Oil price risk and emerging stock markets

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Abstract

The purpose of this paper is to contribute to the literature on stock markets and energy prices by studying the impact of oil price changes on a large set of emerging stock market returns. The approach taken in this paper uses an international multi-factor model that allows for both unconditional and conditional risk factors to investigate the relationship between oil price risk and emerging stock market returns. This paper, thus, represents one of the first comprehensive studies of the impact of oil price risk on emerging stock markets. In general we find strong evidence that oil price risk impacts stock price returns in emerging markets. Results for other risk factors like market risk, total risk, skewness, and kurtosis are also presented. These results are useful for individual and institutional investors, managers and policy makers.

Keywords: Emerging markets; stock market risk; oil price risk

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1. Introduction

Oil is the lifeblood of modern economies. As countries urbanize and modernize their demand for oil increases significantly. Future oil demand is difficult to predict but is generally highly correlated with the growth in industrial production. Consequently, countries experiencing rapid economic growth are the ones most likely to dramatically increase their demand for oil. In particular, countries like China and India are experiencing rapid growth in Gross Domestic Product (GDP). Between 1991 and 2001 China's average annual growth rate in real GDP was 9.8% while India's average annual growth rate in real GDP was 5.4% (The Economist (2004)). In the future, emerging economies in general, and China and India in particular, are expected to consume an increasing share of the world's oil. Energy, financial markets and the economy are all explicitly linked together on a country's path of economic growth.

Table 1 shows data on how oil consumption has changed over the ten year period 1994 – 2004 for the major regions of the world as well as selected countries. The Asia Pacific region experienced the greatest increase in oil consumption (37.2%) while Europe and Eurasia experienced the smallest increase (1.3%). China's oil consumption increased by 112.5% while India's oil consumption increased by 80.9%. By comparison, oil consumption in the United States increased by 15.8% while Japan's oil consumption fell by 8.0% (partially in response to increased energy efficiency and alternative energy sources). The data in Table 1 shows that oil consumption is increasing most rapidly in the developing countries of the world.

Increases in oil demand without offsetting increases in supply lead to higher oil prices. Higher oil prices act like an inflation tax on consumers and producers by 1) reducing the amount of disposable income consumers have left to spend on other goods and services and 2) raising the costs of non-oil producing companies and, in the absence of fully passing these costs on to consumers, reducing profits and dividends which are key drivers of stock prices. In addition to global demand and supply conditions, oil prices also respond to geopolitics, institutional arrangements (OPEC), and the dynamics of the futures market (Sadorsky (2004)). Unanticipated changes in any of these four factors can create volatility, and hence risk, in oil futures prices. Oil price volatility increases risk and uncertainty which negatively impacts stock prices and reduces wealth and investment.

The relationship between oil price changes and stock prices can be explained using an equity pricing model. In an equity pricing model, the price of equity at any point in time is equal to the expected present value of discounted future cash flows (Huang, Masulis and Stoll (1996)). Oil, along with capital, labour and materials represent important components into the production of most goods and services and changes in the prices of these inputs affects cash flows. Rising oil prices, which, in the absence of complete substitution effects between the factors of production, increase production costs. Higher production costs dampen cash flows and reduce stock prices. Rising oil prices also impact the discount rate used in the equity pricing formula. Rising oil prices are often indicative of inflationary pressures which central banks can control by raising interest rates. Higher interest rates make bonds look more attractive than stocks leading to a fall in stock prices. The overall impact of rising oil prices on stock prices depends of course on whether a company is a consumer or producer of oil and oil related products.

Since there are more companies in the world that consume oil than produce oil, the overall impact of rising oil prices on stock markets is expected to be negative.

Developed economies are more energy efficient today than they were 20 years ago with oil consumption per dollar of GDP less than half of what it was in the 1970s. This increase in energy efficiency has occurred because of reduced energy intensity through technological innovation and more reliance on a diversified range of energy sources (like a greater mix between non-renewable and renewable energy sources). Emerging economies tend, however, to be more energy intensive than more advanced economies and are therefore more exposed to higher oil prices. Consequently, oil price changes are likely to have a greater impact on profits and stock prices in emerging economies.

Globalization, broadly defined as the increased flow of goods, services and financial capital between national borders, has increased interdependencies between all economies in the world. Consequently, the growth in world trade is more sensitive to rises in oil prices than in the past due to the growing importance of emerging economies like Brazil, China and India. The increased flow of portfolio money (in the form of stocks, bonds and mutual funds) means that oil price impacts on emerging stock markets affect both domestic and international investors alike.

Moreover, past experience has shown that oil price shocks have a much larger impact on the poorer countries in the world. The OPEC oil embargo of 1973, which increased the price of oil from $3 per barrel to $13 barrel in just over a few short months, created real economic and social hardship for developing countries by raising their costs of imported oil. International lending organizations like the World Bank and the

International Monetary fund (IMF) had to provide loans to developing countries so that they could continue with their economic development projects (Rifkin (2002, chapter 9)). Between 1973 and 1980 commercial bank loans to developing countries increased by 550%. The second oil price shock in 1979 led to global recession and imposed even more hardship on the prosperity of developing countries as the price for their oil imports rose and the price for their other export products fell. By 1985 Third World Debt exceeded $1 trillion dollars. The problem for most developing countries was that any new borrowed money was mostly being used to buy imported oil and pay interest payments on existing debt. Very little money was left over for new economic development projects. This relationship between high oil prices, high debt and low economic development is very much a concern today. In 2000, Kofi A. Annan, the Secretary General of the United Nations, wrote in the International Herald Tribune, that “debt-servicing costs are likely to increase if higher oil prices lead to higher international interest rates” in the coming years (Annan (2000)).

The purpose of this present paper is to contribute to the literature on stock markets and energy prices by studying the impact of oil price changes on a large set of emerging stock market returns. The approach taken in this paper uses an international multi-factor model that allows for both unconditional and conditional risk factors to investigate the relationship between oil price risk and emerging stock market returns. This paper, thus, represents one of the first comprehensive studies of the impact of oil price risk on emerging stock markets. Recognizing that stock returns are non-normally distributed, additional risk factors for skewness and kurtosis are also included in the analysis. Results are presented from models estimated using three different data sets (daily, weekly and monthly). This paper is organized as follows. Section 2 presents a review of the literature. Section 3 discusses the methodology and the data. Section 4 reports on the empirical findings and section 5 concludes.

2. Literature Review

There is now a growing body of published research on the relationship between energy prices and stock prices. Most of the research has focused on the developed countries.

The paper by Chen, Roll and Ross (1986) is one of the first papers to systematically investigate the impact of macroeconomic innovations on stock price returns. They found that interest rates, inflation rates, bond yield spreads, and industrial production have risk that is priced in the stock market. They did not, however, find any evidence that oil price risk is rewarded by the stock market. Hamao (1989) applied the approach of Chen, Roll and Ross (1986) to a sample of Japanese equity data and also found no evidence for the pricing of an oil price factor. Kaneko and Lee (1995), using a more recent sample of Japanese equity data did find some evidence in favour of an oil price factor impacting stock returns. Ferson and Harvey (1995) find evidence that an oil price risk factor does have a statistically significant but different impact on the 18 equity markets that they study.

Jones and Kaul (1996) use quarterly data to test whether the reaction of international stock markets (Canada, Japan, United Kingdom, and the United States) to oil shocks can be justified by current and future changes in real cash flows and/or changes in expected returns. Using the Producer Price Index for Fuels as a measure of oil prices, they do find a relationship between oil prices and stock market returns. After including future industrial production into the analysis, however, they find that the reaction of Canadian and U.S. stock prices to oil price shocks can be completely accounted for by the impact of these shocks on real cash flows. The results for Japan and the United Kingdom are, however, not as strong.

Huang, Masulis and Stoll (1996) focus on the relationship between daily oil futures returns and daily U.S. stock returns. Using a vector autoregression (VAR) approach, they find that oil futures returns do lead some individual oil company stock returns but oil futures returns do not have much impact on broad based market indices like the S&P 500. They also find that oil futures volatility leads the petroleum stock index volatility.

