THREE ESSAYS ON EXCHANGE TRADED FUNDS

AND EMERGING MARKETS

By

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Abstract

In this thesis the author investigate the overreaction effect of Asian country exchange traded funds (ETFs) to US stock market returns, trading strategies of leveraged exchange traded funds (LETFs), and the regime switching behavior of emerging market sovereign credit default swaps.

In the Asian country ETF paper the author studies the overreaction effect of US investors towards US market return when they formulate Asian country ETF prices. The Asian country ETFs are special because when the ETF shares are traded in the US the underlying Asian stock markets are closed resulting in stale Net Asset Values (NAVs) of ETFs. This feature of Asian country ETFs offers a unique setting to study the relation between security price and market sentiment. With a dynamic contrarian trading strategy the author records economically significant abnormal returns over the buy-and-hold benchmark suggesting that US investors' sentiment does lead to abnormal returns in the Asian country ETF market. The author also studies the correspondence of the abnormal return with US market sentiment index and finds that they are positively correlated. Furthermore the author documents asymmetric responses of overreaction in bullish vs. bearish market sentiment. The results pose significant implications for both the academics and practitioners.

The LETF trading strategy paper is a joint work with my supervisor Dr. Peter Miu and my supervisory committee member Dr. Narat Charupat. The authors investigate the market conditions that tip the balance between the market trending effect and the volatility drag in governing the performance of LETFs. The market conditions that promote a stronger former effect than the latter will result in a positive compounding effect, thus enhancing the profitability of a long LETF position at the expense of a short one. On the other hand, those market conditions that promote a dominating latter effect will result in a negative compounding effect, which benefits the short LETF position as opposed to the long position. To address our research questions, we conduct a series of simulation exercises by gauging the sensitivity of the LETF returns on key parameters of the return generating process of the underlying benchmark as represented by the GJR model. We first study the return distributions of a long strategy in a +3x LETF, a short strategy in a -3x LETF, and the pair strategy of a 50% short position in the +3x LETF together with a 50% short position in the -3x LETF, all on the same S&P 500 index. We examine different performance measures and study the risk-return trade-offs of LETF investment. We contribute to the literature by establishing the link between the performance of LETFs and characteristics of the return dynamics of the underlying benchmark through pinpointing the underlying drivers of the compounding effects to facilitate the decision-making process of LETF investors.

In the sovereign Credit Default Swap (SCDS) paper the author investigates the dependency of sovereign CDS spread change on a sovereign's country specific fundamental, local, regional and macro global factors. Using Markov regime switching model the author reveals that in a tranquil state a sovereign market's fundamental factors mainly determine the direction of the SCDS spread movement, while in a turmoil state the global factors become dominant. Cross sectional analysis to examine the behavior of the same explanatory variable on countries of different macroeconomic characters and reveal that more "open" countries are more integrated with the regional economies with the contagion effect being more salient in the bad state, and smaller countries with less diversified economies would be more affected a global crisis because economic links are more important for such countries than larger countries. Furthermore, it shows that the influence of rating is more significant for "closed" than for "open" countries, and the market sentimental effect of flight-to-quality magnifies in the bad state that US equity market return has the strongest influence for small countries indicating stronger economic ties of smaller countries to larger countries with diverse economies in the bad state.

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Contents

Chapter 1 Introduction

Exchange traded funds (ETFs) gained popularity in both practitioners and academia since their inception in late last century due to ETFs' low trading cost and tax efficiency compared to traditional financial instruments like mutual funds. An ETF is a security that is designed to track a stock index, a currency, a commodity or a basket of any assets. An ETF functions much the same as a mutual fund but it can be traded like a stock in a stock exchange throughout the trading day.

Country ETFs track the corresponding countries' stock market indices, which were first introduced in 1996 by American Stock Exchange (AMEX) to track the Morgan Stanley Capital Market (MSCI) country broad market stock indices. The purpose of country ETFs is to provide investors exposure to diversified foreign equity markets. What is special about Asian country ETF is that the ETF and the underlying index are not only traded in different locations but also in completely non-overlapping hours. For example, the iShare Hong Kong ETF is traded in New York 9:30am to 4:00pm Eastern Time but the underlying assets are traded in Hong Kong at daytime in Hong Kong which is 9:20pm to 4:00am Eastern Time. This non-synchronized trading condition of the Asian country ETFs and their underlying assets provides a unique setting that allows us to isolate the influence of market sentiment from that due to changes in a security's intrinsic value. Using S&P 500 as the proxy for US market, we gauge the economic significance of such influences by examining the abnormal returns generated by trading strategies that are designed to exploit the resulting systematic biases in forming market prices. We investigate seven Asian country ETFs whose underlying home markets have no overlapping trading hours with the US, including China, Hong Kong, Japan, Korea, Malaysia, Singapore and Taiwan. we find that ETF price reversion happens at next-day market re-opening. Through implementation of a dynamic contrarian trading strategy, we show that significant abnormal returns can be generated by capitalizing on the overnight price reversion. Confirming the role played by market sentiment, we find that these abnormal returns are positively associated with a proxy of the US market sentiment.

Leveraged exchange-traded funds (LETFs) are relatively new members of the exchange-traded fund (ETF) family which was introduced in 2006 in the US. Like any ETFs, LETFs are publicly-traded funds listed on stock exchanges where investors and traders can buy and sell throughout the trading hours of the market. An LETF promises to provide daily returns that are in a multiple (positive or negative) of the returns on an underlying benchmark index. To meet that promise, the fund uses leverage, which is typically obtained through derivatives such as futures contracts, forward contracts, and total-return swaps. Given the embedded leverage, investment in LETFs are by its very nature risky. Sound LETF trading strategies need to not only consider the expected directional changes of the underlying benchmark but also address the positive and negative compounding effect that will be realized during the investment horizon. In this paper we investigate the market conditions that balance the trending of market and the compounding effect by answering questions like how much market trending is needed to overcome the negative influence of market volatility thus resulting in a net positive compounding effect. We conduct a series of simulation exercises by gauging the sensitivity of the LETF returns on key parameters of the return generating process of the underlying benchmark modelled by the GJR-GARCH(1,1) model. We examine different LETF performance measures and study the risk-return trade-offs of LETF investment. The findings contribute to the literature by pinpointing the underlying drivers of the compounding effects and facilitate the decision-making process of LETF investors by establishing the link between the performance of LETFs and different characteristics of the return dynamics of the underlying benchmark.

A credit default swap (CDS) is a contract that provides insurance against the risk of default by a particular reference entity. The reference entity of a Sovereign CDS (SCDS) is a sovereign government. A country's ability and willingness to re-pay its debt owing to other countries or investors is reflected in the spread paid for the protection offered by the corresponding SCDS. Credit risk indicated by a nation's SCDS spread essentially reflects the same fundamental economic condition and market information as the yield of the underlying government bonds. SCDS has become a more important tool than sovereign bond derivatives in the management of sovereign credit risk due to its high liquidity and its ability to more rapidly adjust to new information than bonds in the price discovery process. Using the Markov regime switching approach, we investigate the dependency of sovereign credit default swap (SCDS) spread change on a sovereign's country-specific fundamental, local, regional and macroeconomic global factors. We find that the significance of the determinants of SCDS spread change differs across the two states of our regime-switching model. Specifically, in the "good" state the weekly SCDS spread changes are mainly determined by local, regional and fundamental factors; whereas global variables have stronger influence in the "bad" regime. In particular, US market return plays a dominant role in influencing the SCDS spread change in the "bad" state suggesting loss aversion and flight to quality behavior of investors. We then examine the cross-sectional difference of the above regime switching effect based on country-specific characters and find that the regime switching effect is associated with a nation’s country-specific characters such as openness, economic size, etc...

Chapter 2 Overreaction, Abnormal Returns, and Market Sentiment: Asian Country Exchange Traded Funds

I. Introduction

This paper studies the overreaction of Asian country exchange traded funds (ETFs) to US market returns due to investors' sentiment. The non-synchronized trading condition of the Asian country ETFs and their underlying assets provides a unique setting that allows us to isolate the influence of market sentiment from that due to changes in a security's intrinsic value.

Investors' biased views form market sentiment and market sentiment plays an important role in pricing securities in the open market, causing a security's price to deviate from its intrinsic value. When the market is in general bullish (bearish), a security is more likely to be priced above (below) its intrinsic value. This paper studies the mechanism that causes the price of Asian country ETFs to deviate from their net asset values (NAVs) during the US trading hours when Asian markets are closed.

Why Asian country ETFs? An Asian country ETF is designed to track the performance of an Asian country's home stock market but the ETF shares are traded in the US market. The Asian country ETF shares are traded in completely non-overlapping hours with their underlying assets because when the US market opens the Asian markets are all closed due to time zone differences (see Table 1). Similar to other ETFs, in order to ensure the market prices to effectively track their underlying assets there is creation/redemption mechanism that enables dealers to directly purchase and redeem ETF shares from the ETF sponsor. The direct purchase and redemption of

ETF shares from the ETF sponsor are supposed to immediately arbitrage away any price discrepancies between the ETF share price and its NAV. However, in order for the arbitrage mechanism to work, it requires the ETF shares and the underlying assets to be traded synchronically.[1] In the Asian country ETF case, during the ETF trading hours in the US the underlying assets cannot be traded in their respective home markets in Asia due to market closure, thus the arbitrage mechanism does not work. Not only does the arbitrage mechanism fail, during the US trading hours, investors of Asian country ETFs have no updated information on NAVs to rely on when they formulate the market prices. Significant price discrepancies are observed and documented (Engle and Sarkar (2006); Martinez and Tse (2007)). More importantly, any deviation of the ETF market price from its intrinsic value is not expected to be uniform throughout the US trading day. If market sentiment plays a role in affecting the ETF price given the lack of timely information regarding the intrinsic value, we would expect the effect is stronger at market close than when market just opens. This special feature of Asian country ETFs makes them the perfect instruments to study the influence of market sentiment. We gauge the economic significance of such influences by examining the abnormal returns generated by trading strategies that are designed to exploit the resulting systematic biases in forming market prices.

Using S&P 500 as the proxy for US market, we first compute the long term correlation between Asian country ETFs' NAV returns and S&P 500 returns and compare it with the correlation between Asian country ETFs' daytime returns and S&P 500 returns. The results show that the correlation between Asian country ETFs' daytime returns and S&P 500 returns exceeds the long term correlation between Asian country ETFs' NAV returns and S&P 500

[1] For details on how the arbitrage mechanism works please refer to Section 2.

returns both in magnitude and in explanation power. Similar to the findings of Levy and Lieberman (2013), the results are consistent with the notion that Asian country ETFs overreact to US returns during the US trading hours. Then we test whether the Asian country ETFs exhibit price reversal at the next day market re-opening and we find that the price reversal effect does exist. Our particular interest is that we want to know whether the price reversal effect can lead to profitable opportunities. To test our hypothesis we form a pair of portfolios for each ETF. One portfolio in the pair serves as the benchmark undertaking a buy-and-hold strategy, the other portfolio implements a dynamic contrarian trading strategy to take advantage of the ETF price reversal process. The results show that the contrarian strategy portfolios generate material and significant excess returns over their benchmarks in all the seven Asian country ETF; whereas the same strategy works in none of the seven American ETFs. Moreover, the dynamic strategies for all Asian country ETFs also produce much higher Sharpe ratios and ending values. The excess returns remain significant after risk-adjusted with the Fama-French three-factor model. If the overreaction is indeed due to market sentiment, we expect the abnormal returns to be correlated with market sentiment. The stronger the market sentiment, the stronger should be the overreaction and hence the higher the abnormal returns. With this in mind, we analyse the relation between our abnormal returns and a proxy of US market sentiment – the Sentiment Index maintained by American Association of Individual Investors (AAII). We find that the abnormal returns are positively correlated with the total percentage of sentiment investors in the market. We also find that the abnormal returns are asymmetric in responding to bullish market sentiment and bearish market sentiment in that the abnormal returns are higher in a bearish market than in a bullish market. The asymmetric effect is consistent with the fact that investors are risk averse in general.

This study has a few important contributions. First, we examine the role played by market sentiment on price efficiency and contribute to the understanding of the market sentiment effect on securities' price formation process. The non-synchronized trading condition of the Asian country ETFs and their underlying assets provides a unique setting that allows us to isolate the influence of market sentiment from that due to changes in a security's intrinsic value. Our findings suggest that market sentiment makes the market for Asian country ETFs less efficient. Second, we demonstrate the economic significance of the market sentiment effect on the pricing efficiency of Asian country ETFs by devising a relatively straightforward mechanical trading strategy that exploits the systematic bias in market prices as a result of the market sentiment effect. Besides contributing to the academic literature, the findings of this paper also have important implications to practitioners in the trading of Asian country ETFs. For example, the dynamic contrarian strategy can be a perfect strategy to implement in a hedge fund. The findings also help to improve the market efficiency of these securities as market participants exploit the abnormal profits demonstrated in this study.

The rest of the paper is structured as follows. Section 2 provides a literature review on ETF and introduces our hypothesis. Section 3 describes the data used in the research including data range and data source. Section 4 presents the regression analysis to prove the existence of price reversal in (and only in) non-synchronized trading Asian country ETFs. Section 5 discusses the dynamic contrarian trading strategy in details, analyzes relation between abnormal returns and sentiment index and summarizes the main findings. Section 6 concludes the paper.

II. Related literature and hypothesis

An ETF is a security that is designed to track a stock index, a currency, a commodity or a basket of any assets. An ETF functions much the same as a mutual fund but it can be traded like a stock in a stock exchange throughout the trading day. An ETF fund sponsor creates an ETF fund by holding a portfolio of assets that replicates the underlying security, for example, a stock index. The fund sponsor divides ownership of the ETF fund into creation units and each creation unit contains a large block of ETF shares, usually ranging from 10,000 shares to 200,000 shares. The creation units are then distributed to dealers like financial institutions and the dealers will sell shares in the creation units to the public on open markets (e.g., a stock exchange) just like selling stock shares. Each ETF share has a Net Asset Value (NAV) that is determined by the value of the assets in the ETF fund. The stock exchange where the ETF shares are publicly traded reports the updated NAV of the shares every 15 seconds throughout the trading day. When ETF shares are traded in the exchange its price can deviate from NAV due to market demand variation, but this deviation can only be temporary because an arbitrage mechanism exists in the ETF design to minimize such deviation. In the arbitrage mechanism ETF dealers can purchase and redeem creation units directly from the ETF sponsor. For example, if the ETF share is traded above its NAV (reported by the exchange), investors are paying more for the shares than what the underlying assets are worth, then the arbitragers will buy the underlying assets, redeem them through dealers for creation units and then sell the ETF shares in the creation units on the open market for a profit. On the contrary if the ETF share is traded below its NAV, arbitragers will buy ETF shares on the open market, form creation units, redeem them through dealers to get the underlying assets, and then sell the assets on the open market for a profit. This arbitrage mechanism keeps the supply and demand of the ETF share in equilibrium to match its NAV. When the ETF shares and the underlying assets are traded simultaneously the arbitrage mechanism can ensure the ETF to effectively track the underlying assets, for example, a US local stock index ETF to simultaneously track the US local stock index.

Researchers examine the arbitrage mechanism and the pricing efficiency of ETFs and show that for domestic stock index ETFs the arbitrage mechanism works well and price deviations from its NAV are in general very small and within transaction costs and bid-ask spreads (Ackert and Tian (2000); Elton et al (2002), Curcio et al (2004); Engle and Sarkar (2006), Charupat and Miu (2013)). However this may not always be the case because for some ETFs the ETF shares and the underlying assets are not traded at the same time, for example, the Asian country ETFs.

A country ETF tracks the corresponding country's stock market index, which were first introduced in 1996 by American Stock Exchange (AMEX) to track the Morgan Stanley Capital Market (MSCI) country broad market stock indices. The purpose of country ETFs is to provide investors exposure to diversified foreign equity markets. Unlike a US local index ETF, of which both the ETF shares and the underlying assets are traded in the same location and at the same time, a typical country ETF share is traded in NYSE (New York Stock Exchange) but its underlying assets are traded in the corresponding foreign home country. For example, the iShare Canada ETF is traded in New York and the underlying assets are traded in Toronto. A more complicated case is for Asian country ETFs, for example, the iShare Hong Kong ETF is traded in New York 9:30am to 4:00pm Eastern Time but the underlying assets are traded in Hong Kong at daytime in Hong Kong which is 9:20pm to 4:00am Eastern Time (Table 1). The two are not only traded in different locations but also in completely non-overlapping hours. The non-overlapping trading hours pose a problem for the arbitrage mechanism outlined above because the arbitrage mechanism fails to bring the ETF share price back into equilibrium to match its NAV due to the fact that the underlying assets are not traded at the same time as the ETF. In the Hong Kong case, the Hong Kong market is closed during the New York trading hours and the NAV becomes stale, now if the Hong Kong ETF share is traded above/below the last reported NAV investors cannot buy/sell the underlying assets to implement the arbitrage mechanism as a consequence the ETF price can keep deviating from its NAV. Studies show that the deviations of the country ETF prices from their NAVs are more material, more frequent and more persistent compared to other types of ETFs (Engle and Sarkar (2006); Martinez and Tse (2007); Delcoure and Zhong (2007); Ackert and Tian (2008)).

Intuitively one may want to know that after Asian home markets are closed and the arbitrage mechanism becomes inapplicable what factors determine the fluctuations of the ETF price since no updated NAV can be relied on during the entire trading time. Gutierrez, Martinez and Tse (2009) study the causes of Asian country ETFs returns and volatilities and find that Asian country ETF returns and volatilities are highly correlated with the US market. Using intraday data Shum (2010) shows that during the US trading day when underlying Asian home markets are closed the intraday returns and volatility of the Asian country ETFs can be explained by S&P 500 to a large extent as if the Asian country ETFs were large-cap US stocks. Researchers (Gagnon et al, 2010; Wang et al, 2013; Cheung, 2014) find similar arbitrage opportunities in other cross-listed securities such as American Depository Receipts (ADRs).

Can the high correlation between returns on the country ETFs and the US market return be justified by the relation between the prospect of the foreign countries and the US economy through perhaps some global factors? Using intraday data, Levy and Lieberman (2013) find the dominating effect of S&P 500 return on Asian country ETFs is not fully reflected in the co-movement between the respective country’s local stock market return and S&P 500 return. The excessive correlation could indicate effects of location of trade and market sentiment. It makes intuitive sense to think that, when the lack of home market fundamental information to rely on, the US investors for Asian country ETFs could be overwhelmingly sentimental to US market fluctuations and overly relying on US market information in the pricing of country ETFs. In other words, during the US trading hours when the foreign markets are closed, country ETF investors tend to overreact to US market conditions that may not be related to the prospect of the foreign country equity markets. That is, when the US market is up (down) in a particular day, US investors in general become bullish (bearish) and tend to bid up (down) the prices of foreign country ETFs to a level above (below) their intrinsic values, given that there is a general lack of information about the foreign country market condition since they are closed. We expect this potential bias from the intrinsic value to worsen throughout the trading hours as we are further away from the last available local market information (updated when the foreign market last closed). If it is indeed an overreaction, we would expect the price to revert back to the level reflecting its intrinsic value as the foreign country stock market opens overnight. Thus, when the US market re-opens on the next day, we conjecture that, although there are other factors that will affect the opening price of the ETF, there will be a correction incorporated in the opening ETF price for the sentiment effect embedded in the-day-before's closing price. Therefore, we hypothesize that, if the above price reversal correction is true, one can formulate trading strategies to profit from it. We develop a dynamic contrarian trading strategy to capture overreactions and trigger transactions to capitalize the excess return.

To carry out our analysis, we investigate seven Asian country ETFs whose underlying home markets have no overlapping trading hours with the US, including China, Hong Kong, Japan, Korea, Malaysia, Singapore and Taiwan. As a robustness check, the analysis also includes seven ETFs whose trading hours are exactly synchronized with the US (NYSE). These seven ETFs include iShares Canada country ETF, iShares Mexico country ETF, S&P 500 ETF, Nasdaq PowerShares ETF, iShares Russell 1000 ETF, iShares Russell 2000 ETF, and iShares Russell 3000 ETF. Details are reported in Table 1.

III. Data

We collect from Bloomberg Database the daily opening and closing prices of seven iShare Asian country ETFs traded in New York Stock Exchange (NYSE Arca), namely China, Hong Kong, Japan, Korea, Malaysia, Singapore, and Taiwan. The iShare country ETFs have the longest history and are the most representative of country ETFs[2]. The iShare ETFs for Hong Kong, Japan, Malaysia and Singapore were introduced in 1996. Korea and Taiwan iShares were launched in 2000 and that of China was incepted in late 2004. To include the maximum number of countries and to have a reasonable span of sample time period, we collect daily data from beginning of January 2005 to end of December 2013 totaling 9 years of observations.

For the seven Asian country ETFs, the corresponding local stock markets are all closed when NYSE opens which is to say that the ETFs and the corresponding local country stock indices are traded in completely non-synchronized hours and the NAVs of the ETFs become stale (except for changes in foreign exchange rate adjustment) during the entire trading time of NYSE. From the same database we collect daily NAVs of the seven ETFs for the same sample time period.

[2] We did the same analysis outlined in this paper on Asian country ETFs issued by other suppliers with reasonably long history such as WisdomTree Asia Pacific ex-Japan Fund (ticker: AXJL) and WisdomTree Japan Hedged Equity ETF (ticker: DXJ). Similar results are obtained as we have shown in this paper.

To show that our hypothesis is true only for non-synchronized trading Asian country ETFs we also collect from Bloomberg daily opening and closing prices of seven synchronized trading American ETFs, namely Canada, Mexico, S&P 500 ETF, and ETFs for Nasdaq stock index, Russell 1000 index, Russell 2000 index, and Russell 3000 index. NAVs of these seven ETFs are collected at the same time. We then collect the corresponding daily opening and closing prices for S&P 500 index. Table 1 summarizes basic information of the ETFs and the corresponding tracking indices. Information includes ETF tickers, tracking index names, and home country stock market open hours in Eastern Time (ET). The home market open hours show that the Asian markets are all traded during time periods that NYSE is closed.

[Insert Table 1 about here]

To address our research questions, we compute three different daily return time series for our sample of ETFs, namely daytime return, overnight return, and day-to-day return. The daytime return is calculated as the natural log difference between the same calendar day's closing price and opening price. The ETFs' overnight return is next-day-open to previous-day-close return which is calculated as the natural log difference between prices of next-day-open and previous-day-close. The day-to-day return is the natural log difference between two adjacent days' closing prices.

Daytime return: $$R_{C\_O_t} = Ln\left(P_{Close_t}\right) - Ln\left(P_{Open_t}\right) \quad (1)$$

Overnight return: $$R_{O\_C_t} = Ln\left(P_{Open_t}\right) - Ln\left(P_{Close_{t-1}}\right) \quad (2)$$

Day-to-day return: $R_{C\_C_t} = Ln(P_{Close_t}) - Ln\ (P_{Close_{t-1}})$ (3)

where P_{Close_t} is the closing price of the ETF at day *t* and P_{Open_t} is the opening price at day *t*.

IV. Regression analysis

In the first set of regressions, we do a similar test as in Levy and Lieberman (2013). We test the overreaction of Asian country ETFs to US market returns by regressing the daily returns of each country ETF based on its market price and NAV, respectively, on the daily returns of the S&P 500 index.

$$NAV\_R_{C\_C_{i,t+1}} = \alpha_i + \beta_i \cdot SP\_R_{C\_C_t} + \varepsilon_i \quad (4)$$

$$ETF\_R_{C\_O_{i,t}} = \alpha_i + \beta_i \cdot SP\_R_{C\_C_t} + \varepsilon_i \quad (5)$$

Equation (4) regresses the next day return of ETF NAVs on daily S&P returns and equation (5) regresses daytime ETF returns on daily S&P returns. Note that although the returns $NAV\_R_{C\_C_{i,t+1}}$ and $ETF\_R_{C\_O_{i,t}}$ are indexed by *t+1* and *t* (both US time) respectively, they actually capture the local market information over an overlapping time period after the local market is closed at time t (local time) since the pricing information consisting the NAV is stale for almost a full day. The return based on NAV captures the change in the fundamental value of the ETF given the change in local market and without any influence from the US market sentiment. Results are summarized in Tables 2 and 3. Consistent with the findings of Levy and

Lieberman (2013), for all the countries, the magnitude of the slope coefficient in Eq. (5) exceeds that of Eq. (4). Furthermore, the $\bar{R}^2$ are all much higher indicating stronger explanatory power for Equation (5). The results confirm that there is overreaction to US market return in the Asian country ETF price formation process that cannot be fully explained by the co-movement of the changes in fundamental values.

[Insert Table 2 and 3 about here]

If the overreaction is indeed the result of changing US market sentiment, we would expect any upward (downward) bias of the closing prices of the country ETFs as a result of bullish (bearish) Us market sentiment given the positive (negative) return on the US market to be corrected when local market information become available. Since the local markets are closed and the NAVs become stale until the local markets re-open at night (Eastern Standard Time at New York), ETFs will only have the chance to adjust to their new NAVs the next morning when US market re-opens. We therefore expect the overnight return on the Asian country ETFs to be negatively related to the lag return on the US market. Moreover, this overnight effect should mainly exist in the non-synchronized trading Asian country ETFs but not the synchronized trading American ETFs. The NAVs of American ETFs are updated continuously throughout the US trading hours tracking the timely changes in their local market indices. To test whether our hypothesis is true our second set of regression regresses ETF overnight return on S&P 500 previous day's day-to-day return, which is as follows.

$$ETF\_R_{O\_C_{i,t}} = \alpha_i + \beta_i \cdot SP\_R_{C\_C_{t-1}} + \varepsilon_i \qquad (6)$$

Table 4 shows the estimated coefficients and corresponding p-values of Equation (6). Confirming our hypothesis, all Asian country ETFs report negative estimated coefficients on S&P 500's lag day-to-day return, and all these coefficients are statistically significant. The S&P 500 lag daily return is negatively associated with the overnight return of Asian country ETFs. The effect is also economically significant. For example, a one percentage point increase in the S&P 500 previous day return is associated with, on average, about 21 basis point decrease in overnight ETF return. On the other hand, the slope coefficients for American ETFs are all far from negatively significant. The absence of a significant negative effect of previous day S&P 500 return is consistent with our expectation that American ETFs are not subject to overreaction which is prevalent among Asian country ETFs.

[Insert Table 4 about here]

Could the negative effect of previous day's S&P 500 return documented in Table 4 simply capture the correlation between the US market and the local markets as opposed to being purely the result of overreaction? Suppose today's local Asian market return, which takes place overnight after the US market closed on previous day, is negatively correlated with previous day's US market return. Then even in the absence of any overreaction to US market it will result in a negative relation between previous day's S&P 500 return and overnight Asian country ETFs return. On the other hand, if the same day local market return is positively correlated with previous day US market return the regression results reported in Table 4 are likely to understate the actual overreaction effect. To rule out this potentially confounding effect, we conduct two more regressions for the overnight returns of the Asian country ETFs by also including the same day return on the respective NAVs (capturing the same day return on the local market) as the explanatory variable.

$$ETF\_R_{O\_C_{i,t}} = \alpha_i + \beta_i \cdot NAV\_R_{C\_C_t} + \varepsilon_i \tag{7}$$

$$ETF\_R_{O\_C_{i,t}} = \alpha_i + \beta_i \cdot SP\_R_{C\_C_{t-1}} + \gamma_i \cdot NAV\_R_{C\_C_t} + \varepsilon_i \tag{8}$$

The results are reported in Table 5. They show that, without any exception, the ETF overnight return is positively associated with same day's NAV return and negatively associated with previous day's S&P return. The effects are always statistically significant at 1% level. After controlling for the returns on the local market taking place overnight, the overreaction of overnight return on the Asian country ETFs to previous day's US market return is actually stronger that what we document previously in Table 4. The slope coefficients of $SP\_R_{C\_C_{t-1}}$ reported in Table 5 are much more negative than those reported in Table 4. For example, based on Table 5, a one percentage point increase in previous day's S&P return is associated with, on average, about 70 basis points decrease in the China ETF's overnight return.

[Insert Table 5 about here]

V. Dynamic contrarian trading strategy and abnormal returns

To further assess the economic significance of the overreaction to US market return, we devise a dynamic contrarian strategy to see if investors of Asian country ETFs can capitalize on the phenomenon to enhance their returns.

5.1 The strategy

Suppose we are near market close on day *t* in New York and we are considering an Asian ETF's opening price at day *t*+1 in NYSE as illustrated in Figure 1. When NYSE opens in the morning at day *t*+1, the ETF's opening price will adjust to the new NAV established at local market in day *t*+1 (local trading time of day *t*+1 is overnight of NYSE), react to any new global and local information transmitted to the US market at the opening of day *t+1*. According to our hypothesis, the overreaction of day *t* closing price due to US market sentiment will be corrected with the availability of NAV information as market opens on day *t +1*. To exploit the overreaction, right before the NYSE closes on day *t*, an investor should sell (buy) the ETF if the US market has been bullish (bearish) and buy (sell) the ETF at the day *t+1* opening when the price bias is being corrected. We already show that the ETF's overnight return from day *t* to *t+1* is significantly negatively correlated with S&P's day-to-day return on day *t*, which is conjectured to be driven by the Us market sentiment on day t.

