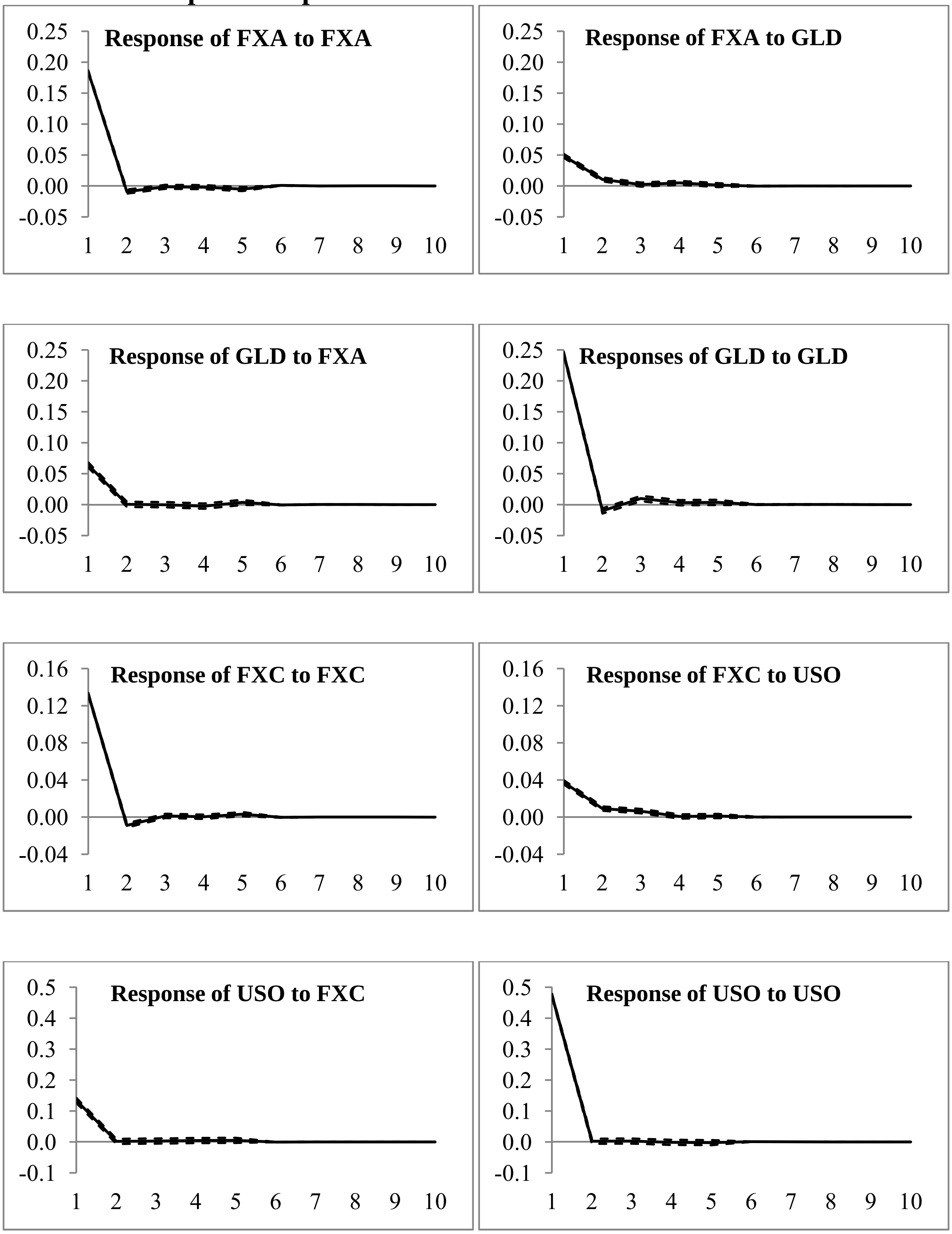


Figure 3
Generalized Impulse Response Functions



While variance decomposition shows the magnitude of the impact of asset shocks, the impulse response function depicts the persistence of such impact. As shown in Figure 3, for both asset pairs, the impact only exists during short periods that is within 30 minutes for the FXA and GLD pair and no more than 45 minutes for the FXC and USO pair, indicating that the system restores itself quickly.