Sadorsky (1999) estimates a vector autoregression model with monthly data to study the relationship between oil prices changes and real stock returns in the United States. In his analysis, he finds that oil price changes and oil price volatility both play important roles in affecting real stock returns. There is evidence that oil price dynamics have changed. After 1986, oil price movements explain a larger fraction of the forecast error variance in real stock returns than do interest rates. There is also evidence that oil price volatility shocks have asymmetric effects on the economy. In particular, positive oil price shocks have a greater impact on stock returns and economic activity than do negative oil price shocks.

Faff and Brailsford (1999) investigate the sensitivity of Australian industry equity returns to an oil price factor. Their analysis is carried out using monthly data over the period 1983 to 1996. They find a positive and significant impact of oil prices on the Oil and Gas and Diversified Resources industries and a negative and significant impact of oil prices on the Paper and Packaging, and Transportation industries.

Sadorsky (2003) uses monthly data from July 1986 to April 1999 to investigate the macroeconomic determinants of U.S. technology stock price conditional volatility. Technology share prices are measured using the Pacific Stock Exchange Technology 100 index. One of the novel features of this paper is to incorporate a link between technology stock price movements and oil price movements. The empirical results indicate that the conditional volatilities of industrial production, oil prices, the federal funds rate, the default premium, the consumer price index, and the foreign exchange rate each have a significant impact on the conditional volatility of technology stock prices. Industrial production and the consumer price index each have the largest direct impact.

In contrast to the work done on developed markets, relatively little research has focused on the relationship between energy prices and emerging stock markets. Recent work in this area includes Papapetrou (2001) and Hammoudeh and Eleisa (2004).

Papapetrou (2001) uses a multivariate vector autoregression model to study the dynamic interaction between oil prices, real stock prices, interest rates, and real economic activity in Greece. His empirical results show that changes in oil prices influence real activity and employment.

Hammoudeh and Eleisa (2004) study the relationship between oil prices and stock prices for five members (Bahrain, Kuwait, Oman, Saudi Arabia, and the United Arab Emigrates) of the Gulf Cooperation Council (GCC). Using daily data they find that only the Saudi Arabia stock market has a bi-directional relationship between oil prices and stock prices.

3. Methodology and Data

The purpose of this present paper is to contribute to the literature on stock markets and energy prices by studying the impact of oil price changes on emerging stock market returns. The approach taken in this paper uses an international multi-factor model that allows for both unconditional and conditional risk factors. This approach is related to the international capital asset pricing model (CAPM), the implications of which have been studied by a large number of people (see Brealey and Myers (2003) for an overview). While the focus of the CAPM (Sharpe (1964), Lintner (1965), Black (1972)) is on market risk, the multi-factor model includes multiple sources of risk (Ross (1976)). The CAPM and multi-factor models are fundamental building blocks of modern portfolio theory. In both models, expected returns are linearly related to risk factors and risk premiums.

To date the CAPM has been extensively tested both domestically and internationally and the general consensus is that the CAPM shows no statistically meaningful relationship between systematic risk (beta) and returns (Fama and French (1992, 1996a,b), Jegadeesh (1992), Harvey and Zhou (1993), Ferson and Harvey (1994)).

Most empirical papers studying the relationship between beta and return use the methodology of Fama and MacBeth (1973). Once assets have been put into portfolios, the Fama and MacBeth (1973) approach involves two steps. In the first step, a CAPM is used to estimate beta and in the second step cross section regressions of beta on returns are estimated. This approach is useful but does have some limitations (Campbell, Lo and MacKinlay (1997, p.216)). For one thing, the approach ignores the estimation error from the first stage regressions. This has the effect of making the coefficient standard errors in the second stage regression too high.

Pettengill, Sundaram and Mathur (1995) propose an alternative to the Fama and MacBeth (1973) approach that focuses on the difference between expected returns (as specified in theory) and realized returns (as observed in practice). Their approach uses a conditional approach that separates positive market returns from negative market returns. According to Pettengill, Sundaram and Mathur (1995), it is important to take into account the fact that ex post returns and not ex ante returns are used in tests of the CAPM. The use of realized returns creates a conditional relationship between risk and return. An investor will hold the low beta portfolio only if there is some positive probability that the return on the low beta portfolio is greater than the returns on a high beta portfolio. This situation occurs when the market return is less than the return on the risk free asset. Furthermore, a positive conditional relationship between beta and returns exists if (i) the average excess market return is positive and (ii) the risk and return relationship is symmetric between positive and negative excess market returns.

Thus, a conditional relationship holds between returns and beta that depends upon the sign and magnitude of market returns. If market returns are positive, then there should be a positive relationship between asset returns and beta. If, on the other hand, market returns are negative, there should be a negative relationship between asset returns and beta. Pettengill, Sundaram and Mathur (1995) find strong support for beta as a measure of risk in the U.S. stock market when the sample period 1936 – 1990 is split into up and down markets. They find a positive (negative) relationship between realized returns and beta when excess market returns are positive (negative).

The methodology of Pettengill, Sundaram and Mathur (1995) has recently been used by Isakov (1999), Fletcher (2000), Hodoshima, Garza-Gomez and Kunimura (2000), and Tang and Shum (2003a,b). Isakov (1999) studies the conditional relationship between realized returns and beta in the Swiss stock market and finds support for a conditional relationship. Fletcher (2000) studies the relationship between beta and returns in a sample of developed stock markets and finds support for a significant positive relationship between beta and returns in up markets and a significant negative relationship between beta and returns in down markets. Hodoshima, Garza-Gomez and Kunimura (2000) provide a detailed analysis of the Japanese stock market and find a significant conditional relationship between beta and returns. They also find that the model fit is better in down markets than in up markets. Tang and Shum (2003a) study the conditional relationship between beta and returns in a sample of developed stock markets and find a significant conditional relationship between beta and returns. Their results are robust for monthly and weekly data sets. Tang and Shum (2003b) recognize that stock returns are, in general, non-normally distributed and extend their previous work to include measures of skewness and kurtosis and show that skewness but not kurtosis to be an important risk factor in pricing international stock returns. The papers by Pettengill, Sundaram and Mathur (1995), Isakov (1999), Fletcher (2000), Hodoshima, Garza-Gomez and Kunimura (2000), and Tang and Shum (2003a,b) are each important papers in establishing a conditional relationship between realized returns and risk.

The data for this present study consists of daily closing prices on 21 emerging stock markets and the Morgan Stanley Capital International (MSCI) World Index. The data are available from Datastream and cover the period December 31, 1992 to October

31, 2005 for a total of 3348 daily observations. All of the data are in U.S. dollars so that investment decisions are made from the perspective of a U.S. investor or an international investor who has a U.S. dollar trading account. The countries included in the study are, Argentina (ARG), Brazil (BRA), Chile (CHL), Colombia (COL), India (IND), Indonesia (IDN), Israel (ISR), Jordan (JOR), Korea (KOR), Malaysia (MYS), Mexico (MEX), Pakistan (PAK), Peru (PER), Philippines (PHL), Poland (POL), South Africa (ZAF), Sri Lanka (LKA), Taiwan (TAI), Thailand (THA), Turkey (TUR), and Venezuela (VEN). These countries were selected for inclusion into our database because of their relatively long (for emerging markets) data on stock markets. Countries like China and Russia are not included because the stock markets of these countries have not been trading long enough. The Moscow Times Index in Russia, for example, has only been actively trading since 1995. Data sampled at higher frequencies are considered to contain more information than lower frequency data and as a result, daily data are selected for most of the analysis in this paper. For comparison purposes, results are also presented from models using weekly data and monthly data.

Daily excess stock returns are calculated by subtracting the daily yield on a three month U.S. T Bill from the continuously compounded daily emerging market stock returns. The average daily stock returns for a country are small in comparison to its standard deviation (Table 2a). Poland has the highest average daily return (0.052%) while the Philippines has the lowest average daily return (-0.032%). Seven of the twenty one countries have negative average returns. The risk of emerging market stock returns is shown by the large standard deviations. Turkey has the highest standard deviation while the world market returns have the lowest standard deviation, illustrating the benefits of portfolio diversification. It is important to realize that the period of time under study, December 31, 1992 to October 31, 2005, was a very volatile period for the world stock market (Asian financial crises in 1997 and 1998, Russia, Brazil and Long Term Capital Management close to default in 1998, Y2K scares in 1999, the bursting of the technology stock bubble in the spring of 2000, and the September 11, 2001 terrorist attacks on the World Trade Center). Many of the stock returns exhibit skewness and all of the stock returns exhibit a high degree of kurtosis. This is important because it suggests that skewness or kurtosis may be an additional source of risk. Unit root tests confirm that each time series is stationary. The estimated correlations of excess returns show that each market is positively correlated with the world stock market index (Table 2b).