Insert Figure 1 about here

We hypothesize that, if the reversal correction is true there should exist trading strategies that can profit from it. To test the hypothesis, we devise our trading strategy by calibrating a GARCH model to the daily return on S&P 500 index. We conjecture that it is not the raw return on S&P 500 but its unexpected return conditional on current market condition that plays a more important role in governing investors' sentiment. For example, a daily return of 2% may not be generating any bullish market sentiment if the average daily return of the last few trading days is already around 2%. The same 2% daily return however is expected to promote a bullish sentiment if the average daily return in the last while is negative. Besides the conditional mean, conditional volatility is also at play in defining the impact of unexpected return. A ±2% daily return may not stir any attention in a volatile market; whereas the same ±2% daily return may result in significant variation in investors' sentiment within a calm market condition. To control for the conditional market condition, for each trading day, we calibrate a GARCH (1, 1) model using the past 252-trading day daily returns on S&P 500 and use the standardised unexpected return to gauge the direction and magnitude of sentiment in the US market. According to our hypothesis, a positive (negative) unexpected return will trigger positive (negative) ETF investors' overreaction to the US market, thus serve as a sell (buy) signal at market close, with the position to be unwound after re-opening of market on the next trading day. The detailed setup of the trading strategy is explained below.

The decision point of the dynamic contrarian strategy is always at market close (e.g., on day *t*). We utilize the calibrated GARCH (1, 1) model to tell us whether today's S&P 500 return ($SP\_R_{C\_C_t}$) is sufficiently high or low to trigger a transaction.

The GARCH (1, 1) model is specified as:

$$SP\_R_{C\_C_t} = a_0 + a_1 \cdot SP\_R_{C\_C_{t-1}} + \varepsilon_t \qquad (9)$$

Where

$$\varepsilon_t = \sigma_t \cdot z_t \tag{10}$$

and

$$\sigma_t{}^2 = \alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}{}^2 + \beta_1 \cdot \sigma_{t-1}{}^2 \tag{11}$$

We use 252-day rolling window to calibrate the GARCH (1, 1) model at market close of each trading day. To illustrate the dynamic contrarian trading strategy we form a pair of portfolios each with starting value \$1 for every ETF. At the opening of the first day of our data (Jan 3, 2005), all portfolios purchased the respective ETF shares with \$1. For any given ETF, one of the portfolios in the pair follows a buy-and-hold strategy and the other portfolio follows our dynamic contrarian trading strategy. The buy-and-hold portfolios hold on to the initially invested ETF position throughout the sample period. On the other hand, the dynamic trading portfolios will be adjusted according to the outcome of a trading test at each decision point outlined below.

Trading Strategy:

Decision point: closing of each trading day at NYSE.

Decision rule:

Case 1:

if

an ETF price moves in the same direction with S&P 500 price, *and*

$\varepsilon_t > \sigma_t \cdot N^{-1}(0.8)$

then

unexpected return on $SP\_R_{C\_C_t}$ is considered to be *High*

- Sell ½ of the ETF portfolio for cash
- The next morning when NYES opens, buy back ETF shares with the cash

Case 2:

if

an ETF price moves in the same direction with S&P 500 price,

and

$\varepsilon_t < \sigma_t \cdot N^{-1}(0.2)$

then

unexpected return on $SP\_R_{C\_C_t}$ is considered to be *Low*

- Borrow cash equivalent to ½ of the portfolio value, buy ETF shares.
- The next morning when NYSE opens, sell sufficient number of ETF shares to exactly pay back the borrowed money

Where N^{-1} denotes the inverse of the cumulative standard normal distribution function.

If neither Case 1 nor case 2 happens, we do not adjust the portfolio, i.e., adopt the buy-and-hold strategy. The sell and buy orders at market-close and market-opening can be achieved by submitting Market-On-Close (MOC) and Market-On-Open (MOO) orders to the stock exchange. To keep transaction costs under control, we only activate the dynamic strategy for relatively strong overreaction cases when the unexpected S&P 500 returns fall within the highest and lowest 20th percentile based on the conditional standard deviation σ_t. Changing to other percentile, e.g., 10%, 30%, does not significantly change the results presented in the rest of the paper. The reason to buy or sell ½ of the portfolio value in each transaction is to provide a safety margin. The above decision rule repeats every day for the dynamic portfolio until the closing of the day before the last day of the sample period.

Note that there is randomness and there is no guarantee that the strategy works 100% of time. But on average it should work assuming equal chances that the underlying foreign market will go up or down overnight. In fact, the long-term daily overnight expected return of each foreign market should be slightly positive but should not be very different from zero given the short time frame. So we expect the strategy to work on average. Sometime it loses, sometime it gains, but on average it should make a profit.

5.2 The abnormal returns

Assuming a round-trip proportional transaction cost of 0.05%[3] for trading ETFs, we compare the performance of the benchmark buy-and-hold strategy and the dynamic contrarian trading strategy. We expect to see that, if our hypothesis is true, the dynamic contrarian trading strategy should outperform the benchmark.

[3] The average bid-ask spreads for the Asian country ETFs are in the range of 0.03% to 0.05%.

The monthly excess return is calculated for each dynamic trading portfolio in the portfolio pair formed for each ETF i. The excess return is defined as the difference between the monthly returns of dynamic portfolio and the buy-and-hold benchmark portfolio within each portfolio pair.

$$R\_ex_i = R\_dynamic_i - R\_benchmark_i \quad i = 1,2, \ldots, 14 \qquad (12)$$

Table 6 summarizes the statistics of the monthly excess return. Panel A shows results for Asian country ETFs and Panel B shows that of American ETFs. The American ETFs serve as our control sample to rule out any possible confounding market microstructure effect. In Panel A we can see that the mean excess returns for all Asian country ETFs are positive and mostly statistically significant. The mean excess returns are also economically significant. Take China as an example, the mean monthly excess return of 0.86% corresponds to a mean annual excess return of about 10.8%. Even for the least profitable case of Malaysia, the dynamic trading strategy generates an excess return of about 2.3% per year after transaction costs.[4] Moreover, based on the positive skewness the excess return distributions presented in Panel A, we can see that the downside risk of the proposed dynamic contrarian strategy is relatively low.

On the contrary, but as expected, Panel B shows that none of the mean excess returns from the same strategy for American ETFs are significantly positive. This result supports our hypothesis that market sentiment only leads to abnormal return in the non-synchronized trading Asian country ETFs but not synchronized trading American ETFs.

[4] The dynamic contrarian trading strategy still generate statistically and economically significant positive excess return for most of these ETFs when we double the transaction costs assumed.

[Insert Table 6 about here][5]

Figure 2 shows the evolution of portfolio values for each of the Asian country ETFs starting with $1 on Jan 3, 2015. The cumulative effect is impressive. For example, an investor on China ETF can accumulate more than 2.5 times the wealth by adopting the proposed dynamic contrarian strategy as opposed to the buy-and-hold strategy over the 9-year period even after transaction costs. The average enhancement in accumulated wealth across the seven Asian country ETFs is about 70% over this 9-year period.

We calculate the annual excess returns of the dynamic contrarian strategy over the bench mark for each portfolio pair and plot them in Figure 3. As shown in Figure 3, China, Hong Kong, Japan, Singapore, Taiwan all report about 80% (7 out of 9 years) of the time that the annual excess returns are higher than 0. Korea and Malaysia report 60% and 70% of such time respectively. We note that the excess returns of most of the seven ETFs peaked at 2008 or 2009, which is during or right after the year of the global financial crisis as market sentiment attained its extreme level.

[Insert Figures 2 and 3 about here]

[5] The results are also robust to simply using the raw S&P 500 returns as the trading trigger as opposed to using unexpected returns from the GARCH model. For example, the trading strategy remains profitable if we buy (sell) when the raw S&P 500 return falls within the lowest (highest) 20^{th} percentile of the unconditional distribution.

5.3 Abnormal returns and Sharpe ratio

How profitable is the proposed trading strategy on a risk-adjusted basis? We compute and compare the Sharpe ratios of the buy-and-hold and dynamic contrarian strategy. Table 7 reports the monthly mean returns, standard deviation and Sharpe ratios for both strategies.[6] Again, to serve as a control sample, we also include the results for American ETFs. In Panel A we see that, based on the standard deviation of returns, the risk of the proposed trading strategy is actually very similar to the buy-and-hold strategy. Sharpe ratios of the contrarian strategy portfolios are all higher than those of the respective benchmarks. While in Panel B, what is observed in Asian country ETFs apparently does not happen in American ETFs. These results further testify our hypothesis of the overreaction effect to US market return of non-synchronized trading Asian country ETFs.

[Insert Table 7 about here]

5.4 Abnormal returns and Fama French three-factor model

To further understand the source of the abnormal returns we regress the monthly excess returns of the dynamic contrarian strategy over the buy-and-hold portfolio on the Fama-French three factors.

$$R\_ex_{i,t} = \alpha_i + \beta_i \cdot (mkt - RF) + \gamma_i \cdot SMB + \delta_i \cdot HML + \varepsilon_i \qquad (13)$$

[6] In calculating the Sharpe ratio, an average risk free rate of 1.5% per annum is assumed for the sample period.

where $(mkt - RF)$, SMB, HML are Fama-French factors. ($mkt - RF$) is the difference between market return and risk free rate. SMB is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks. HML is the difference between the returns on diversified portfolios of high and low B/M (Book/Market) stocks.

Results are shown in Table 8. All the intercepts being positive and significant (Malaysia being weakly significant) confirm that the excess return over the buy-and-hold strategy is not due to higher systematic risks being assumed. According to the slope coefficients and their significance, we may actually say that the dynamic strategy could in fact be less risky than the buy-and-hold for most of the Asian country ETFs. For example, for China and Hong Kong, the beta on the market risk premium (mkt-RF) is negatively significant; whereas the beta on HML is negatively significant for Japan. The intercepts for these countries (representing their risk-adjusted excess returns) should therefore be higher than their respective raw mean excess returns reported in Table 6. A comparison of Table 8 with Table 6 shows that it is indeed the case for all seven countries (for example, 0.96% vs. 0.86% for China).

5.5 Abnormal returns and sentiment index

We hypothesize that the overreaction is due to US investors' market sentiment. When Asian markets are closed, US investors mainly base their judgement on their sentiment to US market returns. It is natural to think that the more sentimental investors are the more overreaction investors will have towards US market return. In terms of the excess return from our strategy, we therefore expect that the profit is positively correlated with the overall market sentiment.

To study whether there is a relation between the excess return and the magnitude of market sentiment we collect data of a market sentiment index constructed by American Association of Individual Investors (AAII). The AAII sentiment index reports the percentage of individual investors who are bullish, neutral, or bearish on the stock market for the next six months. Individual investors who are AAII members are polled on a weekly basis and only one vote per member is accepted in each weekly voting period. To test our hypothesis we regress the monthly excess returns on AAII market sentiment index.

$$R\_ex_{i,t} = \alpha_i + \beta_i \cdot S_{total_t} + \varepsilon_i \tag{14}$$

where $R\_ex_{i,t}$ is the monthly excess return of the dynamic contrarian strategy for each ETF, S_{total_t} is the total percentage of sentimental investors in the market in month *t* as reported in the AAII sentiment index. The total percentage of sentimental investors in the market is the sum of percentage of bullish investors and that of bearish investors.

Results are reported in Table 9. Supportive to our hypothesis, all of the Asian country ETFs report positive β_i's, and except for Singapore all the β_i's are statistically significant. This clearly shows that monthly excess returns of the dynamic contrarian strategy for Asian country ETFs are positively associated with the percentage of sentimental investors in the market

[Insert Table 9 about here]

We conduct a further analysis to find out whether the profitability of the trading strategy is driven by bullish or bearish market sentiment. We regress the monthly excess returns on both the bullish and bearish components of the AAII sentiment index.

$$R\_ex_{i,t} = \alpha_i + \beta_i \cdot S_{bull_t} + \gamma_i \cdot S_{bear_t} + \varepsilon_i \qquad (15)$$

where S_{bull_t} and S_{bear_t} are the percentage of bullish and bearish investors in the market in month *t* as reported in the AAII sentiment index.

Results are presented in Table 10. Almost without any exception, both coefficients for S_{bull_t} and S_{bear_t} are positive. More importantly, the value of the coefficient for S_{bear_t} always exceeds that of S_{bull_t} for all ETFs; whereas the statistical significance of the former is also always stronger than that of the latter again for all ETFs. Based on the point estimates of the two coefficients, and taking the China ETF as an example, a one percentage point increase in the proportion of bearish investors in the market is associated with a 13 basis points increase in the monthly excess return from the dynamic contrarian strategy; whereas the same percentage point increase in the proportion of bullish investors is only associated with a 5 basis points increase in the monthly excess return. This interesting finding suggests that there is asymmetry in overreaction to market sentiment. Investors tend to overreact more in a market that is swamped by bearish sentiment rather than one by bullish sentiment. This is consistent with the fact that investors are in general risk averse.

[Insert Table 10 about here]

VI. Conclusion

The paper studies the overreaction of Asian country ETFs to US market returns utilizing the non-synchronized trading condition of the Asian country ETFs and their underlying assets. The condition provides a unique setting that allows us to isolate the influence of market sentiment from that due to changes in a security's intrinsic value. Using a dynamic contrarian trading strategy, we quantify market sentiment by showing that material and significant abnormal returns can be generated out of the price reversal effect of the Asian country ETFs. By relating the abnormal returns with US market sentiment, we not only find that abnormal returns are positively associated with overall US market sentiment but also reveal that these abnormal returns respond asymmetrically to bullish sentiment and bearish sentiment.

This study has a few important contributions. First, we examine the role played by market sentiment on price efficiency and contribute to the general understanding of how market sentiment affects the price formation process of financial securities. Our findings suggest that market sentiment makes the market for Asian country ETFs less efficient. Second, we demonstrate the economic significance of the market sentiment effect on the pricing efficiency of Asian country ETFs by devising a relatively straightforward mechanical trading strategy that exploits the systematic bias in market prices caused by market sentiment effect. The findings can also help to improve the market efficiency of such securities as market participants exploit the abnormal returns illustrated in this study.

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Appendix 1 Tables

Table 1

This table presents information on ETFs studied in this research including seven Asian country ETFs whose tracking indices are traded in completely non-overlapping hours with New York Stock Exchange, and seven other ETFs that are traded in exactly the same hours as New York Stock Exchange. Data source is Bloomberg Database. Tickers are all Bloomberg tickers. Data range is daily from Jan 3, 2005 to Dec 31, 2013.

Panel A: Asian country ETFs:

Name	ETF Ticker	Tracking Index	Local Stock Exchange Hours (ET)
China	FXI	FTSE Xinhua 25	9:30pm - 3:00am
Hong Kong	EWH	MSCI Hong Kong	9:20pm - 4:00am
Japan	EWJ	MSCI Japan	8:00pm - 2:00am
Korea	EWY	MSCI Korea	8:00pm - 2:00am
Malaysia	EWM	MSCI Malaysia	9:00pm - 5:00am
Singapore	EWS	MSCI Singapore	9:00pm - 5:00am
Taiwan	EWT	MSCI Taiwan	9:00pm - 1:30am

Panel B: American ETFs:

Name	ETF Ticker	Tracking Index	Local Stock Exchange Hours (ET)
Canada	EWC	MSCI Canada Index	9:30am - 4:00pm
Mexico	EWW	MSCI Mexico Index	9:30am - 4:00pm
S&P500	SPY	S&P500 Index	9:30am - 4:00pm
NASDAQ	QQQ	NASDAQ Index	9:30am - 4:00pm
Russell 1000	IWB	Russell 1000 Index	9:30am - 4:00pm
Russell 2000	IWM	Russell 2000 Index	9:30am - 4:00pm
Russell 3000	IWV	Russell 3000 Index	9:30am - 4:00pm

Table 2

Regression results: $NAV\_R_{C\_C_{i,t+1}} = \alpha_i + \beta_i \cdot SP\_R_{C\_C_t} + \varepsilon_{i,t}$.

First row of each ETF reports the estimated coefficients and the second row gives the p-value.

Asian Country ETFs

	$Const.$	$SP\_R_{C\_C_t}$	$\bar{R}^2$
China	0.00	0.67	0.19
	0.48	0.00	
Hong Kong	0.00	0.45	0.18
	0.33	0.00	
Japan	0.00	0.31	0.07
	0.89	0.00	
Korea	0.00	0.65	0.22
	0.46	0.00	
Malaysia	0.00	0.36	0.22
	0.03	0.00	
Singapore	0.00	0.51	0.22
	0.23	0.00	
Taiwan	0.00	0.45	0.18
	0.71	0.00	

Table 3

Regression results: $ETF\_R_{C\_O_{i,t}} = \alpha_i + \beta_i \cdot SP\_R_{C\_C_t} + \varepsilon_i$.

First row of each ETF reports the estimated coefficients and the second row gives the p-value.

Asian Country ETFs

	$Const.$	$SP\_R_{C\_C_t}$	$\bar{R}^2$
China	0.00	0.83	0.58
	0.50	0.00	
Hong Kong	0.00	0.63	0.53
	0.26	0.00	
Japan	0.00	0.50	0.52
	0.05	0.00	
Korea	0.00	0.73	0.57
	0.58	0.00	
Malaysia	0.00	0.42	0.33
	0.00	0.00	
Singapore	0.00	0.58	0.49
	0.79	0.00	
Taiwan	0.00	0.59	0.47
	0.90	0.00	

Table 4

Regression results: $ETF\_R_{O\_C_{i,t}} = \alpha_i + \beta_i \cdot SP\_R_{C\_C_{t-1}} + \varepsilon_i$

Left-hand-side panel shows results for Asian country ETFs and right-hang-side panel shows results for American ETFs. First row of each ETF reports the estimated coefficients and the second row gives the p-value.

Asian Country ETFs	$Const.$	$SP\_R_{C\_C_{t-1}}$	$\bar{R}^2$	American ETFs	$Const$	$SP\_R_{C\_C_{t-1}}$	$\bar{R}^2$
China	0.00	-0.21	0.03	Canada	0.00	0.08	0.01
	0.24	0.00			0.02	0.00	
Hong Kong	0.00	-0.15	0.02	Mexico	0.00	0.01	0.00
	0.10	0.00			0.05	0.68	
Japan	0.00	-0.11	0.02	S&P500	0.00	-0.01	0.00
	0.32	0.00			0.09	0.23	
Korea	0.00	-0.15	0.01	Nasdaq	0.00	-0.02	0.00
	0.30	0.00			0.01	0.07	
Malaysia	0.00	-0.07	0.01	Russell1000	0.00	-0.01	0.00
	0.70	0.00			0.03	0.47	
Singapore	0.00	-0.13	0.01	Russell2000	0.00	-0.02	0.00
	0.19	0.00			0.03	0.09	
Taiwan	0.00	-0.15	0.02	Russell3000	0.00	-0.01	0.00
	0.78	0.00			0.09	0.32	

Table 5

Regression results:

Left-hand side panel: $ETF\_R_{O\_C_{i,t}} = \alpha_i + \beta_i \cdot NAV\_R_{C\_C_t} + \varepsilon_i$

Right-hand side panel: $ETF\_R_{O\_C_{i,t}} = \alpha_i + \beta_i \cdot SP\_R_{C\_C_{t-1}} + \gamma_i \cdot NAV\_R_{C\_C_t} + \varepsilon_i$

First row of each ETF reports the estimated coefficients and the second row gives the p-value.

Asian Country ETFs

	$Const.$	$NAV\_R_{C\_C_t}$	$\bar{R}^2$	$Const.$	$SP\_R_{C\_C_{t-1}}$	$NAV\_R_{C\_C_t}$	$\bar{R}^2$
China	0.00	0.52	0.40	0.00	-0.70	0.72	0.64
	0.54	0.00		0.30	0.00	0.00	
Hong Kong	0.00	0.56	0.38	0.00	-0.49	0.75	0.59
	0.29	0.00		0.15	0.00	0.00	
Japan	0.00	0.42	0.30	0.00	-0.26	0.48	0.39
	0.13	0.00		0.17	0.00	0.00	
Korea	0.00	0.53	0.31	0.00	-0.63	0.74	0.49
	0.62	0.00		0.48	0.00	0.00	
Malaysia	0.00	0.56	0.26	0.00	-0.35	0.78	0.39
	0.07	0.00		0.03	0.00	0.00	
Singapore	0.00	0.56	0.35	0.00	-0.53	0.79	0.56
	0.61	0.00		0.53	0.00	0.00	
Taiwan	0.00	0.63	0.36	0.00	-0.53	0.83	0.54
	0.81	0.00		1.00	0.00	0.00	

Table 6
This table shows descriptive statistics of monthly excess return of dynamic contrarian strategy against buy-and-hold strategy for all ETFs. Based on t-statistics, the mean monthly excess returns for the Asian country ETFs are all significantly larger than 0. Significance level is denoted by "***", "**", and "*" at 1% significant, 5% significant and 10% significant respectively.

Panel A: Asian Country ETFs:

	Mean	Median	St. Dev.	Skewness	Kurtosis
China	0.86%***	0.49%	2.21%	1.5060	5.7012
Hong Kong	0.60%***	0.45%	1.68%	0.8031	2.3205
Japan	0.41%***	0.32%	1.47%	0.1944	2.8443
Korea	0.42%**	0.10%	2.08%	1.9873	11.5803
Malaysia	0.19%*	0.09%	1.23%	0.6823	1.4466
Singapore	0.33%**	0.31%	1.70%	1.3322	9.2404
Taiwan	0.64%***	0.45%	1.78%	1.4159	10.6024

Panel B: American ETFs:

	Mean	Median	St. Dev.	Skewness	Kurtosis
Canada	-0.53%***	-0.38%	1.61%	-3.6238	23.6479
Mexico	-0.15%	-0.09%	1.97%	-2.5527	16.1542
SP_SPY	0.02%	-0.01%	0.83%	-1.0092	6.5958
Nasdaq	0.05%	0.01%	0.88%	-0.2899	3.7724
Russel1000	0.00%	-0.02%	0.89%	-1.1999	6.0060
Russell2000	0.07%	0.06%	1.06%	-0.4740	4.1720
Russell3000	0.03%	-0.04%	0.86%	-1.0201	6.6673

Table 7
This table reports Sharpe ratios of the ETF monthly returns of buy-and-hold and dynamic contrarian strategies. It can be seen that the contrarian strategy overwhelmingly outperforms the buy-and-hold strategy for all Asian country ETFs.

Panel A: Asian Country ETFs

	Buy-and-Hold			Dynamic Contrarian		
	μ	σ	*Sharpe Ratio*	μ	σ	*Sharpe Ratio*
China	0.83%	8.62%	0.082	1.69%	8.48%	0.185
Hong Kong	0.73%	6.46%	0.094	1.33%	6.32%	0.191
Japan	0.21%	5.01%	0.018	0.63%	5.15%	0.097
Korea	0.82%	8.91%	0.078	1.23%	9.10%	0.122
Malaysia	1.01%	5.24%	0.169	1.20%	5.26%	0.204
Singapore	0.88%	7.23%	0.105	1.21%	7.28%	0.149
Taiwan	0.41%	7.23%	0.040	1.06%	7.31%	0.127

Panel B: American ETFs

	Buy-and-Hold			Dynamic Contrarian		
	μ	σ	*Sharpe Ratio*	μ	σ	*Sharpe Ratio*
Canada	0.63%	6.74%	0.075	0.10%	7.62%	-0.004
Mexico	1.05%	7.75%	0.119	0.90%	8.89%	0.087
SP_SPY	0.56%	4.46%	0.098	0.58%	4.61%	0.099
Nasdaq	0.79%	5.47%	0.122	0.84%	5.53%	0.130
Russel1000	0.59%	4.54%	0.102	0.59%	4.74%	0.097
Russell2000	0.66%	5.86%	0.091	0.73%	6.07%	0.100
Russell3000	0.59%	4.65%	0.101	0.62%	4.81%	0.103

Table 8

Regression results of monthly excess returns of Asian country ETFs against Fama-French three factors.

$$R\_ex_{i,t} = \alpha_i + \beta_i \cdot (mkt - RF) + \gamma_i \cdot SMB + \delta_i \cdot HML + \varepsilon_i$$

First row of each ETF reports the estimated coefficients and the second row gives the p-value.

Asian Country ETFs	$Const$	$mkt\text{-}RF$	SMB	HML	$\bar{R}^2$
China	0.96%	-0.15	-0.08	0.04	0.10
	0.00	0.00	0.44	0.69	
Hong Kong	0.68%	-0.13	-0.01	0.02	0.10
	0.00	0.00	0.91	0.82	
Japan	0.43%	-0.01	-0.03	-0.13	0.03
	0.00	0.86	0.72	0.04	
Korea	0.45%	0.01	-0.13	-0.12	0.01
	0.02	0.79	0.20	0.16	
Malaysia	0.21%	-0.01	-0.09	-0.07	0.03
	0.07	0.71	0.15	0.20	
Singapore	0.39%	-0.06	-0.03	-0.13	0.06
	0.02	0.16	0.75	0.08	
Taiwan	0.69%	-0.03	-0.08	-0.05	0.01
	0.00	0.49	0.35	0.54	

Table 9
Regression results of monthly excess returns of Asian country ETFs against AAII sentiment index. S_{total} is the total percentage of investors who are either bullish or bearish on the stock market.

$$R\_ex_{i,t} = \alpha_i + \beta_i \cdot S_{total_t} + \varepsilon_i$$

First row of each ETF reports the estimated coefficients and the second row gives the p-value.

Asian Country ETFs

	$Const.$	S_{total_t}	$\bar{R}^2$
China	-0.08	0.12	0.07
	0.01	0.00	
Hong Kong	-0.07	0.10	0.08
	0.00	0.00	
Japan	-0.03	0.05	0.02
	0.12	0.08	
Korea	-0.08	0.11	0.06
	0.01	0.00	
Malaysia	-0.04	0.06	0.05
	0.01	0.01	
Singapore	-0.01	0.01	-0.01
	0.82	0.71	
Taiwan	-0.05	0.08	0.04
	0.03	0.02	

Table 10
Regression results of monthly excess returns of Asian country ETFs against bull and bear components of AAII sentiment index.

$$R\_ex_{i,t} = \alpha_i + \beta_i \cdot S_{bull_t} + \gamma_i \cdot S_{bear_t} + \varepsilon_i$$

First row of each ETF reports the estimated coefficients and the second row gives the p-value.

Asian Country ETFs

	$Const.$	S_{bull}	S_{bear}	$\bar{R}^2$
China	-0.06	0.05	0.13	0.12
	0.05	0.27	0.00	
Hong Kong	-0.05	0.04	0.11	0.13
	0.04	0.23	0.00	
Japan	-0.02	0.02	0.05	0.03
	0.29	0.55	0.06	
Korea	-0.07	0.09	0.11	0.06
	0.02	0.07	0.00	
Malaysia	-0.04	0.05	0.06	0.05
	0.03	0.10	0.01	
Singapore	0.01	-0.03	0.02	0.02
	0.72	0.40	0.53	
Taiwan	-0.04	0.05	0.09	0.05
	0.10	0.24	0.01	

Appendix 2 Figures

Figure 1

This figure illustrates time zone differences in the trading of Asian country ETF and their underlying markets, where "NAV" represents the local market and "ETF; S&P" represents the US market.

