FINANCIAL CRISIS, RISK PERCEPTION AND THE IMPLIED VOLATILITY TRANSMISSION: A CROSS-REGION STUDY*

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This study uses the newly released Hang Seng Volatility Index (VHSI) data set to explore differences of the risk perception between the US and Hong Kong (HK) financial markets as well as the direct sentiment spillover effects across the regions. Results show no fear or exuberance in HK market while significant fear in the USA when the market closes losses two days in a row. Cross-market evidence indicates the existence of fear in the HK market is completely imported from the USA. Direct implied volatility flows one way from USA to HK at first but shows reversal after the financial crisis.

1 INTRODUCTION

Thanks to the development of the Hong Kong financial market† after the 1998 Asian financial turmoil, a barometer of investors’ general sentiment has been badly in need. By the end of February 2011, the Hang Seng Indexes Co. Ltd. (HSIL) announces this index, the ‘Chinese version of the VIX’, which is designed to track the expected volatility implied by the Hang Seng Index (Bloomberg ticker: HSI) option traded in HK market, namely the HSI Volatility Index (Bloomberg ticker: VHSI). The release of this new explicit index of the implied volatility ever since creates the exact counterpart of the tradable Chicago Board Option Exchange volatility index (CBOE VIX) which is already widely deemed as a key indicator in the US financial market. Although the VHSI has great potential to perform as a precise forecast of future volatility in one of the most important Asian market, there is currently not a study that looks into it. This study analyze unique properties within the VHSI as opposed to its US counterpart. Most importantly, we examine the cross-region transmission (contagion) in terms of the implied volatility.

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1In the following texts, HK is used as an abbreviation of Hong Kong.
It is nowadays a shared view among practitioners that only the downside risk poses meaningful disturbance, while the upside is no more than some neglectable noise. Techniquely, mainstream financial academia uses the outright historical variance, namely the realized volatility, as a convenience metrics of risk. Although the statistical variance provides a sense of possible losses an investor might sustain, it also accounts for the potential profit a trader might earn. It is empirically true, and it follows intuition that only the downward pressure disturbs investors and potentially triggers widespread fear especially if it falls largely and consistently. Thus, risk as defined in the research literature seems to be misaligned to risk as perceived in financial markets.

It is even more important to learn how investors perceive risk. Pioneer behavioral finance literature as in Kahneman and Tversky (1979) posits a phenomenon known as the ‘loss aversion’, in which losses loom larger than gains. Loss aversion could translate into a greater responsiveness of downside price pressure on rising risk relative to the responsiveness of upside price pressure on fading risk. Following this line, a school of scholars start to recalibrate models which allows asymmetries to discriminate upside volatility apart from the downside one, for instance, Low (2004) uses simple partitional ordinary least squares (OLS) regressions and finds that prior gains appear to have some mitigating effects on the fear of loss relative to prior losses which lead to the ‘house money’ effect. Behavioral finance theory suggests that overcoming this bias may help investors profit more over the long term.

Although Low’s finding indicates investors being driven by irrational illusions, the ‘house money’ effect is problematic even in its nature: hypothetically, investors should possibly regard falls as low-cost opportunities to step in and therefore speculate on consecutive drops, while on the contrary, it is also logical that given consecutive run-ups, they may show concern on the perceived more likely falls in the near future. As a result, the ‘house money’ assumption is violated when risk perception behaves otherwise, especially when the market fluctuates wildly as investors perceive risk of a sudden fall following consecutive gains, but exuberance from market drops due to the belief of a looming rise.

It is, however, also possible that such a developed and mature financial market as the US market distinguishes itself from others. Therefore, the US evidence as in Low (2004) might not be universally true. It may depend on ‘local’ interpretations of information from across the globe. A study by Chui et al. (2010) indicates that culture has a surprising effect on stock return patterns, which is consistent with the idea that markets dominated by investors from particular cultures interpret information differently. Therefore markets in various cultures are subject to distinct biases. Specifically, individuals in less individualistic cultures (like China) act less like the

2The ‘house money’ effect predicts investors will be more likely to purchase risky stocks after closing out a profitable trade.
overconfident/self-attribution biased investors as in Daniel et al. (1998), and thus tend not to make investment choices that generate momentum profits.

