The Relationship between Equity and Commodity Markets during the Credit Crisis

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ABSTRACT

This study explores the linkage between equity markets and commodity markets, finding that the stock price indices of Australia, Canada, Chile, New Zealand, and South Africa contain information about future movements in the commodity markets. We also show that these patterns are different before and after the recent financial crisis. In the pre-crisis period, models based on stock price indices do not outperform the benchmark model. However, in the post-crisis period we see that stock price indices help forecast the price changes of the associated commodity markets as well as aggregated commodity price movements.

1. INTRODUCTION

Rising energy prices in recent years have caused heated debates on whether higher commodity and energy prices negatively impact the global economy. Understanding how shocks on equity and commodity markets affect the economy is an important issue for policy makers around the world. Economists treat commodity prices not only as leading indicators for inflation, but also as a major determinant of the global economy. Due to the forward-looking characteristics of commodity prices, several researchers demonstrate the usefulness of them as predictors for future consumer price indices. For example, Blomberg and Harris (1995) show that certain commodity price indices are good predictors of future inflation during the 1970s and early 1980s. Cecchetti, Chu and Steindel (2000) suggest that models incorporating commodity price indices outperform an autoregression model from 1975 to 1998. Moreover, Stock and Watson (2003) find that commodity index-based model increases forecast accuracy for change in the monthly consumer price index relative to the autoregressive benchmark from 1970 to 1984, but the commodity model fails to forecast inflation during 1985 to 1999. Finally, Furlong and Ingenito (1996) find that the ability of the non-oil commodity price index to Granger-cause inflation weakens considerably after 1984.

Changes in commodity prices also influence macroeconomic conditions. Rising prices for energy commodities, such as crude oil, gasoline, and natural gas, are considered particularly worrisome to the development of the global economy. Yoshikawa (1990) suggests that the long-run equilibrium exchange rate depends on the relative price of natural resources (Throop, 1993; Camarero and Tamarit, 2002). Krugman (1983) notes that oil prices can affect the level of exchange rates. Rautava (2004) shows that when the international oil price increases (decreases) by 10%, the level of Russian GDP grows (declines) by 2.2% over the long run.

The predictability of commodity prices is also an important issue for policy makers. In a 2008 speech, Federal Reserve Chairman Ben Bernanke argues that there are inadequate price forecasts based on signals obtained from the commodity futures market, and emphasizes the importance of alternative ways to predict commodity price movements. Therefore, this paper investigates the relationship between equity markets and commodity markets. There are many reasons to consider equity markets as a useful predictor. First, previous research studies suggest that equity markets might provide some useful information for future economic development (e.g. Levine, 1991; Obstefeld, 1994; Bencivenga et al., 1995; Levine and Zervos, 1998). They conclude that as a stock market becomes more liquid, it facilitates productivity growth and further hastens economic growth. It is clear that equity markets affect the wealth and health of economies. When equity markets are falling, wealth diminishes, which then directly influences consumer spending.

Second, as global equity markets have become more integrated, stock prices should provide more information about the future state of the global economy and the demand in commodity markets (Chen, 2014). Kilian and Vega (2011) also find that stock prices tend to respond more fully than oil prices to macroeconomic news announcements. Hence, following this analogy, we expect equity and commodity markets to have some lead-lag relationship. Therefore, a well-functioning stock market promotes a country’s long-run economic growth and the development of its commodity market. Despite the increasing importance of stock markets, empirical works addressing the relationship between stock markets and commodity markets are sparse.

The issue of commodity price prediction has been investigated by Chen, Rogoff and Rossi (2010), Rossi (2012) and Chen (2013). Chen et al. (2010) look at the linkage between the exchange rate of commodity exporters and future commodity prices through the channel of terms of trade. They suggest that commodity currencies, which include the Australian, Canadian, and New Zealand Dollars, South African Rand, and Chilean Peso, contain important information on market expectations. They also show that commodity currencies help predict price movements in the aggregate commodity market for both in-sample and out-of-sample tests. In contrast, Rossi (2012) uses quarterly stock price data from Australia, New Zealand, Canada, Chile and South Africa to forecast country specific and global commodity prices. However, both papers conclude that exchange rates are a better predictor of commodity prices than equity markets. More interestingly, Chen (2013) examines the linkage between equity and commodity markets, showing that oil-sensitive equity price indices have strong power to forecast nominal and real crude oil prices. Chen (2014) further investigates this issue using a broader range of commodities, including base metals, precious metals, and energy and agricultural products. In sum, the predictability of an equity market does not reach conclusive results.

In this paper we use monthly data to examine whether stock price indices in Australia, Canada, New Zealand, South Africa, and Chile[1] offer useful information for commodity price movements. We also explore the relationships between equity, commodity, and exchange rate markets and whether this predictability depends on the aggregate state of the economy. Our results suggest that stock price indices help

[1] We choose these 5 countries due to following reasons. First, they are rich in natural resources and are major exporters of agricultural products such as wheat, wool or logs, minerals such as gold and platinum, and energy in the forms of liquefied natural gas and coal. These products contribute substantially to the 5 countries’ export performance (Chen et al., 2010). Second, based on a Morgan Stanley report, Australia, New Zealand, and Canada are large net commodity exporters as a percentage of their GDP, respectively.

forecast individual and aggregate commodity prices, and that the relationship holds both in-sample and out-of-sample. We also find that some commodity prices Granger-cause stock price indices, but the relationship is not robust out-of-sample.

Our results support some of Rossi's (2012) findings, and we provide some possible reasons to explain the differences between our research and hers. Overall, we show that the exchange rate is not the only factor that can help predict commodity prices, but rather that stock price indices also embody information about future movements of commodity prices. However, the results do not hold if we use stock price indices of commodity importers. In addition, we note that firm-level equity prices also offer information about future commodity price behavior, including country specific and global commodity price indices. We also consider other fundamentals (interest rate, CPI, GDP, inflation rate, and industrial production), with the results indicating that New Zealand's interest rate improves forecastability, but other variables are inconsistent across countries. We further show that data frequency also matters in forecasting. When we use quarterly data, we find that the stock price model does not outperform benchmark models, which is consistent with Rossi's (2012) finding[2]. Therefore, we suggest that higher frequency data might improve forecastability. Finally, we discover that forecastability differs before and after the recent financial crisis. In the pre-crisis period, we find that the stock price-based model fails to outperform the benchmark. However, in the post-crisis period, equity markets show significant predictive power in commodity price movements.

The rest of this article is organized as follows. Section 2 describes the data and methodology used in the empirical analysis. Section 3 presents empirical results. Section 4 concludes.

2. DATA AND METHODOLOGY

We use monthly data for the following countries and time periods: Australia (1982 July to 2013 January), Canada (1980 January to 2013 January), Chile (1996 January to 2013 January), New Zealand (1986 January to 2013 January), and South Africa (2000 January to 2013 January). We extend the sample period in Chen et al. (2010) to 2013 January and find similar results during the credit crisis period. Following Chen et al. (2010), we aggregate the relevant dollar spot prices in the world commodity markets to construct country-specific, export-earnings-weighted commodity price indices (labeled *Cp*). Individual commodity price data are collected from the International Monetary Fund (IMF), Bloomberg, the Bank of Canada, the Reserve

[2] She finds that equity price indices has significant predictive ability relative to benchmark models (autoregressive and random walk) at the two quarter-ahead forecasts, but not at the one quarter-ahead forecast.