Daily excess world stock returns are calculated by subtracting the daily yield on a three month U.S. T Bill from the continuously compounded daily returns on the MSCI World Stock Index. The average excess market return is positive but statistically insignificant from zero (the t statistic is $.015 \Big/ \left(.802 \big/ \sqrt{3347} \right) = 1.082$).

The model estimation follows a two step process. In the first step, country stock market betas, oil price betas, and exchange rate betas are estimated using ordinary least squares (OLS) from the following multi-factor model.

$$R_{it} = c + \beta_{mit} MR_t + \beta_{oit} OIL_t + \beta_{eit} TWEX_t + \varepsilon_{it} \qquad (1)$$

In equation (1) the country excess returns are R_{it} (i=1,…,21 denotes the country and t denotes the time period), world market excess returns are MR_t, oil returns are OIL_t, and exchange rate returns are TWEX. World market excess returns are measured by the excess returns on the MSCI World Market Index. Oil returns are measured as the log difference of the daily return on the West Texas Intermediate (WTI) crude oil futures contract which trades on the NYMEX. The WTI futures contract is the most widely traded oil futures contract in the world and is used as a benchmark to set other oil product related prices. Moreover, The NYMEX oil futures contract is the most heavily traded futures contract on a physical commodity in the world and therefore represents an efficient flow of information between buyers and sellers (www.nymex.com). The oil price futures series is available from Datastream.

Extending beta pricing models to an international setting requires a number of assumptions including integrated capital markets, purchasing power parity, and no informational or transactions costs or taxes. When purchasing power parity does not hold then individuals face exchange rate risk when investing internationally (Adler and Dumas (1983)). Exchange rate risk can be separated into an individual factor for each country or it can be approximated using a single variable. Because of the large number of countries that we are studying, we follow Ferson and Harvey (1994) and use a single variable to approximate exchange rate risk. The variable TWEX is the log difference of a weighted average of the foreign exchange value of the U.S. dollar against a subset of the broad index currencies that circulate widely outside the country of issue. A positive change indicates a depreciation of the dollar. The exchange rate series is available from the Federal Reserve Board of St. Louis (http://research.stlouisfed.org/fred2/). The random error term, ε, is assumed to be independently and identically distributed with zero mean and constant variance.

The estimation strategy is to use ordinary least squares (OLS) to estimate equation (1) for each country using a rolling fixed window length of 1250 trading days (approximately five years of daily trading data). Five years of data is the recommended length of data to use in most financial analysis (Brealey and Myers (2003)). For each estimation period the market beta, oil beta, exchange rate beta and other risk measures (skewness and kurtosis) are estimated and recorded. The estimation window is then moved forward by adding one new day and dropping the most distant day and obtaining new estimates of the risk variables. In this way the estimation window stays fixed at 1250 observations. For analysis using weekly and monthly frequencies we use 260 and 60 observations respectively (which approximate five years of data at these frequencies) in the estimation window. Although not reported, the empirical results in our paper are reasonably robust to small changes (one or two years) in the estimation window. One advantage of using a rolling regression approach is that structural shocks work through the data set by the length of the fixed window and do not have lasting impacts over the entire data range. Recursive estimation allows for risk factors that may not be constant through time.

In the second step, unconditional and conditional cross section regressions are estimated for a pooled data set of realized stock returns and risk parameters. Betas from period t are matched with realized stock returns from period t+1.

$$R_{it} = \gamma_0 + \gamma_{m1}\beta_{mit} + \gamma_{o1}\beta_{oit} + \gamma_{e1}\beta_{eit} + \varepsilon_{2t} \qquad (2)$$

The market betas, oil betas, and exchange rate betas are estimated from equation (1). Equation (2) specifies an unconditional relationship between returns and risk that is estimated using pooled OLS.

Following Pettengill, Sundaram and Mathur (1995), a conditional relationship between realized returns and risk can be specified as

$$R_{it} = \gamma_0 + \gamma_{m2} D1_t \beta_{mit} + \gamma_{m3}(1 - D1_t)\beta_{mit} + \gamma_{o2} D2_t \beta_{oit} + \gamma_{o3}(1 - D2_t)\beta_{oit} + \gamma_{e1}\beta_{eit} + \varepsilon_{3t} \quad (3)$$

where D1 is a dummy variable that takes on a value of one (zero) if excess market returns are positive (negative) and D2 is a dummy variable that takes on a value of one (zero) if oil price returns are positive (non-positive). A priori, it is expected that γ_{m2} (γ_{m3}) and γ_{o2} (γ_{o3}) each have positive (negative) signs. Symmetry between up and down markets can be tested from the hypothesis that $\gamma_{m2} + \gamma_{m3} = 0$ versus the alternative, $\gamma_{m2} + \gamma_{m3} \neq 0$. In a similar manner, symmetry between up and down oil price changes can be tested from the hypothesis that $\gamma_{o2} + \gamma_{o3} = 0$ versus the alternative, $\gamma_{o2} + \gamma_{o3} \neq 0$. The importance of additional risk factors (such as skewness or kurtosis) can be studied by adding additional risk factors to equations (2) and (3). In this paper additional risk factors include squared beta, total risk, skewness, and kurtosis.

Total risk is the combination of systematic (market) risk and unsystematic (firm specific) risk. Total risk is a widely used measure of risk and is useful because financial distress is most likely to occur for firms with high total risk (Shapiro (2003), p.26). Total risk is an appropriate risk measure for emerging markets because emerging markets are not fully integrated with the world stock market (Bekaert and Harvey (1995)). Alternatively, total risk is an appropriate measure of risk when investors do not hold well diversified portfolios. Total risk is measured using the variance of market returns, estimated over the same sample period as used to estimate the market beta. The unconditional and conditional relationship between returns and risk incorporating total risk, respectively, is given by equations (4) and (5).

$$R_{it} = \gamma_0 + \gamma_{m1}\beta_{mit} + \gamma_{o1}\beta_{oit} + \gamma_{T1} TR_{it} + \gamma_{e1}\beta_{eit} + \varepsilon_{4t} \qquad (4)$$

$$R_{it} = \gamma_0 + \gamma_{m2} D1_t \beta_{mit} + \gamma_{m3}(1 - D1_t)\beta_{mit} + \gamma_{o2} D2_t \beta_{oit} + \gamma_{o3}(1 - D2_t)\beta_{oit}$$

$$+ \gamma_{T2} D1_t TR_{it} + \gamma_{T3}(1 - D1_t) TR_{it} + \gamma_{e1}\beta_{eit} + \varepsilon_{5t} \quad (5)$$

where TR_{it} is country *i*'s total risk. The inclusion of higher moments (skewness and kurtosis) of stock returns is justified when stock returns are not normally distributed. Harvey and Siddique (2000) suggest that investors care about the skewness of their portfolio. Investors may also care about kurtosis (Bekaert and Harvey (1997) and Bekaert, Erb, Harvey and Viskanta (1998)). The study by Scott and Horvath (1980) analytically showed that rational risk adverse investors prefer odd statistical moments of stock returns like mean and skewness, but dislike even statistical moments like variance and kurtosis. In the case of skewness, investors will accept smaller returns for positive skewness but demand higher returns for negative skewness. In other words, risk adverse investors should prefer portfolios that are skewed to the right and dislike portfolios that are skewed to the left. Kurtosis, the fourth moment of asset returns is interesting to study because kurtosis can be related to the variance of the variance and thus be used to check on the specification of the variance dynamics. Following equations (4) and (5), the unconditional and conditional relationship between realized returns and risk incorporating higher moments (skewness and kurtosis), respectively, can be specified by equations (6)-(9)

$$R_{it} = \gamma_0 + \gamma_{m1}\beta_{mit} + \gamma_{o1}\beta_{oit} + \gamma_{S1} SKEW_{it} + \gamma_{e1}\beta_{eit} + \varepsilon_{6t} \quad (6)$$

$$R_{it} = \gamma_0 + \gamma_{m2} D1_t \beta_{mit} + \gamma_{m3}(1 - D1_t)\beta_{mit} + \gamma_{o2} D2_t \beta_{oit} + \gamma_{o3}(1 - D2_t)\beta_{oit}$$