Using the newly released VHSI data sets, we manage to recalibrate and generalize the risk–return relationship against various previous (cross-)market conditions, and also examine the implied volatility flow across regions with consideration of possible impact from the 2008 financial crisis. The incremental contribution of this article is fourfold. First, we reveal the risk (perception)–return relationship differs across markets (HK vs. USA). Second, we document that cross-market condition introduces fear to the HK market. Third, one-way direct implied volatility transmission from USA to HK is persistent with reversals only after the financial crisis. Finally, because the Low’s (2004) study ignores crisis that might revise investors’ perception of risk, therefore an artificially smoothened relationship may be subject to misspecifications. In this paper, we make the model to distinguish the post-crisis period based on the hypothesis that a systemic market meltdown may influence trading strategies through the channel of risk perception. Minor contributions of this paper include the possible significant impact from broader market conditions towards perception of risk, and that leverage hypothesis is a plausible but weak non-behavioral explanation (similar results are also confirmed by Hibbert et al., 2008).

The following content of this article is organized as follows: Section 2 reviews the implied volatility as a source of risk; Section 3 describes the data sets; Section 4 investigates the partitional regressions to reveal asymmetry and nonlinearity in the risk–return relationship; Section 5 examines the cross-market evidence and the direct implied volatility flow; Section 6 provides evidence conditional on broader market conditions; Section 7 tests the non-behavioral leverage hypothesis; Section 8 concludes the paper.

2 Implied Volatility as a Source of Risk

Lots of studies on volatility dynamics rely on volatility estimated from historical data (namely the realized volatility), but statistical estimation may produce sampling and model specification errors, and its lack of prediction power also limits the connection to real tradings. Therefore, the implied volatility derived from derivative price has caught heavy attention in recent years. The implied volatility of an option contract is the volatility implied by the price of that option based on an option pricing model. Since it is not a statistical estimate, implied volatility does not induce estimation errors. And because the underlying option-pricing model3 is robust and widely used in the market, so model misspecification is trivial.

Financial literature finds conclusive relationship between the implied volatility and the realized volatility. Such literature dates back to the work by

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Feinstein (1989), which demonstrates that implied volatility from ATM and near expiration option provides the closest approximation to the average volatility over the life of the option. Poon and Granger (2003) review 93 papers on the forecast performance of various volatility models (historical, stochastic and the implied volatility). The key conclusion is that the performance of option implied standard deviation surpasses that of the alternative methods. More recent articles about the US equity markets suggest that, in general, implied volatility is a superior predictor for future volatility. Three representative articles are as follows: Giot (2005) evaluates the information content of VIX and CBOE NASDAQ 100 implied volatility (VXN) as the predictors of the realized volatility and finds meaningful forecast results; Corrado and Miller (2005) report that the CBOE implied volatility indices (VIX, CBOE S&P100 implied volatility (VXO) and VXN) act as an outperforming estimators of the future realized volatility compared with the forecast from the historical volatility; Jiang and Tian (2005) investigate the characteristics of the model-free approximation. They discover that the model-free implied variance, represented by the new VIX, subsumes all information contained in the Black–Scholes implied volatility.

As for the performance of the implied volatility outside the USA, empirical studies are mainly consistent with those dealing with the implied volatility in the USA. For example, Bluhm and Yu (2001), Skiadopoulos (2004), Nishina et al. (2006) and Areal (2008) all find implied volatility indices from different markets to be superior estimators of the future standard deviation.