Bank of Australia, Government of Chile (Chilean Copper Commission) and the Reserve Bank of New Zealand. For nominal exchange rates (*S*), we extract the end-of-period US dollar rates from the International Monetary Fund and Datastream. We also collect the stock price indices (*Stk*) of Australia, Canada, Chile, New Zealand, and South Africa from the Global Financial Database. We also employ the Dow Jones-AIG Futures and Spot indices to construct forward index as a benchmark to compare the forecastability of our stock-price-based models. Finally, to capture the price movements in the overall aggregate world commodity markets, we use the aggregate commodity price index (Cp^W) from the IMF, which is a world export-earnings-weighted price index for over forty products traded on various exchanges.

Because standard unit root tests (ADF and the Phillips-Perron tests) fail to reject the hypothesis that these series contain unit roots, we analyze the data in first differences. We investigate the dynamic relationship between equity and commodity markets in terms of both Granger causality and out-of-sample forecastability. The in-sample tests take advantage of the full sample size and thus are likely to have higher power in the presence of constant parameters. However, the in-sample test is more likely to detect predictability, which often fails to show out-of-sample success. Because an out-of-sample forecast is more robust to time-variation and misspecification problems, we also use a rolling forecast method to estimate model parameters and generate one-month-ahead forecasts.

The benchmark models we use are random walk and autoregressive models. Table 3 reports the MSE differences among alternative (stock-price-based) and benchmark (autoregressive model, random walk, and exchange-rate-based) models. A negative number (from the difference between the alternative model and the benchmark models) indicates that the alternative model outperforms the benchmark. When the benchmark and alternative models are non-nested, we use Diebold and Mariano's (1995) DM tests of equal MSE to compare these models. A rejection of the null hypothesis implies that additional regressors contain out-of-sample forecastability for the dependent variable. On the other hand, if two sets of models are nested, we use Clark and McCracken's (2001) ENCNEW statistics to test equal MSEs.

3. EMPIRICAL RESULTS

In this section we analyze the dynamic relationship between stock price indices and commodity prices by examining both in-sample and out-of-sample forecastabilities. We first examine whether stock price indices can predict future movements in commodity prices, as a test of the present-value model. We then investigate whether commodity prices can predict stock price indices.

3.1 Can Stock Price Indices Predict Individual Commodity Prices?

We find that our sample's five countries rely heavily on commodity exports and that commodity price fluctuations do affect their overall economy such as GDP, exchange rate, or inflation. It is clear that equity markets affect the wealth and health of economies, which hence directly influence consumer spending. Therefore, we expect the equity and commodity markets to have a lead-lag relationship. In this section we apply in-sample and out-of-sample methods to evaluate whether stock price indices can predict individual commodity price indices. We also compare the predictability of our stock-price-based model with exchange-rate-based models in Chen et al. (2010). The results indicate that both models forecast the price movements of commodity markets quite well.

In-Sample Granger-Causality Tests

The present-value models of exchange rate determination imply that exchange rates must Granger-cause fundamentals, such as commodity prices. Chen et al. (2010) suggest that exchange rates forecast commodity prices very well, but not vice versa. Likewise, we also examine the relationship between stock price indices and commodity prices. We test the hypothesis that $\beta_0 = \beta_1 = 0$ in the following regression:

$$\Delta Cp_{t+1}^{i} = \beta_0 + \beta_{1i}\Delta Stk_t^{i} + \beta_{2i}\Delta Cp_t^{i}. \tag{1}$$

Table 1 reports the results based on the standard Granger-causality regressions for the stock price indices and their corresponding commodity price indices. We take first differences of both the dependent and explanatory variables.

We see that stock price indices Granger-cause commodity prices except for New Zealand and South Africa, whereas we find little evidence that commodity price indices Granger-cause stock price indices. Our results are robust to the inclusion of additional lags based on the Bayesian information criterion (BIC). Test statistics from the Jarque-Bera normality test and Box-Pierce Q test indicate that the model's residuals are white noises. Table 1 also shows that when including additional lags, the result from New Zealand is in favor of Granger-causality from its stock price index to the commodity price index. However, we offer little evidence that commodity price indices Granger-cause stock price indices.

Table 1 Bivariate Granger-Causality Tests

	AUS	CAN	CHI	NZ	SA
Panel A. Granger-Causality Tests					
Stk → Cp	0.01***	0.00***	0.00***	0.35	0.25
Cp → Stk	0.19	0.08*	0.12	0.09*	0.95
Panel B. Granger-Causality Tests Robust to Additional Lags					
Stk → Cp	0.01***	0.00***	0.01***	0.10*	0.25
Cp → Stk	0.19	0.15	0.85	0.59	0.95

Note: The table reports p-values for the Granger-causality test. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively, indicating evidence of Granger causality.

Out-of-Sample Forecasts

In this section we examine whether in-sample Granger causality translates to out-of-sample forecastability using rolling forecast methods. First, we estimate the model $\mathrm{E}t\Delta Cp_{t+1}^{i} = \beta_0 + \beta_1 \Delta Stk_t^{i} + \beta_2 \Delta Cp_t^{i}$, where i = Australia, Canada, New Zealand, Chile, and South Africa, and test for forecast-encompassing relative to an autoregressive (AR) model of order one as well as the random walk benchmark. Second, Chen et al. (2010) show that commodity exchange rates have strong and robust power in predicting world commodity prices (we refer to their model as the CRR model), and therefore we compare whether stock price indices outperform the CRR model. Specifically, the procedures of out-of-sample forecast are as follows. First, we divide all the time series (T) into two parts: in-sample observations (from t = *1* to R) and out-of-sample observations (from $t = R + 1$ to $R + Q$, otherwise, $R + Q = T$). Second, we use the rolling forecast method for the in-sample period ($t = R$) and then calculate the absolute forecasting error (MAE), square root of mean square forecasting error (RMSE), and mean square prediction error (MSE) within the out-of-sample period. We adapt the rolling forecast scheme because it is robust to the presence of time-varying parameters and does not require some explicit assumptions for the data. We use a rolling window, as it adapts more quickly to possible structural changes during our sample period. Third and finally, we compare the prediction performance of benchmark models with various alternative models.

We use MAE, RMSE, and MSE to compare the prediction performance of the benchmark model with that of a series of alternative models. For instance, we denote y as an endogenous variable, and the MAE, RMSE, and MSE of h-step estimators can be denoted as follows:

$$\mathrm{MAE}(y,h) = \frac{\sum_{\mathrm{n}=0}^{\mathrm{N}-1} \left| y_{t+h+n} - \hat{y}_{t+h+n,t+n} \right|}{N}, \tag{2}$$

$$\mathrm{RMSE}(y,h)=\sqrt{\frac{\sum_{\mathrm{n=0}}^{\mathrm{N-1}}(y_{t+h+n}-\hat{y}_{t+h+n,t+n})^2}{N}}, \tag{3}$$

$$\mathrm{MSE}(y,h)=\frac{\sum_{\mathrm{n=0}}^{\mathrm{N-1}}(y_{t+h+n}-\hat{y}_{t+h+n,t+n})^2}{N}. \tag{4}$$

By comparing the prediction performance of the benchmark model with that of various alternative models, we can evaluate whether stock price indices help predict commodity prices. We use a rolling window to measure three sets of forecast errors (MAE, RMSE, and MSE). Specifically, we use half of the total sample size as the size of the rolling windows so as to estimate model parameters and calculate one-month-ahead forecasts as well as forecast errors.