$$+ \gamma_{S2} D1_t SKEW_{it} + \gamma_{S3}(1 - D1_t) SKEW_{it} + \gamma_{e1}\beta_{eit} + \varepsilon_{7t} \quad (7)$$

and

$$R_{it} = \gamma_0 + \gamma_{m1}\beta_{mit} + \gamma_{o1}\beta_{oit} + \gamma_{K1}KURT_{it} + \gamma_{e1}\beta_{eit} + \varepsilon_{8t} \tag{8}$$

$$R_{it} = \gamma_0 + \gamma_{m2}D1_t\beta_{mit} + \gamma_{m3}(1-D1_t)\beta_{mit} + \gamma_{o2}D2_t\beta_{oit} + \gamma_{o3}(1-D2_t)\beta_{oit}$$

$$+ \gamma_{K2}D1_t KURT_{it} + \gamma_{K3}(1-D1_t)KURT_{it} + \gamma_{e1}\beta_{eit} + \varepsilon_{9t} \tag{9}$$

where $SKEW_{it}$ and $KURT_{it}$ are, respectively, country *i*'s relative skewness and kurtosis coefficients risk factors. Symmetry between up and down markets can be tested for equations (5), (7) and (9) in a similar manner explained above. Hypotheses about individual slope coefficients in the unconditional (conditional) models are tested using two (one) tail *t*-statistics.

Correlations of the risk factors are reported in Table 2c. Notice that some of the risk factors (like the squared market betas or squared oil betas) correlate highly with some of the other risk measures. Also notice that some of the skewness and kurtosis risk factors correlate highly. Consequently, it would not be desirable to estimate a model with all of the risk factors because multicollinearity would become a problem.

4.0. Empirical Results

4.1 Risk factors on daily excess returns

Table 3 presents the pooled regression results for unconditional and conditional models investigating the relationship between returns and different risk measures using daily data. Model 1 investigates the relationship between returns, market risk, oil price risk and exchange rate risk. Model 2 investigates the relationship between returns, market risk, oil price risk, squared market price risk, and exchange rate risk. Model 3 investigates the relationship between returns, market risk, oil price risk, squared oil price risk, and exchange rate risk. Model 4 investigates the relationship between returns, market risk, oil price risk, total risk, and exchange rate risk. Model 5 investigates the relationship between returns, market risk, oil price risk, skewness, and exchange rate risk. Model 6 investigates the relationship between returns, market risk, oil price risk, kurtosis, and exchange rate risk.

The estimated coefficient on the intercept term is positive and statistically significant at the 5% level in all models (unconditional and conditional). The estimated coefficient on the exchange rate risk factor is statistically insignificant in all models (unconditional and conditional) indicating that at a daily frequency, exchange rate risk is not an important driver of excess stock market returns in emerging markets.

The results from all of the unconditional models show that the estimated coefficient on the market risk variable is negative and statistically significant at the 5% level, which is inconsistent with the expectation of a positive tradeoff between risk and returns. By contrast, the estimated coefficient for the oil price risk factor is positive and statistically significant at the 10% level for five out of the six unconditional models suggesting that there is a positive risk premium on the oil price beta of the emerging stock market returns.

Turning now to the conditional models, an interesting pattern emerges. There is strong support for a systematic, but conditional, relationship between the market beta and realized returns. In up markets, there is a significant positive relationship between the market beta and stock returns implying that high-beta markets receive a larger positive risk premium than low-beta markets. In down markets, there is a significant negative relationship between the market beta and returns suggesting that high-beta markets incur higher losses than low-beta markets. Importantly, the results are robust across all the six conditional models. Our results are in agreement with those found by Pettengill, Sundaram and Mathur (1995), Isakov (1999), Fletcher (2000), Hodoshima, Garza-Gomez and Kunimura (2000), and Tang and Shum (2003a,b) in their studies of developed stock markets.

On the other hand, for the relationship between the oil market beta and returns, there is a strong positive conditional significant relationship between the oil price beta and returns but only when the oil prices are up. In contrast, when oil prices are down, the relationship between oil price beta and returns are found negative (in five out of the six models studied) but statistically insignificant at the 10% level. The above results reveal that for both unconditional and conditional cases, oil price beta plays a significant role in determining returns in the emerging stock markets.

Model 2 investigates whether there is any non-linear relationship between market risk and emerging market stock returns. While no unconditional relationship is found between squared market risk and emerging stock returns, a conditional relationship is found. In comparison, an unconditional and conditional relationship between squared oil price risk and emerging market stock returns (Model 3) is also found. Importantly, conditional nonlinearity is found for both Models 2 and 3 irrespective of types of beta (i.e., market versus oil beta).

The results from estimating Model 4 show a conditional relationship between total risk and emerging market returns. The conditional model (column 9) shows that the regression coefficients for total risk are positive (negative) in up (down) markets, and are statistically significant at the 5% level, implying that total risk plays a significant role in pricing risky assets for daily returns.

Model 5 presents the results of adding skewness to the risk-return relationship of the emerging markets. The unconditional model (column 10) shows that skewness is negatively related to returns, but the relationship is insignificant at the 5% level. The conditional model (column 11) also shows a weak relationship where the estimated coefficients of skewness are statistically insignificant at the 5% level for both up and down markets. The overwhelming rejection of skewness indicates that it does not play a significant role in emerging markets' daily asset returns. On the contrary, Tang and Shum (2003b) documented that skewness is a significant factor for conditional returns in up and down markets in most of the developed capital markets they studied.

The results of Model 6 show that for the unconditional model (column 12), the estimated coefficient of kurtosis is negative and statistically insignificant at the 5% level. In contrast, the results of the conditional model (column 13) show that kurtosis is positively (negatively) related to realized returns in up (down) markets, but the estimated coefficient is significant at the 5% level only for the down market. These results are similar to Tang and Shum (2003b) who also find that kurtosis does not play a significant role in pricing asset returns.

Overall, the results of Table 3 can be summarized as follows. First, the oil price beta has been consistently found to be positive and significant (at the 10% level) in five out of six of the unconditional models. Second, for all six conditional models, the market beta is found significant at the 5% level and maintains positive (negative) relationship in up (down) markets. Third, for all six conditional models, the oil price beta is found positive and significant in up markets only, while it is negative (in five out of six models) but insignificant in down markets. Fourth, a nonlinear relationship between the market or oil beta and return is significantly evident in the conditional models, except for Model 3 where nonlinearity is also present in the unconditional model. Fifth, although total risk exhibits an insignificant negative role to returns in the unconditional model, it plays a crucial role in up and down markets. Finally, skewness shows a negative and insignificant relationship with returns, while kurtosis is found important for conditional returns but only when the market is down.

Regression fit statistics demonstrate the vast improvement in the unconditional version of a model relative to its conditional version. The values of the coefficient of determination (adjusted R^2) show that the explanatory power of the model always increases by at least one order of magnitude for the conditional version of a model relative to its unconditional version. The significant F-statistic values (which are much larger in the conditional version) of the models indicate that the slope regression parameters are nonzero and the regression equations do have some validity in fitting the data. Finally, the conditional version of a model has values of the Durbin-Watson statistic that are closer to 2 indicating that these representations are likely to be free from any first-order serial correlation. Taken together, these results suggest that for each model, the conditional version has a much better fit than the corresponding unconditional version. Also notice that the Durbin-Watson statistics are generally indicative of little first order serial correlation. To control for possible heteroskedasticity and serial correlation, heteroskedasticity period robust standard errors are used in calculating t statistics.

4.2 Robustness over different data frequencies

The empirical results of the previous section are based upon daily data. The robustness of these results can be investigated by re-estimating the models using weekly and monthly data. Tables 4 and 5 present the estimated results for risk-return relationships for weekly and monthly data, respectively.

Comparing the results of Tables 4 and 5 with the results in Table 3 we see some obvious commonalities between the unconditional models in each table. First, the estimated coefficient on the intercept term is positive and statistically significant in most of the models reported. Second, the market beta is negatively correlated with excess market returns. This result is significant at the 5% level in most of the unconditional models. Third, the oil price beta is positively correlated with excess market returns and this result is statistically significant at the 10% level in most unconditional models. Risk measures for total risk, skewness and kurtosis, each have a statistically insignificant impact on excess market returns independent of the data frequency being used.