The widely used approach to look into the implied volatility index is to calculate its percentage change, which can be regarded as sentiment change due to changing anticipation on daily basis. It is also termed as the innovation of risk perception. The adoption of such a proxy as a risk perception is justified thanks to a pioneer work by Chen (2003) which demonstrates that changes in the expectation of future market volatility are a source of risk. This argument is further verified by Ang et al. (2006). They find that sensitivities to changes in implied market volatility have a cross-sectional effect on firm-level returns. Numerous empirical papers have already used the innovation of CBOE VIX as a measurement of risk. For example, Dennis et al. (2006) and Christensen and Nielsen (2007) examines the risk–return correlation, Low (2004) also uses directly the percentage change of VIX to study the sentiment shift towards different market conditions in the US market.

In the present paper, we follow the calculation by dividing daily innovations against previous VHSI and VIX levels (namely the percentage change of the VHSI (or VIX). We then denote them by %VHSI and %VIX, respectively. In such a way, they comfortably perform as proxies of daily change in the anticipated market volatility.

4Abbreviation for the at-the-money option.

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3 Data Set

The market-traded implied volatility, namely the CBOE VIX is introduced in 1993. It ever since quickly became the benchmark for stock market volatility and is widely followed and cited in hundreds of articles in the Wall Street Journal, Barron’s and other leading financial publications. The VIX measures the market expectations of near term volatility conveyed by stock index option prices. Since the VIX signifies financial turmoil, it is commonly referred to as the ‘investor fear gauge’ by the market practitioners and academics. The VIX is based on weighted averages of Black–Scholes put and call implied volatility which predicts the volatility of the following 30 calendar days (22 trading days) for S&P500 index (CBOE ticker: SPX). Since the depth of the index option market ensures that transacted prices are representative of the aggregate consensus, the VIX index is often regarded as market participants’ best guess of the volatility associated with the SPX index. The CBOE VIX data are from Bloomberg with a ticker VIX.

Thanks to a boom in the HK stock market after the 1998 Asian financial turmoil, a barometer of investors’ general sentiment in the market is badly in need. By the end of February 2011, HSIL announced a ‘Chinese version of the VIX’ designed to track the expected volatility in the HK stock market, the HSI Volatility Index (Bloomberg ticker: VHSI).

The VHSI measures the implied volatility of options on the HK stock indices in the most liquid derivatives markets. Its period is between 2 January 2001 and 15 November 2010, where 2 January 2001 is the farthest the VHSI can be back-dated. The VHSI is based on forming portfolios of at-the-money options traded in the HK market and measures the market’s expectation of next 30 calendar days (22 trading days) forward HSI index volatility implicit in the prices of near-term and next-term Hang Seng Index Options which are now traded in the Hong Kong Exchanges and Clearing Limited’s derivatives market. The calculation is the same as that of the CBOE VIX.

Plots of the VHSI and VIX levels are shown in Fig. 1 with dotted lines, and their daily percentage change are drawn on the right-hand side of Fig. 2.

The daily closing levels of the Hang Seng Index and S&P500 index are also from Bloomberg (ticker: HSI and SPX), and we further compute their daily returns. Plots of the HSI and SPX indices are shown as solid lines in Fig. 1 and daily returns are plotted on the left in Fig. 2.

6 The exact calculation of CBOE VIX can be found in the VIX white paper at: http://www.cboe.com/micro/vix/vixwhite.pdf.
We can easily see a dramatic downturn of prices in both markets from the late summer of 2007 onward. We can also establish the fact that a much more volatile period has come and has persisted until now as shown by the implied volatility in both markets.

In addition, we employ the AlphaShares New China All Cap Index (Bloomberg ticker: ACNAC) as our proxy of the broader market conditions for HK market. The ACNAC Index measures the performance of all Chinese companies in terms of capitalization that are currently listed in HK and New York.
York stock exchanges. It currently excludes China A-Share or B-Share stocks listed in mainland China. The time span for all series is between 3 January 2005 and 15 November 2010.