In order to compare the out-of-sample predictability of different models, we also use the ENCNEW statistic (Clark and McCracken, 2001) or DM test (Diebold and Mariano, 1995) to detect the predictability. The total out-of-sample period is Q. We apply two different models (benchmark as well as alternative models) to predict the value under the same time series y_t and obtain the prediction values for each model, $\hat{y}_{1,t}$ and $\hat{y}_{2,t}$, respectively. The forecast error is $e_{j,t}=y_t-\hat{y}_{j,t}$ (j=1, 2). We define the loss function as $g(e_t)=|e_t|$ and the statistics as $d_t=g\left(e_{1,t}\right)-g(e_{2,t})$. As for the null hypothesis, "H0: MSE(1) = MSE(2)" or "H0: The prediction performance is the same between models one and two", we calculate the DM test as follows:

$$\mathrm{DM}=\frac{\bar{d}}{\sqrt{\frac{\hat{\gamma}(0)+2\sum_{\mathrm{j=1}}^{\mathrm{q}}\hat{\gamma}(j)}{Q-1}}},\text{ where } q=Q^{\frac{1}{3}},\bar{d}=\frac{1}{Q}\sum_{\mathrm{t=1}}^{\mathrm{T}}d_t, \tag{5}$$

and where q represents the truncation lag, and $\hat{\gamma}(j)$ is the auto-covariance of $d_{t,j}$. Diebold and Mariano (1995) suggest that the DM statistics are asymptotically close to normal distribution, and the only exception when DM statistics present a non-traditional distribution happens when the out-of-sample period is a finite sample. Therefore, we use Monte Carlo methods to simulate the critical value under the finite sample condition. However, if the benchmark and alternative models are nested (e.g. AR(1) and AR(2) models), Clark and McCracken (2001) note that the test of Diebold and Mariano (1995) does not have a normal distribution. Therefore, they propose the ENCNEW statistic as a new test to evaluate predictability. The ENCNEW statistic (1-step ahead) can be written as:

$$\mathrm{ENCNEW}=Q\times\frac{Q^{-1}\sum_t\left(\hat{e}_{1,t+1}^2-\hat{e}_{1,t+1}\hat{e}_{2,t+1}\right)}{Q^{-1}\sum_t\left(\hat{e}_{2,t+1}^2\right)}. \tag{6}$$

Its limiting distribution is non-standard, and the critical values are provided by Clark and McCracken (2001).

Table 2 Tests for Out-of-Sample Forecasting Ability (Full Sample)

		AUS	CAN	CHI	NZ	SA
Panel A. MSE Differences Between Stock-Price-Based Model and AR (1) Benchmark						
AR (1) Benchmark:	Stk → Cp	-0.0000***	-0.0002***	-0.0005***	0.0000	0.0001
	Cp → Stk	-0.0001**	-0.00001	0.0000	0.0000	0.0002
Panel B. MSE Differences Between Stock-Price-Based Model and RW Benchmark						
RW Benchmark:	Stk → Cp	-0.0003***	-0.0004***	-0.0010***	0.0000	0.0004
	Cp → Stk	0.0001*	-0.0000**	-0.0001***	0.0001	0.0002
Panel C. MSE Differences Between Stock-Price-Based and Exchange-Rate-Based Model						
Exchange-Rate-Based Model:	Stk → Cp	-0.0000***	-0.0003**	-0.0025***	-0.0000	-0.0001

Note: The table reports MSE differences between the stock-price-based model and the benchmark forecasts. Negative values indicate that stock-price-based model forecasts outperform the benchmark. In addition, if two sets of models are nested (Panel A and Panel B), then we use critical values based on Clark and McCracken (2001) tests. If models are non-nested (Panel C), then we use critical values based on Diebold and Mariano (1995). ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

Table 2 shows that stock price indices help forecast commodity prices in the out-of-sample test, except for New Zealand and South Africa. The model of stock price indices outperforms both AR(1) ($\mathrm{E}t\Delta Cp_{t+1}^{i} = \beta_0 + \beta_1 \Delta Cp_t^{i}$, i = Australia, Canada, Chile, New Zealand, and South Africa) and the random walks models ($\mathrm{E}t\Delta Cp_{t+1}^{i} = 0$, i = Australia, Canada, Chile, New Zealand, and South Africa) in forecasting changes of individual commodity prices. To be more specific, we find that the MSE differences are quite significant across Australia, Canada, and Chile. However, the MSE differences of New Zealand and South Africa are not significant. Furthermore, as we compare the exchange rate-based model of Chen et al. (2010), we support their result in which exchange rates have surprisingly robust power in predicting commodity prices. In some cases, we see that the stock-price-based model outperforms the exchange-rate-based model, including for Australia, Canada, and Chile. Therefore, our results suggest that both exchange rate and stock price indices embody information about future movements in the commodity markets. According to the in-sample and out-of-sample tests, we conclude that stock price indices and exchange rates are both forward-looking.

Table 2 indicates that the Granger causality tests find little evidence of commodity price indices Granger-causing stock price indices. In fact, the out-of-sample analyses in Table 2 also show little evidence that stock price indices outperform a random walk and AR(1) model. The previous literature suggests that the spread between long and short interest rates, the change in expected inflation, unexpected inflation, industrial production, and the spread between high- and low-grade bonds should systematically affect stock market returns. Chen et al. (1986) find that these sources of risk are significantly priced, but neither a market portfolio nor aggregate consumption is priced. They also note that oil price risk is not priced in the stock market. In sum, results in this section show that commodity price indices do not play an important role in stock market prediction.

3.2 Can Stock Price Indices Predict Aggregate World Commodity Price Movements?

We find that individual equity prices can improve commodity price forecasts. Therefore, we next consider whether combining the information from all stock price indices can help predict price changes in the aggregate world commodity market. For the world market index, we use the aggregate commodity prices from the IMF (Cp_{t+1}^{W}). We report the results based on the non-fuel commodity index, because it covers a broader set of products and can be traced back to 1980. We show that the forecastability of commodity prices improves by combining multiple stock price indices. Intuitively, one would expect that global commodity prices will be influenced by global shocks, and stock price indices of individual countries depend on country-specific shocks. Therefore, a weighted average of stock price indices should average out some of the countries' specific shocks and enhance predictive power of the aggregate global commodity price. In addition, the global commodity price index is calculated by using a world export-earning weighted measure of 40 products. Our sample's 5 countries are rich in energy and hard or soft commodities, and they are major global exporters of commodities. If the individual stock price index can improve individual commodity price forecastability, then we expect that combining multiple stock price indices will also enhance the forecastability of global commodity prices.

We first examine the in-sample predictability of the world price index and then consider multivariate regressions using the three longest stock price indices series:

$$\mathrm{E}t\Delta Cp_{t+1}^{W} = \alpha_0 + \beta_1 \Delta Stk_t^{AUS} + \beta_2 \Delta Stk_t^{CAN} + \beta_3 \Delta Stk_t^{CHI} + \gamma_1 \Delta Cp_t^{W}. \qquad (7)$$

Panel A in Table 3 shows that the results are consistent with previous findings for a single stock price index. The Granger causality tests indicate that stock price indices have predictive power and that the four stock price indices can jointly predict the aggregate commodity price index. For the out-of-sample forecast, Panel B in Table 3 shows that, after combining the stock price indices of Australia, Canada, and Chile,

Table 3 Stock Prices and the Aggregate Global Commodity Price Index (Full Sample)

Panel A. Multivariate Granger-Causality tests	
0.00***	
Panel B. Out-of-sample forecasting ability (MSE difference test)	
AR (1) benchmark	-0.0002***
Random walk benchmark	-0.0004***
Exchange rate benchmark	-0.0004*
Panel C. Another forecast ability (MSE difference test)	
AR (1) benchmark	-0.0003***
Random walk benchmark	-0.0005***
Exchange Rate benchmark	-0.0009***

Note: The table reports results from tests using the stock price indices of Australia, Canada, and Chile to jointly predict aggregate global commodity prices. Panel A reports p-values, and Panels B and C report the MSE differences between the stock-price-based model and the benchmark forecasts, respectively. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

the stock-price-based model forecasts the world commodity price index significantly better than the benchmark random walk and autoregressive models at the 1% level based on the ENCNEW statistics. We do not include New Zealand's stock price index, because of the following reasons. First, we tend to choose the longest series to preserve a larger sample size. Second, results in Table 2 show that the stock-price-based model of New Zealand does not outperform the benchmark. Third, we also perform Granger-Causality tests for five individual stock price indices and the global commodity price index. The results suggest that, in most of the cases, individual stock price indices tend to Granger-cause commodity prices except for New Zealand.[3] The exchange-rate-based model also outperforms both benchmarks. More surprisingly, our stock-price-based models even outperform the exchange rate-based model. We conclude that the model of stock price indices outperforms the random walk model and an exchange rate-based model. Figure 1 shows that the model of stock price indices tracks the actual world price series quite well even when we extend the sample size to cover the financial crisis period.