Comparing the results from the conditional models in Tables 4 and 5 with the results from the conditional models in Table 3 we see that market betas generally have a positive (negative) relationship with excess market returns in up (down) markets for the models estimated using daily or monthly data. In the case of weekly data, however, the conditional market beta for up markets has a negative relationship with excess market returns (although the result is generally insignificant). When oil prices are positive, oil betas have a positive and significant relationship with excess returns in the daily and monthly models. When oil prices are negative, oil price betas have a positive and significant relationship with excess market returns in the weekly and monthly models.

This suggests that in addition to the relationship between oil price changes and excess returns in emerging markets being non-symmetrical, there may also be some time dependency effects. Time dependent, non-symmetrical oil price change effects could be due to a confluence of changes in global oil demand and supply conditions, responses to geopolitics, institutional arrangements (OPEC), and the dynamics of the futures market (Sadorsky (2004)). Some evidence of a conditional relationship between squared market beta (or squared oil beta) and excess returns is found across all three data frequencies. Similarly, evidence of a conditional relationship between total risk and excess returns is also present across the three data frequencies. In comparison, no evidence of a conditional relationship between skewness and excess market returns or kurtosis and excess market returns is found.

The results on the exchange rate risk factor are mixed. The exchange rate risk factor is statistically insignificant in models estimated with daily data but is statistically significant in models estimated with weekly data. The exchange rate risk factor is significant in approximately half of the models estimated using monthly data. These results suggest that the impact of exchange rate risks is greatest over weekly data.

In summary, the results show that oil price risk comes out as a significant factor in explaining the asset returns in emerging capital markets although the exact relationship depends somewhat on the frequency of the data being used. Furthermore, for each model, the adjusted R squared values are higher for the conditional version relative to the unconditional version. These results are independent of the data frequency being used.

4.3 Test of symmetry

In order to investigate whether the regression coefficients are symmetric in up and down markets we employ the test of symmetry which is reported in Table 6. The results reported in Panel A (daily data) show that the null hypothesis of a symmetrical relationship between the regression coefficients of the risk measures for market returns or oil prices in up and down markets is significantly different from zero at the 5% level. Importantly, the findings are, with a few exceptions at the monthly frequency, consistent across the three data frequencies of the asset returns considered in the study. These results show that a significant asymmetrical relationship exists between market betas and returns in up and down markets. These findings support the results presented in Tables 3-5 that both market and oil price beta are significant elements to the assets returns in emerging markets. This result also supports the evidence presented in Sadorsky (1999) who finds that oil price volatility shocks have asymmetric effects on stock returns and the economy.[1] For the remaining models, the results show that the regression coefficients for total risk, skewness, and kurtosis are symmetrical in up and down markets and this result is maintained throughout for daily, weekly and monthly returns. For the case of regression coefficients of squared-beta (market or oil), the relationship is symmetrical for weekly returns but is found asymmetrical for both daily and monthly returns.

4.4 The impact of risk factors on developed markets

Although the focus of this paper is on the impact of oil price risk on emerging stock markets, we include Tables 7 and 8 which present pooled regression results from estimating the impact of risk factors on monthly excess returns in developed markets

[1] The asymmetrical relationship between oil price changes and economic activity is currently a topic of much debate (see for example the paper by Jones, Leiby and Paik (2004) and the references cited).

(measured in U.S. dollars) for further comparison purposes. The sample of developed markets includes Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and the USA. The data set covers the same period as the data set used for the emerging market analysis.

In the unconditional version of each model, neither market betas nor oil price betas show much explanatory power with excess market returns (Table 7). For the conditional version of each model, some of the down market betas show significant correlation with excess market returns but conditional oil betas show almost no significant correlation with excess market returns. The result on market betas is consistent with Hodoshima, Garza-Gomez and Kunimura (2000) who find model fits are better in down markets than in up markets. The result on the oil price betas is expected because emerging economies use oil much less efficiently compared to developed economies. As a result we would expect oil price risk to have a greater impact on emerging stock markets. Like Tang and Shum (2003b) kurtosis has little impact on developed stock market returns. Unlike Fletcher (2000) and Tang and Shum (2003a), however, little evidence is found that conditional up market betas significantly impact stock returns in developed markets. This difference could be due to differences in choice of, countries, units of measurement, estimation techniques, risk measures, and sample size. Little evidence is found against symmetric risk factors (Table 8).

5. Summary and Conclusions

There is now a growing body of literature on the relationship between stock markets and oil prices. Most of this literature has focused on developed economies. The purpose of this paper is to contribute to the literature on stock markets and energy prices by studying the impact of oil price changes on emerging stock market returns. This is an important and interesting topic to study because emerging economies are expected to consume an increasing share of the world's oil and become larger players in the global financial markets. The rising economic importance of the BRIC (Brazil, Russia, India, and China) economies means that if these countries continue to develop along the same path as the United States, they will use up enormous amounts of fossil fuels. Russia is currently producing more oil than Saudi Arabia (although with much smaller reserves) and has the largest deposits of natural gas on the planet (26.7% of proven world natural gas reserves (BP (2005)). The other countries are, however, net importers of fossil fuels. The risk from oil price changes and the impact on profits of companies in these countries is, thus, likely to play a large role in the development of these economies and their financial markets.

This paper uses both unconditional and conditional risk analysis to investigate the relationship between oil price movements and stock returns in 21 emerging stock markets. The unconditional relationship between market beta and emerging stock market returns is generally significant but negative. By comparison, oil price risk plays an important role in pricing emerging market stock returns. Oil price risk is positive and statistically significant at the 10% level in most models. This result is robust across three different data frequencies. Other sources of unconditional risk like total risk, skewness and kurtosis have little impact on emerging market stock returns.

A conditional risk analysis overcomes some of the weaknesses of using an unconditional risk analysis and reveals some important and interesting results. Our results show that for daily and monthly data there is a positive and significant relationship between market betas and returns in up markets and a negative and significant relationship between market betas and returns in down markets. These results from emerging markets are in agreement with the papers by Pettengill, Sundaram and Mathur (1995), Isakov (1999), Fletcher (2000), Hodoshima, Garza-Gomez and Kunimura (2000), and Tang and Shum (2003a,b) in establishing a conditional relationship between realized returns and risk in developed markets.

In general we find strong evidence that oil price risk impacts stock price returns in emerging markets although the exact relationship depends somewhat on the data frequency being used. The conditional relationship is not, however, symmetrical. For daily and monthly data, oil price increases have a positive impact on excess stock market returns in emerging markets. For weekly and monthly data, oil price decreases have positive and significant impacts on emerging market returns.

In addition there is some evidence of a non linear conditional relationship between market risk and emerging stock returns and a non linear conditional relationship between oil price risk and stock market returns. There is also evidence that total risk impacts emerging stock market returns. There is little evidence that skewness or kurtosis have much of an impact on emerging stock market returns. These results are consistent across the three data frequencies.

We find that the explanatory power of the conditional version of a model increases relative to the unconditional version of a model. These main results are consistent across all models and three data frequencies. These results are also consistent with what other researchers have found in studying the conditional risk and return tradeoff in developed markets. The results in this paper are useful for individual and institutional investors, managers and policy makers who are concerned with oil price risk in emerging stock markets.

While the conditional multi-factor model used to investigate the relationship between market returns and risk is an improvement over the unconditional multi-factor model, there are still some limitations that need to be pointed out. The fact that the true market portfolio is unobservable creates a potential problem for the cross-sectional regression approach. As Roll and Ross (1994) show, if the true market portfolio is efficient, the cross-sectional regression approach, which uses a proxy for the market portfolio, can be sensitive to small deviations from the true market portfolio. Moreover, extending beta pricing models to an international setting requires a number of assumptions including integrated capital markets, purchasing power parity, and no informational or transactions costs or taxes. In addition, the world CAPM model may not hold in all countries. Even with these limitations, the results in this present paper are very useful in establishing a significant statistical relationship between oil price risk and emerging market stock returns.

There are several avenues for future research. As more data on emerging market economies becomes available it will be possible to include more countries in the analysis. Using a broader set of emerging market data then the one used in this paper will help to further our understanding of the relationship between oil price risk and emerging stock markets. While the analysis in this paper has employed more risk factors than included in other previous studies investigating the conditional relationship between risk and returns, it may also be of interest to expand the set of risk factors to include other macroeconomic risks to see if the inclusion of additional risk factors improves upon the fit of the conditional model relating risk and returns.