4 Semi-dimensional Risk from 2001 to 2010

Empirical evidence suggests that only sizable and persistent losses may disturb the financial market and would potentially cause extreme sentiment (fear). In contrast, gains should not bear too much negative information. Hence, the aggregate risk perception of option traders is hypothetically semi-dimensional in nature, which implies losses should be far more painful than volatile profits. Low (2004) justifies this hypothesis by examining the correlation of SPX returns and innovations of the VIX. However, the data set (1986–98) covers mostly an over-heated period\(^7\) while avoids the financial market meltdown since 2000 which leads to an eight-month macroeconomic recession in USA. Therefore, it is not theoretically uncommon that people exhibit irrational exuberance during that period and also possible that people may behave otherwise after the booming period.

In this section, we use the approach by Low (2004) to study the financial market of HK as well as the USA. We also distinguish our study by allowing a known structural break led by the 2007 Credit Crunch, which is highly contagious and causes economic recession worldwide. The crisis becomes apparent in the last week of July 2007 when German bank regulators and government officials organized a $5 billion bail out of IKB Deutsche Industriebank AG (IKB), a small bank in Germany. We therefore treat the beginning of August 2007 as a date of the onset of the subprime crisis, although the realities in terms of rising mortgage delinquencies commenced earlier. This pinpoint has been widely agreed by academia.\(^8\) Because the aftershocks still persist and the fear of a double-dip still pervades the world market, we therefore do not explicitly place an end to the global instability until November of 2010 (when our data set ends). We hence divide our total sample into a pre-crisis subset and the one that is after the date.

The following study in this section is facilitated by dividing the market into groups in terms of magnitudes of gains/losses. We then further refine the partitions to include an extreme tail on each downside and upside partition. The four-partition contemporaneous asymmetric regressions are as follows:

\[
(D_d): \% y_t^+ = \alpha^+ + \eta^+ r_t^+
\]

\[
(D_u): \% y_t^- = \alpha^- + \eta^- r_t^-
\]

\(^7\)Especially the 1990s, namely the ‘dot.com bubble’ in terms of stock market value.

\(^8\)Phillips and Yu (2010) provides great details on a recursive regression to analyze the bubble characteristics of various financial time series during the subprime crisis. Timeline of the 2007–9 crisis is also dated.
\[ (U_y): \% y_t^+ = \alpha^+ + \eta^+ r_t^+ \]  
\[ (U_x): \% y_t^{x+} = \alpha^{x+} + \eta^{x+} r_t^{x+} \]  
(3)  
(4)  

Here, \( \% y_t^\pm \) and \( r_t^\pm \) in days of the extreme five percentiles of losses; \( \% y_t^\pm \) and \( r_t^\pm \) in days of the remaining 95 percentiles; \( \% y_t^{x\pm} \) and \( r_t^{x\pm} \) in days of the extreme 5 percentiles of gains; \( \% y_t^{x\pm} \) and \( r_t^{x\pm} \) in days of the remaining 95 percentiles of positive \( r_t \). Tables 1 and 2 report empirical results from equation (1) to (4) in both markets.

Although Table 1 (HK case) shows a downside-concave feature \((\eta^- < \eta^-_x < 0)\), this is not justified by the auxiliary tests which tracks significant difference between the slopes implied by extreme values and the ordinary ones (see the statistical significance of the coefficient \( \eta_d \) in Table 1). Therefore auxiliary tests targeting the HK financial market fail to reject the null hypothesis that there does not exist any variations of slopes \((H_0 : \eta_d = 0)\) in each subset. This suggests that visible slope changes as shown in Table 1 are driven by outliers.