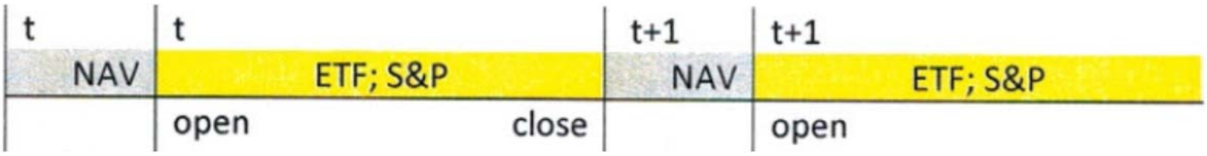
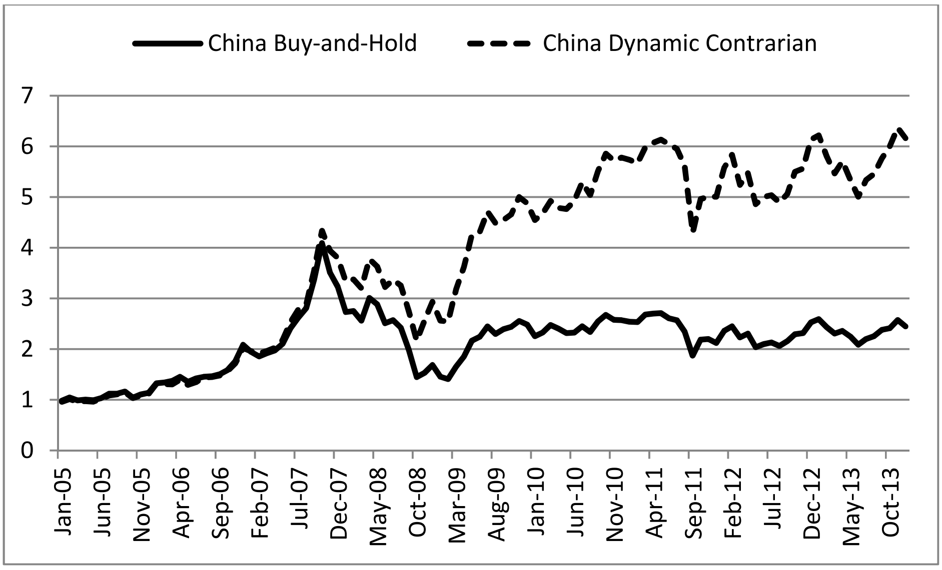
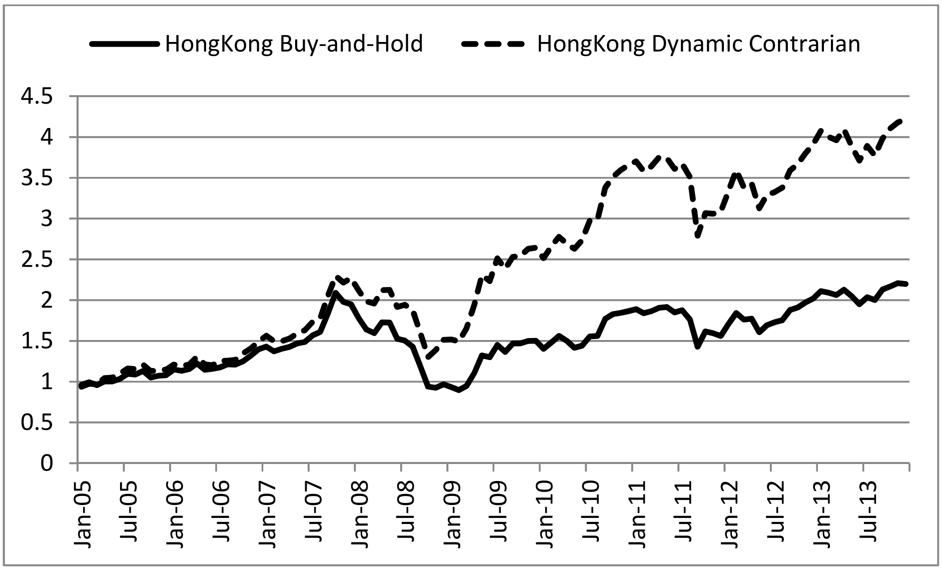


Figure 2
This figure illustrates the value evolution of the portfolio pair for all seven Asian country ETFs. Each portfolio pair contains two portfolios, the buy-and-hold portfolio and the dynamic contrarian trading strategy portfolio. Both of the portfolios start with $1 at initiation.

Y – axis : portfolio value ($)

X – axis : time




HongKong Buy-and-Hold
HongKong Dynamic Contrarian
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Jan-05
Jul-05
Jan-06
Jul-06
Jan-07
Jul-07
Jan-08
Jul-08
Jan-09
Jul-09
Jan-10
Jul-10
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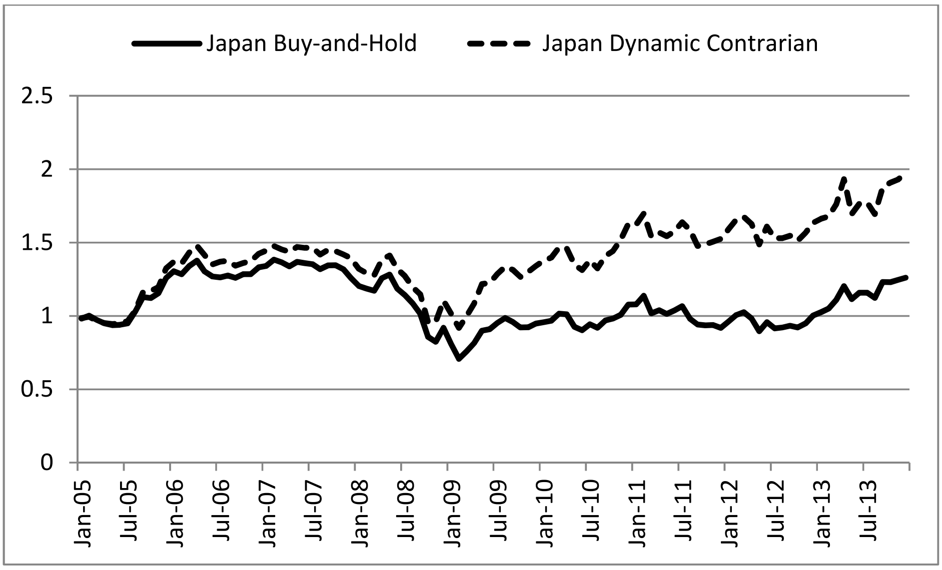
Jul-12
Jan-13
Jul-13


Japan Buy-and-Hold
Japan Dynamic Contrarian
2.5
2
1.5
1
0.5
0
Jan-05
Jul-05
Jan-06
Jul-06
Jan-07
Jul-07
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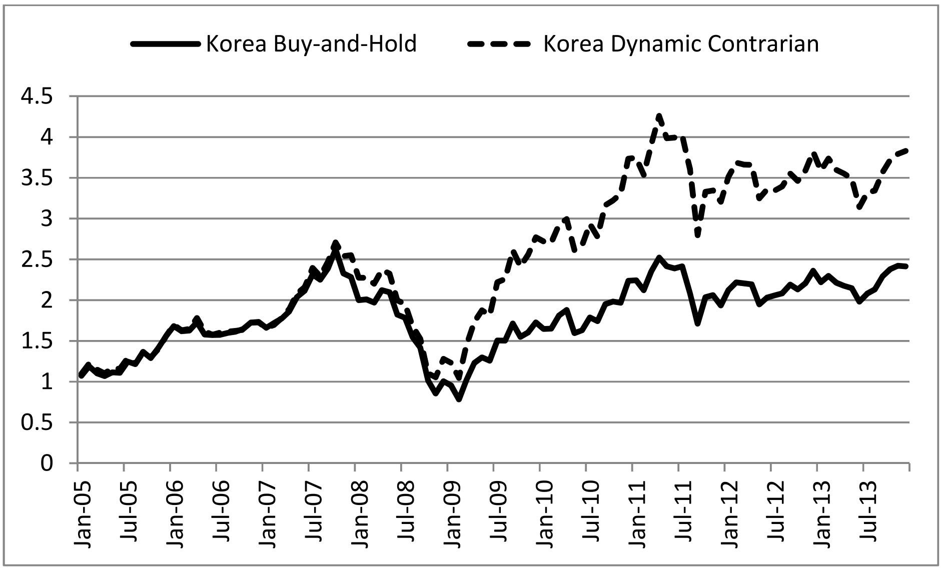
Jul-12
Jan-13
Jul-13


Korea Buy-and-Hold
Korea Dynamic Contrarian
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Jan-05
Jul-05
Jan-06
Jul-06
Jan-07
Jul-07
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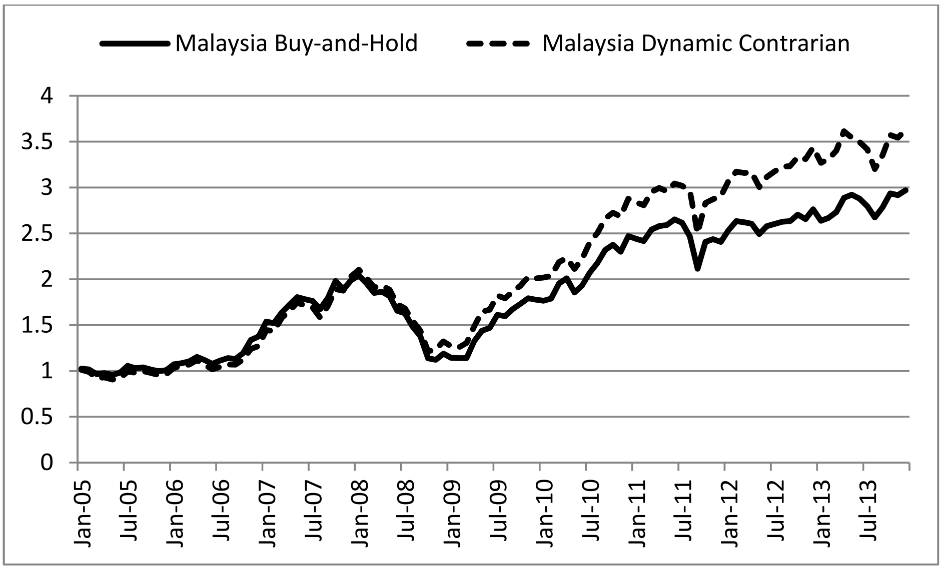
Jul-12
Jan-13
Jul-13


Malaysia Buy-and-Hold
Malaysia Dynamic Contrarian
4
3.5
3
2.5
2
1.5
1
0.5
0
Jan-05
Jul-05
Jan-06
Jul-06
Jan-07
Jul-07
Jan-08
Jul-08
Jan-09
Jul-09
Jan-10
Jul-10
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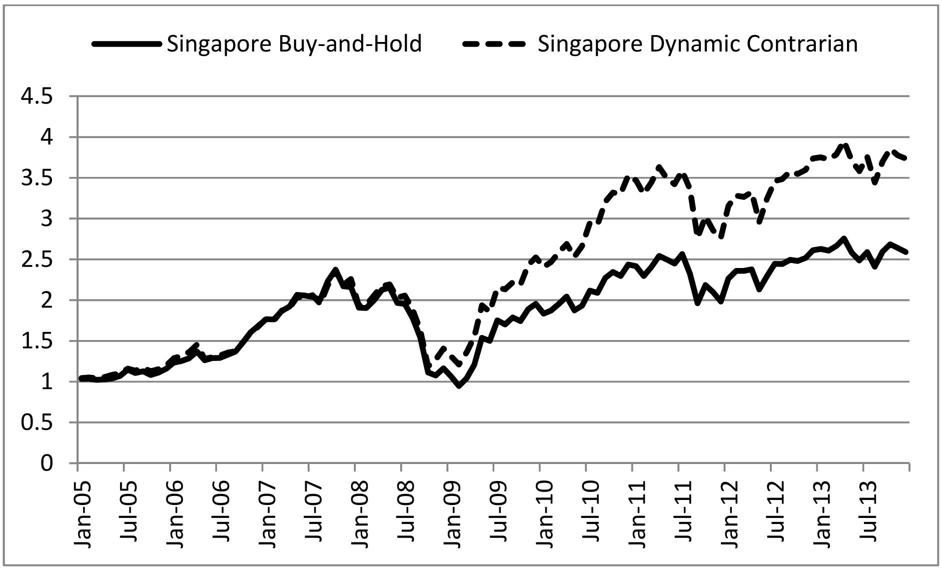
Jul-12
Jan-13
Jul-13



Singapore Buy-and-Hold
Singapore Dynamic Contrarian
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Jan-05
Jul-05
Jan-06
Jul-06
Jan-07
Jul-07
Jan-08
Jul-08
Jan-09
Jul-09
Jan-10
Jul-10
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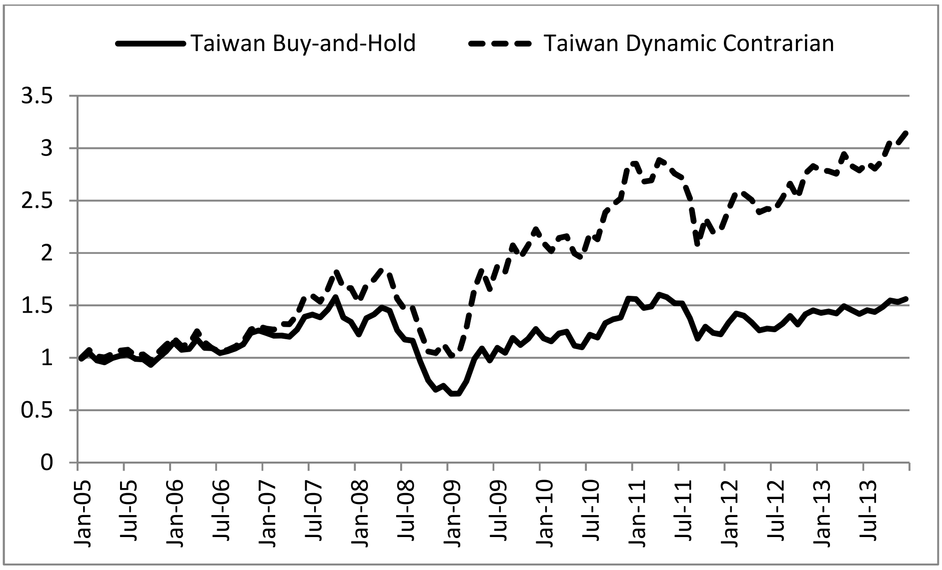
Jul-12
Jan-13
Jul-13



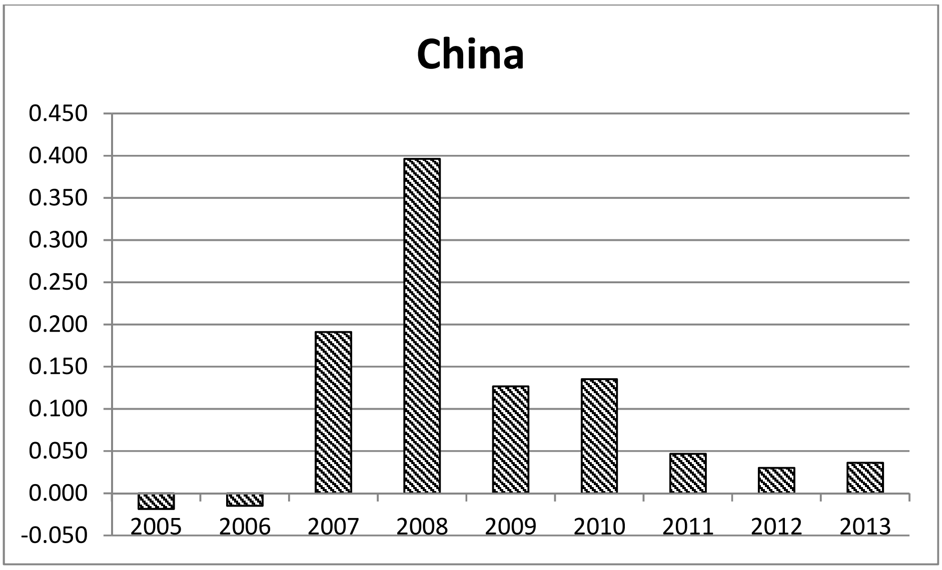
Taiwan Buy-and-Hold
Taiwan Dynamic Contrarian
3.5
3
2.5
2
1.5
1
0.5
0
Jan-05
Jul-05
Jan-06
Jul-06
Jan-07
Jul-07
Jan-08
Jul-08
Jan-09
Jul-09
Jan-10
Jul-10
Jan-11
Jul-11
Jan-12
Jul-12
Jan-13
Jul-13

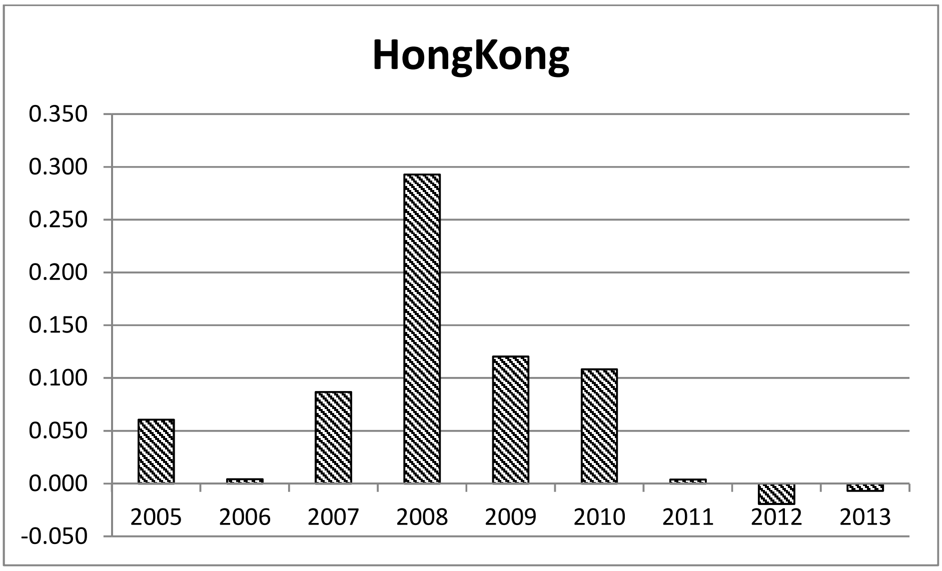
Figure 3

This figure presents the distribution of annual excess returns for the dynamic contrarian trading strategy portfolio in each portfolio pair for all seven Asian country ETFs. The excess return is defined as the difference between the returns of the portfolio with dynamic contrarian trading strategy and the portfolio with buy-and-hold benchmark within each portfolio pair.

Y – axis : annual excess return $R\_ex_i = R\_dynamic_i - R\_benchmark_i$

X – axis : time




HongKong
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0.300
0.250
0.200
0.150
0.100
0.050
0.000
-0.050
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2006
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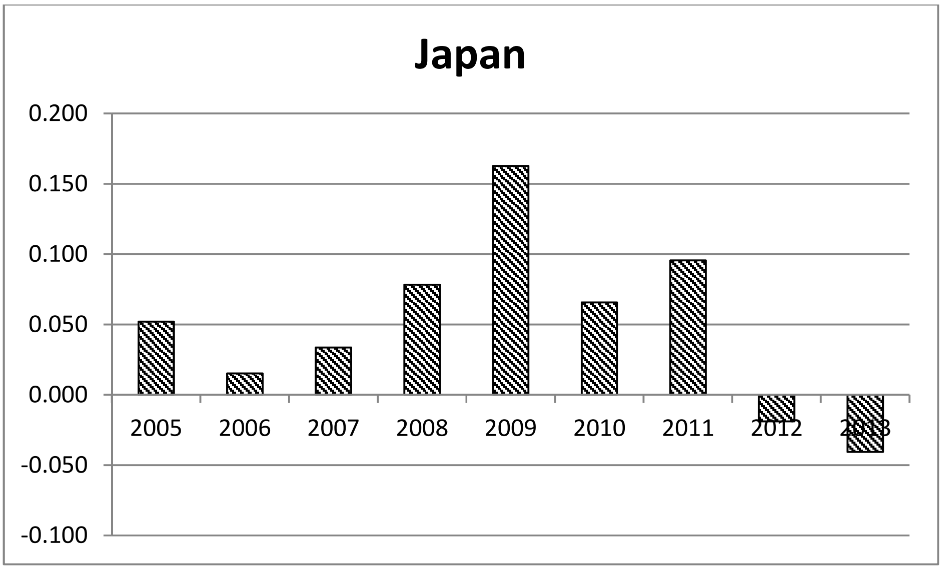
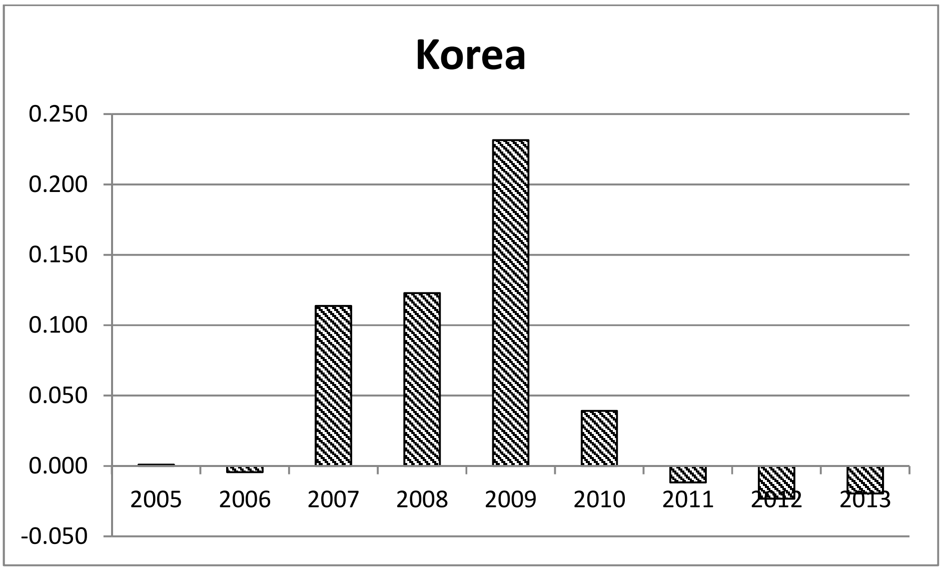
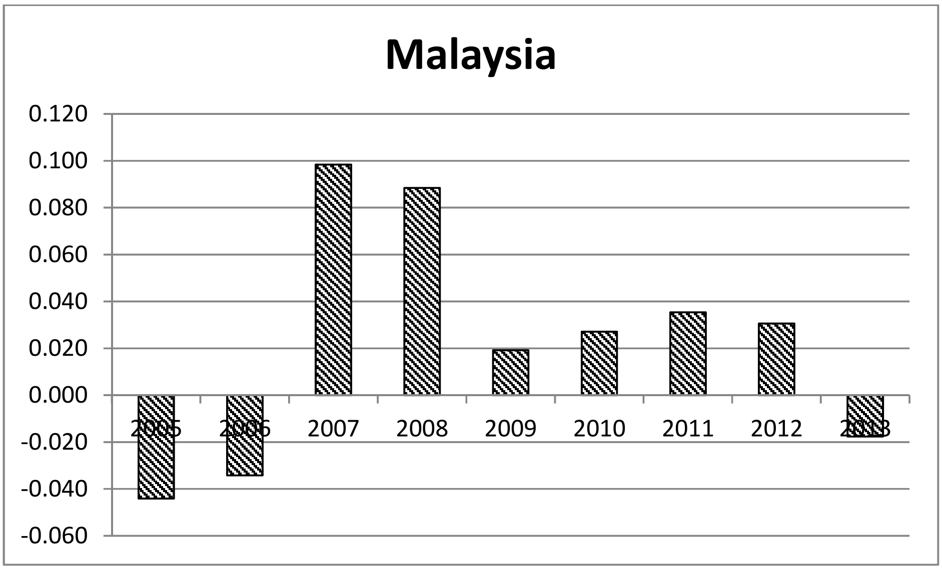
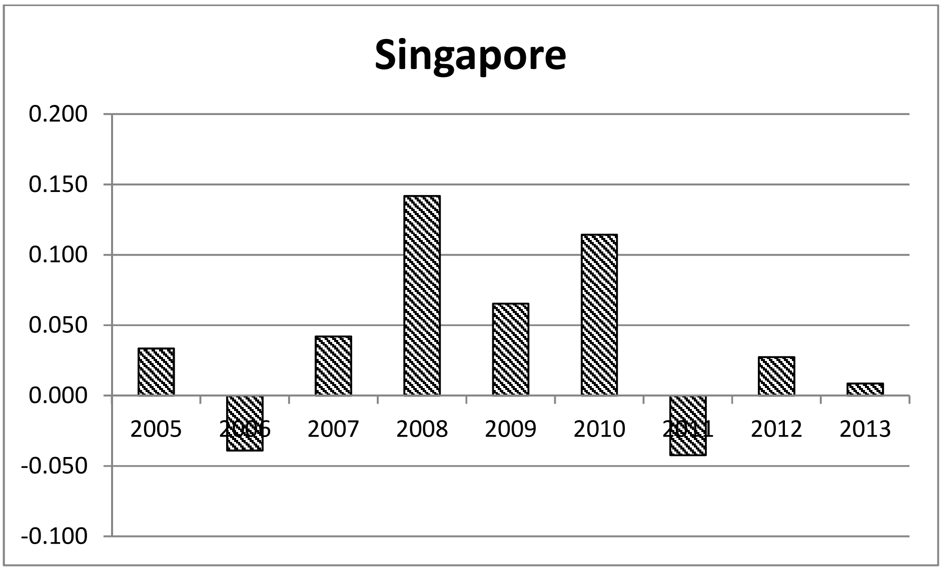
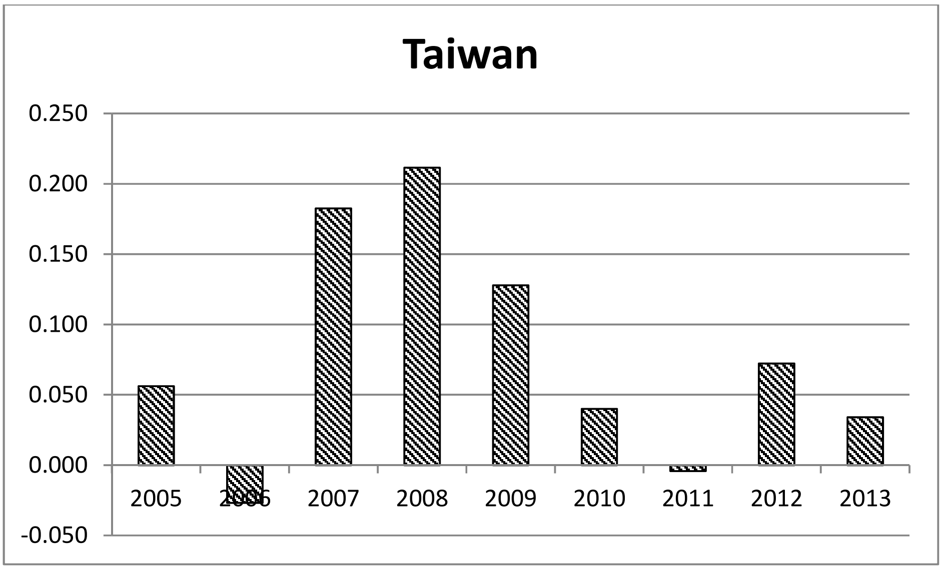
2009
2010
2011
2012
2013


Japan
0.200
0.150
0.100
0.050
0.000
-0.050
-0.100
2005
2006
2007
2008
2009
2010
2011
2012
2013


Korea
0.250
0.200
0.150
0.100
0.050
0.000
-0.050
2005
2006
2007
2008
2009
2010
2011
2012
2013


Malaysia
0.120
0.100
0.080
0.060
0.040
0.020
0.000
-0.020
-0.040
-0.060
2005
2006
2007
2008
2009
2010
2011
2012
2013


Singapore
0.200
0.150
0.100
0.050
0.000
-0.050
-0.100
2005
2006
2007
2008
2009
2010
2011
2012
2013


Taiwan
0.250
0.200
0.150
0.100
0.050
0.000
-0.050
2005
2006
2007
2008
2009
2010
2011
2012
2013

Chapter 3 Profitability of Leveraged Exchange-Traded Funds Investment Strategies

I. Introduction

With their inception in 2006 in the US market, leveraged exchange-traded funds (LETFs) are relatively new members of the exchange-traded fund (ETF) family. Like any ETF, an LETF is a publicly-traded fund listed on stock exchanges where investors and traders can buy and sell its shares throughout the trading hours of the market. An LETF promises to provide daily returns that are in a multiple (positive or negative) of the returns on an underlying benchmark index. In the US, the multiple, which usually referred to as the *targeted leverage ratio* of the LETF, could be +2x, +3x, -2x, and -3x.[7] For example, if the return on the underlying benchmark for a particular day is 1.5%, a +2x LETF tracking this benchmark is supposed to deliver a return of 3.0% on the same day; whereas that for a -3x LETF should be -4.5%. On the other hand, if the return on the benchmark on the next day is -0.7%, the +2x and -3x LETFs should deliver corresponding returns of -1.4% and 2.1% respectively. To meet that promise, the fund uses leverage, which is typically obtained through derivatives such as futures contracts, forward contracts, and total-return swaps.[8]

[7] Recently, LETFs with leverage ratio of +1.25 have been introduced by *Direxion*, one of the fund providers in the US.
[8] There are also inverse ETFs that promise returns of the opposite of that of the underlying benchmark (i.e., the multiple is -1x). In the market, it is quite common to categorize inverse ETFs as LETFs.

Given the embedded leverage, investment in LETFs is by its very nature risky. Traders use LETFs to express their directional views on the underlying benchmarks. A bullish trader may buy *bull* LETFs (i.e., those with positive leverage ratios) so as to magnify their return in anticipation of a run-up of the underlying benchmark, while a bearish trader may buy *bear* LETFs (i.e., those with negative leverage ratios) so as to realize a magnified profit if there turns out to be a market downturn. LETFs offer a relatively low cost solution for retail investors to implement such leveraged strategies without the need to arrange for financing and/or to satisfy any margin requirements.

According to Blackrock (2012), among the 1,200 or so ETFs trading in the US in 2012, 273 of them are LETFs. The assets under management (AUM) of all the LETFs added up to about $32 billion, which was about 3% of the total AUM of all ETFs trading in the US. Although the assets under their management are only a small fraction of the entire ETF market, LETFs attract a disproportionately large trading volume. As a fraction of their AUMs, the trading volume of LETFs could easily exceed those of non-leveraged ETFs. For example, the ratio of average daily volume (ADV) to AUM of *ProShares Ultra S&P 500*, the most popular +2x LETF tracking the S&P 500 index, was 0.29 as of the end of the third quarter of 2012 (Blackrock, 2012). This level of trading intensity is almost twice that of *SPDR S&P 500 ETF*, the most popular S&P 500 tracking non-leveraged ETF. The latter had an ADV to AUM ratio of only 0.15 during the same time period.