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Table 1: Oil consumption (thousands of barrels per day).

Region	Consumption in 2004	1994-2004 % change
North America	24619	16.0%
South and Central America	4739	19.2%
Europe and Eurasia	20017	1.3%
Middle East	5289	30.8%
Africa	2647	24.3%
Asia Pacific	23446	37.2%
World	80757	18.4%

Selected Countries	Consumption in 2004	1994-2004 % change
Brazil	1830	29.0%
China	6684	112.5%
India	2555	80.9%
Indonesia	1150	48.6%
Japan	5288	-8.0%
Malaysia	504	35.5%
Pakistan	296	1.9%
Russia	2574	-21.2%
Thailand	909	47.4%
United States	20517	15.8%

Source: BP Statistical Review of World Energy, June 2005 (www.BP.com).

Table 2a: Descriptive statistics and unit root test of daily excess dollar returns (December 1992 to October 2005).

	ARG	BRA	CHL	COL	IND	IDN	ISR	JOR	KOR	MYS	MEX	PAK
Mean	0.008	0.041	0.013	0.031	0.010	-0.021	0.008	0.029	0.012	-0.009	0.017	-0.004
Std. Dev.	2.318	2.455	1.195	1.440	1.590	2.983	1.551	0.996	2.507	2.017	1.912	1.938
Skewness	-1.008	-0.183	0.041	0.189	-0.452	-1.143	-0.242	0.678	0.251	-1.028	-0.584	-0.431
Kurtosis	22.817	7.854	6.754	8.211	8.423	31.537	7.177	22.680	13.809	62.484	15.325	10.030
Jarque-Bera	55334	3305	1966	3807	4216	114300	2466	54270	16329	494040	21376	6996
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PP unit root test*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	PER	PHL	POL	ZAF	LKA	TAI	THA	TUR	VEN	WRLD	OIL	TWEX
Mean	0.029	-0.032	0.052	0.009	0.004	-0.002	-0.031	0.038	-0.012	0.015	0.033	-0.002
Std. Dev.	1.643	1.736	2.271	1.411	1.587	1.786	2.206	3.357	2.945	0.802	2.211	0.390
Skewness	0.004	0.937	-0.081	-0.534	1.168	0.049	0.830	-0.202	-5.303	-0.153	-0.270	-0.097
Kurtosis	8.551	17.668	6.922	8.768	42.163	5.567	12.362	8.835	133.362	6.009	6.891	4.458
Jarque-Bera	4297	30496	2149	4799	214655	920	12609	4771	2385682	1276	2152	302
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PP unit root test*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

For each country, an excess dollar return is the daily dollar return minus the daily riskless rate based on the Treasury-Bill rate. A daily dollar return is the log of the change in the market index expressed in U.S. dollar as reported in the DATASTREAM. There are 3347 daily return observations. The figures represent p-values of the Phillips-Perron (PP) unit root test which is a test of the significance of the coefficient c_2 in the regression of $R_{it} = c_1 + c_2 R_{it-1} + \varepsilon_t$. Andrews bandwidth and quadratic spectral kernel is used for lag selection and spectral method, respectively.

Table 2b: Correlations of excess daily returns.

	ARG	BRA	CHL	COL	IND	IDN	ISR	JOR	KOR	MYS	MEX	PAK	PER	PHL	POL	ZAF	LKA	TAI	THA	TUR	VEN	WRLD	OIL	TWEX
ARG	1.00																							
BRA	0.44	1.00																						
CHL	0.35	0.45	1.00																					
COL	0.07	0.08	0.11	1.00																				
IND	0.05	0.10	0.11	0.02	1.00																			
IDN	0.06	0.06	0.13	0.08	0.11	1.00																		
ISR	0.13	0.19	0.20	0.07	0.10	0.07	1.00																	
JOR	-0.02	0.01	0.04	0.03	0.03	0.02	0.00	1.00																
KOR	0.10	0.13	0.14	0.06	0.18	0.18	0.12	0.06	1.00															
MYS	0.08	0.05	0.11	0.04	0.11	0.31	0.08	0.02	0.18	1.00														
MEX	0.40	0.47	0.41	0.08	0.09	0.08	0.25	0.01	0.16	0.11	1.00													
PAK	-0.01	0.02	0.06	0.02	0.09	0.07	0.04	0.04	0.03	0.10	0.04	1.00												
PER	0.25	0.30	0.27	0.13	0.06	0.07	0.10	0.04	0.09	0.10	0.30	0.01	1.00											
PHL	0.08	0.08	0.13	0.06	0.10	0.33	0.09	0.02	0.19	0.25	0.11	0.06	0.11	1.00										
POL	0.09	0.14	0.17	0.07	0.10	0.15	0.18	0.03	0.20	0.13	0.16	0.08	0.12	0.16	1.00									
ZAF	0.17	0.23	0.27	0.13	0.14	0.15	0.27	0.01	0.21	0.17	0.27	0.09	0.25	0.16	0.28	1.00								
LKA	0.01	0.01	0.04	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.00	0.06	0.01	0.03	0.03	0.00	1.00							
TAI	0.05	0.07	0.14	0.06	0.13	0.17	0.11	0.04	0.24	0.17	0.09	0.08	0.05	0.17	0.14	0.17	0.05	1.00						
THA	0.10	0.11	0.18	0.07	0.14	0.34	0.11	0.04	0.29	0.34	0.13	0.08	0.12	0.34	0.18	0.24	0.05	0.21	1.00					
TUR	0.06	0.13	0.16	0.05	0.09	0.03	0.14	0.04	0.13	0.06	0.11	0.05	0.12	0.05	0.16	0.19	0.04	0.11	0.11	1.00				
VEN	0.09	0.14	0.13	0.08	0.03	0.06	0.08	0.02	0.06	0.06	0.13	0.03	0.14	0.04	0.08	0.11	0.00	0.04	0.09	0.08	1.00			
WRLD	0.30	0.37	0.38	0.08	0.10	0.11	0.42	0.02	0.20	0.12	0.47	0.02	0.21	0.12	0.23	0.38	0.01	0.13	0.18	0.14	0.12	1.00		
OIL	0.03	0.00	0.00	0.01	-0.01	0.03	0.02	-0.02	0.01	0.03	0.03	-0.01	0.01	0.01	0.01	0.03	-0.01	-0.01	0.02	0.00	0.01	0.00	1.00	
TWEX	0.01	-0.01	0.00	-0.05	0.01	-0.04	0.03	-0.04	-0.03	-0.04	0.02	0.00	-0.12	-0.04	-0.10	-0.16	-0.02	-0.01	-0.08	-0.04	0.01	-0.09	-0.03	1.00