[3] We also consider multivariate regressions where country-specific commodity prices are predicted by both the country's equity market as well as its exchange rate. The results show that if we consider the equity market and exchange rate, then the prediction performance outperforms our benchmark. However, the prediction performance does not outperform an individual-equity-based model and exchange-rate-based model.

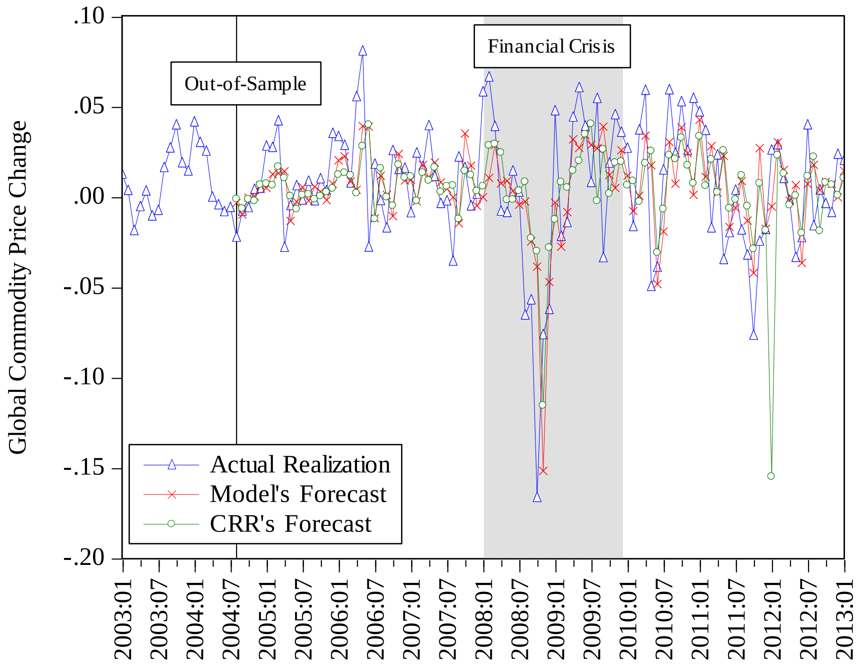

Figure 1 Forecasting the Aggregate Global Commodity Price with Multiple Stock Price Indices and Exchange Rates

We also use an alternative method to examine the predictability of stock price indices. First, we construct an equally weighted commodity index of Australia, Canada, and Chile ($\Delta Cp_{t+1}^{AL} = (\Delta Cp_{t+1}^{AUS} + \Delta Cp_{t+1}^{CAN} + \Delta Cp_{t+1}^{CHI})/3$) to test whether the stock-price-based model can forecast this index better than the benchmark models (AR, RW, and exchange-rate-based model). We use the three stock price indices from Australia, Canada, and Chile to forecast the spot index ΔCp_{t+1}^{AL}, using rolling regressions. Table 3 Panel C indicates that the stock-price-based model outperforms most of the benchmarks. In sum, we find strong evidence that the stock price indices help to forecast individual and aggregate commodity price movements (both in-sample and out-of-sample). In the individual commodity price forecast, the results indicate that our stock-price-based model outperforms the benchmark models except for New Zealand and South Africa. As for the aggregate commodity price forecast, we also show that equity price indices predict price changes for the aggregate world commodity market, supporting our expectation.

For robustness checks, we also investigate whether each individual stock price index series can predict global commodity price movements. This test aims to examine whether there is a strong co-movement between single stock price indices and the global commodity market rather than any combined stock price index forecast. Panel B in Table 4 shows the results for the performance of each single stock price

Table 4 Aggregate Global Commodity Price and Individual Stock Price In-Sample and Out-of-Sample Forecasts

	AUS	CAN	CHI	NZ	SA
Panel A. Granger-causality tests					
Stk GC Cpw	0.00***	0.00***	0.05**	0.42	0.00***
Cpw GC Stk	0.27	0.47	0.11	0.45	0.27
Panel B. Out-of-sample forecasting ability					
AR (1) benchmark					
Stk → Cpw	-0.0001***	-0.0001***	-0.0000**	-0.0000*	-0.0002***
Cpw → Stk	0.0000	0.0000	0.0000	0.0000	0.0002
Random walk benchmark					
Stk → Cpw	-0.0003***	-0.0002***	-0.0003*	-0.0002***	-0.0004***
Cpw → Stk	0.0001	0.0000	-0.0001**	0.0001	0.0002
Exchange rate benchmark					
Stk → Cpw	-0.0001***	-0.0001*	-0.0002	0.0000	-0.0004

Note: The table reports results from tests using individual stock price indices to predict aggregate global commodity prices. Panel A reports p-values, and Panel B reports the MSE differences between the stock-price-based model and the benchmark forecasts. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

index. The findings suggest that most of the cases are robust, and individual stock price indices have strong predictive power for global commodity price changes, except for New Zealand. Surprisingly, for Australia and Canada, the stock-price-based model even outperforms the exchange-rate-based model.

3.3 Forecasting Performance before the Financial Crisis

To evaluate the forecast performance for different sample periods, we compare the stock-price-based model against AR(1), RW, and exchange-rate-based benchmarks, using the out-of-sample forecast model discussed in Section 3. Panels A and B in Table 5 illustrate that, for most of the countries, the stock-price-based model only outperforms the random walk benchmark. We also find that the exchange-rate-based model outperforms most of the benchmarks in Panel C of Table 5. We then use the aggregate commodity price from the IMF (Cp_{t+1}^{W}). As for the out-of-sample forecast, Panel B in Table 6 shows that the stock-price-based model forecasts the world commodity price index significantly better than both benchmarks (AR(1) and RW), but the results show that the stock-price-based model does not outperform the exchange-rate-based model.