However, in the US market (Table 2), partitional regression model \( D_x \) captures a dramatic fear (accelerating VIX as loss increases) in the downside \((\eta^- < \eta^-_x < 0)\), and this convexity is also statistically significant by adopting auxiliary tests (difference in slopes is \(-2.86\) with \( t \) statistic \(-2.57\)). In addition, slope differences \((\eta_d) \) in the upside is also significant which shows concave feature \((\eta^+ < \eta^{x+} < 0)\) and robust after the financial crisis starts. However, Table 2 suggests the fear does not persist by observing a significantly positive \( \eta_d \) (which implies a concavity \( \eta^- < \eta^-_x < 0 \) in Model \( D'_x \) and \( D'_0 \)) after the onset of the crisis. Results in Table 2 indicate that fear in the US market appears to revert to a significant (sentimental) easing towards big losses rather than even deeper jitters during the crisis.

For both markets, empirical evidence does not point to any exuberance (decelerating VIX as gain increases) at all whose existence is revealed by Low (2004) using the US data set well before the year 2001. It is true that the sentiment pervading the market has encountered dramatic shift after the dot.com crisis (after 2001) and yet another shift after the recent financial crisis starts.

It is nonetheless surprising that we find no evidence of fear in the HK market (nor exuberance). It could be the case that contemporaneous information does not provide such evidence. Another plausible explanation could be that the fear is imported from other markets and the HK market its own does not reflect it well. We discuss this topic later in this paper.

5 Previous Market Conditions

It is possible that fear/exuberance is fueled by consecutive losses/gains. Low (2004) argues that previous market conditions can influence option traders’ perception of risk, so that a run of desirable events might boost exuberance.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Downside return</th>
<th>Upside return</th>
<th>Auxiliary regressions and tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( D_x )</td>
<td>( D'_x )</td>
<td>( D_o )</td>
</tr>
<tr>
<td>( r^x )</td>
<td>-1.87*</td>
<td>-1.93*</td>
<td>(-2.17)</td>
</tr>
<tr>
<td>( r^- )</td>
<td>-2.36*</td>
<td>-2.54*</td>
<td>(-11.90)</td>
</tr>
<tr>
<td>( r^+ )</td>
<td>-1.87*</td>
<td>-1.93*</td>
<td>(-2.17)</td>
</tr>
<tr>
<td>( r^y )</td>
<td>-0.05</td>
<td>-0.97*</td>
<td>(-0.05)</td>
</tr>
<tr>
<td>( \alpha_o )</td>
<td>-0.61</td>
<td>-1.16</td>
<td>(-0.28)</td>
</tr>
<tr>
<td>( \alpha_d )</td>
<td>3.07</td>
<td>2.39</td>
<td>(-0.27)</td>
</tr>
<tr>
<td>( \eta_o )</td>
<td>-2.36</td>
<td>-2.54</td>
<td>(-11.90)</td>
</tr>
<tr>
<td>( \eta_d )</td>
<td>0.49</td>
<td>1.09</td>
<td>(-1.76)</td>
</tr>
<tr>
<td>Const.</td>
<td>2.46</td>
<td>1.09</td>
<td>(-1.76)</td>
</tr>
</tbody>
</table>

**Notes:** The \( t \) statistics are in parentheses. The table reports regressions of \( \% \text{VHSI} \) on four partitions of the HSI returns \( (r_t) \). Regression equations are:

- \( D_x : \% \text{VHSI}^x = \alpha + \eta r^x \)
- \( D'_x : \% \text{VHSI}^x = \alpha + \eta r^x \)
- \( D_o : \% \text{VHSI}^o = \alpha + \eta r^o \)
- \( D'_o : \% \text{VHSI}^o = \alpha + \eta r^o \)
- \( U_o : \% \text{VHSI}^o = \alpha + \eta r^o \)
- \( U'_o : \% \text{VHSI}^o = \alpha + \eta r^o \)
- \( U_s : \% \text{VHSI}^s = \alpha + \eta r^s \)
- \( U'_s : \% \text{VHSI}^s = \alpha + \eta r^s \)

Here, \( \% \text{VHSI}^x \) and \( \% \text{VHSI}^o \) are \( \% \text{VHSI} \); \( \% \text{VHSI}^s \) denotes the extreme cases and the after-crisis subsample as well. The prime mark denotes the data set used is the one after August 2007.
**Table 2**