Table 2c: Correlations of risk factors.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	R	1.00																						
2	β_m	-0.01	1.00																					
3	$D_1\ \beta_m$	0.10	0.52	1.00																				
4	$(1\text{-}D_1)\beta_m$	-0.11	0.50	-0.48	1.00																			
5	β_o	0.00	0.41	0.20	0.22	1.00																		
6	$D_2\ \beta_o$	0.02	0.28	0.14	0.15	0.66	1.00																	
7	$(1\text{-}D_2)\beta_o$	-0.02	0.28	0.14	0.14	0.68	-0.10	1.00																
8	β_m^2	-0.01	0.94	0.49	0.47	0.32	0.22	0.21	1.00															
9	$D_1\ \beta_m^2$	0.07	0.59	0.93	-0.34	0.19	0.13	0.13	0.62	1.00														
10	$(1\text{-}D_1)\beta_m^2$	-0.07	0.57	-0.34	0.93	0.20	0.14	0.13	0.61	-0.24	1.00													
11	β_o^2	-0.01	0.29	0.15	0.15	0.71	0.48	0.47	0.24	0.15	0.15	1.00												
12	$D_2\ \beta_o^2$	0.01	0.19	0.09	0.10	0.47	0.75	-0.11	0.16	0.09	0.10	0.66	1.00											
13	$(1\text{-}D_2)\beta_o^2$	-0.02	0.20	0.11	0.10	0.46	-0.11	0.72	0.16	0.10	0.09	0.67	-0.12	1.00										
14	TR	0.00	0.29	0.15	0.15	0.37	0.25	0.25	0.18	0.11	0.11	0.44	0.29	0.29	1.00									
15	D_1 TR	0.11	0.15	0.62	-0.47	0.18	0.12	0.12	0.09	0.45	-0.34	0.23	0.15	0.15	0.52	1.00								
16	$(1\text{-}D_1)$TR	-0.10	0.15	-0.47	0.63	0.21	0.14	0.14	0.10	-0.33	0.46	0.23	0.16	0.15	0.52	-0.46	1.00							
17	SKEW	0.00	-0.12	-0.07	-0.05	-0.18	-0.13	-0.12	-0.05	-0.03	-0.02	-0.26	-0.18	-0.17	-0.26	-0.15	-0.12	1.00						
18	D_1 SKEW	-0.01	-0.09	-0.13	0.04	-0.13	-0.09	-0.09	-0.03	-0.07	0.03	-0.19	-0.13	-0.12	-0.19	-0.24	0.04	0.73	1.00					
19	$(1\text{-}D_1)$SKEW	0.02	-0.08	0.04	-0.13	-0.13	-0.09	-0.08	-0.03	0.03	-0.07	-0.18	-0.13	-0.11	-0.18	0.04	-0.23	0.68	0.00	1.00				
20	KURT	0.00	-0.01	0.00	-0.01	0.21	0.15	0.13	-0.03	-0.01	-0.02	0.24	0.17	0.16	0.22	0.12	0.10	-0.79	-0.58	-0.53	1.00			
21	D_1 KURT	0.04	-0.01	0.23	-0.24	0.13	0.09	0.09	-0.02	0.14	-0.17	0.16	0.11	0.11	0.14	0.39	-0.24	-0.55	-0.77	0.02	0.69	1.00		
22	$(1\text{-}D_1)$KURT	-0.05	-0.01	-0.25	0.24	0.14	0.10	0.09	-0.02	-0.18	0.16	0.16	0.12	0.10	0.14	-0.25	0.39	-0.49	0.02	-0.75	0.63	-0.13	1.00	
23	β_e	-0.01	0.50	0.27	0.24	0.00	0.00	0.00	0.58	0.37	0.35	-0.01	-0.01	0.00	-0.12	-0.06	-0.07	-0.12	-0.09	-0.08	0.10	0.07	0.06	1.00

Table 3: Pooled regression results from risk factors on daily excess returns.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Variable	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
Constant	0.038	0.037	0.046	0.046	0.042	0.042	0.040	0.039	0.040	0.038	0.041	0.043
	3.667*	3.406*	4.815*	4.726*	3.987*	3.799*	3.785*	3.331*	2.666*	2.487*	4.084*	4.225*
β_m	-0.062		-0.120		-0.057		-0.059		-0.065		-0.065	
	-2.756*		-2.435*		-2.808*		-2.643*		-2.364*		-3.096*	
$D_1 \beta_m$		0.283		0.651		0.289		0.113		0.281		0.259
		4.813*		4.892*		5.067*		1.844*		4.619*		4.410*
$(1-D_1)\beta_m$		-0.437		-0.974		-0.431		-0.252		-0.440		-0.423
		-6.209*		-5.886*		-6.158*		-3.823*		-5.949*		-5.989*
β_o	0.761		0.765		1.368		0.792		0.733		0.804	
	1.687+		1.740+		2.170*		1.747+		1.602		1.771+	
$D_2 \beta_o$		2.589		2.603		3.235		2.664		2.567		2.690
		4.543*		4.736*		3.841*		4.585*		4.391*		4.529*
$(1-D_2)\beta_o$		-0.578		-0.560		0.117		-0.469		-0.595		-0.491
		-1.039		-1.020		0.164		-0.844		-1.073		-0.911
β_m^2			0.051									
			1.377									
$D_1 \beta_m^2$				-0.392								
				-3.472*								
$(1-D_1)\beta_m^2$				0.541								
				4.098*								
β_o^2					-20.586							
					-2.229*							
$D_2 \beta_o^2$						-21.646						
						-1.744*						
$(1-D_2)\beta_o^2$						-24.134						
						-2.352*						
TR							-0.001					
							-0.566					
D_1 TR								0.032				
								3.572*				
$(1-D_1)$TR								-0.036				
								-4.139*				
SKEW									-0.005			
									-0.378			
D_1 SKEW										0.000		
										0.008		
$(1-D_1)$SKEW										-0.009		
										-0.373		
KURT											0.000	
											-0.350	
D_1 KURT												0.001
												0.833
$(1-D_1)$KURT												-0.002
												-2.184*
β_e	-0.018	-0.020	-0.027	-0.030	-0.019	-0.020	-0.020	-0.022	-0.018	-0.020	-0.016	-0.016
	-0.666	-0.751	-0.985	-1.165	-0.717	-0.822	-0.779	-0.871	-0.693	-0.766	-0.635	-0.657
Adjusted R^2	0.000	0.015	0.000	0.019	0.000	0.016	0.000	0.018	0.000	0.015	0.000	0.016
F-stat	3.42*	138.55*	2.84*	120.51*	3.86*	99.92*	2.60*	117.44*	2.70*	99.06*	2.59*	100.70*
D.W. Stat	1.781	1.827	1.781	1.829	1.781	1.827	1.781	1.828	1.780	1.827	1.781	1.827

* denotes $p < .05$, + denotes $p < .10$
Cross section weights used in estimation. T statistics reported below coefficient estimates.
One tail t test used for conditional models and two tail t test used for unconditional models.
Heteroskedasticity period consistent standard errors used in the calculation of t statistics.

Table 4: Pooled regression results from risk factors on weekly excess returns.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Variable	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
Constant	0.242	0.239	0.256	0.254	0.249	0.246	0.243	0.235	0.252	0.246	0.227	0.229
	7.617*	7.206*	5.742*	5.732*	7.325*	6.871*	6.754*	6.170*	3.806*	3.658*	2.311*	2.382*
β_m	-0.330		-0.399		-0.299		-0.327		-0.346		-0.331	
	-4.468*		-1.866+		-4.042*		-3.852*		-3.478*		-4.487*	
$D_1\ \beta_m$		-0.028		-0.011		-0.002		-0.218		-0.029		-0.047
		-0.323		-0.036		-0.025		-2.265*		-0.256		-0.545
$(1\text{-}D_1)\beta_m$		-0.663		-0.851		-0.641		-0.459		-0.685		-0.642
		-6.947*		-2.645*		-6.641*		-3.426*		-5.619*		-6.048*
β_o	1.514		1.536		1.768		1.519		1.504		1.483	
	1.798+		1.794+		1.639		1.807+		1.729+		1.684+	
$D_2\ \beta_o$		-0.229		-0.189		0.858		-0.224		-0.242		-0.247
		-0.243		-0.198		0.890		-0.237		-0.249		-0.249
$(1\text{-}D_2)\beta_o$		3.860		3.874		3.457		3.874		3.844		3.845
		2.979*		2.981*		2.291*		3.013*		2.936*		2.948*
β_m^2			0.049									
			0.418									
$D_1\ \beta_m^2$				-0.031								
				-0.145								
$(1\text{-}D_1)\beta_m^2$				0.155								
				0.628								
β_o^2					-8.063							
					-1.097							
$D_2\ \beta_o^2$						-18.389						
						-2.399*						
$(1\text{-}D_2)\beta_o^2$						3.559						
						0.369						
TR							0.000					
							-0.082					
D_1 TR								0.007				
								2.111*				
$(1\text{-}D_1)$TR								-0.007				
								-2.127*				
SKEW									-0.022			
									-0.218			
D_1 SKEW										0.022		
										0.218		
$(1\text{-}D_1)$SKEW										-0.063		
										-0.534		
KURT											0.003	
											0.162	
D_1 KURT												0.004
												0.225
$(1\text{-}D_1)$KURT												-0.002
												-0.107
β_e	-0.134	-0.136	-0.134	-0.136	-0.145	-0.148	-0.135	-0.137	-0.130	-0.133	-0.131	-0.134
	-2.101*	-2.218*	-2.110*	-2.218*	-2.382*	-2.500*	-2.069*	-2.140*	-2.252*	-2.395*	-2.083*	-2.224*
Adjusted R^2	0.001	0.005	0.001	0.005	0.001	0.005	0.001	0.005	0.001	0.005	0.001	0.005
F-stat	4.34*	9.79*	3.27*	7.04*	3.56*	7.50*	3.25*	7.62*	3.27*	7.05*	3.27*	7.01*
D.W. Stat	1.953	1.994	1.953	1.994	1.953	1.994	1.953	1.994	1.953	1.993	1.953	1.994

* denotes $p < .05$, + denotes $p < .10$
Cross section weights used in estimation. T statistics reported below coefficient estimates.
One tail t test used for conditional models and two tail t test used for unconditional models.
Heteroskedasticity period consistent standard errors used in the calculation of t statistics.