The high trading intensity of LETFs is consistent with their relatively short holding periods. Charupat and Miu (2013) find that none of the popular US equity-based LETFs in their sample had average holding period of more than six days. This is not surprising given the fact that, unlike traditional non-leveraged ETFs, LETFs are generally believed to be unsuitable for buy-and-hold investors with the intention of holding on to their positions for more than a few months. Because of the constant rebalancing of its exposure in delivering the promised daily leveraged return, the long-term compounded returns on LETFs could fall short of the leveraged compounded returns of their underlying benchmarks (Cheng and Madhavan, 2009). This is sometimes referred to as the *compounding effect*. The amount of return deviation is specific to the realized path of daily returns on the underlying benchmark index over the holding period. In general, the more volatile the realized daily returns, the more negative is the influence on the LETFs' compounded returns.[9] This slippage in return is commonly referred to as the *volatility drag* or *volatility decay*, and is particular salient in a sideways market when the underlying index remains at roughly the same level at the end of the holding period. This generally negative impression of the long-term performance of LETFs is further reinforced when we witnessed their poor performance during the recent financial crisis in 2008-2009. Market regulatory bodies have also expressed their concerns regarding the general lack of understanding of the implications of the compounding effect among LETF investors (e.g., FINRA, 2009; SEC, 2009).

It is important to point out that the compounding effect does not have to be always negative. Whereas a volatile and sideways market tends to result in a *negative* compounding effect where LETFs underperform their benchmarks (after adjusted for leverage); a calm and trending market, on the contrary, will lead to a *positive* compounding effect where LETFs outperform their benchmarks. We will illustrate these opposing effects with a numerical example in the next section. The direction and magnitude of the effect are dictated by the prevailing market condition and the dynamics of the return process of the underlying benchmark. Given the short historical data since their debut in 2006, it is still too early to reach a final verdict on the

[9] Avellaneda and Zhang (2010) provide a formula demonstrating how the compounded return of an LETF is related to the realized variance of the underlying benchmark return.

long-term performance of LETFs with the limited empirical evidence. The simulation analysis conducted by Loviscek et al. (2014) using more than a century's history of Dow Jones Industrial Average index data suggest that LETFs' performance could in fact be more or less on par with their leveraged benchmark. They attribute their findings to the fact that the distribution of real-world historical equity index return has a much higher kurtosis and is more leptokurtic than the normal distribution. These distribution characteristics could enhance the chance of realizing a positive compounding effect that will offset any negative compounding effect realized over time.

When an LETF investor formulates his or her trading strategy, the expected directional change of the underlying benchmark is of course of paramount importance. On top of that, the investor also needs to know how likely the positive vs. negative compounding effect will be realized during the investment horizon. What are the market conditions that tend to strengthen the former at the expense of the latter, and vice versa? How much *market trending* is needed to overcome the negative influence of *market volatility*, thus resulting in a net positive compounding effect? In this study, we address this issue by conducting a series of simulation exercises by gauging the sensitivity of the LETF returns on different key parameters of the return generating process of the underlying benchmark. In doing so, we examine different LETF performance measures and study the risk-return trade-offs of LETF investment. Through these analyses, we contribute to the literature by pinpointing the underlying drivers of the compounding effects. Our findings will facilitate the decision-making process of LETF investors by establishing the link between the performance of LETFs and different characteristics of the return dynamics of the underlying benchmark.

If indeed the compounding effect is more likely to be negative than positive under typical market condition resulting in the underperformance of LETFs, then shorting LETFs should be a rewarding strategy. A short strategy will look like this. Suppose you are bullish about the underlying benchmark, you will be shorting a bear LETF as opposed to buying a bull LETF tracking the benchmark. If the value of the benchmark index does go up, the price of the bear LETF will drop resulting in a profit in your short position. At the same time, unlike a long position in the bull LETF, which will be hurt by the volatility drag, your short position will benefit from it. On the other hand, if you are bearish about the underlying benchmark, you should be shorting the bull LETF rather than buying its bear counterpart. Besides profiting from a drop in the benchmark index, the former also allows you to benefit from the volatility drag.[10] As much as this added benefit can offset the financing costs of maintaining the margin for your short position and the borrowing costs charged by your brokerage firm for the LETF that you have shorted, the above short strategy should be a profitable proposition.[11] There is however a drawback of the short strategy. It has a limited upside gain but an unlimited downside risk. Suppose you short a bear LETF in anticipation of a run-up in the benchmark. Regardless of how high the benchmark index turns out to be, your maximum profit is capped at 100% of the dollar amount of bear LETF you have shorted. In contrast, your profit could be unlimited and could well exceed 100% if you had simply bought a bull LETF instead.[12] On the other hand, if, contrary to your expectation, the benchmark index drops, you could potentially lose much more than 100% of your short position when you adopt the short strategy. The loss from simply

[10] In contrast to a long LETF position where the investor will be paying the fund management fees usually charged as a percentage of the net asset value (NAV), a short position will allow the investor to essentially *earn* the management fees.

[11] Although it is in general not difficult to borrow most of the popular LETFs, there is always the risk of being forced to close out the short position if it becomes difficult for the brokerage firm to borrow a particular LETF.

[12] Suppose you have shorted $100 of a -3x LETF. Your best case scenario is when the LETF price drops to zero, since it will then cost you nothing to close out your short position. This will happen when the value of the benchmark increases by more than 33.3% in one day. Your profit could not exceed $100 even if the benchmark increases by more than that. But if you had bought a +3x LETF instead of shorting the -3x LETF, your profit is unlimited and could well exceed $100. For example, if the value of the benchmark increases by 50%, your profit will be $150.

buying the bull LETF is always limited to 100% of the money you have invested. In this study, we examine and compare the performance of long and short strategies of LETFs with the objective of identifying the market conditions under which one is more likely to outperform the other.

We also conduct a comprehensive analysis on the performance of *pair strategies* on LETFs. The above mentioned short strategies are risky if it turns out that you have placed the wrong bet on the directional change of the market. If you are not interested in taking either a bullish or bearish view of the benchmark asset, you may still profit from the volatility drag by having balanced short positions in both a bull LETF and a bear LETF on the same underlying benchmark. Nevertheless, this kind of pair strategy will not be exactly *delta-neutral* with respect to the benchmark index unless you frequently rebalance your two short exposures as the index value changes over time. Suppose you do not rebalance when the index goes up, the liability under your short position on the bull will exceed that of your short position on the bear. The subsequent return from your pair position will therefore be negatively related to that of the benchmark. Therefore, if the benchmark index continues with its upward trend, the return from your pair strategy will tend to be negative. On the other hand, if the index drops, the liability under your short position on the bear will exceed that of the bull, leading to the subsequent return from the unbalanced pair to become positively related to that of the benchmark. Therefore, if the index keeps on dropping, your pair strategy will again tend to deliver a negative return. The performance from the pair strategy is thus expected to be particularly poor if the benchmark assumes either an upward or downward trend. In implementing the strategy of shorting a pair of bull and bear LETFs, one is essentially betting on a volatile sideways market where the underlying benchmark bounces up and down within a certain price range. This is the market condition that promotes the strongest negative compounding effect, which benefits the short positions in both the bull and bear LETFs.

Given the relatively short history of LETFs, the literature on LETFs is still small but is growing quickly. Cheng and Madhavan (2009) provide a comprehensive discussion on the underlying dynamics of LETFs by illustrating their impact on market volatility and liquidity, unusual design features and questions of investor suitability. Quite a few researchers study the pricing efficiency of LETFs (i.e., premiums/discounts relative to their net asset values) and their tracking errors (e.g., Lu et al., 2009; Guedj et al., 2010; Shum and Kang, 2013; Charupat and Miu, 2013, 2014; Loviscek et al., 2014). Avellaneda and Zhang (2010) study the pricing behavior of equity LETFs and find minimal daily tracking errors among the most liquid US equity LETFs. However, LETFs' tracking errors could be substantial if they are held over long time period (Tang and Xu, 2013). Lu et al. (2009) show that LETFs are not long-term substitutes for long or short positions of the underlying benchmark indices, and that deviations from the benchmark returns occur earlier for bear LETFs than for bull LETFs. Guo and Leung (2015) find that many commodity-based LETFs underperform significantly against their benchmarks. Most of the empirical studies on LETFs, based on limited historical data since their inception in 2006, conclude that the long-term performance of LETFs leaves a lot to be desired. There is general consensus that the poor performance could to a large extent be attributable to the volatility drag. Nevertheless, the results of the simulation study recently conducted by Loviscek et al. (2014) rebuke the general perception that LETFs are not suitable for long-term investors. It seems that the jury is still out on the long-term performance of LETFs.

There are a number of previous studies that examine LETF trading strategies, which is the topic that the present study is focusing on. For example, Guo and Leung (2015) examine the performance of a number of LETF trading strategies by backtesting with historical price data. There are also studies that provide guidance on selecting the appropriate leverage ratio. For example, Giese (2010) shows that, contingent on observable market parameters, an *optimal* leverage ratio exists for the LETF strategies to maximize the expected return. By incorporating risk in the decision process, Leung and Santoli (2013) introduce the notion of *admissible* leverage ratio to help investors to exclude LETFs that are deemed too risky. The present study is most related to those trading strategy studies that focus on LETF pair strategy. Dobi and Avellaneda (2013) investigate the profitability from shorting pairs of bull and bear LETFs on the same underlying benchmarks while rebalancing the short positions daily such that the exposures are equalized at the end of each day. They find that the profit of their pair strategies are mostly offset by the borrowing costs of the LETFs. The potential profitability of this kind of pair strategy could however be more substantial if the investors are willing to hold their short positions for a longer period of time without rebalancing. Jiang and Peterburgsky (2013) analyze such longer-term trading strategies involving +3x and -3x LETF pairs tracking the S&P 500 index and show that many such strategies significantly outperform the underlying index on a risk-adjusted basis.

The rest of this paper is organized as follow. The compounding effect of LETFs is explained and illustrated in the next section. In Section 3, we describe the data and the simulation methodology adopted. In Section 4, we examine and compare the risk-return characteristics of a long LETF position, a short LETF position, and a pair of short positions on LETFs. In Section 5, we demonstrate how the changing of the key characteristics of the return dynamics of the underlying benchmark could influence the performance of our LETF trading strategies. We finally conclude with a few remarks in Section 6.

II. Compounding effect

Because the objective of an LETF is to deliver leveraged returns at the promised multiple on a daily basis, it has to maintain constant leverage (as a percentage of its "equity") through time. As a result, it has to rebalance its (dollar) exposure every day in response to the movements of its underlying index. The daily rebalancing can have a positive or negative impact on its returns compounded over a given holding period longer than one day, depending on the volatility of the underlying index. To see this, consider a simple two-day example of a +2x (bull) LETF. Its compounded return over a two-day period is:

$$r_{t,t+2}^{+2x} = \left(1 + 2 \cdot i_{t,t+1}\right) \cdot \left(1 + 2 \cdot i_{t+1,t+2}\right) - 1 = 2 \cdot i_{t,t+1} + 2 \cdot i_{t+1,t+2} + 4 \cdot i_{t,t+1} \cdot i_{t+1,t+2}, \qquad (1)$$

where $r_{t,t+2}^{+2x}$ is the return on the +2x LETF between day t and day $t+2$ and $i_{t,t+1}$ is the return on its underlying index between day t and day t+1, respectively. The compounded return of a +2x LETF is the sum of twice the daily index returns on the two days (the first two terms in Equation (1)), and the cross-product term, which captures the "compounding effect." If the path that the underlying index takes is not volatile, its returns tend to have the same sign on both day 1 and day 2, and so the cross-product term in Equation (1) is positive, adding to the total LETF return. On the other hand, under a volatile return path, the index return fluctuates, being positive on one day and negative on the other. As a result, the cross-product term is negative, reducing the total LETF return. Accordingly, the LETF will perform better under the former path than the latter path, given the same level (positive or negative) of the index's compounded return under the two paths.

In Panel A of Table 1, we present a numerical example of two-day compounded returns of the +2x LETFs under five stylized paths for its underlying index. Under return paths #1 and #2, the underlying index moves in different ways over day 1 and day 2, but ends up with the same compounded two-day return of 4.50%. Path #1 is volatile, as the index return is positive on one day and negative on the next. On the other hand, path #2 is stable, as the index return is the same on both days. The +2x LETF ends up with a compounded two-day return of 8% and 9.10% under paths #1 and #2 respectively. The lower performance under path #1 is consistent with the effect of the cross-product term (which is negative under this path). Intuitively, after the (big) positive return on the first day, the LETF has to increase its (dollar) exposure to the underlying index to maintain its +2x leverage ratio. The higher exposure increases the amount of loss when the index drops on the second day. In contrast, under path #2, after the positive return on the first day, the increase in the LETF's exposure allows it to take advantage of the positive return on the second day.

Insert Table 1 about here

Next, consider return paths #3 and #4, which represents a down market. As before, the index moves differently under the two paths, but ends up with the same two-day compounded return of -5.50%. In this case, the LETF's compounded return is -12% under path #3, and -10.84% under path #4. Again, the LETF performs worse under path #3 because the underlying index returns are volatile under this path (and so the cross-product term is negative). Intuitively, after the (big) negative return on the first day, the LETF has to decrease its exposure. With a smaller exposure, it cannot benefit as much when the index goes up on the second day.

In the last column of Table 1, we calculate the difference between the LETF's two-day compounded return and the return that some investors may mistakenly expect to earn, given the underlying index compounded return. For example, because the index goes up by 4.50% under paths #1 and #2, it may lead some investors to believe that they should get a return of 9% from this +2x LETF. We will refer to this type of expectation as "naïve expectation". We can see that volatility (paths #1 and #3) *can* cause the LETF's returns to be below the naively expected returns. On the other hand, there is no volatility under paths #2 and #4, and the LETF's returns end up being higher than the naively expected returns.

The effect of volatility (i.e., compounding effect) is more pronounced in a *sideways* market, where the underlying index moves up and down but remains around the same level. Consider path #5, which has the same return volatility as paths #1 and #3. However, unlike path #1 (an *up-trending* market) and path #3 (a *down-trending* market), path #5 represents a sideways market with hardly any return on the index over the 2-day period. The +2x LETF realizes the most negative deviation from the stated multiple under path #5. Its compounded return is 1.13 % lower than the naively expected return. Given similar realized volatility, a sideways market will result in a more negative deviation from the naïve expectation than either an up-trending or down-trending market.

Next, consider the two-day compounded return on a -2x LETF:

$$r_{t,t+2}^{-2x} = \left(1 - 2 \cdot i_{t,t+1}\right) \cdot \left(1 - 2 \cdot i_{t+1,t+2}\right) - 1 = -2 \cdot i_{t,t+1} - 2 \cdot i_{t+1,t+2} + 4 \cdot i_{t,t+1} \cdot i_{t+1,t+2}. \quad (2)$$

Again, the compounding effect is captured by the cross-product term, which can add to or subtract from the total LETF return. When volatility is low, the returns on the two days tend to have the same sign, and so the cross-product term in Equation (2) tends to be positive, adding to the total LETF return. When volatility is high, the index returns can switch back and forth between being positive and negative, causing the total LETF return to be lower.

A numerical example for the -2x LETF is presented in Panel B of Table 1. The LETF has a negative compounded return under paths #1 and #2. Although the underlying index's two-day compounded return is the same under both paths, the LETF does worse under path #1 because the underlying is more volatile under this path than under path #2. Here, after the (big) negative return on the first day (because the underlying index goes up on the first day), the LETF has to reduce its (dollar) exposure to the underlying index to maintain its -2x leverage ratio. With a smaller exposure, it cannot benefit as much when the index goes down on the second day. As a result, its two-day compounded return (i.e., -12%) is worse than the naïve expectation (i.e., -9%). The compounding effect also works against the -2x LETF when the underlying index declines, as in return paths #3 and #4. Here again, path #3 is more volatile, and the LETF does worse. After the (big) positive return on the first day, the LETF increases its exposure to the underlying index to maintain its -2x leverage ratio. This sets it up for a larger loss when the index increases on the second day. In contrast, the underlying index returns are stable under path #4. After the positive return on the first day, the increase in the LETF's exposure allows it to take advantage of another drop in the index on the second day. The negative influence of the compounding effect is again more salient under a sideways market like path #5. It results in the most negative deviation of -3.37% from the naïve expectation (see last column of Panel B).

In summary, the compounding effect affects both bull and bear LETFs in the same manner. When there is no or low volatility, the compounding effect is positive and benefits LETFs. In contrast, when volatility is high, the compounding effect is negative and hurt the performance of LETFs. Traders can attempt to devise strategies to take advantage of this fact. For example, a trader who has a bullish view on the market can either buy a bull LETF or short a bear LETF. If the trader expects the market to be volatile, he/she will be better off with the latter strategy. This is because in a volatile market, the compounding effect hurts both a long bull and a long bear LETF positions. Therefore, shorting a bear LETF will help the trader capture the compounding effect.[13]

III. Data and simulation methodology

We will examine the performance of different LETF strategies through a number of simulation analyses. We focus on the LETFs tracking the S&P 500 index, which are very popular among LETF investors.[14] To simulate different market conditions, we first calibrate a benchmark model of the daily return on the S&P 500 index using 30 years of daily return data from 1985 to 2014 (obtained from Bloomberg). We then modify the calibrated parametric values of the model so that we can replicate the S&P 500 index return under these different market conditions. The goal is to generate the return distributions of the LETFs assuming that they can deliver the targeted leveraged return of the index without any tracking errors. With the distributions of the compounded returns of the LETFs over a specific holding period, we can then measure their performance and risks under the different market conditions.[15]

[13] For example, consider again the numerical examples in Table 1. Return path #1 corresponds to an increasing but volatile market. A long position in the +2x LETF (Panel A) will yield a return of +8%, while a short position in the -2x bear LETF will yield a return of +12%.
[14] According to Blackrock (2012), three of the top five LETFs (by AUM) trading in the US are tracking the S&P 500 index.
[15] In this study, we focus on the performance over a one-year holding period.

We choose the modified generalized autoregressive conditional heteroscedasticity (GARCH) model proposed by Glosten et al. (1993) as our benchmark model for S&P 500 index return. The Glosten-Jagannathan-Runkle model (hereafter referred to as the GJR model) is commonly used in the literature to model daily return on equity. The GJR model is a more generalized version of the GARCH model, where an additional term is included in the conditional variance equation to model the asymmetric volatility clustering effect commonly observed in the equity market. It stems from Black (1976) who finds that, in the equity market, higher (lower) stock returns than expected tends to lead to lower (higher) future volatility. Black attributes this observation to a "leverage effect" of the firm's capital structure in which, when a firm's stock price drops, its debt to equity ratio will increase resulting in increased equity return volatility, and vice versa when the stock price goes up. The standard GARCH model does not address this volatility asymmetry because the conditional variance equation is symmetric between positive and negative returns. Glosten et al. extend the standard GARCH model to capture this effect by adding another term to the conditional variance equation that is contingent on the sign of the residual on the previous trading day. Equations (3) to (5) below define the GJR model used in this paper.

$$r_t = \mu + \rho \cdot r_{t-1} + \varepsilon_t \tag{3}$$

where r_t is the return on the S&P 500 index on day *t*. The residual ε_t is specified as:

$$\varepsilon_t = \sigma_t \cdot z_t \tag{4}$$

where σ_t is the conditional standard deviation at day t and z_t is a standardized normally distributed random variable. The conditional variance equation is specified as:

$$\sigma_t{}^2 = a + b \cdot \varepsilon_{t-1}{}^2 + c \cdot \sigma_{t-1}{}^2 + d \cdot I(\varepsilon_{t-1} < 0) \cdot \varepsilon_{t-1}{}^2 \tag{5}$$

where

$$I(\varepsilon_{t-1} < 0) = 1, \text{ if } \varepsilon_{t-1} < 0$$

$$I(\varepsilon_{t-1} < 0) = 0, \text{ otherwise}$$

The parameters μ and ρ govern the expected return and autocorrelation of the daily return respectively. The intercept a measures the component of the return variance that are unrelated to the residual and variance realized previously. The coefficients b and c (which are expected to be positive) measure the extent of short-term and long-term volatility clustering respectively. The coefficient d (which is expected to be positive) together with the indicator variable I capture the asymmetric volatility effect. If the return on the previous trading day (i.e., at time t-1) is lower than the expected value, the residual ε_{t-1} is negative and thus today's value of I equals to unity. The square of the residual of the previous trading day will therefore have a larger impact on today's conditional variance, as represented by the sum of the coefficients b and d. If the residual ε_{t-1} is positive, the short-term volatility clustering is weaker since the last term of Equation (5) disappears.

Empirical studies have confirmed the validity of the GJR model. For example, in examining the relative out-of-sample predictive ability of different variants of the GARCH model using the S&P 500 index and with particular emphasis on the predictive content of the asymmetric volatility component, Awartani and Corradi (2005) find that the GJR model beats the traditional GARCH model in both one step ahead and longer horizon predictions. More recently, Lee and Liu (2014) find that the GJR model does a better job than the traditional GARCH model in capturing the volatility characteristics of the NASDAQ index.

Using 30 years of daily returns on the S&P 500 index, the calibrated parameters of the GJR model are: μ = 3.422 basis points, ρ = 0.00238, a = 0.0210 basis points, b = 0.0091, c =

0.9022, and d = 0.1372.[16] This is our benchmark model of the daily return on the S&P 500 index used in the subsequent simulation analysis. We will be modifying some of these parameters in replicating different market conditions of interest. Given a specific set of these parameters, we will simulate the daily returns on the S&P 500 index over a one-year period (i.e., 252 trading days) using Equations (3) to (5). In simulating the returns over time, we impose a daily return floor of -100%. That is, if it happens that the simulated return on a particular day from the GJR model is worse than -100%, the index return on that day is set at -100% and all subsequent returns on the index for the rest of the year are set to zero. We simulate a total of 1,000,000 daily return paths each lasting for a year for the S&P 500 index.[17] Based on each simulated return path of the index, we can then generate the return path for any LETF tracking the index by multiplying the simulated index return with the targeted leverage ratio of the LETF. That is, suppose the simulated return on the S&P 500 index in a particular day is 1.5%, the replicated return on a +3x (-3x) LETF on the S&P 500 index will be 4.5% (-4.5%) on the same day.[18] If it happens that the replicated return on an LETF is worse than -100% on a particular day, the LETF return on that day is set to -100% and all subsequent returns on the LETF for the rest of the year are set to zero. In other words, the LETF price remains at zero for the rest of the year. With the replicated daily returns on the LETF, we then calculate its one-year compounded return for that particular return path of the underlying index. By repeating this process for each of the 1,000,000 simulated return paths of the index, we obtain a distribution of the one-year return on the LETF for us to assess its performance and risk. To calculate the return on a short position in the LETF,

[16] The mean and standard deviation of daily returns on the S&P 500 index over our sample period are 0.0333% and 1.158% respectively. They correspond to an annual return of about 8.4% and an annual standard deviation of about 18.3%.

[17] In the simulations, the initial values of ε_t, r_t, and σ_t are set at their respective unconditional values based on the 30 years of daily return data on the S&P 500 index.

[18] We thus ignore any tracking errors.

we assume we can borrow LETF shares at no costs, while earning zero interest return on the proceeds from shorting. In the subsequent analysis, we also examine the performance of pair short strategy. In simulating the returns from a pair strategy of shorting both a bull LETF and a bear LETF on the same index, we start with a balanced short positions in both LETFs at the beginning of the year and hold them until the end of the year without rebalancing their exposures during the year. Transaction costs are typically negligible in the buy-and-hold strategies therefore we ignore transaction costs in our analysis. Conclusions in this paper are expected to be robust to any transaction costs considerations.

IV. Return distribution

In the first sets of simulation analysis, we present the return distributions of different LETF strategies based on the calibrated GJR model. Here we want to highlight the key characteristics of their return distributions, so as to facilitate the subsequent discussion on their performance when key parametric values of the distribution vary.

In Figure 1, we present the distributions of the one-year holding period returns of, respectively, a long position in a +3x LETF and a short position in a -3x LETF on the S&P 500 index based on the GJR model calibrated above. As described in the previous section, we simulate a total of 1,000,000 one-year daily return paths for the S&P 500 index so as to replicate the daily returns on the bull and bear LETFs while ignoring any tracking errors. The summary statistics of the one-year compounded returns from the two strategies are reported in Table 2.

The mean, standard deviation, and percentiles are measured across the 1,000,000 possible realizations of one-year compounded returns.

Insert Table 2 and Figure 1 about here

As mentioned earlier, these two are alternative strategies to potentially profit from a bullish outlook of the underlying benchmark. The long strategy is negatively affected by volatility drag; whereas the short strategy tends to benefit from it. Figure 1 and Table 2 tell us that they are in fact very different strategies with distinct risk-return profile. First of all, the long strategy has a return distribution that is positively skewed, while that of the short strategy is negatively skewed. The median return of 22.85% from the long position in the +3x LETF is lower than its mean return of 29.59%. In other words, the return actually realized from the long strategy is more likely to be lower than the average return. As we will find out from the detailed simulation analysis conducted later, the higher the return volatility of the S&P 500 index, the more the median return is lower than the mean return. It is in fact a manifestation of the volatility drag on the long strategy. On the other hand, the median return (33.89%) from the short position in the -3x LETF is above its mean return of 22.89%. Again, as we will find out later, the higher the volatility of the S&P 500 index, the higher is the median return relative to the mean return and thus the more chance that the realized return is above the average return. This represents the benefit of the short strategy from the volatility drag. Comparing the returns from the two strategies, although the long strategy has a much higher mean return, it is actually more likely for investors to realize a higher return from the short strategy. Among the one million scenarios considered, the short strategy beats the long strategy 57% of the time. The median value of the outperformance of the short strategy relative to the long strategy is 5.41%.

How consistent is the superior performance of the short strategy across different return path scenarios of the underlying benchmark? From Figure 1, we notice that the return distribution of the short strategy is much more leptokurtic than that of the long strategy. There is more clustering around its average value together with a heavy left-hand (i.e., downside) tail. The upside of the short strategy is capped while its downside is unlimited. On the contrary, the upside of the long strategy is unlimited while its downside is capped. We expect the long strategy to outperform the short strategy when the underlying benchmark either goes up substantially or goes down substantially. In the former case, the upward trending of the benchmark benefits the long strategy as the dollar amount exposure increases (as a result of daily rebalancing) with the returns on the benchmark magnifying the overall compounded return. The short strategy however does not benefit from the upward trending because the short exposure on the bear LETF actually decreases when the benchmark keeps on going up, leading to a smaller dollar amount return. In the latter case, the downward trending of the benchmark hurts the short strategy more than the long strategy. When the benchmark goes down, the dollar amount exposure of the bear LETF increases as a result of daily rebalancing. This magnifies the subsequent dollar amount loss from the short position in the bear LETF when the benchmark continues with its downward trend. On the other hand, the loss from the long strategy on the bull LETF will be limited since the dollar amount exposure of the bull decreases with the benchmark value. This is indeed what we find from our simulation results. When we consider only the subsample of the simulated return paths where the return on the S&P 500 index falls within either the top 25% or the bottom 25% among all the return path scenarios, the long strategy tends to outperform the short strategy. The median value of the outperformance of the former relative to the latter is 18.73%. The superior performance of the long strategy is more salient when we focus on even more extreme returns. When we consider only the subsample where the return on the index falls within either the top 10% or the bottom 10%, the median value of the outperformance of the long strategy becomes 52.29%. Therefore, the short strategy only pays off handsomely when the benchmark return is moderate where the index ends at a value that is not very different from where it starts. We are most able to benefit from the volatility drag in implementing the short strategy under a sideways market. Based on our simulation results, when we consider only the subsample where the return on the S&P 500 index falls within the range between the 25th and 75th percentiles, the short strategy outperforms the long strategy with a median value of 9.83%. In Figure 2, we plot the one-year return of the short strategy in excess of that of the long strategy against the corresponding one-year return on the index across the simulated scenarios. The short strategy consistently outperforms the long strategy when the *realized* annual return on the underlying index is within ± 10%.

Insert Figure 2 about here

Will risk consideration tip the balance in comparing the two strategies? From Table 2, the two strategies in fact have similar standard deviations. Thus, the short strategy can deliver a higher median return than the long strategy per unit of standard deviation. Nevertheless, the short strategy has a much higher *tail risk*. There is a one percent chance that the return of the short strategy will be lower than -145%, which is almost twice the magnitude of that of the long strategy. The short strategy actually delivers a lower median return per unit of the one percentile loss than the long strategy, indicating its inferior risk-adjusted performance based on tail risk consideration.

Next, let us examine the return distribution of the pair strategy of a 50% short position in the +3x LETF together with a 50% short position in the -3x LETF both tracking the S&P 500 index. Suppose we adopt a *buy-and-hold* strategy and do not reset and equalize the two short exposures when they deviate from each other over the one-year holding period. As mentioned earlier, this strategy allows an investor to profit from the volatility drag while he or she is not interested in taking either a bullish or bearish view of the benchmark asset. To demonstrate the performance of this pair strategy under a *market-neutral* condition, we simulate the S&P 500 index returns using the previously calibrated GJR model but setting the mean return (i.e., the parameter μ) to zero. Using the simulated return paths of the index over a one-year period, we then compute the compounded returns of the above pair strategy by ignoring any tracking errors. The one-year return distribution of the pair strategy is presented in Figure 3. Not surprisingly, the mean return of the pair strategy is essentially zero given zero-mean return assumption of the index. But, thanks to the negative skewness of the distribution, it is more likely to realize a positive return than a negative return from the short strategy. Our simulation results suggest that the chance of realizing a positive return is close to 70%. The median return is about 5.13% per annum. The standard deviation of return across the simulations is 31.10%, which is much lower than the standard deviation of returns of a long position in the +3x LETF or a short position in the -3x LETF (see Table 2). We however should not understate the riskiness of this pair strategy. Given the unlimited downside risk, the tail risk could be substantial. There is in fact a one (five) percent chance that the return will be lower than -70.93% (-26.77%). Like any short strategies, the upside gain is capped at 100% of the initial short exposure.