Table 5 Tests for Out-of-Sample Forecasting Ability (Before the Crisis)

		AUS	CAN	CHI	NZ	SA
Panel A. MSE Differences Between Stock-Price-Based Model and AR (1) Benchmark						
AR (1) Benchmark:	Stk → Cp	-0.0000***	-0.0000	0.0001	0.0000	0.0001
	Cp → Stk	0.0000	0.0000	0.0001	0.0001	-0.0000
Panel B. MSE Differences Between Stock-Price-Based Model and RW Benchmark						
RW Benchmark:	Stk → Cp	-0.0001***	-0.0000*	0.0003	0.0000	-0.0002**
	Cp → Stk	0.0000**	-0.0000*	-0.0001**	0.0001	-0.0002***
Panel C. MSE Differences Between Stock-Price-Based and Exchange-Rate-Based Model						
Exchange-Rate-Based Model:	Stk → Cp	-0.0000	-0.0001**	0.0001***	0.0001***	0.0001

Note: The table reports MSE differences between the stock-price-based model and the benchmark forecasts. Negative values indicate that stock-price-based model forecasts outperform the benchmark. In addition, if two sets of models are nested (Panels A and B), then we use critical values based on Clark and McCracken (2001). If models are non-nested (Panel C), then we use critical values based on Diebold and Mariano (1995). ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

Table 6 Stock Prices and the Aggregate Global Commodity Price Index (Before the Crisis)

Panel A. Multivariate Granger-Causality tests	
0.04**	
Panel B. Out-of-sample forecasting ability (MSE difference test)	
AR (1) benchmark	-0.0000**
Random walk benchmark	-0.0001**
Exchange rate benchmark	-0.0000
Panel C. Another forecast ability (MSE difference test)	
AR (1) benchmark	-0.0000
Random walk benchmark	-0.0001*
Exchange rate benchmark	-0.0000

Note: The table reports results from tests using the stock price indices of Australia, Canada, and Chile to jointly predict aggregate global commodity prices. Panel A reports p-values, and Panels B and C report the MSE differences between the stock-price-based model and the benchmark forecasts, respectively. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

3.5 Robustness Analysis

The previous sections find that the equity price indices of these five commodity exporters can predict price movements in country-specific and global commodity markets. In this section we provide several robustness tests, including: (1) forecast behavior of commodity derivatives; (2) forecast behavior of commodity importers; (3) incorporating other data such as firm-level equity price; (4) incorporating quarterly data to forecast commodity prices; and (5) forecasting performance by using alternative fundamentals.

Robustness to Commodity Derivatives

Our results provide strong and robust evidence that stock price indices in commodity currency countries can forecast future spot commodity price movements. An obvious concern then is whether their predictive power is better than the information provided by the derivatives markets. We use the Dow Jones-AIG commodity futures indices as another robustness check. First, let f_{t+1}^{DJ-AIG} denote the one-month-ahead forward price of Dow Jones-AIG at time t. Here, Cp_{t+1}^{DJ-AIG} is the Dow Jones-AIG spot price, and Stk_t are the stock price indices of each country. Specifically, we construct the benchmark model (forward index) as well as the alternative model (stock-price-based model) as:

$$\text{Benchmark: } \mathrm{E}t\Delta Cp_{t+1}^{DJ-AIG} = f_{t+1}^{DJ-AIG} - Cp_t^{DJ-AIG}, \text{ (Forward Index)} \quad (8)$$

$$\text{Alternative: } \mathrm{E}t\Delta Cp_{t+1}^{DJ-AIG} = \alpha_0 + \beta_1 \Delta Stk_t^{AUS} + \beta_2 \Delta Stk_t^{CAN} + \beta_3 \Delta Stk_t^{CHI}. \quad (9)$$

We investigate the role of aggregate commodity markets by comparing our model against the three-month DJ-AIGCI forward index of futures contracts in predicting the corresponding DJ-AIG spot commodity price index. Figure 2 plots the realized change in the DJ-AIG global commodity spot price index (labeled “Actual realization”), the stock-price-based model (labeled “Model’s Forecast”), and the prediction based on the DJ-AIG three-month forward index (labeled “Forward Index”). We see that our model’s prediction power outperforms the forward index.

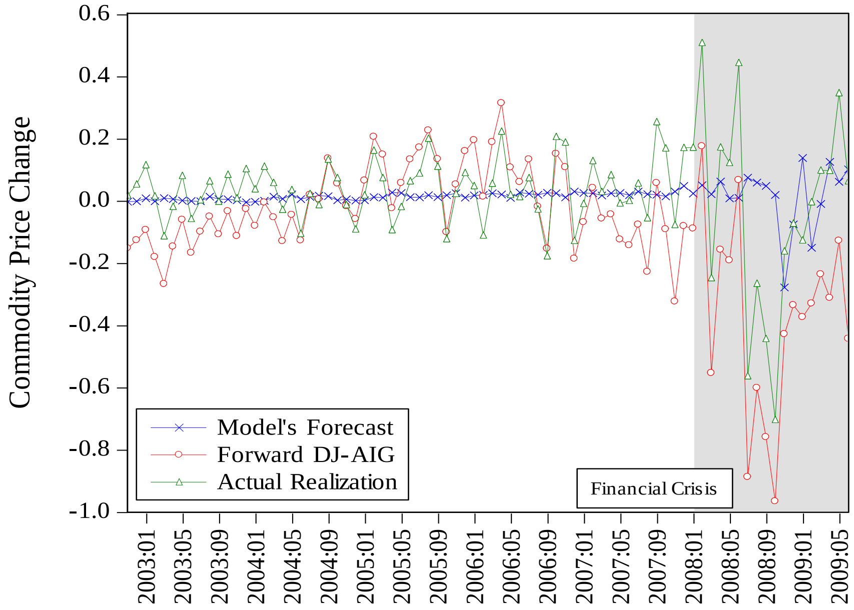

Figure 2 Forecasting the DJ-AIG Spot Commodity Price Index: Forward Index vs. Stock Price Indices

The results also show that the prediction based on futures prices is worse than the stock-price-based prediction. The mean average error for the stock-price-based model is smaller than that based on the forward index, implying that forward looking information is less useful than historical information for such a prediction. One possible explanation for this finding is that the markets for longer-dated futures contracts are illiquid, and the DJ-AIG commodity index is one of the few indices to have a floor and ceiling on individual commodities and component classes. Therefore, futures prices may not effectively incorporate all available information (Chen et al., 2010; Chen, 2013 and Chen, 2014).

Robustness to Commodity Importers

In order to make sure that our main results hold for the commodity exporters that we consider, we also collect data of equity indices for commodity importers — in particular, Germany, Japan, U.K., France, and the U.S. The untabulated results present the bivariate granger-causality tests, with the results based on the standard GC regressions for the stock price indices and global commodity price index. Even when there are several stock price indices in a country, the results are quite similar in which most of our sample countries' stock price indices do not Granger-cause commodity prices except Germany and the U.S. On the other hand, we extend the analysis and in-

Table 7 Robustness on Firm Level Forecast

	Suncor	Imperial Oil	Canadian Energy Resource
Panel A. Granger-causality tests			
Stk GC Cpcan	0.00***	0.00***	0.00***
Stk GC Cpw	0.01***	0.00***	0.00***
Panel B. Out-of-sample forecasting ability			
AR (1) benchmark			
Stk → Cpcan	-0.0005***	-0.0001***	-0.0005***
Stk → Cpw	-0.0001***	-0.0001***	-0.0001***
Random walk benchmark			
Stk → Cpcan	-0.0006***	-0.0003***	-0.0006***
Stk → Cpw	-0.0003*	-0.0002***	-0.0003**

Note: The table reports results from tests using individual stock price indices to predict Canadian commodity prices. Panel A reports p-values, and Panel B reports the MSE differences between the stock-price-based model and the benchmark forecasts. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

vestigate out-of-sample forecasts. The results show that after using the stock price indices of commodity importers, our importer stock-price-based model does not outperform either the random walk model or an autoregressive model. In addition, we reduce our sample period to 2008 January (before the credit crisis), and the results are similar to the full sample period.[4] In sum, our main results are robust for currencies of countries with heavy commodity exports.

Robustness on Firm-level Data

To evaluate whether the equity values of exporting firms have the same predictive power, we collect some firm-level data for Canada. We mainly focus on Canada due to the following reasons. First, Canada is one of the few developed nations that is a net exporter of energy and energy resources, which plays an important role in its overall economy. In addition, Atlantic Canada possesses enormous offshore deposits of natural gas, while Alberta in central Canada hosts large oil and gas resources. Second, most of the other companies that export commodities are state-owned, and other firms' data are available only for a fraction of the sample that we consider.