Table 5: Pooled regression results from risk factors on monthly excess returns.

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Variable	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
Constant	0.759	0.691	1.353	1.296	0.982	0.916	0.700	0.527	0.794	0.726	0.554	0.677
	1.992*	1.679*	3.240*	2.923*	3.140*	2.602*	1.887+	1.247	1.816+	1.567+	0.618	0.790
β_m	-0.544		-2.125		-0.321		-0.759		-0.614		-0.538	
	-1.661+		-2.130*		-1.112		-1.566		-1.566		-1.657+	
$D_1\ \beta_m$		0.732		0.786		0.912		-0.727		0.652		-0.129
		2.302*		0.651		3.533*		-1.464+		1.657*		-0.377
$(1-D_1)\beta_m$		-2.116		-6.075		-1.908		-1.323		-2.167		-1.044
		-5.658*		-5.853*		-5.389*		-2.101*		-5.173*		-2.259*
β_o	3.290		3.641		3.769		3.331		3.173		3.348	
	2.308*		2.517*		2.119*		2.364*		2.095*		2.488*	
$D_2\ \beta_o$		3.379		3.962		5.827		3.485		3.238		3.514
		1.937*		2.205*		2.103*		2.025*		1.795*		2.039*
$(1-D_2)\beta_o$		5.655		6.064		5.257		5.903		5.539		5.974
		3.343*		3.569*		2.976*		3.744*		3.095*		3.866*
β_m^2			0.724									
			1.609									
$D_1\ \beta_m^2$				-0.356								
				-0.577								
$(1-D_1)\beta_m^2$				2.234								
				4.079*								
β_o^2					-17.412							
					-2.513*							
$D_2\ \beta_o^2$						-26.070						
						-2.798*						
$(1-D_2)\beta_o^2$						-9.708						
						-1.348+						
TR							0.003					
							0.808					
D_1 TR								0.016				
								3.424*				
$(1-D_1)$TR								-0.007				
								-1.652*				
SKEW									-0.438			
									-0.632			
D_1 SKEW										-0.548		
										-0.762		
$(1-D_1)$SKEW										-0.312		
										-0.444		
KURT											0.050	
											0.173	
D_1 KURT												0.286
												1.030
$(1-D_1)$KURT												-0.389
												-1.260
β_e	-0.413	-0.360	-0.426	-0.316	-0.491	-0.451	-0.374	-0.275	-0.435	-0.381	-0.410	-0.279
	-2.001*	-1.733+	-2.085*	-1.448	-2.366*	-2.343*	-1.981*	-1.472	-1.922+	-1.673+	-2.008*	-1.325
Adjusted R^2	0.003	0.028	0.004	0.035	0.007	0.032	0.003	0.033	0.003	0.028	0.003	0.033
F-stat	3.18*	12.68*	2.90*	11.24*	4.29*	10.30*	2.49*	10.72*	2.61*	9.20*	2.38*	10.86*
D.W. Stat	1.978	2.096	1.980	2.093	1.981	2.092	1.978	2.093	1.978	2.094	1.979	2.090

* denotes $p < .05$, + denotes $p < .10$
Cross section weights used in estimation. T statistics reported below coefficient estimates.
One tail t test used for conditional models and two tail t test used for unconditional models.
Heteroskedasticity period consistent standard errors used in the calculation of t statistics.

Table 6: P-values from symmetry test for regression coefficients in up and down markets.

A: Daily data

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
β_m	0.001	0.002	0.000	0.003	0.006	0.000
β_o	0.041	0.032	0.010	0.027	0.048	0.026
β_m^2		0.045				
β_o^2			0.019			
TR				0.395		
SKEW					0.774	
KURT						0.374
Notes: All values represent p-value of F-statistic.						

B: Weekly data

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
β_m	0.000	0.040	0.000	0.000	0.000	0.000
β_o	0.038	0.037	0.038	0.035	0.045	0.047
β_m^2		0.601				
β_o^2			0.279			
TR				0.970		
SKEW					0.841	
KURT						0.935
Notes: All values represent p-value of F-statistic.						

C: Monthly data

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
β_m	0.028	0.006	0.065	0.037	0.046	0.078
β_o	0.002	0.001	0.004	0.001	0.005	0.000
β_m^2		0.032				
β_o^2			0.007			
TR				0.182		
SKEW					0.521	
KURT						0.857
Notes: All values represent p-value of F-statistic.						

Table 7: Pooled regression results from risk factors on monthly excess returns (developed markets).

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Variable	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
Constant	-0.021	0.221	1.690	1.619	0.063	0.367	-0.030	0.431	-0.108	0.131	0.071	-0.061
	-0.031	0.367	0.703	0.693	0.096	0.583	-0.042	0.695	-0.163	0.225	0.102	-0.111
β_m	0.024		-3.487		0.019		0.049		0.112		0.076	
	0.034		-0.726		0.029		0.054		0.163		0.098	
$D_1\ \beta_m$		0.691		-1.103		0.647		-0.303		0.776		-0.351
		1.093		-0.243		0.995		-0.327		1.259		-0.373
$(1\text{-}D_1)\beta_m$		-1.419		-6.032		-1.447		-1.398		-1.326		0.042
		-2.262*		-1.219		-2.244*		-1.982*		-2.199*		0.077
β_o	2.118		2.448		2.508		2.137		2.163		2.090	
	1.245		1.438		1.723+		1.175		1.260		1.225	
$D_2\ \beta_o$		3.276		3.294		5.125		2.944		3.363		3.001
		1.195		1.244		2.912*		1.033		1.250		1.119
$(1\text{-}D_2)\beta_o$		1.057		1.098		0.958		0.701		1.148		0.652
		0.276		0.284		0.282		0.185		0.295		0.172
β_m^2			1.709									
			0.741									
$D_1\ \beta_m^2$				0.372								
				0.172								
$(1\text{-}D_1)\beta_m^2$				3.103								
				1.247								
β_o^2					-12.878							
					-0.879							
$D_2\ \beta_o^2$						-57.610						
						-3.221*						
$(1\text{-}D_2)\beta_o^2$						20.999						
						0.848						
TR							0.000					
							-0.055					
D_1 TR								0.023				
								2.036*				
$(1\text{-}D_1)$TR								-0.006				
								-0.711				
SKEW									0.277			
									0.577			
D_1 SKEW										0.177		
										0.298		
$(1\text{-}D_1)$SKEW										0.458		
										1.266		
KURT											-0.044	
											-0.249	
D_1 KURT												0.404
												1.516+
$(1\text{-}D_1)$KURT												-0.344
												-3.062*
β_e	-0.624	-0.536	-0.505	-0.447	-0.651	-0.692	-0.631	-0.384	-0.694	-0.620	-0.624	-0.540
	-1.544	-1.440	-1.324	-1.323	-1.598	-1.716+	-1.400	-0.977	-1.571	-1.514	-1.525	-1.529
Adjusted R^2	0.001	0.029	0.001	0.032	0.001	0.035	0.000	0.029	0.001	0.028	0.000	0.032
F-stat	1.474	10.691*	1.420	8.522*	1.285	9.281*	1.106	7.926*	1.228	7.734*	1.119	8.553*
D.W. Stat	1.889	2.072	1.891	2.081	1.889	2.078	1.889	2.077	1.890	2.073	1.889	2.082

* denotes $p < .05$, + denotes $p < .10$
Cross section weights used in estimation. T statistics reported below coefficient estimates.
One tail t test used for conditional models and two tail t test used for unconditional models.
Heteroskedasticity period consistent standard errors used in the calculation of t statistics.

Table 8: P-values from symmetry test for regression coefficients in up and down markets (developed markets).

Monthly data

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
β_m	0.560	0.451	0.534	0.280	0.649	0.798
β_o	0.198	0.195	0.047	0.298	0.190	0.268
β_m^2		0.478				
β_o^2			0.093			
TR				0.234		
SKEW					0.765	
KURT						0.816
Notes: All values represent p-value of F-statistic.						