Insert Figure 3 about here

Similar to the previous strategy of shorting only the bear LETF, the pair short strategy examined here also exhibits similar return profile as a function of the realized return of the underlying index. To maximize the benefit of volatility drag, we need a sideways market where the index remains at a level that is not very different from its starting value. On the other hand, a trending market (either upward or downward) will offset the volatility drag, benefiting long positions on both bull and bear LETFs and thus penalizing the respective short positions. The performance of the pair short strategy therefore tends to be particularly poor when the realized return of the underlying index is either very positive or very negative. In Figure 4, we plot the one-year return of our pair short strategy against the corresponding one-year return on the index across the simulated scenarios. The return on the pair short strategy is almost always positive when the *realized* annual return on the underlying index is within ± 12%.[19]

Insert Figure 4 about here

V. LETF performance under different distribution assumptions

In the previous section, we examine the characteristics of the return distribution of different LETF strategies under the calibrated GJR model of the underlying S&P 500 index using 30 years of historical data from 1985 to 2014. Empirical studies tell us that the distribution of

[19] The shape of the plots in Figures 2 and 4 are quite similar. This is not by coincidence. We are essentially plotting similar variables in the two figures. Let r^{+3x} and r^{-3x} denote the returns on the +3x LETF and -3x LETF respectively. In Figure 2, the y-axis is the return of the short strategy in excess of the long strategy, which therefore equals to $(-r^{-3x}) - (r^{+3x})$. In Figure 4, the y-axis is the return of the pair short strategy, which is $-0.5 \times r^{+3x} - 0.5 \times r^{-3x}$. If the assumed return process of the underlying index is the same, the former will be exactly twice of the latter. However, in generating Figures 2 and 4, we use different GJR models to simulate the returns on the underlying index. In Figure 2, we directly use the calibrated GJR parameters. We however assume a value of μ of zero together with other calibrated GJR parameters in simulating the returns for Figure 4.

the index is far from static over time. In this section, through a number of simulation analyses, we investigate how the changes in the distribution assumption of the underlying index may affect the performance of the LETF strategies. In conducting the analysis, we modify the values of three key parameters of the GJR model one at a time and measure their impact on the return and risk of the strategies. By changing only one parameter while holding the others fixed, we can isolate the effect of that parameter and find out the significance of that parameter in dictating the performance. The findings will be useful in helping us to choose among different LETF strategies. For example, from the previous discussion, we know that the strategy of a long position in a bull LETF tends to outperform a short position in a bear LETF when the return on the underlying benchmark is high. The trending in the benchmark return offsets any negative influence of the volatility drag benefiting the long strategy at the expense of the short strategy. But then, given a certain level of return volatility, how high an expected return on the benchmark is needed before we expect such a result to prevail? How will the *break-even* point between the long and short strategies vary with the return volatility of the underlying benchmark? These are some of the questions we want to address in this section. The findings will be useful for those who want to devise dynamic LETF trading strategies that are contingent on the prevailing market condition.

The first set of analyses is on the long position in the +3x LETF in comparison with the short position in the -3x LETF. We repeat the simulations of one million return paths of the S&P 500 index while changing three key model parameters, namely μ, ρ, and a, one at a time. From the simulated return paths of each set of parametric values, we calculate for the long and short strategies the mean, median, standard deviation, and the first percentile (i.e., the value-at-risk (VaR) at 1%) of their one-year returns. We also find out the proportion of time where the LETF returns exceed the corresponding *naively expected returns*. The naively expected return is defined as the return of the underlying index over the same period of time multiplying by the targeted leverage ratio. This is the return an investor, who is unfamiliar with the compounding effect, may naively expect the LETF to deliver. In our demonstration here, the leverage ratio is 3. Suppose the one-year return of the underlying index is 2% based on a particular simulated return path. The naively expected return will therefore be 6% for both the strategy of having a long position on the +3x LETF and the strategy of having a short position on the -3x LETF. The results are reported in Table 3.

Insert Table 3 about here

Table 3 Panel A presents the variation of the performance metrics of the long and short strategies as we vary μ, which (together with ρ) dictates the expected return of the underlying index. We keep the other parameters at their respective calibrated values. The calibrated value of μ is 0.0003422 (i.e., 3.422 basis points). This is equivalent to about 8.6% per annum and represents the average return of the S&P 500 index over the last three decades. Besides presenting the results based on this calibrated value, we also consider two hypothetical values of μ at -2.578 basis points (bps) and 9.422 bps, respectively. The former (latter) corresponds to an annual return of about -6.4% (23.6%), representing a bearish (bullish) market outlook. Among the three cases under consideration, the case with μ at -2.578 bps resembles the most of a sideways market; whereas that with μ at 9.422 bps delivers the strongest trending in index return. We therefore expect the short position on the -3x LETF to outperform the long position on the +3x LETF by the most when μ equals to -2.578 bps. On the other hand, the long strategy is more likely to outperform the short strategy when μ equals to 9.422 bps. This is indeed what we find when we examine the performance results in Panel A. By comparing the respective median returns, the short strategy outperform the long strategy by about 17.8% (= -0.042 – (-0.220)) in the former case. Under the latter case, the long strategy outperforms the short strategy by 35.4% (= 0.935 – 0.581) in terms of its median return, indicating that the trending effect has more than offset the negative influence of volatility drag on the performance of the long strategy. The same pattern of relative ranking of performance can also be observed when we compare the proportion of time where the returns from the two strategies exceed their respective naïve expected returns. The more trending the underlying index, the higher (lower) the chance that the return on the long (short) strategy beat its naïve benchmark.

How does the changing of the value of μ affect the risks of the two strategies? According to the standard deviation of returns, the higher the value of μ, the more (less) risky is the long (short) strategy. This is consistent with the fact that, as the downside (upside) risk of the long (short) strategy is capped, the variability in return of the long (short) strategy tends to be more restricted as expected return decreases (increases). If we use the ratio of median return to standard deviation of return as a risk-adjusted performance measure, the short strategy outperforms the long strategy in all three cases under consideration (see the second last column of Table 3 Panel A). From the VaR at 1% level, we notice that the short strategy tends to have much larger tail risk than the long strategy, except when μ is very high. This is not surprising given the unlimited downside risk of the short position. Tail risk is of particular concern in managing trading positions in financial institutions, since it dictates the amount of capital required to support the positions. The amount of tail risk could be measured by the difference between VaR and the central tendency of the risk distribution. Here we use the difference between VaR and the median return as our tail risk measure. When we use the ratio of median return to the difference between VaR and the median return as a risk-adjusted performance measure, we find that the short strategy cannot generate sufficient amount of median return to compensate for its excessive tail risks when compared with the long strategy (see the last column of Table 3 Panel A).

Table 3 Panel B presents the results when we change the autoregressive coefficient ρ, while keeping other variables fixed. The benchmark case is the second case where ρ is set at the calibrated value of 0.0024. We examine the performance under two other values of ρ (-0.1 and 0.1) that are considered to be plausible for broad-based equity index like the S&P 500 index. There are two ways through which changing the autoregressive coefficient may affect the performance of the strategies. First of all, the higher the value of ρ, the higher is the expected return on the index, which benefit both the long and short strategy. Second, the higher the value of ρ, the more persistent is the daily return over time, thus promoting the trending in returns. It benefits the long strategy but hurts the short strategy. Judging from the median returns as reported in Panel B, the first effect tends to dominate. The median returns of both the long and short strategies increase with the value of ρ. Not surprisingly, the increase is less for the short strategy given the offsetting trending effect. The negative influence of the increasing trending effect on the short strategy also shows up in the proportion of time the short strategy return exceeds its naïvely expected value. For the short strategy, the chance of exceeding decreases as ρ increases. The negative influence of the trending effect also manifests itself in both risk-adjusted performance measures. For the short strategy, both performance metrics decrease as ρ increases. On the contrary, the risk-adjusted performance of the long strategy is enhanced by positive autocorrelation in daily index return. Nevertheless, the effect of changing ρ on the performance is not as dramatic as when we change μ.

Next, we turn to the intercept a of the variance equation. Table 3 Panel C presents the performance statistics under three different cases of a. The second case is our benchmark case when we set a at the calibrated value of 0.021 bps. We try two other values for a: 0.010 bps and 0.060 bps. The former, with only about half of the calibrated volatility, represents a relatively calm market episode; whereas the latter, at about three times the calibrated volatility, represents a market in turmoil. As expected, the higher the volatility, the more the performance of the long (short) strategy is hurt by (benefits from) the volatility drag. The median return of the long (short) strategy decreases (increases) when a increases. The chance of exceeding the naively expected return for the long (short) strategy also decreases (increases) when the underlying benchmark becomes more volatile. Of course, the risks of both strategies increase as a goes up. Doubly hit by both a decreasing return and an increase in risk, the risk-adjusted performance of the long strategy decreases dramatically as volatility increases. The risk-adjusted performance for the short strategy decreases by a much more manageable amount. In a turmoil market condition where volatility is about three times that of the normal level (i.e., when a equals to 0.060 bps), the short strategy outperforms the long strategy regardless of whether we adjust for risk or not and regardless of whether standard deviation or tail risk is considered to be the appropriate risk metrics.

In summary, the above simulation results suggest that, although the short strategy tends to outperform the long strategy in delivering a higher median return, its relative advantage is weakened when the expected return of the underlying index increases and/or when the daily return of the index becomes more positively correlated. These are market conditions that promote a trending index return, which tends to offset the benefit from volatility drag. Another drawback of the short strategy is its significant tail risk, which may significantly hinder its risk-adjusted performance. Nevertheless, the short strategy is far more superior to the long strategy when the underlying benchmark exhibits volatility that is more than a couple of times of its normal value.

To illustrate the interaction effect between μ and ρ in influencing the performance of the long and short strategies, in Figure 5, we plot the one-year median returns of the two strategies (from the simulations) against the values of μ based on two different values of ρ. The other parameters of the GJR model are fixed at their respective calibrated values. Let us start with the pair of curves for the case of $\rho = 0.1$. As explained earlier, the short strategy dominates the long strategy in terms of its median return when μ is low, and vice versa when μ is high. The break-even point of μ is about 4.8 bps, which corresponds to an expected return of approximately 12% per annum. In other words, given a positive autocorrelation of 0.1 of the underlying index return, the trending effect will more than offset the volatility drag when the expected return on the index exceeds 12% per annum. If the expected return is below 12% per annum, the volatility drag dominates the trending effect, thus giving the short strategy a comparative advantage over the long strategy. The break-even expected return is much higher if the daily return of the index is negatively correlated. Turning to the pair of curves for the case where $\rho = -0.1$. The short strategy outperforms the long strategy in terms of its median return when the expected return is below 15.3% per annum (i.e., $\mu = 6.1$ bps). The long strategy dominates when the expected return is above this break-even point. The higher break-even point is solely attributable to the negative autocorrelation of return that is more likely to result in a sideways market, thus benefiting the short strategy at the expense of the long strategy. In Figure 6, we examine the trade-off between expected return and volatility in influencing the performance of the two strategies by plotting their median returns against the values of μ based on two different values of a. The break-even value of μ is much higher when a = 0.060 bps than when a = 0.021 bps. In the former case, the break-even expected return is about 24% per annum (i.e., μ = 9.6 bps). At this high value of volatility, the short strategy almost always dominates the long strategy unless the expected return of the benchmark is extraordinarily high. At a more normal level of volatility when a = 0.021 bps, the break-even expected return is only about 14% per annum (i.e., μ = 5.5 bps).

Insert Figures 5 and 6 about here

Let us now turn to our short pair strategy. How will changes in the parameters affect its performance? We repeat the simulations by modifying the values of three parameters μ, ρ, and a one at a time. In comparing the results, we consider a benchmark case where the market outlook is neutral (i.e., setting μ to zero). The other parameters of the GJR model are fixed at their calibrated values. Through these analyses, we want to understand the interaction and trade-off among the expected return, autocorrelation, and the volatility of the index return in governing the profitability of our short pair strategy. Table 4 Panel A presents the performance statistics of the short pair strategy (i.e., shorting equal amount of +3x LETF and –3x LETF on the S&P 500 index). The benchmark case is when μ is equal to zero. The pair strategy attains the highest median return under this sideways market condition where the volatility drag is most salient. The performance degenerates when the expected return on the index deviates from zero. When μ is equal to 10 bps (-10 bps), which is equivalent to an annual index return of about 25% (-25%), the median return becomes -21.6% (-13.7%). Those are the cases where the trending effect more than offset the volatility drag. We also witness the same pattern in the relative performance when we examine the proportion of time where the return on the pair strategy exceeds its naively expected return. For our pair strategy, the naively expected return is zero. This is what an unsophisticated investor might (wrongfully) expect to obtain from shorting a pair of bull and bear LETFs of the same leverage ratio. From Panel A, we see that the chance of exceeding this naively expected return decreases when μ starts deviating from zero. The two risk-adjusted performance metrics reported in the last two column of Panel A also exhibit the same pattern.

Given the stronger trending effect, we expect the performance of the pair strategy to become worse as the index return is more positively autocorrelated. This is indeed what we find when we look at the results in Table 4 Panel B. Median return decreases as ρ changes from negative to positive. Together with the higher standard deviation and tail risk, the risk-adjusted profitability dissipates quickly as ρ increases. It is cut by more than half when we change from a value of ρ equals to -0.1 to a value of 0.1. From Panel C, we witness the positive influence of market volatility. Thanks to the stronger volatility drag, the median return from our pair strategy increases from 2.5% to 14.4% when a changes from 0.010 bps to 0.060 bps. However, the risk of the strategy also increases at the same time. The ratio of median return to standard deviation actually decreases as the index return becomes more volatile. It is interesting to note that the tail risk increases at a slower rate than the standard deviation of return. The risk-adjusted performance based on the ratio of median return to the tail risk (see last column of Panel C) still increases with market volatility. This is quite different from the case where we only short the bear LETF. In Table 3 Panel C, the risk-adjusted performance of the *single short strategy* based on the tail risk decreases when a increases. It seems that the tail risk of the *pair short strategy* is more controllable than that of the *single short strategy*. This could be attributable to the partially offsetting of the tail risks between the bull and bear LETFs in a pair strategy.

Insert Table 4 about here

Within what level of expected return on the underlying index do we expect the pair strategy to pay off? It depends on the degree of autocorrelation of the daily index returns and the level of market volatility. We answer this question by plotting the one-year median returns of the pair strategy from the simulations against the values of μ under different values of ρ and a. The other parameters of the GJR model are fixed at their respective calibrated values. Figure 7 presents the plots when we vary the degree of autocorrelation. With an autocorrelation of 0.1, the pair strategy is profitable (based on its median return) when the expected return on the benchmark index is between -15% (μ = -5.8 bps) and 10% (μ = 4.0 bps). This range is likely to cover the S&P 500 index returns that are typically expected by most market participants in most market conditions. Even at this relatively high level of autocorrelation, that promotes an unfavorable trending market condition for the pair strategy, it may still deliver a median return of as much as 5% per annum provided that the return on the index is not very different from zero. The window of opportunity for the pair strategy is even wider in more favorable market condition. At an autocorrelation of -0.1, the pair strategy is profitable when the expected return on the benchmark index is between -18% (μ = -7.3 bps) and 15% (μ = 5.5 bps). In Figure 8, we plot the median returns against μ under two different values of a. At a market volatility corresponding to the calibrated value of a of 0.021 bps, the pair strategy is profitable when the expected return on the benchmark index is between -17% (μ = -6.8 bps) and 13% (μ = 5.0 bps). It essentially covers most of the possible return expectations on any equity-based index under normal market condition. In a turmoil market, in which volatility could be much higher than the calibrated value, the chance of the pair strategy not delivering a positive median return is very slim. At a volatility that is about three times the calibrated value (i.e., when a becomes 0.060

bps), the pair strategy is profitable when the expected return on the benchmark index is between -29% (μ = -11.5 bps) and 21% (μ = 8.5 bps).

Insert Figures 7 and 8 about here

VI. Conclusion

Sound LETF trading strategies need to not only consider the expected directional changes of the underlying benchmark but also to address the positive and negative compounding effect that could be realized during the investment horizon. In this paper, we investigate the market conditions that will tip the balance between the market trending effect and the volatility drag in governing the performance of LETFs. The market conditions that promote a stronger former effect than the latter will result in a positive compounding effect, thus enhancing the profitability of a long LETF position at the expense of a short one. On the other hand, those market conditions that promote a dominating latter effect will result in a negative compounding effect, which benefits the short LETF position as opposed to the long position. To address our research questions, we conduct a series of simulation exercises by gauging the sensitivity of the LETF returns on key parameters of the return generating process of the underlying benchmark as represented by the GJR model. We examine different LETF performance measures and study the risk-return trade-offs of LETF investment.

We first study the return distributions of a long strategy in a +3x LETF, a short strategy in a -3x LETF, and the pair strategy of a 50% short position in the +3x LETF together with a 50% short position in the -3x LETF, all on the same S&P 500 index. We find that, although the long strategy has a much higher mean return, the short strategy is more likely to outperform the long strategy. The outperformance is found to be quite consistent when the realized annual return on the underlying index lies between -10% and +10%. The short strategy, however, tends to underperforms the long strategy when the underlying benchmark realizes either a very high or very low return over the investment horizon. Such extremely good or bad index return also results in a poor performance for the pair short strategy. On the other hand, the pair short strategy can deliver a positive return in a consistent fashion provided that the realized index return is within the range of -12% to +12% per annum.

We then study the performance of the same set of strategies under different benchmark return distribution assumptions by modifying the key parameters of the GJR model. Risk-adjusted performance measures show that the short strategy tends to outperform the long strategy for most of the time, but the advantage is weakened under market conditions that promote a trending index return that more than offset the benefit from volatility drag. A trending index return is characterized by a higher expected return on the underlying index and/or a more positively autocorrelated daily index return. The short strategy is far more superior to the long strategy when the underlying benchmark exhibits volatility that is more than a couple of times of its normal value. By examining the trade-off between expected return and volatility in influencing the performance of the long and short strategies, we find that the break-even value of expected return that dictates the choice between the two strategies increases with volatility. The higher the volatility, the larger is the expected index return we need before we want to optimally switch from the short strategy to the long strategy. Similar analysis on the pair short strategy shows that the pair strategy performs the best when the expected return of the benchmark is not too different from zero where the volatility drag is most salient. Moreover, we find that the *pair short strategy* displays more controllable tail-risk than the *single short strategy* and the range of expected benchmark return where the pair strategy is profitable widens dramatically as market volatility climbs.

Our findings contribute to the literature by pinpointing the underlying drivers of the compounding effects and facilitate the decision-making process of LETF investors by establishing the link between the performance of LETFs and different characteristics of the return dynamics of the underlying benchmark.

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Appendix 1 Tables

Table 1: LETF's two-day compounded returns under different scenarios.

This table displays the two-day compounded return of a +2x and a -2x LETFs under different return paths of the underlying index.

Panel A: +2x LETF

Path	Underlying index return			LETF return			Difference from stated multiple
	Day 1	Day 2	2-day compounded	Day 1	Day 2	2-day compounded	
1	+10%	-5%	+4.50%	+20%	-10%	+8.00%	-1.00%
2	+2.2252%	+2.2252%	+4.50%	+4.4504%	+4.4504%	+9.10%	+0.10%
3	-10%	+5%	-5.50%	-20%	+10%	-12.00%	-1.00%
4	-2.7889%	-2.7889%	-5.50%	-5.5778%	-5.5778%	-10.84%	+0.16%
5	+7.5	-7.5%	-0.56%	+15%	-15%	-2.25%	-1.13%

Panel B: -2x LETF

Path	Underlying index return			LETF Return			Difference from stated multiple
	Day 1	Day 2	2-day compounded	Day 1	Day 2	2-day compounded	
1	+10%	-5%	+4.50%	-20%	+10%	-12.00%	-3.00%
2	+2.2252%	+2.2252%	+4.50%	-4.4504%	-4.4504%	-8.70%	+0.30%
3	-10%	+5%	-5.50%	+20%	-10%	+8.00%	-3.00%
4	-2.7889%	-2.7889%	-5.50%	+5.5778%	+5.5778%	+11.47%	+0.47%
5	+7.5	-7.5%	-0.56%	-15%	+15%	-2.25%	-3.37%

Table 2: Summary statistics of simulated one-year compounded returns

	Long +3x LETF	Short -3x LETF
Mean	29.59%	22.89%
Standard deviation	58.63%	59.04%
1st percentile	-77.27%	-144.88%
5th percentile	-53.80%	-50.21%
Median	22.85%	33.89%
95th percentile	135.84%	64.57%
99th percentile	198.33%	72.14%

Table 3: Performance statistics of long and short strategies

Panel A

μ (in bps)	Strategy	Mean	Median	Std. dev.	VaR 1%	Proportion of time exceeding naïve expected return	Median/Std. dev	Median/(Median-VaR1%)
-2.578	Long	-0.178	-0.220	0.372	-0.857	0.365	-0.593	-0.345
	Short	-0.216	-0.042	0.847	-2.816	0.710	-0.050	-0.015
3.422	Long	0.295	0.229	0.585	-0.774	0.397	0.391	0.228
	Short	0.228	0.339	0.539	-1.426	0.545	0.629	0.192
9.422	Long	1.039	0.935	0.919	-0.643	0.683	1.017	0.593
	Short	0.511	0.581	0.343	-0.541	0.240	1.695	0.518

Panel B

ρ	Strategy	Mean	Median	Std. dev.	VaR 1%	Proportion of time exceeding naïve expected return	Median/Std. dev	Median/(Median-VaR1%)
-0.1000	Long	0.240	0.193	0.513	-0.749	0.345	0.376	0.205
	Short	0.229	0.321	0.438	-1.184	0.590	0.733	0.213
0.0024	Long	0.295	0.229	0.585	-0.774	0.397	0.391	0.228
	Short	0.228	0.339	0.539	-1.426	0.545	0.629	0.192
0.1000	Long	0.361	0.270	0.677	-0.802	0.445	0.398	0.252
	Short	0.226	0.361	0.694	-1.742	0.502	0.520	0.172

Panel C

a (in bps)	Strategy	Mean	Median	Std. dev.	VaR 1%	Proportion of time exceeding naïve expected return	Median/Std. dev	Median/(Median-VaR1%)
0.010	Long	0.295	0.277	0.406	-0.583	0.480	0.681	0.322
	Short	0.228	0.290	0.315	-0.807	0.467	0.922	0.265
0.021	Long	0.295	0.229	0.585	-0.774	0.397	0.391	0.228
	Short	0.228	0.339	0.539	-1.426	0.545	0.629	0.192
0.060	Long	0.295	0.051	1.015	-0.956	0.341	0.050	0.051
	Short	0.232	0.476	1.562	-3.067	0.609	0.305	0.134

Table 4: Performance statistics of short pair strategy

Panel A

μ (in bps)	Mean	Median	Std. dev.	VaR 1%	Proportion of time exceeding naïve expected return	Median/Std. dev	Median/(Median-VaR1%)
-10.000	-0.300	-0.137	0.677	-2.386	0.255	-0.202	-0.061
-5.000	-0.073	0.030	0.426	-1.362	0.596	0.070	0.021
0.000	0.000	0.051	0.269	-0.697	0.700	0.191	0.069
5.000	-0.072	-0.004	0.256	-0.865	0.491	-0.017	-0.005
10.000	-0.299	-0.216	0.396	-1.547	0.248	-0.545	-0.162

Panel B

ρ	Mean	Median	Std. dev.	VaR 1%	Proportion of time exceeding naïve expected return	Median/Std. dev	Median/(Median-VaR1%)
-0.1000	0.022	0.058	0.195	-0.521	0.749	0.298	0.100
-0.0500	0.012	0.055	0.227	-0.601	0.725	0.242	0.084
0.0024	0.000	0.051	0.269	-0.697	0.700	0.191	0.069
0.0500	-0.012	0.048	0.318	-0.807	0.678	0.151	0.056
0.1000	-0.027	0.044	0.386	-0.942	0.653	0.115	0.045

Panel C

a (in bps)	Mean	Median	Std. dev.	VaR 1%	Proportion of time exceeding naïve expected return	Median/Std. dev	Median/(Median-VaR1%)
0.010	-0.000	0.025	0.120	-0.346	0.695	0.205	0.066
0.021	0.000	0.051	0.270	-0.697	0.700	0.191	0.069
0.030	0.000	0.073	0.406	-0.975	0.704	0.180	0.070
0.060	0.003	0.144	0.973	-1.830	0.718	0.148	0.073

Appendix 2 Figures

Figure 1: Distributions of one-year returns on a long position in a +3x LETF and a short position in a -3x LETF

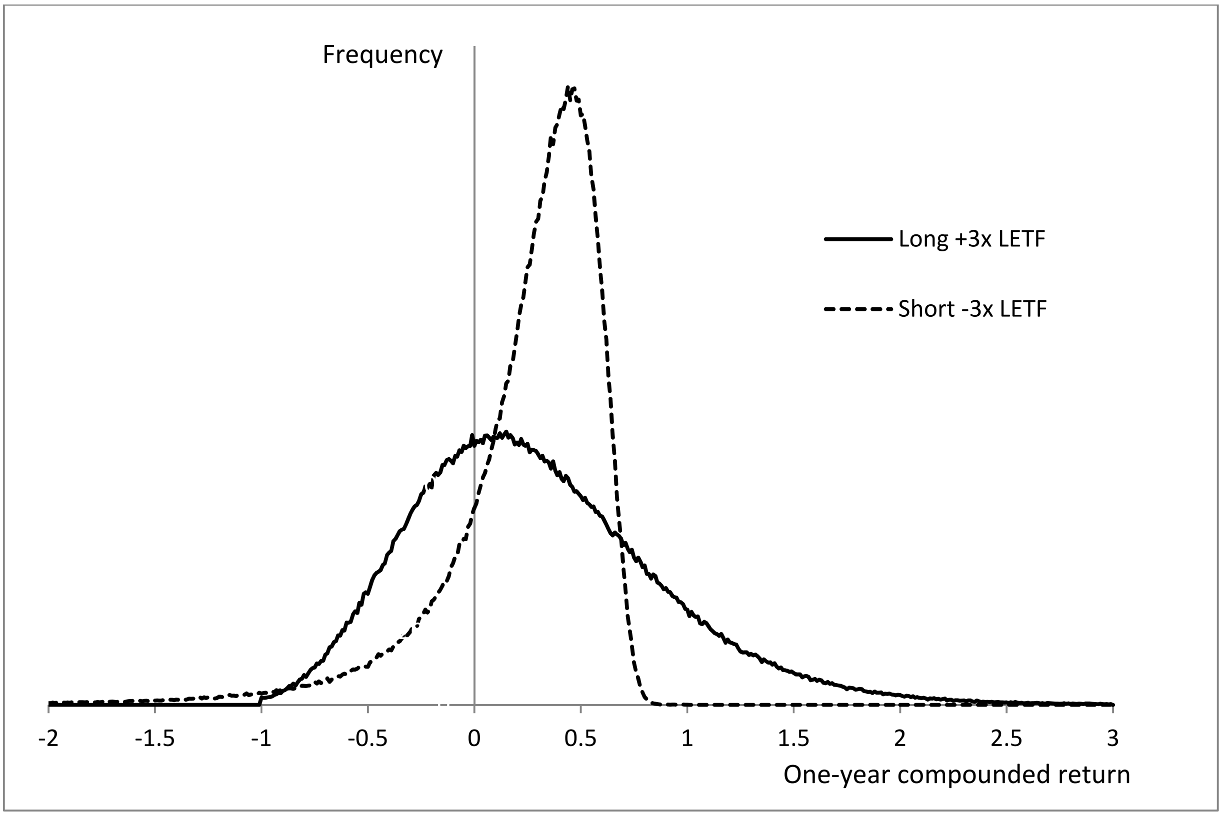


Figure 2: A plot of the one-year return of the short strategy in excess of that of the long strategy against the one-year return on the underlying index.