[4] Results are not reported herein, but are available upon request.

Therefore, we collect data from the top three Canadian petroleum companies (from CRSP database): Suncor, Imperial Oil Ltd. and Canadian Natural Resources. They are engaged in the exploration, production, and sale of crude oil and natural gas and have sufficient data for analysis. Table 7 presents the results. Let *ft* denote the firms' equity price at time *t*, and we consider the following regressions:

$$\mathrm{E}_t \Delta Cp_{t+1}^{CAN} = \beta_0 + \beta_1 \Delta f_t^i + \beta_2 \Delta Cp_t^{CAN}, \tag{10}$$

$$\mathrm{E}_t \Delta Cp_{t+1}^{w} = \beta_0 + \beta_1 \Delta f_t^i + \beta_2 \Delta Cp_t^{w}. \tag{11}$$

Here, i = Suncor, Imperial Oil Ltd. and Canadian Natural Resources equity prices.

Our results show that the firm equity values of Suncor, Imperial Oil Ltd. and Canadian Natural Resources Granger-cause the Canadian commodity price index and Global commodity price index (Panel A in Table 7). The results are robust in out-of-sample forecast comparisons (Panel B in Table 7) and also hold before the credit crisis period (untabulated to save space). In sum, our main results also hold when we use firm-level equity price data.

Robustness on Quarterly Data

Quarterly or monthly frequency might have some influence on the relationship between equity and commodity markets. Therefore, we use quarterly stock price data to forecast quarterly commodity prices for all 5 countries during the same sample period. We note that the GC tests overall find that most of the stock price indices Granger-cause individual commodity prices (except for New Zealand and South Africa) as well as global commodity prices (Panels A and C in Table 8). However, we find little evidence that quarterly stock prices help forecast individual commodity prices (except for Australia and Chile) and global commodity prices (Panels B and D in Table 8). Data frequency really matters in commodity price forecasting. Tseng and Tsaur (2008) suggest that sample size affects forecastability. In other words, when total sample size drops, this might reduce the accuracy of forecastability. Therefore, we suggest that it is proper to use higher data frequency (e.g. monthly data) to predict commodity prices. However, most of our data are only available on a monthly basis, and therefore we do not consider daily frequency to forecast commodity prices.

Table 8 Quarterly In-Sample and Out-of-Sample Forecasts

	AUS	CAN	CHI	NZ	SA
Panel A. Granger-causality tests (Individual Commodity Price Forecast)					
Stk GC Cp	0.00***	0.09*	0.02**	0.32	0.25
Panel B. Out-of-sample forecasting ability (Individual Commodity Price Forecast)					
AR (1) benchmark					
Stk → Cp	-0.0009***	0.0001	-0.0003*	-0.0001	-0.0001
Random walk benchmark					
Stk → Cp	-0.0013***	0.0002	0.0082	-0.0000	0.0001
Panel C. Multivariate Granger-Causality tests (Aggregate Global Commodity Price Forecast)					
			0.02**		
Panel D. Out-of-sample forecasting ability (Aggregate Global Commodity Price Forecast)					
AR (1) benchmark				0.0007	
Random walk benchmark				0.0015	

Note: The table reports results from tests using quarterly individual stock price indices to predict individual and aggregate global commodity prices. Panels A and C report p-values, and Panels B and D report the MSE differences between the stock-price-based model and the benchmark forecasts. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

Forecasting Performance by Using Alternative Fundamentals

In addition to stock price indices, we also consider alternative fundamentals to forecast commodity prices. The additional fundamentals that we consider are interest rate, CPI, GDP, inflation rate, and industrial production (we extract all the data from the IMF).[5] The un-tabulated results indicate that most other fundamental models do not outperform our benchmark models (AR(1) and RW). More interestingly, we find that the New Zealand and Australia interest rates improve the predictability of commodity prices. Chile's quarterly GDP also improves the predictability of quarterly commodity prices. However, the results for other fundamentals are much more mixed and sporadic. We show that stock prices improve forecast performance, and the results are more consistent.[6]

[5] Some of the fundamentals are only available on a quarterly basis (e.g. GDP for all countries; AUS CPI, inflation rate, and industrial production; NZ CPI, inflation rate, and industrial production), and therefore we use quarterly variables to forecast quarterly commodity prices.

[6] Unreported results indicate that most of the fundamentals do not Granger-cause commodity prices.

3.6 Implications for Equity Price Forecastability

In the previous section, our results suggest that stock price indices help forecast individual and aggregate commodity prices, and that the relationship holds in-sample and out-of-sample. However, some countries (especially New Zealand) fail to outperform our benchmark model. In addition, when we reduce the sample size to the first month in 2008,[7] we find that the stock-price-based model does not outperform AR(1) and the exchange-rate-based model. Therefore, this section discusses what caused the strong predictive performance of the stock-price-based model in some countries and during the post-crisis period. To answer this question, we provide two possible explanations as follows.

Implications for Different Forecastability Across Countries

Our results show that no matter whether we use monthly or quarterly data to forecast individual commodity prices or even if we use individual equity prices to forecast global commodity prices, which New Zealand equity prices still fail to outperform both of our benchmarks. We suggest that stock market development might play an important role in a commodity market forecast. In other words, as a stock market becomes more complete and developed, firms tend to issue equity more easily for investors who might be willing to trade in the market and release more information to enhance the prediction for the commodity market. Based on the measures of Claessens et al. (2006), stock market development is defined as market capitalization over gross domestic product. They also use stocks traded over gross domestic product as another measure to evaluate how active a stock market is. We use annual data of the stock market measurement collected from the World Bank. We also calculate the growth rate of market capitalization as well as the turnover ratio to evaluate stock market development.

We present summary statistics of each country in Table 9. Panel A indicates that for most of the countries, stock market development is higher than 0.90, except for New Zealand (0.41). As for the average growth rate of market capitalization, the results in Panel B show that most of the countries are higher than 0.10. Panel C shows that the results for Australia, Canada, and South Africa are higher than 0.50, and the results for New Zealand and Chile are lower than 0.15. Finally, the average turnover

[7] We focus on the subprime mortgage crisis in 2008 for the following reasons. First, CFTC (2008) show that the total value of various commodity index-related instruments purchased by institutional investors increased from U$15 billion in 2003 to U$200 billion in June 2008. Second, we also find that, in most of our sample countries, the breakpoint of stock market development (Market Capitalization / GDP and Stocks Traded / GDP) is 2008.

Table 9 **Summary Statistics of Stock Market Development**

Countries	AUS	CAN	CHI	NZ	SA
Panel A. Market Capitalization / GDP					
Mean	0.90	0.91	0.93	0.41	1.70
Median	0.87	0.89	0.93	0.41	1.66
Std. Dev.	0.35	0.34	0.29	0.10	0.53
QLR test of	0.01***	0.02**	0.62	0.99	0.95
Breakpoint	(2008)	(2008)	(2003)	(1992)	(2008)
Rankings	4	3	2	5	1
Panel B. Growth Rate of Market Capitalization					
Mean	0.13	0.13	0.22	0.14	0.11
Median	0.11	0.16	0.21	0.06	0.17
Std. Dev.	0.28	0.28	0.37	0.46	0.33
Rankings	3	4	1	2	5
Panel C. Stocks Traded / GDP					
Mean	0.60	0.58	0.11	0.14	0.58
Median	0.54	0.54	0.09	0.15	0.58
Std. Dev.	0.38	0.33	0.07	0.05	0.46
QLR test of	0.00***	0.99	0.68	0.84	0.11
Breakpoint	(2008)	(2006)	(2007)	(1993)	(2008)
Rankings	1	2	5	4	3
Panel D. Turnover Ratio					
Mean	0.63	0.61	0.13	0.36	0.32
Median	0.57	0.62	0.11	0.37	0.34
Std. Dev.	0.24	0.20	0.05	0.14	0.21
Rankings	1	2	5	3	4

Note: ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

ratio suggests that the results of Australia and Canada are higher than 0.60, those of New Zealand and South Africa are respectively 0.36 and 0.32, and that of Chile is lower than 0.15. Figure 3 also plots the time series trend of each stock market development measure.