Taken together, the results of generalized variance decompositions and impulse response functions provide supplementary and intuitive information about the interrelationship between economic variables in addition to the Granger causality test. Not only do the shocks to an asset in one market not significantly explain the forecast error variance of the cross asset in the other market, but the IRF analysis also indicates that such minor impact is very short-lived. Thus, the Granger causality test and the innovation accounting analysis lead us to the conclusion that there is virtually no causal relationship in asset returns between GLD (USO) and FXA (FXC).

5.5 Out-of-Sample Forecasts

To investigate whether cross-asset returns can help better forecast an asset's future returns, we compare the out-of-sample forecast accuracy between a cross-asset augmented model and a single-asset autoregressive model. The percentage difference in RMSE is extremely small in magnitude in all cases. In particular, it is positive (i.e., 0.16% for the FXA and Gold pair, and 0.46% for the FXC and USO pair) when we augment the commodity autoregressive model with currency returns, while it is negative (i.e., -0.05% for the FXA and GLD pair, and -0.55% for the FXC and USO pair) when the currency model is augmented with commodity returns. Given the fact that the most negative number is -0.55%, the improvement in the forecasting power of the benchmark model by including a cross asset is not economically significant. Thus, the past performance of the GLD (USO) does not help investors to reach a better out-of-sample prediction of FXA (FXC), and vice versa.

In summary, the insignificant RMSE improvement for return model indicates that investors cannot predict future movement of currency assets (commodity assets) any better when the prediction is based on the previous performance of commodity assets (currency assets).

6. Conclusion

Commodity/currency movements between gold and the Australian dollar as well as those between crude oil and the Canadian dollar are widely reported in the media. In particular, the Australian dollar (Canadian dollar) is highly correlated with gold (oil) prices over long periods. Because Australia and Canada are major producers and exporters of gold and oil, respectively, the Australian and Canadian dollars are vulnerable to fluctuations of world commodity prices. Although investors are often advised to pay close attention to these cross-asset movements, no prior research has provided empirical evidence of a lead-lag relationship between these commodity/currency pairs on short time horizons. In this paper, we examine the lead-lag relationships between gold (oil) and the Australian dollar (Canadian dollar) using high frequency data, and we find evidence of cross-market efficiency at the intraday level. Thus, our study provides important information for practitioners when forming their trading strategies.

We use four ETFs (FXA, FXC, GLD, and USO), all of which trade on the NYSE Arca, to proxy for the Australian dollar, the Canadian dollar, gold, and oil prices. Our intraday sample spans from January 2008 to December 2009 and is divided into 15-minute intervals. For the pair (FXC, USO), there is no conclusive result from the Granger causality test in asset returns given the inconsistent statistical and economic significance. Further exploring the economic interrelations across assets using the generalized variance decompositions and impulse response technique confirms that there is no causality in returns from either direction for both asset pairs. In particular, less than 10% in the forecast error variance in one asset can be explained by the shock to its corresponding cross asset, and the impact on asset returns of such shocks disappears quickly within a short time horizon. Our results are not biased by the non-synchronous trading problem.

By contrast, significant volatility spillovers between currency and commodity ETFs are found at both directions, indicating the existence of information flows across markets. The overall results may indicate a strong informational linkage between commodity and currency ETFs with significant volatility spillovers but no causality in returns. In addition, we do not find forecasting power between the currency and the commodity ETF markets in both directions.

Despite the prior literature and media recommendations, the lack of causality in returns and the insignificant forecasting improvement imply that gold-Australian and oil-Canadian relationships are not economically exploitable. Thus, commodity/currency linear forecasting models used in this study do not have practical value for most investors. On a more general level, our findings provide additional evidence that, in terms of cross-asset causality, the market is still efficient even at intraday frequencies, wherein information is efficiently incorporated into both assets.