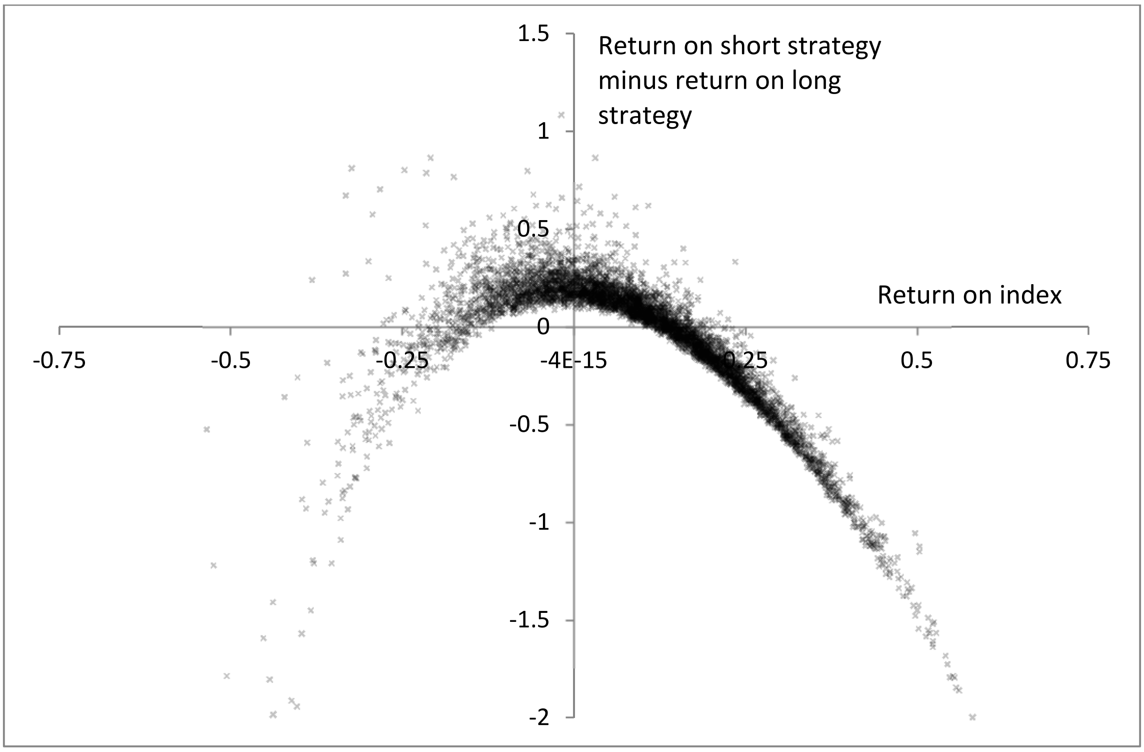


Figure 3: Distribution of one-year return on the pair strategy.

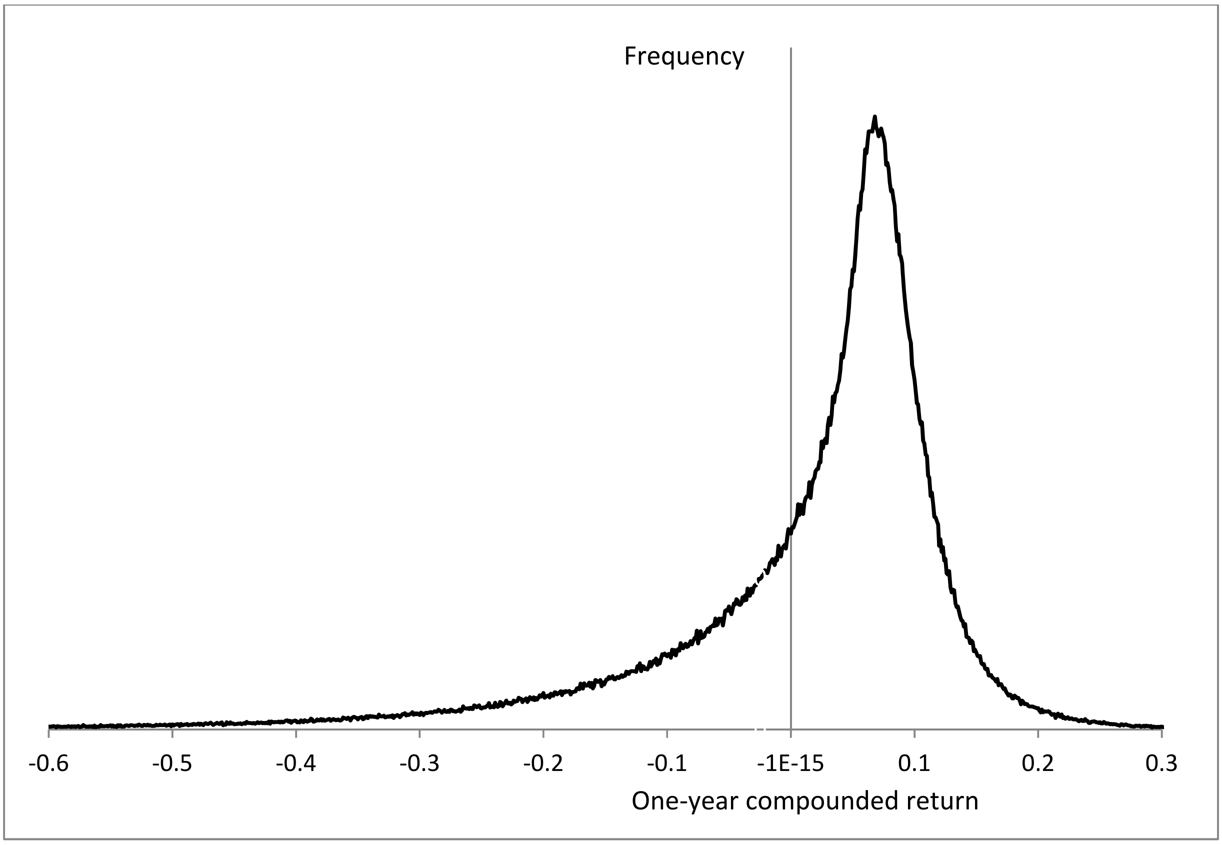


Figure 4: A plot of the one-year return of the pair strategy against the corresponding one-year return on the underlying index.

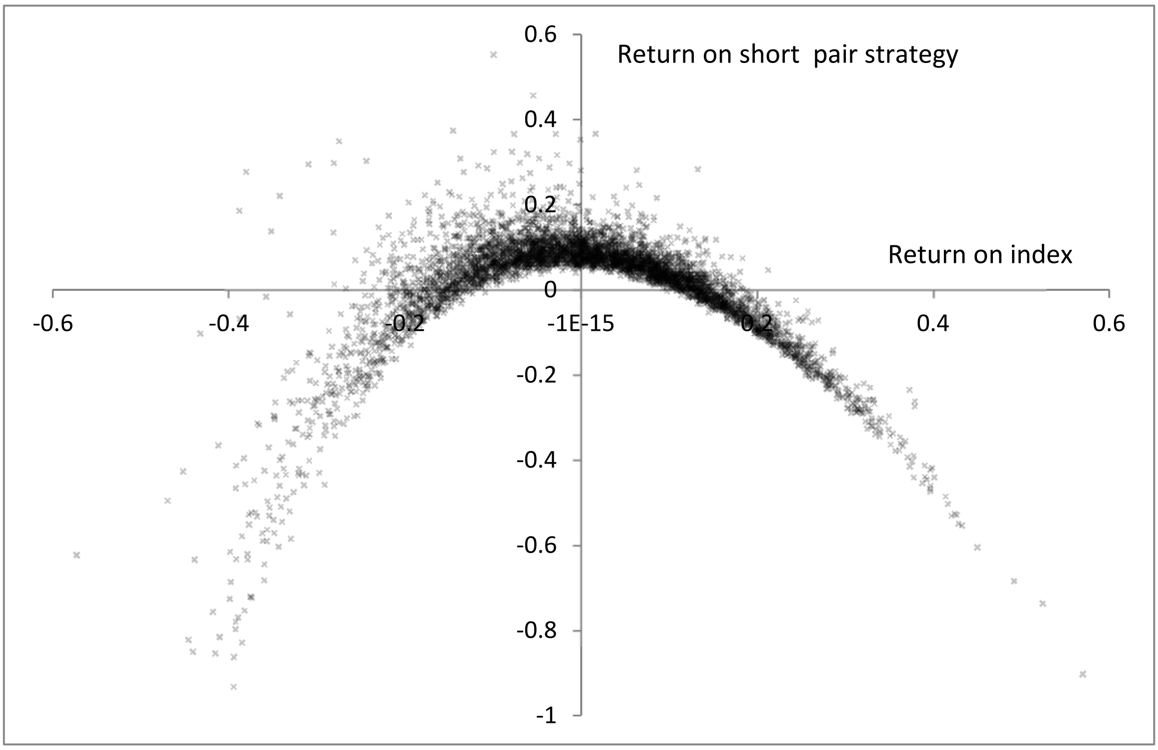


Figure 5: Plot of one-year median returns of long and short strategies against different values of μ (for ρ = -0.1 and 0.1 respectively)

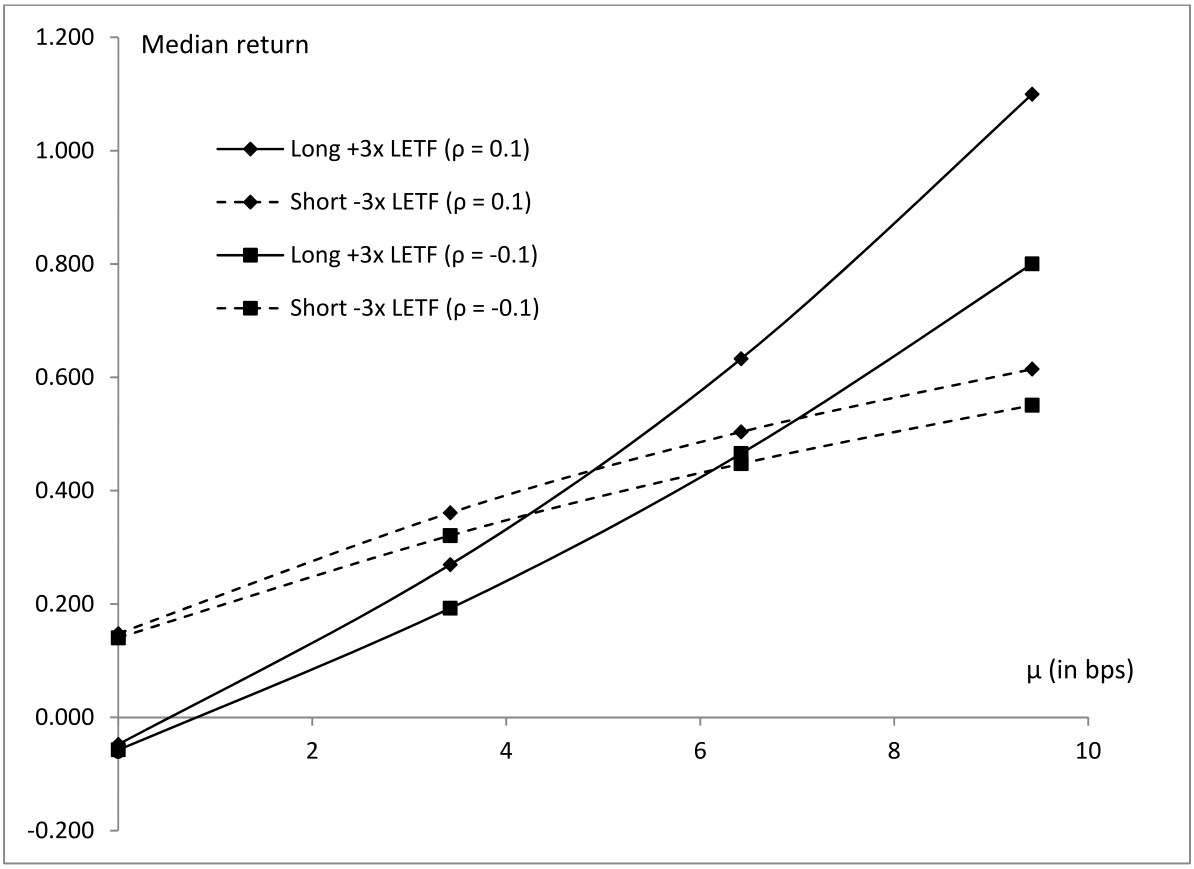


Figure 6: Plot of one-year median returns of long and short strategies against different values of μ (for a = 0.021 bps and 0.060 bps respectively)

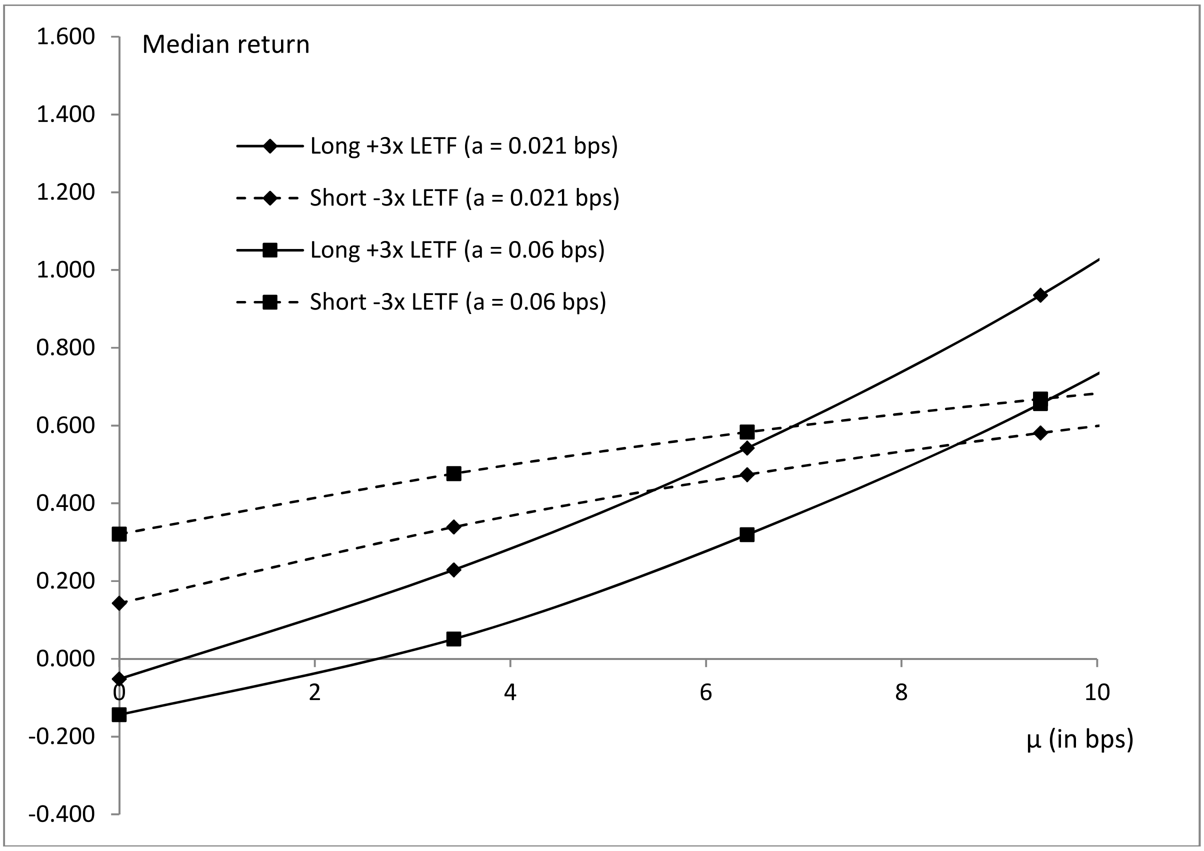


Figure 7: Plot of one-year median returns of pair strategy against different values of μ (for ρ = -0.1 and 0.1 respectively)

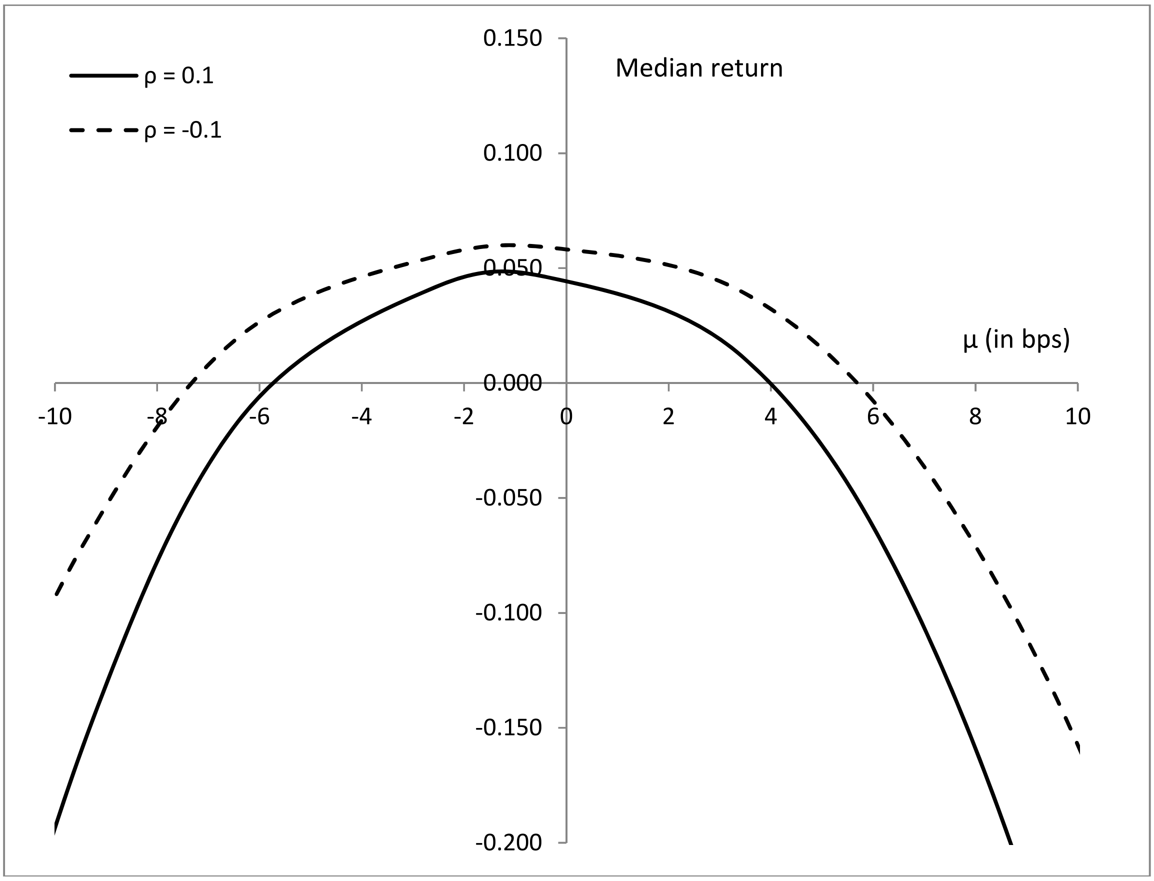
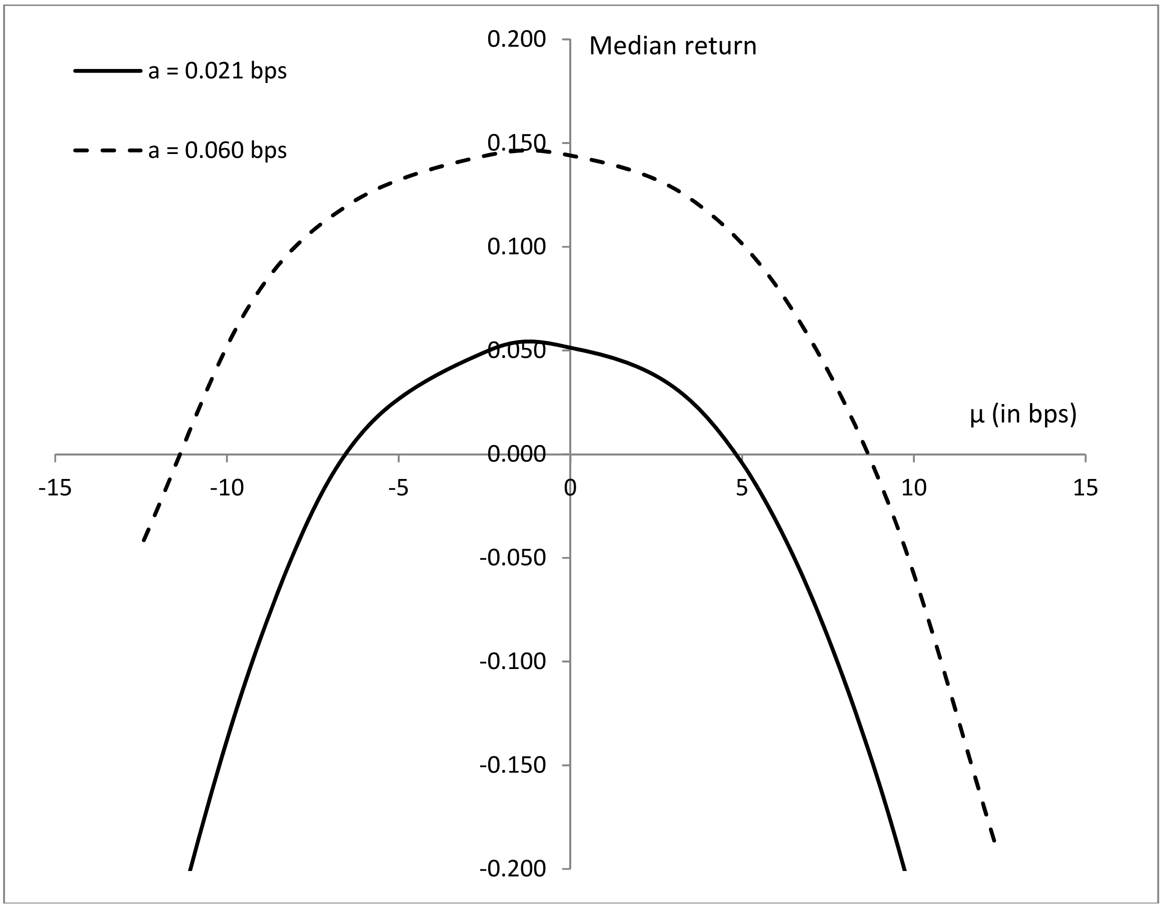


Figure 8: Plot of one-year median returns of pair strategy against different values of μ (for a = 0.021 bps and 0.060 bps respectively)



Chapter 4 Determinants of Sovereign Credit Risk in Emerging Markets: Markov Regime Switching Approach

I. Introduction

The sovereign default of Greece in 2012 and the credit crisis in other Euro Zone countries have raised people's concern on sovereign credit risk. The restructuring of the national debt of the Republic of Greece in March 2012 has resulted in the biggest sovereign default in history. The private holders of Greek government bonds agreed "voluntarily" (some were essentially forced to agree) to trade their bond holdings for longer-maturity bonds with less than half of the original face value and with a lower coupon rate. The Greek government wiped out around 100 billion euros of its total debt of 350 billion euros in the restructuring.

At the time of the restructuring, about 69 billion euros of the outstanding sovereign debt of Greece was insured by sovereign credit default swaps (SCDS). A SCDS is a CDS contract with a sovereign's credit as the underlying and is used to protect investors from losses on sovereign debt incurred at sovereign debt default or sovereign debt restructuring (such as the Greek one). Upon such events, SCDS holders are able to avoid the loss by swapping their holdings of the defaulted debt for the full face value.

A country's ability and willingness to re-pay its debt owing to other countries or investors is reflected in the spread paid for the protection offered by the corresponding SCDS. Credit risk indicated by a nation's SCDS spread essentially reflects the same fundamental economic condition and market information as the yield of the underlying government bonds. SCDS has become a more important tool than sovereign bond derivatives in the management of sovereign credit risk due to its high liquidity and its ability to more rapidly adjust to new information than bonds in the price discovery process (Coudert and Gex, 2010).

In this paper, we examine the deterministic factors that affect a nation's credit risk as captured by its SCDS spread. An understanding of the determinants of a nation's sovereign risk is crucial for investors in deciding whether to invest in or lend to the country. Evidence shows that SCDS spread is affected by different factors in different economic and market conditions. For example, Fender et al. (2012) find that the spreads are particularly related to global and regional risk premium as opposed to country specific risk factors during periods of market stress from Aug 2007 to Dec 2011. They attribute it to market contagion effect in global turmoil markets.

In the existing literature, researchers mostly use linear empirical model (e.g., ordinary least square regression) to study the determinants of credit spread change (e.g., Fender et al., 2012; Longstaff et al., 2011). To the extent that the effects are time-varying, such approach forbids us from accurately pinpointing the potentially different dictating factors at different states of the economic/market condition. With the objective of recovering any time-varying effect, some researchers like Fender et al conduct subsample analysis on different time periods that might or might not accurately capture the different states of the particular sovereign market. In this study, we use the regime switching approach to examine the state-dependent effect so, rather than exogenously define the subsamples, both the state and the sensitivities on the factors are endogenously determined. This allows us to accurately recover the state-dependent effect that could be country specific. Although regime switching model has been commonly used in the finance literature, we are the first to adopt this approach to study sovereign credit risk.

In this study, we focus on the sovereign credit market of emerging nations which are by far the most liquid. Emerging market has become increasingly attractive to investors for the past few decades. Emerging market SCDS has become an indispensable tool for these investors to manage their exposure to sovereign risk, which tends to be more vulnerable to global and country–specific shocks than developed nations.

II. Background and Literature

A credit default swap (CDS) is a contract that provides insurance against the risk of default by a particular reference entity (Hull, 2012). The reference entity of a SCDS is a sovereign government. The default by the reference entity is called a credit event. In a typical CDS contract, the buyer and the seller of the CDS enter into an agreement that the buyer makes periodic payments to the seller until the maturity date specified in the agreement of the CDS contract or until a credit event occurs. In exchange, the buyer has the right to sell to the seller a specified quantity of bonds issued by the CDS reference entity at face value when a credit event occurs, while the seller unconditionally buys the bonds at face value from the buyer regardless what the market value of the bonds are. There is a major difference for the treatment of default between corporate CDS and SCDS. In a corporate default event, the default company may be ordered to liquidate its asset to repay its debt by a bankruptcy court. In a sovereign default event, the recovery value of creditors is rarely derived from the liquidation of any assets. It is more likely to be the outcome of a negotiation between the creditors and the government in question as happened in the Greek default. This complicates the valuation and risk analysis of a SCDS.

The corporate and sovereign CDS markets have been highly active since the early 2000s. CDS market size experienced rapid growth from the early 2004 to mid-2008 and then experienced a sharp decline after the financial crisis in 2008. According to the Bank of International Settlement (BIS, 2012), at the peak in 2008, the total gross notional value of outstanding corporate and sovereign CDS contracts amounted to approximately 57,000 billion dollars. The gross notional value of CDS contracts in the middle of 2012 decreased to approximately 27,000 billion dollars.

Despite the drop of the overall CDS market subsequent to the recent financial crisis, the share of SCDS in the total CDS market has been growing steadily throughout the past decade. It grew from roughly 15% of net notional value of total CDS market at the end of 2008 to almost 25% at the end of 2011 (BIS, 2012). SCDS is normally used by government bond investors to hedge against potential losses from a credit event. It is also used by institutional investors to speculate on the credit outlook of the issuing country of the underlying bonds. Some investors execute a strategy known as basis trading in which they take positions in both the SCDS and the corresponding underlying sovereign debt in order to profit from any short-term variation of their prices. With the huge demand for credit protection, SCDS of emerging market issuers remain the most actively traded contracts throughout the years, while that of distressed developed economies is the next most active class of SCDS (BIS, 2012).

Both a country's SCDS spread and its government bond spread indicate its credit worthiness. A number of theoretical models are developed to price sovereign debt. Duffie and Singleton (1999) construct reduced-form models which apply term structure model of interest rates to value corporate and sovereign bonds. Duffie et al. (2003) develop a framework to price sovereign bond that takes into account several risk factors including default, restructuring and liquidity risk. Pan and Singleton (2008) explore the nature of default arrival intensity and recovery value implicit in the term structures of SCDS spreads by applying the framework they develop earlier (Duffie et al., 2003). They examine several emerging market countries and show that a single-factor model captures most of the variation in the term structures of spreads of these countries and the risk premiums associated with the unpredictable variation in default arrival intensity are found to be economically significant and highly correlated with several economic measures of the global and local financial market.

Empirical work also arouses extensive interests among researchers. Due to the dominancy of trading activities of emerging market SCDS market and their higher credit risk, the empirical literature on SCDS focuses on those on emerging markets. The credit quality of a sovereign issuer is usually indicated by ratings provided by rating agencies like Moody's and Standard & Poor's. However, empirical research shows that, besides ratings, there are a broad range of fundamental and general market variables that affect a sovereign's credit spread. Research shows that a country's external debt, debt service, and measures on international trade activities are the key determinants of its SCDS spread. Macroeconomic variables such as domestic inflation rate, net foreign assets, terms of trade index, and real exchange rate also play a significant role in explaining SCDS spread (Edwards, 1984; Min, 1998). Baldacci et al. (2011) investigate the key determinants of country risk premiums as measured by sovereign bond spreads and find that both political and fiscal factors matter for credit risk in emerging markets. Lower levels of political risk are associated with tighter spreads particularly during financial turmoil. In examining the balance sheet effects on emerging market sovereign spreads, Malone (2009) finds that the terms-of-trade volatility and the level of current account leverage play a major role in explaining spread variation. Dailami et al. (2005) argue that global factors are becoming increasingly important in determining SCDS spreads as opposed to country-specific factors. Remolona et al. (2008) also find that global risk aversion is the dominant determinant of the sovereign risk premium.