In the previous section we show that the forecastability of the stock-price-based model is different before and after the financial crisis. In the pre-crisis period we find for most of the cases that the stock-price-based model does not outperform the benchmark (except for the random walk model). Our results support the findings of Chen et al. (2010), who show that commodity currency exchange rates have strong power to predict out-of-sample commodity movements. More interestingly, as we extend the sample time frame to the post-crisis period, we find that an individual stock price can forecast the price changes of its associated commodity market as well as aggregated commodity price movements. In the Australia and Canada markets, the stock-price-based models even outperform the exchange-rate-based models. In sum, we conclude that forecastability is different before and after the financial crisis.

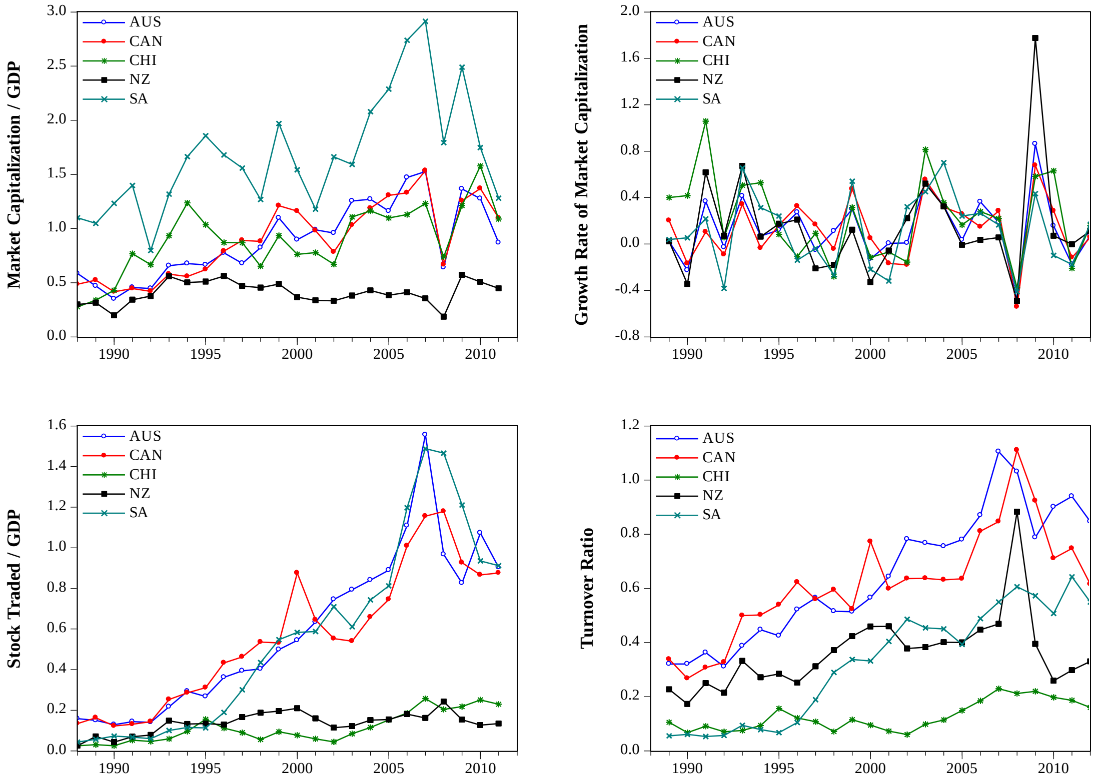

Figure 3 Stock Market Development

Table 10 Difference Tests of Stock Market Development

	Market Capitalization / GDP	Growth Rate of Market Capitation	Stocks Traded / GDP	Turnover Ratio
Panel A. Mean Score				
(1) AUS	0.90	0.13	0.60	0.63
(2) CAN	0.91	0.13	0.58	0.61
(3) CHI	0.93	0.22	0.11	0.13
(4) NZ	0.41	0.14	0.14	0.36
(5) SA	1.70	0.11	0.58	0.32
Panel B. Mean Difference Tests				
(4) - (1)	-0.49***	0.01	-0.46***	-0.27***
(4) - (2)	-0.50***	0.01	-0.44***	-0.25***
(4) - (3)	-0.52***	-0.08	0.03	0.23***
(4) - (5)	-1.29***	0.03	-0.44***	0.04

Note: ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

We also use the Quandt-Andrews breakpoint test to examine whether or not stock market developments in these countries have breakpoints. Table 9 suggests that most of the countries' breakpoints appear after the 2000s (in Australia and Canada, the breakpoint is significant under the 1% and 5% levels, respectively). The results show that the forecast behaviors are different before and after the financial crisis. Table 10 further investigates the difference in test results between New Zealand and other countries. The results show that most of the countries' stock market are more developed than New Zealand's except for the growth rate of market capitalization. In sum, less active stock market development might explain why stock price indices in New Zealand fail to predict commodity price movements.

Implications for Different Forecastability during the Credit Crisis

Previous studies in the literature (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Tang and Xiong, 2012) show that commodity markets were partly segmented from outside financial markets and from each other before the early 2000s. Erb and Harvey (2006) indicate that the positive return correlations of commodities with each other are low. Gorton and Rouwenhorst (2006) also conclude that correlations between commodity returns and S&P 500 returns are negligible, especially for short horizons such as daily and monthly. However, after the equity markets crashed in 2000 following the Internet bubble, many institutions began to consider commodities as a new asset type for allocation, because of the negative correlation between commodity returns and stock returns (Greer, 2000; Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). Based on the staff report from the U.S. Commodity Futures Trading Commission (CFTC 2008), the total value of various commodity-index investments purchased by institutional investors increased from US$15 billion in 2003 to US$200 billion in June 2008. As a result, commodity futures have become a popular asset for institutions.

Tang and Xiong (2012) suggest that financialization is an important factor for the rapid growth of commodity investment and further leads to more efficient sharing of commodity price risk. They show after 2004 that the dramatic increase in the volatility of commodities coincides with the increasing volatility of the world equity index. Therefore, we interpret the evidence as pointing towards the synchronization of movements between commodity markets and equity markets. In order to investigate the relationship between commodity and equity markets, we plot the annualized monthly return volatilities of the equity price indices of Australia, Canada, and Chile and the global commodity index. We also use Dow Jones-AIG commodity futures as