References

Booth, G.G., Lin, J.-C., Martikainen, T., and Tse, Y., 2002. Trading and pricing in upstairs and downstairs stock markets. *Review of Financial Studies*, 15, 1111-1135.

Capie, F., Mills, T.C., and Wood, G., 2005. Gold as a hedge against the dollar. *Journal of International Financial Markets, Institutions & Money*, 15, 343-352.

Chan, K., Tse, Y., and Williams, M., 2011. The relationship between commodity price and currency exchange rate. Commodity Prices and Markets, *NBER Book Series East Asia Seminar on Economics*, Vol. 20 (ed. Takatoshi Ito and Andrew K. Rose), The University of Chicago Press, March 2011, 47-75.

Chang, Y., and Taylor, S.J., 2003. Information arrivals and intraday exchange rate volatility. *Journal of International Financial Markets, Institutions & Money*, 13, 85-112.

Chen, Y.-C., 2004. Exchange rates and fundamentals: Evidence from commodity economies. Unpublished Working Paper.

Chen, Y.-C., Rogoff, K., and Rossi, B., 2010. Can exchange rates forecast commodity prices? *Quarterly Journal of Economics*, 125, 1145-1194.

Cheung, Y.-W., Chinn, M.D., and Pascual, A.G., 2005. Empirical exchange rate models of the nineties: are any fit to survive? *Journal of International Money and Finance*, 24, 1150-1175.

Engle, C., and West, K.D., 2005. Exchange rates and fundamentals. *Journal of Political Economy*, 113, 485-517.

Fleming, J., Kirby, C., and Ostdiek, B., 2006. Information, trading, and volatility: Evidence from weather-sensitive markets. *Journal of Finance*, 61, 2899-2930.

Forex Correlations: Canadian and Australian Dollar Strongly Linked to Oil, Gold. *DailyFX*, December 2010.

French, K.R., and Roll, R., 1986. Stock return variances: the arrival of information and the reaction of traders, *Journal of Financial Economics*, 17, 5-26.

Harris, F.H., McInish, T.H., Shoesmith, G.L., and Wood, R.A., 1995. Cointegration, error correction, and price discovery on informationally linked security markets. *Journal of Financial and Quantitative Analysis*, 30, 563-579.

Koutmos, G., and Booth, G.G., 1995. Asymmetric volatility transmission in international stock markets. *Journal of International Money and Finance*, 14, 747-762.

Kyle, A.S., 1985. Continuous auctions and insider trading. *Econometrica*, 53, 1315-1336.

Meese, R.A., and Rogoff, K., 1983. Empirical exchange rate models of the seventies: Do they fit out-of-sample? *Journal of International Economics*, 14, 3-24.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 59, 347-370.

October 2010 import highlights: Crude oil and total petroleum imports top 15 countries. *U.S. Energy Information Administration*, December 30, 2010.

Pesaran, H.H., and Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. *Economic Letters*, 58, 17-29.

Pearce, D.K., and Solakoglu, M.N., 2007. Macroeconomic news and exchange rates. *Journal of International Financial Markets, Institutions & Money*, 17, 307-325.

SA slips down gold production rankings. *BusinessDay*, March 15, 2010.

Sims, C.A., 1980. Macroeconomics and Reality. *Econometrica*, 48, 1-47.

Spot the currency link. *Investors Chronicle*, July 3, 2009

Sweet, E., 2010. Oil still driving loonie. *National Post (Canada)*, April 9, 2010.

Triennial Central Bank Survey: Report on global foreign exchange market activity in 2010. *Monetary and Economic Department*, *Bank for International Settlements*, December 2010.

Tse, Y., 1999. Price discovery and volatility spillovers in the DJIA index and futures markets. *Journal of Futures Markets*, 19, 911-930.