As a result of the recent EU crisis affecting both developed and emerging markets, including Greece, Italy, Spain, Turkey, etc., we witness a surge of interests in examining non-emerging market SCDS. Delatte et al. (2011) assesses the influence of the SCDS market on the borrowing cost of the SCDS issuing countries during the European sovereign crisis. They conclude that the more severe the distress the more dominant the SCDS market is in the information transmission between SCDS and bond markets. Constancio (2012) brings to our attention that the sovereign debt problem in the euro area was exacerbated by a contagion effect, in which financial instability becomes so widespread that a crisis reaches systemic dimensions. He warns policy makers that, when managing the crisis, they should focus on policy measures that are able to contain and mitigate the systematic risk contagion.

SCDS spread is considered to be a more timely measure of sovereign credit risk than government bond yield spread. Adler and Song (2010) compare the behavior of emerging market SCDS spreads and the corresponding bond yield spreads and reject the widely accepted parity relationship between SCDS spreads and bond spreads in the literature. Ammer and Cai (2011) examine the relationships between SCDS spreads and bond yield spreads for nine emerging market sovereigns and find that these two measures of credit risk deviate significantly in the short run with the former leading the later in price discovery. They attribute the deviation to the higher liquidity in the trading of SCDS.

More recently, a couple of empirical studies confirm the importance of global and regional factors in dictating the sovereign credit risk of emerging countries. Longstaff et al. (2011) study the nature of sovereign credit risk using monthly SCDS data from October 2000 to January 2010 and find that global factors explain the majority of sovereign credit risk. They apply the principal component analysis to the changes of SCDS spreads and the results indicate that more than 60 percent of the variation in SCDS spreads is accounted for by the first principal component. The first three principal components explain nearly 80% of the variation of SCDS spreads during the entire sample periods. Further correlation analysis using the first principal component reveals that the principal source of variation of monthly SCDS spread changes across almost all counties is highly correlated with the US equity market returns and its volatility. Using daily SCDS data of 12 emerging market countries, Fender et al. (2012) study the determinants of emerging market SCDS spreads over the period of April 2002 to December 2011. They use the generalized autoregressive conditional heteroskedasticity model to study the time-series behavior of SCDS spreads. Consistent with the results of Longstaff et al., they reveal that the spreads are more related to global and regional risk premia than to country-specific risk factors. This finding is particularly evident during periods of market stress (from Aug 2007 to Dec 2011).

The above research findings suggest that SCDS spreads cannot be fully explained by country specific economic fundamental variables. Global factors do play a significant role in influencing the sovereign risk of emerging countries. There are two possible channels through which global factors may exert their influence. First of all, the global effect could be the result of the fundamental economic relation between the emerging country and its global trading partners. Second, it may as well be through the actions in the international financial markets. We expect to witness an elevation of the sovereign risk of an emerging nation if foreign investors lose their appetite on the local financial assets. This type of global effect is expected to be time varying with the effect being more salient during the downturn and/or volatile market condition, in which the market is more prone to a flight-to-quality phenomenon. None of the above-mentioned studies explores the determinants of sovereign credit risk in a state-contingent framework. This study contributes to the literature by examining how the influence of different factors may vary in different states of the markets. In particular, rather than classifying the state based on exogenous information that may not be directly relevant to the SCDS market, we let the data to speak for themselves by using the Markov regime switching model to identify the good vs. the bad states of the market.

Markov regime switching model is used in a variety of economic and finance research. Goldfeld and Quandt (1973) introduce Markov model for switching regressions in econometric analysis. Cosslett and Lee (1985) use Markov switching in their discrete time models. Hamilton (1989) applies Markov switching model to explain the dependence of real output growth on business cycle. In a subsequent paper, Hamilton (1994) formally developes the statistical representation to use discrete-time and discrete-space Markov chain to model the transition of unobservable regime switching states in time series data. Since then, the Markov switching framework is widely exploited in a number of studies to model different financial time series that exhibit regime varying effect. For example, Turner et al. (1989), Perez-Quiros and Timmermann (2000), and Alexander and Dimitriu (2005) use it to examine stock market returns. Taylor (2004) considers the regime switching behavior of exchange rate in examining the effectiveness of market intervention. Clarida et al. (2006) investigate the regime shifting effect in the term structure of interest rates. From our knowledge, regime switching model has not been used to study the time series behavior of SCDS. The use of the regime switching model allows us to capture the potential state-contingent behavior of SCDS spread allowing for the influence of different explanatory variables to vary under different economic and market conditions.

In analyzing the regime switching effect of the explanatory variables we also witness a significant difference among the countries in terms of the extent of which these explanatory variables are associated with a country's SCDS spread change. To identify the determinants of these cross-sectional differences we conduct a cross sectional analysis to investigate the variation of the significance of explanatory variables across several categories of sub-groups of our sample of emerging market countries. We expect that the more open an economy and the more it is integrated to the global economy, the stronger will be the influence of regional and global factors on its SCDS spread change. We also expect that there is likely to be a size effect, the smaller the economy, the more vulnerable it is to the regional and global shocks. The findings of this cross sectional research will be useful for emerging market investors formulating sovereign credit risk management strategy that is specific to the characteristics of each emerging market country.

We conduct one of the most comprehensive empirical studies on SCDS covering a total of 11 emerging market countries across different geographical regions and at different stage of economic development. The time period under investigation is also one of the longest in the literature. The sample period covers a number of market turmoils such as the burst of the internet bubble in 2000-2011 and the recent global crisis started in 2008.

This study has important practical implications that are important to global credit portfolio managers. First, by being able to pinpoint the determinants of the change in SCDS spread in a state-contingent framework, global credit portfolio managers can have a better understanding of the evolution of sovereign default risk that is crucial in affecting the risk-return tradeoff of their credit portfolios. Second, the understanding of state-dependent factors for SCDS spread changes can help global credit portfolio managers to formulate dynamic trading strategies that vary across different states of market conditions. Finally, portfolio managers who like to hedge their global credit portfolios using liquid SCDS may find our findings important as the results suggest the need to consider regime dependent hedge ratios to effectively manage credit risk exposure.

III. Methodology

We consider the following two-state Markov regime switching regression model introduced by Hamilton (2005) for the weekly change of the spread of SCDS (y_{s_t}) written on a particular emerging market sovereign.

$$y_{s_t} = \beta_{0,s_t} + \sum_{i=1}^{K} \beta_{i,s_t} x_{i,t} + \varepsilon_{s_t} \qquad i = 1,2,3 \ldots K \qquad (1)$$

where $x_i{}'s$ are the different factors affecting the SCDS spread of the country. Indicator variable $s_t = 1$ or 2 denotes the two possible regime switching states and ε_{s_t} is the normally distributed error term with zero mean and standard deviation σ_{s_t}. All the coefficients and the error term ε_t are allowed to switch between the two states. The transition probability from state 1(2) to state 2(1) over the time period t to t+1 is governed by the Markov transition probability p_{12} (p_{21}), which is assumed to be constant over time. The distribution of y_{s_t} is fully described by σ_{s_t}, β_{0,s_t}, β_{i,s_t}, p_{11} and p_{22}, and $0 < p_{11} < 1, 0 < p_{22} < 1$. The transition matrix P is therefore represented by

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \qquad (2)$$

Since we can never be certain about what s_t is at any given time t, we can only infer what s_t might be based on what we observe at time t. The probability of having s_t at a given time t to be in regime j is given by

$$\xi_{jt} = \Pr(s_t = j | \Omega_t; \theta) \qquad (3)$$

where j =1, 2 and Ω_t is the information observed from time 0 up to time t including both the dependent and independent variables and θ is the set of population parameters of the regime switching regression. That is,

$$\boldsymbol{\theta} = (\beta_{i,1}, \beta_{i,2}, p_{11}, p_{22}, \sigma_1, \sigma_2)' \qquad (4)$$

Since the regime of the state can either be 1 or 2, the two probabilities $\xi_{1,t}$ and $\xi_{2,t}$ always sum to 1.

The probabilities can be inferred iteratively from *t = 1, 2, ... T*. Under Gaussian assumption of the error terms for the two regimes, the conditional densities needed to perform the iteration is given by:

$$\eta_{j,t} = f(y_t |\, s_t = j, \Omega_{t-1}; \theta) = \frac{1}{\sqrt{2\pi}\sigma_j} \exp[-\frac{(y_t - \boldsymbol{x_t}'\boldsymbol{\beta_j}')^2}{2\sigma_j{}^2}]$$

(5)

Thus, the conditional density of the tth observation is the probability weighted sum of both states, which is:

$$f(y_t |\, \Omega_{t-1}; \theta) = \sum_{i=1}^{2} \sum_{j=1}^{2} p_{ij} \xi_{i,t-1}\, \eta_{j,t} \qquad (6)$$

The log likelihood function associated with the iteration is then:

$$\mathrm{Log}\, f(\boldsymbol{\theta}) = \sum_{t=0}^{T} \log f(y_t |\, \Omega_{t-1}; \boldsymbol{\theta}) = \sum_{t=0}^{T} \log(\sum_{i=1}^{2} \sum_{j=1}^{2} p_{ij} \xi_{i,t-1}\, \eta_{jt}) \qquad (7)$$

The parameters $\boldsymbol{\theta}$ can be estimated by maximizing the log likelihood function of Equation (7) (Perlin, 2010).

IV. Data

We use weekly data from the beginning of May 2001 to the end of December 2012 which covers the longest time period for SCDS study in the literature. We consider 11 representative emerging countries in four different geographic regions, namely Asia (China, Korea, and Malaysia), Europe (Poland, Russia, and Turkey), Latin America (Brazil, Colombia, and Venezuela), and Middle East/Africa (Israel and South Africa). The benefit of using weekly rather than daily data is that the former is less noisy than the latter. Monthly data on the other hand will not give us sufficient data points for the regime switching analysis.

The SCDS data are collected from Bloomberg. We validate the data by cross checking them against the CDS data from Markit. In the regressions, we use the weekly change in SCDS spread as the dependent variable. Table 1 summarizes the descriptive statistics of the levels of the weekly SCDS spreads of the 11 emerging market countries being studied spanning periods from May 2001 to end of 2012. As can be seen, the SCDS spreads vary considerably across countries with China the lowest (with mean value of 60.02 basis points) and Venezuela the highest (with mean value of 860.52 basis points). The variation in spreads of each country during the sample period is quite substantial as evidenced by the large difference between the maximum and minimum spread values. The time-series plots of the SCDS spreads are provided in Figure 1. We observe the spikes in spreads during the 2002-2003 period and the 2008-2009 period as a result of the fall of Enron and Leman Brothers respectively. Table 2 summarizes the descriptive statistics of the weekly changes in SCDS spreads of the 11 countries. The means of the weekly SCDS changes are small in general but the variations in the changes are substantial for all the 11 countries. The high measures of skewness and kurtosis suggest non-normal distributions of SCDS spread changes and reaffirm the regime switching behavior of the SCDS spread changes.

[Insert Table 1 and 2 and Figure 1 about here]

We consider a number of explanatory variables in the regressions including local financial variables, fundamental economic variables, and global financial variables. Among the many local financial variables we select, local stock market return and the change in exchange rate against US Dollar (USD) as the explanatory variables representing local market. As widely acknowledged in the literature (Longstaff et al. 2011; Fender et al. 2012), the changes in SCDS spreads tend to be associated with the changes in local financial variables such as local stock index and exchange rates. Local stock indices are denominated in local currency and exchange rates are quoted as local currency per USD. A higher return of the local stock market indicates good market condition that results in a tightening of SCDS spread. We therefore expect the local stock market return and the change in SCDS spreads to move in opposite directions. On the contrary, increasing local currency exchange rate (as denoted by local currency value per USD), suggesting depreciating local currency value and deteriorating local economy, is expected to be related to an increase in SCDS spread.

Besides the above two financial market variables, we also consider the sovereign credit rating of the country as assigned by Standard & Poor's (S&P's) as another potential variable in explaining the variation of the country's SCDS. A country's sovereign rating is considered to be a measure of the fundamental economic and political outlook of the country. It therefore captures information regarding the long-term fundamental condition of the country that may not be captured by the above financial market variables.[20] We expect an improvement in the credit rating (e.g., from "A" to "AA") to be associated with a decrease in the country's SCDS spread.

We expect a country's sovereign risk is also affected by regional and global factors through interactions in international trades, international financial market, and geopolitical incidence. The world has become more and more integrated. All countries (emerging markets with no exception) have all kinds of economic and political relation with other countries. A stock in the regional and/or global economy could have significant impact on many countries though the extent of such impact may vary given the current state of the economy. One of

[20] In the literature, other researchers (e.g., Edward et al., 1984; Min, 1989; Baldacci, et al., 2011; Maone, 2009; Dailami, et al., 2005; Remolona, et al., 2008) use various fundamental variables (e.g., GDP, import/export activities, term of trade, foreign reserves, debt ratio, political structure, etc.) to explain sovereign risks. They are not considered in this study because these variables are only updated in quarterly (and for some of them, even annually) frequency. In this study, we are interested in finding out the timely impact on the weekly change in SCDS spread under a regime-switching model.

the contributions of this study is in the examination of how the local, regional, vs. global factors are related to a country's sovereign risk under different states of the SCDS market. To achieve this objective, besides the local financial and fundamental variables mentioned above, we also consider the role played by several global financial market variables. Following Longstaff et al. (2011) and Fender et al. (2012), we use the US stock market return, change in US T-Bill yield, and the change of VIX to proxy for the global financial market changes.[21] A higher return on the US stock market indicates good global market conditions so does an increase in the US T-Bill yield. We therefore expect increases of US stock market return and T-Bill yield lead to a tightening of the SCDS spreads of all emerging countries. On the other hand, increasing VIX means a worsening outlook of the global market hence leading to a widening of SCDS spreads for all countries.

We also include regional average SCDS as an explanatory variable to capture the regional effect. Economies in the same geographic vicinity (e.g., China, Korea, and Malaysia within Asia) are expected to be more integrated with each other than with countries outside the region. For each country, we calculate the regional SCDS spread change as the average SCDS spread change of the other countries in the same region. To better capture the effect of regional influence, we consider both the raw average regional spread change and the residuals of the

[21] VIX is the CBOE volatility index defined as the forward looking volatility of US stock market return.

average regional spread changes after controlling for the global effects. The residual is obtained by running an ordinary least square (OLS) regression of the average regional spread changes against the above global variables (i.e., US stock market return, US T-Bill yield, and VIX change). We expect a country's SCDS spread to move in the same direction as its regional SCDS spread.

Table 3 summarizes the explanatory variables providing their descriptions, expected sign of coefficients in the model, and data sources.

[Insert Table 3 about here]

V. Ordinary Least Square (OLS) Regressions

We provide the results of two OLS regressions here as benchmark for the regime switching models to be reported later in Section 5. In the first OLS regression (Equation (8)), we regress the weekly SCDS spread change on only the local (both financial and fundamental) and regional variables to see how much the change in sovereign risk can be explained by local and regional factors.

$$\Delta CDS = b0 + b1(R_{local}) + b2(\Delta FX) + b3(\Delta Rating) + b4\left(\Delta CDS_{Regional}\right) + \varepsilon \qquad (8)$$

Table 4 shows the result of regression equation (8). The coefficients for the variable R_{local} are negative for all countries and are all significant at the 1% level (except for Israel at 2%). This is consistent with our expectation that an increase in the return of the local stock market indicates good market condition resulting in a tightening of SCDS spreads. For the variable ΔFX, seven out of the 11 countries have positive and statistically significant coefficients, which is consistent with our expectation that currency depreciation and sovereign risk are positively related. Three of the remaining four countries have positive coefficients; albeit not statistically significant. The insignificant results for China, Russia, and Venezuela could be due to the fact that their pegged exchange rate policies incur no significant variations of exchange rates during the sample period. For the variable $\Delta Rating$, nine countries have the expected negative coefficients, but with only one country (Turkey) being statistically significant. This generally insignificant result could be due to the fact that credit rating for most countries tends to stay unchanged for a long period of time. The coefficients for $\Delta CDS_{Regional}$ are significantly positive for all countries, which suggests strong regional economic integration and is consistent with the expectation that a country's SCDS spread moves in the same direction as its regional SCDS spread. Finally the high adjusted R-squareds suggest a substantial amount of the variation of SCDS spreads is explained by these local and regional factors.

[Insert Table 4 about here]

In the second OLS regression, we regress the weekly SCDS spread change not only on the local and regional variables but also on the global variables. To clearly separate the impact of the local and regional factors from the impact of the global factors on a country's SCDS spread, we use the residuals of the local and regional variables obtained from first regressing each of these variables against the three global factors as our explanatory variables representing the pure local and regional effects. For example, in order to strip out the global effects, we first regress the regional CDS spread change on the US Stock Return, changes in T-Bill yield and VIX (Eq. (9)) and use the residuals (ε') of this regression as a new explanatory variable - regional CDS residual, in the OLS regression of each country's SCDS change.

$$\Delta CDS_{Regional} = a0 + a1(R_{S\&P}) + a2(\Delta VIX) + a3(\Delta TYield) + \varepsilon' \qquad (9)$$

Note that the regional CDS residual (denoted as $\Delta CDS_{Regional}$) is orthogonal to $R_{S\&P}$, ΔVIX , and $\Delta TYield$. Thus using this regional CDS residual allows us to eliminate the effect of global factors on regional CDS in explaining the change in a country's SCDS spread. The same applies to local stock return residual, $\_R_{\text{local}}$, and the exchange rate percentage change residual, Res_ΔFX., which are obtained in a similar fashion.

The second OLS regression can be expressed as:

$$\Delta CDS = b0 + b1(Res\_R_{local}) + b2(Res\_\Delta FX) + b3(\Delta Rating) + b4\left(Res\_\Delta CDS_{Regional}\right) + b5(R_{S\&P}) + b6(\Delta VIX) + b7(\Delta TYield) + \varepsilon \quad (10)$$

Table 5 shows the result of regression equation (10). The sign and significance of the coefficients of the local and regional variables are essentially consistent with those of the first OLS regression results as reported above when the global factors are ignored. We see that, after removing the global effects within these local and regional variables, they still behave more or less in the way consistent with our expectation. Now we turn to the global variables in Equation (10). The coefficients for $R_{S\&P}$ are all negative and statistically significant. This is consistent with our expectation that a higher US stock market indicates good global market conditions leading to lower sovereign risk for all emerging market countries. Except for Israel, all the countries have positive coefficients for ΔVIX and this is consistent with our expectation of the positive relation between VIX, as a global "fear factor", and sovereign risks. Nevertheless, only the coefficients for China, Russia, and Turkey are statistically significant. Note that China, Russia, and Turkey are relatively larger economies within our sample of countries and are well integrated to the global economy. We therefore expect these countries are likely to be more sensitive to global risk outlook as proxied by VIX being the forward looking volatility of the US stock market return. The coefficients for

ΔTYield are all positive and significant for most countries (except for Israel, Poland, and South Africa), which is again consistent with our expectation.

[Insert Table 5 about here]

The OLS regression results show that local, regional, and global factors are all important in determining the spread change of SCDS consistent with the findings in Longstaff et al (2011) and Fender et al. (2012). We now turn to the Markov regime switching model to study how these factors evolve with the switching of market regimes.

VI. Markov Regime Switching Analysis

We use a two-state Markov regime switching model to explain how the weekly change of a country's SCDS spread is related to the set of explanatory variables. To better capture and identify the effect of individual variables on the change of SCDS spreads, we categorize the variables into three groups (i.e., local, regional, and global) and examine the effects of different subsets of these variables. Our goal is to find out if and how the explanatory power of these groups of variables differs across the two regimes. Specifically, we consider two specifications of the regime-switching model using:

(a) Only local and regional variables

(b) All local, regional, and global variables.

As confirmed by our preliminary OLS regression results reported in Section 4, SCDS spread change is affected by local, regional, and global factors. The research question we are asking here is: Do these different groups of factors behave uniformly across different states of the market?

Equation (11) depicts model specification (a) where the local financial and fundamental variables, namely local stock return (financial), exchange rate change (financial), rating change (fundamental), and the regional SCDS changes are used as explanatory variables, while leaving out the global financial market variables.

$$\Delta SCDS_{s_t} = \beta_{0,s_t} + \beta_{1,s_t} \cdot R_{local} + \beta_{2,s_t} \cdot \Delta FX + \beta_{3,s_t} \cdot \Delta Rating + \beta_{4,s_t} \cdot \Delta CDS_{Regional} + \varepsilon_{s_t} \tag{11}$$

We consider a two-state regime switching regression model where all coefficients and error term are allowed to take on different values in the two states as denoted by s_t. The "good state" is defined as the market condition that is characterized by tightening SCDS spreads (negative changes) and low volatility in spread changes, while the "bad state" is the market condition with widening SCDS spreads (positive changes) and high volatility in spread changes. We calibrate this regime-switching model for the SCDS spread changes of each country and the results are reported in Table 6. Below is a summary of our findings regarding the regime switching effect of each explanatory variable.

[Insert Table 6 about here]

R_{local} - *Local stock index return:* We expect local stock return affect SCDS change in a negative way, i.e. a positive local stock return indicating a good market condition, hence the SCDS spread should tighten (negative change) . The coefficient is indeed negative in the good state for all countries except Israel and Korea. For most of the countries, the coefficient is also statistically significant in the good state. Taking as an example, for Brazil the estimated coefficient is -1.023 which means that each percentage point increase in the Brazil local stock market return is associated with an 1.023 basis point decrease in Brazil SCDS spread. The effect is found to be weaker in the bad state, the coefficient for quite a few countries (e.g., China, Korea, Malaysia, and Venezuela) are insignificant. It seems that the local stock index return is more influential to a SCDS spread change when the economy is good, while in the bad time, other factors weigh in (refer to below discussion on global factors).

ΔFX - *Exchange rate percentage change (domestic/USD)*: Venezuela and China adopt a pegging currency policy. We therefore do not expect to detect any meaningful effect of ΔFX on their SCDS spread changes. Ignoring these two countries, we observe positive exchange rate change associated with positive SCDS spread change; and similar to local stock market return as outlined above, we witness the same regime-contingent behavior for the effect of exchange rate change that it is in general significant in both good and bad states but is more influential in the good state than in the bad state of the SCDS market. For example, Israel, Korea, Poland, South Africa all report positive and strongly significant coefficients.

$\Delta Rating$ - *Rating Change*: In the good state, the coefficient for rating change is negative and significant for five countries. In the bad state, the negative effect is only significant for Malaysia. It seems that the SCDS spread change of most of the countries is not significantly related to rating change, but if it does, it mostly happens in the good state. Note that rating is a fundamental factor capturing a country's political, economic, and other country-specific characters. These characters change infrequently, thus any foreseeable significant change may have already been captured in the SCDS spread before the actual rating changes.

$\Delta SCDS_{Regional}$ - *Regional CDS*: This variable has significant effect for all countries in both the good state and the bad state. It affirms that countries in close geographic vicinity have strong relations with each other. No matter the economies is in a good time or bad time, these countries are strongly inter-coupled together.

In general, the above findings seem to suggest that the local and fundamental variables have stronger influence on the SCDS change in the good state than in the bad state. This is consistent with our expectation that the governing role of local and fundamental variables may be weakened as global factors exert more influence during market downturn (i.e., in the bad state of our regime-switching process).

We hypothesize that global variables have stronger influence in a bad regime of SCDS spread change. In model specification (b), we test this hypothesis by using not only local, fundamental and regional variables but also including global factors in our regime-switching model (see Eq. (12)). The estimation results are reported in Table 7.

$$\Delta SCDS_{s_t} = \beta_{0,s_t} + \beta_{1,s_t} \cdot Res_{R_{local}} + \beta_{2,s_t} \cdot Res_{\Delta FX} + \beta_{3,s_t} \cdot \Delta Rating + \beta_{4,s_t} \cdot Res_{\Delta CDS_{Regional}} + \beta_{5,s_t} \cdot R_{S\&P500} + \beta_{6,s_t} \cdot \Delta VIX + \beta_{7,s_t} \cdot \Delta TYield + \varepsilon_{s_t} \quad (12)$$

Res_R_{local} - *Local stock index return residual:* Now the coefficient of this variable is negative and significant for 10 countries (with Israel being the exception) in the good state with Poland having the most negative coefficient of -5.265 with Israel being the exception. Only 5 countries have both negative and significant coefficient for Res_R_{local} in the bad state. This demonstrates that, after stripping out the global effect in the local stock index return, it has a stronger effect on a country's SCDS spread change in the good state while tends to be weaker in the bad state. This reinforces our expectation that the local stock market is more influential on SCDS spread change in the good state.

$Res\_\Delta FX$ - *Exchange rate percentage change residual:* After removing the global factor influence, the coefficient of exchange rate percentage change residual is positive and significant for 10 countries out of 11 (except for China) in the good state. But in the bad state, it has positive and significant effect for only five countries, namely Brazil, Israel, Korea, Malaysia, and Poland. Consistent with the previous results, we conclude that exchange rate percentage change residual contributes to SCDS spread change strongly in the good state and but relatively weakly in the bad state. This is consistent with our expectation that the governing role of local factors is limited in the bad state with the contemporaneous influence of global factors.

$\Delta Rating$ *- Rating change:* The expected negative effect of rating change is significant in six countries (Colombia, Israel, Korea, Poland, Russia and Turkey) in the good state. It is significant in only one country, Russia, in the bad state. This tells us that rating change is also a good state player which is consistent with our expectation.

$Res\_\Delta CDS_{Regional}$ *- regional CDS residual:* It can be seen that regional SCDS residual has significant and positive effect in ten countries in the good state but the positive effect is significant only for four countries in the bad state, namely Malaysia, Poland, South Africa and Israel. After removing the effect of the global factors, regional SCDS residual is better able to capture the regional effect and influences the SCDS spread more heavily in the good state. This is consistent with our hypothesis that regional factor is expected to influence SCDS spread change more in the good state than in the bad state.

$R_{S\&P500}$ *- US Stock S&P 500 Return:* The negative effect of S&P 500 stock index return on emerging market countries' SCDS spread change is overwhelmingly significant in almost all countries in both good and bad states. But a closer examination at the coefficients reveals that S&P 500 stock index return contributes much stronger in the bad state than in the good state. The magnitude of the coefficient for the bad state is typically 2 to 5 times that for the good state. For a few countries, the difference between good and bad states is even larger. For example, for China, the coefficient is -0.281 in the good state however it is -2.016 in the bad state. The results show that the impact of US stock market return on China's SCDS spread change magnifies to ~seven folds in the bad state than in the good state. The findings are consistent with our expectation that global factors are more important in determining emerging market's SCDS spread change in the bad state.

ΔVIX - *VIX percentage change:* VIX is a measure of the implied volatility of S&P 500 index options. It represents the market's expectation of US stock return volatility over the next 30 day period and is often referred to as the "fear index". We expect VIX to also play a strong role in affecting emerging market's SCDS spread change. But surprisingly, the effect is much weaker than that of S&P 500 return. From Table (7), we see that ΔVIX is only significant with the expected positive effect for three countries in the good state (Colombia, Korea, and Malaysia). It is significant in the bad state for only two countries (Israel and Korea) in the expected direction. This suggests that SCDS spread change is only weakly sensitive to VIX movement contrary to its sensitivity to stock index return.

$\Delta TYield$ - *US T Bill yield:* In general, the effect of US T-Bill yield is also weak. This variable is significant for five countries (Brazil, China, Korea, Russia and Venezuela) in the good state, while in the bad state it is significant for Israel and Russia but not in the expected direction.

[Insert Table 7 about here]

The above findings show that global influence magnifies itself mainly through the US stock index return. Especially, the effect is exacerbated in the bad state. This is consistent with loss aversion and flight-to-quality-assets behavior of investors when the SCDS market becomes volatile. The findings in this section are consistent with our hypothesis. The SCDS spread change of emerging market countries is more subject to the changes of local, fundamental, and regional variables when the market is in the good regime; while in the bad regime, the global effect as represented by the US stock index return, is dominant in determining the SCDS spread change. The other global variables such as the change in the VIX index and the change in the US T-Bill yield have limited influence on SCDS spread change regardless of the state of the market.

VII. Cross Sectional Analysis

From the empirical analysis in the previous section we see that all the explanatory variables have an impact on the SCDS spread changes where local and regional variables show more influence in the good state and global variables have more influence in the bad state. We also witness a significant difference among the countries in terms of the extent of which these explanatory variables are associated with a country's SCDS spread change. What are the determinants of these cross-sectional differences? The answer to this research question will be useful for emerging market investors in formulating sovereign credit risk management strategy that is specific to the characteristics of each emerging market country. First of all, we expect the more open an economy and the more it is integrated to the global economy, the stronger will be the influence of regional and global factors on its SCDS spread change. Second, there is likely to be a size effect, the smaller the economy, the more vulnerable it is to the regional and global shocks. Thus, both regional and global factors may play a more important role in affecting smaller country's SCDS spread changes. Finally, there may be a regional effect. For example, due to their geographical and/or cultural characteristics, Asian countries may behave differently from European countries in terms of the determinants of their sovereign credit risks.

In conducting our cross-sectional analysis, we classify our countries into different subgroups independently based on four country-specific indicators representing openness/global integration (Kaopen Index of Chinn and Ito (2007); trade-to-GDP ratio; foreign direct investment (FDI) to GDP ratio), and size of economy (as proxied by GDP). We then examine and compare the sensitivities of SCDS spread change to the representative explanatory variables across the subgroups. Table 8 summarizes the average values of four market and economic indicators of the 11 countries during period of 2001 to 2012. From Table 8, we observe significant cross-section variations of country characteristics as captured by these indicators. For example, the trade-to-GDP ratio of Malaysia is almost eight times that of Brazil; whereas the FDI ratio of Israel is again almost eight times that of Korea.