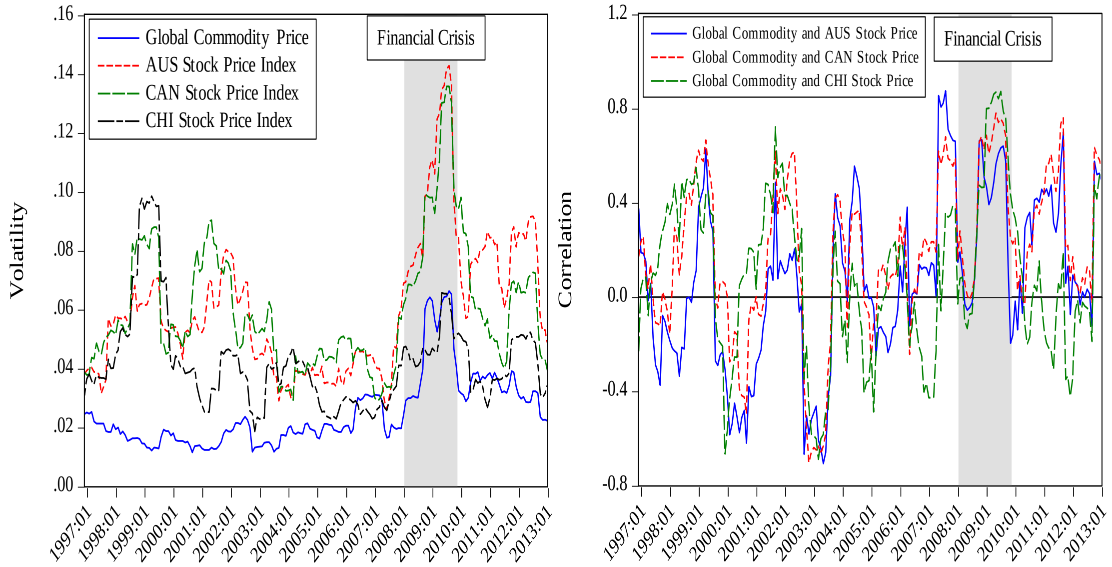

Figure 4 Volatility of the Global Commodity Price, Stock Price Indices, and Correlation between the Global Commodity Price and Stock Price Indices

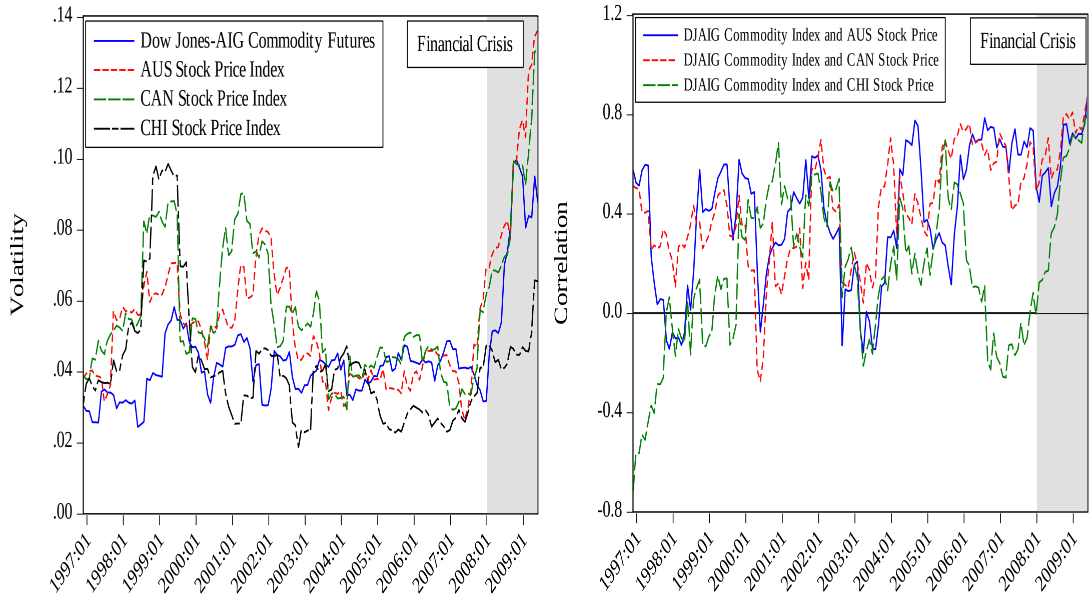

Figure 5 Volatility of DJAIG Commodity Price, Stock Price Indices, and Correlation between DJAIG Commodity Price and Stock Price Indices

another robustness check to examine the relationship between equity markets and commodity derivatives markets.

Figure 4 presents the one-year rolling volatility of global commodity price and stock price indices (Australia, Canada, and Chile) and the correlation between commodity and equity indices, respectively. We note during the credit crisis period that the volatility of stock prices is twice as high as the volatility before the 2000s, especially for Australia and Canada. On the other hand, global commodity prices became more volatile during the crisis period. Moreover, we plot the one-year rolling correlation between global commodities and stock price indices, showing that the correlation increases dramatically. Although the correlation stays in a band between -0.8 and 0.4 for several years before 2008, it increases from 0 to 0.8 during the crisis period and remains high even after the crisis, except for the Chilean case. The results are similar to the relationship between volatility and correlation for the DJ-AIG Commodity Price and stock price indices in Figure 5.

Our results are consistent with the findings of Tang and Xiong (2012), who indicate that the relationship between commodity and equity prices has become closer in recent years (especially in mid-2000), further enhancing the predictive power of equity indices. The stock-price-based model performs poorly before the credit crisis, but its performance improves after the crisis, indicating that the commodity markets were less segmented before the credit crisis. In addition, because investors have recently been paying more attention to commodity markets, there is a spill-over shock from stock markets to commodity markets. As a result, the information from equity markets becomes more predictive. Büyüksahin, Haigh, and Robe (2010) and Silvennoinen and Thorp (2010) also find that the return correlation between commodities and stocks rose during the recent credit crisis.

4. CONCLUSIONS

This paper investigates the dynamic relationship between commodity price movements and stock price fluctuations. Because commodity price uncertainty imposes large costs on society, it is important for policy makers around the world to be able to predict their movements accurately. Our results suggest that stock price indices help forecast individual and aggregate commodity prices, and the relationship holds both in-sample and out-of-sample. Likewise, we also find that commodity prices Granger-cause stock indices, but the relationship is less robust out-of-sample. Our results are robust to multivariate regressions, commodity derivatives market data, and firm-level equity price data, but our results do not hold for the countries that are commodity importers. Finally, we suggest that it is proper to forecast commodity prices by using higher frequency data, because the data might contain more information content that could improve forecast performance. Our research also considers other fundamentals to forecast commodity prices, with the results showing that some variables do improve forecast performance and are even better than the stock price model (e.g. the New Zealand interest rate outperforms our benchmark model), but the results for other fundamentals are inconsistent across the 5 countries.

We further show that the forecast performance is different before and after the financial crisis. In the pre-crisis period, we find that the models based on stock indices fail to outperform the benchmark model. Our results are consistent with Chen et al. (2010) and show that commodity currencies have predictive power in out-of-sample commodity forecasts. However, we also show that the role of equity markets has become more important in the post-credit-crisis period. There are two possible explanations for this phenomenon. The first explanation is that as a stock market becomes more developed and more liquid, its predictive power is more enhanced. The second explanation is that when more institutional investors pay attention to commodity markets, a trend arises to encourage more information to be released, generating a higher correlation between equity markets and commodity markets.

Our research might have some limitations. First, we focus on short-run predictions (one-month ahead), because if we adapt multi-step forecasts, then the asymptotic distributions of the tests might depend on the parameters of the data-generating process (Clark and McCracken, 2001). Therefore, longer-horizon predictions might provide more useful information. In addition, different forecast methods such as a non-linear approach might also result in forecast improvements. We leave these interesting issues for future research.

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金融海嘯期間股票市場及商品市場之關聯性

魏品揚*

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摘　要

本文主要是探討股票市場及商品市場的關聯性，實證結果發現澳洲、加拿大、智利、紐西蘭以及南非之股票市場的確可以預測商品市場現貨價格的走勢。除此之外，我們也發現在金融海嘯前後，股票市場之預測行為存在顯著差異。在金融海嘯之前，相比基準組模型，股票市場並無法顯著改善商品市場之預測成效。然而，在金融海嘯之後，我們發現股票市場不論在預測個別商品市場及全球商品市場之價格走勢，皆有良好的成效。