[Insert Table 8 about here]

To examine how these country-specific factors may be related to the influence of different variables on SCDS, we divide the countries into two subgroups for the four indicators. The first subgroup of each indicator consists of six countries with lower values of the indicator and the second subgroup consists of the remaining five countries with higher values of the indicator. Table 9 shows the sub-grouping of countries for each indicator.

[Insert Table 9 about here]

As outlined in the previous sections, Eq. (12) is our most comprehensive regime switching model that incorporates all local, regional, and global factors. Based on regression results for Eq. (12) as shown in Table 7, we select the four most significant explanatory variables to conduct the cross-sectional analysis. The four variables are $\_R_{local}$, $\Delta Rating$, $Res\_\Delta CDS_{Regional}$, and $R_{S\&P}$. Table 10 shows the average of the coefficients of these four variables (obtained from running our regime-switching model of Eq. (12)) of the countries within each subgroup. The columns labelled by S1 (S2) consist of results for the good (bad) state. For example, the average coefficient of $\mathrm{Res\_R_{local}}$ for the "closed" group for "Kaopen" in the good state (S1) is denoted as -1.364**. The "closed" group for "Kaopen" has six countries namely China, South Africa, Turkey, Venezuela, Colombia, and Malaysia, and their coefficients of $\mathrm{Res\_R_{local}}$ in the good state (S1) are respectively, -4.452*, -0.629***, -1.054***, -1.057***, -0.809***, and -0.186* as shown in Table 7. The average in value therefore equals to -1.364 and the average in statistical significance is at 5% level (i.e. **). Below is a summary of the main findings from examining the average variations of the average coefficients of these four variables across subgroups of each indicator.

[Insert Table 10 about here]

$Res\_\Delta CDS_{Regional}$: This factor, in general, has larger impact on "open" countries than "closed" countries for the "openness" indicator subgroups. This is especially true in the bad state (S2). This is consistent with the expectation that the "open" countries are more integrated with the regional economies with the contagion effect being more salient in the bad state. Comparing the two "size" indicator subgroups, $Res\_\Delta CDS_{Regional}$ has larger impact on small countries both in good and bad states. This is expected because, the smaller the economy, the easier it could be influenced by the surrounding economies. Especially in a global crisis, smaller countries with less diversified economies would be more affected because economic links are more important for such countries than larger countries. Larger countries are expected to be less affected by the surrounding economies than by its own local factors. Besides, larger countries tend to have more diverse economic composition and thus less susceptible to industry-specific shocks that propagates across borders.

$\Delta Rating$: Rating change has stronger impact in the good state than in the bad state for all indicator subgroups. This is consistent with our expectation that fundamental factors as captured by rating plays a stronger role in the good state, whereas its effect is weakened in the bad state as other financial factors dominate. The influence of rating is also more significant for "closed" than for "open" countries, suggesting fundamental factors are more influential in dictating the sovereign risk of "closed" countries.

Res_R_{local} *and* $R_{S\&P}$: For "open" countries, in the bad state, their SCDS spreads are more affected by $R_{S\&P}$; whereas in the good state, they are more affected by Res_R_{local}. This asymmetry reflects the market sentimental effect of flight-to-quality that only manifests itself in the bad state. For "closed" countries, their SCDS spreads are more affected by Res_R_{local} in the bad state, while $R_{S\&P}$ plays a stronger role in the good state. Finally, we find that $R_{S\&P}$ has the strongest influence for small countries in the bad state. This could be attributed to the fact that economic links are more important for smaller countries than larger countries with diverse economies. The strong effect of $R_{S\&P}$ in the good state suggests that the S&P 500 return captures fundamental global improvement that even benefits "closed" economies.

VIII. Conclusion

The weekly change of emerging market sovereign CDS spreads is affected by many market and economic variables. This paper examines the effect of a broad range of such variables including local financial, fundamental, and global financial. The objective of the paper is to find the varying behavior of these variables on emerging market sovereign CDS in a two-state Markov regime switching environment.

We find that local, regional and fundamental variables such as local stock index return, exchange rate change, regional SCDS spread and credit rating change of the country influence the SCDS change more when the market is in a good state. Whereas global variables, such as US stock index return, have in general stronger influence in a bad state. Especially, when the regime is in a bad state, the single factor of US stock market return dominates other factors and its significance is much larger in the bad state than it is in the good state. This is consistent with the risk aversion and flight-to-quality assets behavior of investors when global market becomes volatile.

We also conduct cross sectional analysis to examine the behavior of the same explanatory variable on countries of different macroeconomic characters and reveal valuable findings. First, we find that more "open" countries are more integrated with the regional economies with the contagion effect being more salient in the bad state. Second, smaller countries with less diversified economies would be more affected a global crisis because economic links are more important for such countries than larger countries. Third, the influence of rating is more significant for "closed" than for "open" countries indicating that fundamental factors are more influential in dictating the sovereign risk of "closed" countries. Finally, we find that the market sentimental effect of flight-to-quality magnifies in the bad state and that $R_{S\&P}$ has the strongest influence for small countries in the bad state which could be attributed to the fact that economic links are more important for smaller countries than larger countries with diverse economies.

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Appendix 1 Tables

Table 1 - Descriptive Statistics of the Level of SCDS Spread

	Brazil	China	Colombia	Israel	Korea	Malaysia	Poland	Russia	South Africa	Turkey	Venezuela
Mean	465.49	60.02	311.86	99.17	90.45	86.52	85.69	244.74	143.24	375.30	860.52
Median	169.83	51.50	179.77	98.75	78.22	81.75	51.67	179.53	140.10	252.16	819.18
Max	3717.13	277.31	1373.22	272.86	708.64	505.40	415.00	1063.64	654.96	1348.33	3218.44
Min	61.14	9.35	67.61	16.92	14.39	11.96	8.17	37.95	24.87	116.78	119.89
St. Dev.	632.45	44.60	251.18	59.35	77.04	58.80	79.96	204.59	85.60	282.63	550.40
Skewness	2.86	1.76	1.61	0.36	2.87	1.53	1.30	1.56	1.68	1.48	1.05
Kurtosis	8.79	3.81	2.81	-0.86	12.16	5.30	1.11	1.76	5.27	1.18	1.85

This table summarizes the descriptive statistics of the level of weekly SCDS spreads (in basis points) of the 11 countries being studied spanning the time period from May 2001 to end of 2012.

Table 2 - Descriptive Statistics of SCDS Spread Change

	Brazil	China	Colombia	Israel	Korea	Malaysia	Poland	Russia	South Africa	Turkey	Venezuela
Mean	-2.24	-0.09	-1.35	-0.19	-0.15	-0.22	0.06	-2.06	-0.38	-2.04	-1.76
Median	-1.95	-0.13	-1.02	-0.07	-0.43	-0.39	-0.13	-0.99	-0.50	-2.71	-3.30
Max	153.97	17.06	76.62	23.57	43.44	25.13	43.33	64.78	32.23	80.47	192.44
Min	-130.59	-18.15	-69.58	-22.63	-32.55	-23.31	-36.15	-72.15	-36.85	-81.60	-173.98
St. Dev.	41.99	5.67	23.73	7.39	11.45	8.44	11.25	21.96	11.27	28.99	64.24
Skewness	0.53	-0.08	0.34	0.13	0.69	0.29	0.63	-0.29	-0.19	0.16	0.28
Kurtosis	4.97	3.21	3.09	3.41	4.89	2.45	6.28	3.30	2.71	1.67	2.15

This table summarizes the descriptive statistics of the weekly SCDS spread change (in basis points) of the 11 countries being studied. The spread change data was winsorized at 2% and 98% window.

Table 3 – Explanatory Variables

Variable	Expected Sign	Description	Data Source
$\boldsymbol{R_{local}}$	-	The country's local stock index return	Bloomberg
$\Delta\boldsymbol{FX}$	+	Weekly exchange rate percentage change (per USD)	Bloomberg
$\Delta\boldsymbol{CDS_{Regional}}$	+	Average regional CDS spread excluding the subject country	Bloomberg
$\Delta\boldsymbol{Rating}$	-	Sovereign Rating change (positive change means credit improvement)	S&P
$\boldsymbol{Res\_R_{local}}$	-	Residual of $\boldsymbol{R_{local}}$ regressed on global variables	Bloomberg
$\boldsymbol{Res\_}\Delta\boldsymbol{FX}$	+	Residual of $\Delta\boldsymbol{FX}$ regressed on global variables	Bloomberg
$\boldsymbol{Res\_}\Delta\boldsymbol{CDS_{Regional}}$	+	Residual of $\Delta\boldsymbol{CDS_{Regional}}$ regressed on global variables	Bloomberg
$\boldsymbol{R_{S\&P}}$	-	US Stock SP500 weekly return	Yahoo Finance
$\Delta\boldsymbol{VIX}$	+	Weekly VIX percentage change	Yahoo Finance
$\Delta\boldsymbol{TYield}$	-	US T-Bill yield weekly difference	Federal Reserve

This table provides description of the explanatory variables, expected sign of each variable in the model, and the data source of the variables.

Table 4 – OLS result of local and regional variables

	intercept		R_{local}		ΔFX		$\Delta Rating$		$\Delta CDS_{Regional}$		
Country	$b0$	*p*	$b1$	*p*	$b2$	*p*	$b3$	*p*	$b4$	*p*	$\overline{R^2}$
Brazil	-1.67	0.19	-1.91	0.00	5.50	0.00	-13.70	0.28	0.19	0.00	0.45
China	-0.03	0.86	-0.35	0.00	-0.59	0.56	-0.36	0.87	0.13	0.00	0.41
Colombia	-0.60	0.42	-0.94	0.00	2.37	0.00	-2.11	0.87	0.18	0.00	0.41
Israel	-0.17	0.49	-0.22	0.02	0.24	0.29	3.26	0.45	0.18	0.00	0.32
Korea	0.04	0.90	-0.38	0.00	2.45	0.00	-2.19	0.64	0.32	0.00	0.51
Malaysia	0.05	0.84	-0.88	0.00	2.50	0.00	-4.98	0.24	0.25	0.00	0.50
Poland	0.27	0.44	-0.52	0.00	1.43	0.00	-0.30	0.97	0.11	0.00	0.40
Russia	-1.54	0.01	-1.21	0.00	0.53	0.38	4.51	0.38	0.45	0.00	0.52
South Africa	-0.23	0.50	-0.94	0.00	1.29	0.00	-5.40	0.37	0.39	0.00	0.52
Turkey	-1.62	0.05	-1.25	0.00	4.24	0.00	-37.18	0.00	0.41	0.00	0.50
Venezuela	0.26	0.92	-2.76	0.00	0.75	0.16	-2.54	0.51	0.39	0.00	0.11

This table presents the OLS regression result of the weekly SCDS change of the 11 emerging market countries on local and regional variables. Left column of each variable reports the estimated coefficient, and right column reports the *p-value* of t-test.

Regression

$$\Delta CDS = b0 + b1(R_{local}) + b2(\Delta FX) + b3(\Delta Rating) + b4\left(\Delta CDS_{Regional}\right) + \varepsilon$$

Table 5 – OLS result of all variables

	intercept		Res_R_{local}		$Res\_\Delta FX$		$\Delta Rating$		$Res\_\Delta CDS_{Regional}$		$R_{S\&P}$		ΔVIX		$\Delta TYield$		
Country	*b*	*p*	*b1*	*p*	*b2*	*p*	*b3*	*p*	*b4*	*p*	*b5*	*p*	*b6*	*p*	*b7*	*pl*	$\overline{R^2}$
Brazil	-2.39	0.07	-3.11	0.00	6.03	0.00	-10.73	0.42	0.04	0.43	-4.50	0.00	0.21	0.15	-29.43	0.01	0.42
China	-0.12	0.50	-0.37	0.00	-0.30	0.78	0.48	0.84	0.05	0.00	-0.85	0.00	0.04	0.05	-4.15	0.01	0.36
Colombia	-1.40	0.08	-0.79	0.00	2.70	0.00	-4.65	0.74	0.12	0.00	-3.81	0.00	0.06	0.46	-18.10	0.02	0.31
Israel	-0.17	0.51	-0.04	0.68	0.62	0.01	4.00	0.39	0.09	0.00	-1.14	0.00	-0.02	0.48	-2.50	0.31	0.23
Korea	-0.19	0.59	-0.50	0.00	3.52	0.00	-1.65	0.74	0.06	0.00	-1.71	0.00	0.06	0.11	-8.24	0.01	0.45
Malaysia	-0.28	0.29	-0.98	0.00	3.72	0.00	-2.77	0.55	0.06	0.00	-1.14	0.00	0.04	0.13	-10.77	0.00	0.41
Poland	0.07	0.85	-0.63	0.00	1.75	0.00	-0.64	0.94	0.10	0.00	-1.77	0.00	0.04	0.34	-2.25	0.50	0.37
Russia	-2.25	0.00	-1.84	0.00	-0.08	0.90	5.91	0.28	0.25	0.00	-3.27	0.00	0.14	0.06	-18.64	0.00	0.45
South Africa	-0.39	0.28	-0.84	0.00	1.41	0.00	-3.26	0.60	0.12	0.00	-1.85	0.00	0.06	0.11	-3.25	0.32	0.41
Turkey	-1.94	0.02	-1.48	0.00	5.45	0.00	-36.30	0.00	0.30	0.00	-3.70	0.00	0.21	0.02	-13.18	0.09	0.48
Venezuela	-2.18	0.36	-2.76	0.00	0.76	0.15	-1.54	0.68	0.33	0.00	-6.22	0.00	0.44	0.10	-45.40	0.04	0.17

This table presents the OLS regression result of the weekly SCDS change of the 11 emerging market countries on all variables including local, regional and global variables.

Left column of each variable reports the estimated coefficient, and right column reports the *p-value* of t-test.

Regression: $\Delta CDS = b0 + b1(Res\_R_{local}) + b2(Res\_\Delta FX) + b3(\Delta Rating) + b4\left(Res\_\Delta CDS_{Regional}\right) + b5(R_{S\&P}) + b6(\Delta VIX) + \ b7(\Delta TYield) + \varepsilon$

Table 6 - Regime Switching Regression Summary – Model Specifications (a)

	$intercept$	R_{local}	ΔFX	$\Delta Rating$	$\Delta CDS_{Regional}$
Country	β_0	β_1	β_2	β_3	β_4
Brazil	-0.222	-1.023***	0.827**	-11.170*	0.114***
	3.741	-1.403**	10.724***	-24.400	0.140***
China	0.124*	-0.015	0.366	-8.602	0.713***
	6.911	-1.425	0.654	5.446	0.104***
Colombia	-0.433	-0.804***	1.097***	-2.832	0.191***
	2.067	-1.878**	6.743***	2.492	0.206***
Israel	-0.184***	4.390*	0.176***	15.496	0.151***
	0.823*	-0.352**	-0.288	1.451	0.353***
Korea	-8.611	4.276	0.333***	4.973***	1.104***
	0.144	0.231	-2.378	25.795	1.676***
Malaysia	0.241***	-0.117***	9.244	-25.140	0.943***
	-0.285	-6.037	2.074**	-7.935***	0.589***
Poland	-5.518***	-4.139***	6.499***	-0.785***	1.557***
	0.108***	3.197***	1.159***	3.197***	0.583***
Russia	0.484	-0.597***	-0.863*	-1.991	0.713***
	1.949	-2.241***	0.751	-17.560	0.632***
South Africa	0.221	-0.337***	0.285**	-26.220***	0.350***
	-1.974	-1.173***	-0.263	25.655	1.832***
Turkey	-0.303	-0.881***	2.816***	-27.830***	0.699***
	2.871	2.757*	12.517***	21.942	0.798***
Venezuela	2.702***	-0.895***	0.848	-4.209***	0.939***
	-5.347	0.233	0.283	4.407	0.285***

This table summarizes the Markov regime switching regression results of specification in Eq. (11):

$$y_{s_t} = \beta_{0,s_t} + \beta_{1,s_t} \cdot R_{local} + \beta_{2,s_t} \cdot \Delta FX + \beta_{3,s_t} \cdot \Delta Rating + \beta_{4,s_t} \cdot \Delta CDS_{Regional} + \varepsilon_{s_t}$$

First row of each country reports the estimated coefficients for the good Markov state, and second row reports those of the bad state. Significance of the regression coefficients at the one-percent level is denoted by ***, significance at the 5-percent level is denoted by **, and significance at the 10-percent level is denoted by *. Significance is based on t-statistics.

Table 7 - Regime Switching Regression Summary – Model Specifications (b)

	$intercept$	Res_R_{local}	$Res\_\Delta FX$	$\Delta Rating$	$Res\_\Delta CDS_{Regional}$	$R_{S\&P500}$	ΔVIX	$\Delta TYield$
Country	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7
Brazil	-1.249***	-0.727***	1.831***	4.928	1.830	-3.659***	9.038	-10.121***
	-30.230***	-0.339	11.684***	80.565	-0.599	-7.194***	-1.394**	-27.261
China	-0.425***	-4.452*	-0.849	-3.004	1.851***	-0.281***	-3.719***	-3.607***
	0.146	-0.825***	-1.612	-5.086	-2.971*	-2.016***	-5.887	2.612
Colombia	-1.479	-0.809***	1.636***	-9.779*	8.008***	-2.505***	0.138***	-4.788
	1.966	0.194	2.634	-24.57	0.128	-3.774***	-4.181	10.758
Israel	-0.201**	0.119***	0.350***	-2.416***	4.047***	-0.315***	-0.008	-1.491
	0.550***	5.197	0.710**	5.217	0.101***	-1.180***	8.821**	5.632***
Korea	-0.103	-0.499***	1.264***	-13.801***	2.5884**	-0.583***	4.928**	-8.623***
	-0.122	1.096*	6.489***	11.219	1.303	-2.071***	0.589***	44.304
Malaysia	-0.328**	-0.186*	1.358**	-12.320	4.525*	-0.242	3.545*	-0.471
	0.765*	-0.485**	4.432***	5.237	4.559***	-1.961***	-0.114**	-3.576
Poland	-0.124**	-5.265**	0.142***	-6.770*	1.244***	-0.129***	9.006	2.443
	3.139	-0.612*	1.974***	0.167	7.933**	-3.787***	-0.265***	1.535
Russia	0.198***	-1.205***	1.958***	-3.312***	0.419***	-3.890***	-5.852***	-11.701***
	6.435***	1.279***	-4.397***	-8.370***	-0.757***	4.162***	-0.113***	34.018***
South Africa	-0.118	-0.629***	1.186***	-2.156	0.169***	-1.826***	-8.533	-0.806
	-3.322	-4.190	-0.618	-0.305	0.454*	-7.107*	-0.695	-2.407
Turkey	-0.609	-1.054***	5.317***	-54.330***	0.569***	-5.202***	6.530	-2.242
	-5.299	-7.917***	-3.203	-116.201	0.487	21.228***	9.172	19.485
Venezuela	0.188	-1.057***	1.595**	-1.214	0.981***	-5.199***	3.802	-24.240*
	0.943	-7.450**	-1.023	2.805	0.110	-16.270***	-1.288	17.403

This table summarizes the Markov regime switching regression results of specification in Eq. (12):

$$\Delta SCDS_{s_t} = \beta_{0,s_t} + \beta_{1,s_t} \cdot Res\_R_{local} + \beta_{2,s_t} \cdot Res\_\Delta FX + \beta_{3,s_t} \cdot \Delta Rating + \beta_{4,s_t} \cdot Res\_\Delta CDS_{Regional} + \beta_{5,s_t} \cdot R_{S\&P500} + \beta_{6,s_t} \cdot \Delta VIX + \beta_{7,s_t} \cdot \Delta TYield + \varepsilon_{s_t}$$

First row of each country reports the estimated coefficients for the good state, and second row reports those of the bad state. Significance of the regression coefficients at the one-percent level is denoted by ***, significance at the 5-percent level is denoted by **, and significance at the 10-percent level is denoted by *. Significance is based on t-statistics.

Table 8 – Average Values of Indicators for Each Country

Country	kaopen index	Import + Export (% of GDP)	FDI, net inflows (% of GDP)	GDP (MM)
Brazil	0.03	20.56	2.71	1,320,903.88
China	-1.17	67.82	3.67	2,753,506.67
Colombia	-0.29	29.20	3.56	200,148.08
Israel	2.13	55.35	3.83	175,681.59
Korea	0.13	74.00	0.49	862,100.87
Malaysia	-0.19	162.42	3.01	183,676.38
Poland	-0.05	64.96	3.46	364,760.02
Russia	-0.13	45.62	2.69	1,085,489.40
South Africa	-1.17	41.90	1.82	261,131.15
Turkey	-0.72	47.65	1.81	535,179.14
Venezuela	-0.62	25.75	1.05	202,169.33

This table summarizes average values of four market and economic indicators of the 11 countries being studied during the period of 2001 to 2012. Kaopen index is based on Chinn and Ito (2007).

Table 9 – Sub-grouping of Countries

	kaopen	Import + Export (% of GDP)	FDI, net inflows (% of GDP)	GDP size
subgroup of lower indicator value	China	Brazil	Korea	Israel
	South Africa	Venezuela	Venezuela	Malaysia
	Turkey	Colombia	Turkey	Colombia
	Venezuela	South Africa	South Africa	Venezuela
	Colombia	Russia	Russia	South Africa
	Malaysia	Turkey	Brazil	Poland
subgroup of higher indicator value	*Russia*	*Israel*	*Malaysia*	*Turkey*
	Poland	Poland	Poland	Korea
	Brazil	China	Colombia	Russia
	Korea	Korea	China	Brazil
	Israel	Malaysia	Israel	China

This table shows the sub-grouping of countries for each indicator. We divide the countries into two subgroups for the four indicators. The first subgroup consists of six countries with lower value of the indicator and the second subgroup consists of the remaining five countries with higher value of the respective indicator.

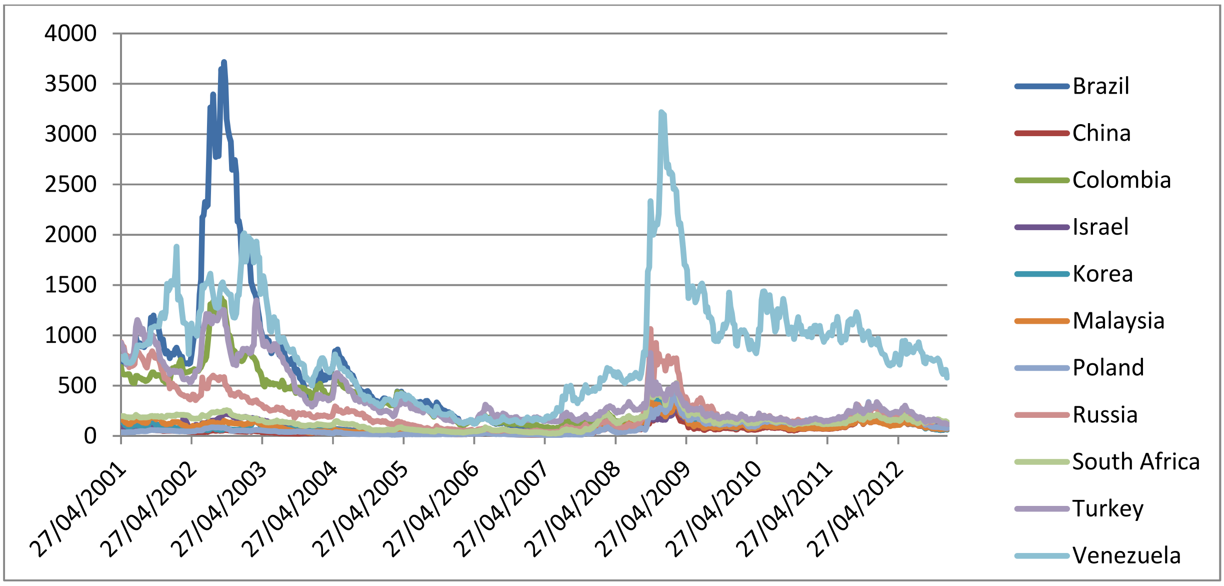
Table 10 – Cross Sectional Analysis of Selected Explanatory Variables

			Res_R_{local}		$\Delta Rating$		$Res\_\Delta CDS_{Regional}$		$R_{S\&P}$	
	Indicator	Subgroup	S1	S2	S1	S2	S1	S2	S1	S2
Openness/ Global Integration	kaopen	Closed	-1.364**	-3.445*	-13.802	-23.029	2.683**	0.461	-2.542**	-1.65**
		Open	-1.515**	1.324	-4.274*	17.760	2.026*	1.596*	-1.715**	-2.014**
	Import + Export (% of GDP)	Closed	-0.913**	-3.070*	-10.977*	-11.021	1.996**	-0.030	-3.713**	-1.492**
		Open	-2.056*	0.874*	-7.663*	3.351	2.851**	2.184*	-0.31*	-2.203**
	FDI, net inflows (% of GDP)	Closed	-0.861**	-2.920*	-11.648*	-5.055	1.092**	0.166	-3.393**	-1.208**
		Open	-2.118*	0.693*	-6.858*	-3.809	3.935**	1.949*	-0.694*	-2.543**
Size	GDP size	Small	-1.304**	-1.224*	-5.776*	-1.910	3.162**	2.214*	-1.702**	-5.679**
		Big	-1.587**	-1.341*	-13.904*	-7.583	1.451*	-0.507	-2.723**	2.821**

This table shows the average of the coefficients of the selected four explanatory variables (obtained from running our regime-switching model of Eq. (12)) of the countries within each subgroup. The columns labelled by S1 (S2) consist of results for the good (bad) state.

Appendix 2 Figures

Figure 1 – Time Series Plot of SCDS Spread from 2001 to 2012



This figure shows the time-series plots of the SCDS spreads from 2001 to 2012, SCDS spreads (vertical axis) are in basis points.

Chapter 5 Conclusion

This thesis studies the market sentiment effect on Asian country ETF price formation due to non-synchronized trading of the ETf and the underlying market, the profitability of LETF trading strategies as dictated by the compounding effect, and the regime switching behavior of sovereign CDS spreads determined by the local, regional and global factors.

The overreaction of Asian country ETFs to US market returns utilizing the non-synchronized trading condition of the Asian country ETFs and their underlying assets. The condition provides a unique setting that allows us to isolate the influence of market sentiment from that due to changes in a security's intrinsic value. Using a dynamic contrarian trading strategy, we quantify market sentiment by showing that material and significant abnormal returns can be generated out of the price reversal effect of the Asian country ETFs. By relating the abnormal returns with US market sentiment, we not only find that abnormal returns are positively associated with overall US market sentiment but also reveal that these abnormal returns respond asymmetrically to bullish sentiment and bearish sentiment. This study has a few important contributions. First, we examine the role played by market sentiment on price efficiency and contribute to the general understanding of how market sentiment affects the price formation process of financial securities. Our findings suggest that market sentiment makes the market for Asian country ETFs less efficient. Second, we demonstrate the economic significance of the market sentiment effect on the pricing efficiency of Asian country ETFs by devising a relatively straightforward mechanical trading strategy that exploits the systematic bias in market prices caused by market sentiment effect. The findings can also help to improve the market efficiency of such securities as market participants exploit the abnormal returns illustrated in this study.

LETF trading strategies need to not only consider the expected directional changes of the underlying benchmark but also to address the positive and negative compounding effect that could be realized during the investment horizon. In this paper, we investigate the market conditions that will tip the balance between the market trending effect and the volatility drag in governing the performance of LETFs. The market conditions that promote a stronger former effect than the latter will result in a positive compounding effect, thus enhancing the profitability of a long LETF position at the expense of a short one. On the other hand, those market conditions that promote a dominating latter effect will result in a negative compounding effect, which benefits the short LETF position as opposed to the long position. To address our research questions, we conduct a series of simulation exercises by gauging the sensitivity of the LETF returns on key parameters of the return generating process of the underlying benchmark as represented by the GJR model. We examine different LETF performance measures and study the risk-return trade-offs of LETF investment. Our findings contribute to the literature by pinpointing the underlying drivers of the compounding effects and facilitate the decision-making process of LETF investors by establishing the link between the performance of LETFs and different characteristics of the return dynamics of the underlying benchmark.

Emerging market sovereign CDS spreads is affected by many market and economic variables. We examine the effect of a broad range of such variables including local financial, fundamental, and global financial. The objective of the paper is to find the varying behavior of these variables on emerging market sovereign CDS in a two-state Markov regime switching environment. We find that local, regional and fundamental variables such as local stock index return, exchange rate change, regional SCDS spread and credit rating change of the country influence the SCDS change more when the market is in a good state. Whereas global variables, such as US stock index return, have in general stronger influence in a bad state. Especially, when the regime is in a bad state, the single factor of US stock market return dominates other factors and its significance is much larger in the bad state than it is in the good state. This is consistent with the risk aversion and flight-to-quality assets behavior of investors when global market becomes volatile. We also conduct cross sectional analysis to examine the behavior of the same explanatory variable on countries of different macroeconomic characters and reveal valuable findings such as more "open" countries are more integrated with the regional economies with the contagion effect being more salient in the bad state and smaller countries with less diversified economies would be more affected a global crisis because economic links are more important for such countries than larger countries.