**Four-partition Regressions/Tests of Innovations of Risk Perception on Equity Returns: US Data Set**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Downside return</th>
<th>Upside return</th>
<th>Auxiliary regressions and tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$D_x$</td>
<td>$D'_x$</td>
<td>$D_o$</td>
</tr>
<tr>
<td>$r^-$</td>
<td>-7.61*</td>
<td>-2.46*</td>
<td>-3.19</td>
</tr>
<tr>
<td>$r^-$</td>
<td></td>
<td></td>
<td>-4.75*</td>
</tr>
<tr>
<td>$r^+$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$r^{+*}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_o$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_o$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_d$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\eta_o$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\eta_d$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Const.</td>
<td>-11.05</td>
<td>1.27</td>
<td>0.03</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.22</td>
<td>0.23</td>
<td>0.31</td>
</tr>
</tbody>
</table>

*Notes:* The $t$ statistics are in parentheses. The table reports regressions of $\%VIX_t$ on four partitions of the SPX returns ($r$). Regression equations are: $D_x: \%VIX_t = \alpha x + \eta^x r^-; D'_x: \%VIX_t = \alpha x + \eta^x r^-; U_o: \%VIX_t = \alpha o + \eta o r^-; U'_o: \%VIX_t = \alpha o + \eta o r^-$. Here, $\%VIX_t$ and $r^-$ are $\%VIX_t$ and $r$ in days of the remaining 95 percentiles of negative $r$; $\%VIX_t$ and $r^-$ are $\%VIX_t$ and $r$ in days of the extreme 5 percentiles of negative $r$; $\%VIX_t$ and $r^-$ are $\%VIX_t$ and $r$ in days of the extreme 5 percentiles of positive $r$; $\%VIX_t$ and $r^-$ are $\%VIX_t$ and $r$ in days of the remaining 95 percentiles of positive $r$. $\alpha_x$ denotes the constants in the regressing equations $D_x$ and $U_o$ in this table; $\alpha_o$ denotes the differences of the constants in the two partitions; $\eta_x$ denotes the slopes in the regressing equations $D_x$ and $U_o$; $\eta_o$ denotes the differences of the slopes in the two partitions. The same rules apply to the extreme cases and the after-crisis subsample as well. The prime mark denotes the data set used is the one after August 2007.
while consecutive undesirable events might do the opposite. Low (2004) manages to prove this pair of phenomena using simple asymmetric regressions. However, it is also sensible that continuous losses may signal looming rebound while consecutive gains worry traders as corrections may take place soon. Furthermore, these perceptions may differ upon a dramatic market meltdown which leads to recessions.

Hence, in this subsection, we re-examine Low’s (2004) argument using updated data sets across different financial markets and repeat the asymmetric regressions. In addition, we further allow the onset of the financial crisis to distinguish any difference in the risk perception that may take place according to the chronology of business cycles. Specifically, we try to examine the existence of a possible market sentiment shift from a booming to the recent recession. We therefore construct models by conditioning the original samples on the signs of one-day lagged returns $r_{t-1}$. We then test the effect of previous market conditions on the perception of risk by comparing the slopes of matching partitions across the two conditions (negative or positive).

5.1 Partitions Based on Realized Loss and Profit

Models $A$, $B$, $C$ and $D$ in Tables 3 and 4 report results from the conditional two-partition asymmetric regressions using HK and US data sets before the financial crisis, respectively.

1. For the HK market (Table 3): The slope in the contemporaneous downside return partition is $-2.51$ following a market loss ($r_{t-1} < 0$) and $-2.65$ after a previous gain ($r_{t-1} > 0$). The difference in between, $\eta_d = 0.14$ is with a $t$ statistic of 0.46 and therefore not statistically significant (see the auxiliary test of $\eta_d$). Such insignificant difference in the slopes implies the risk–return relation in the downside partition remains unchanged regardless of the previous market conditions. Similarly, the difference of slopes in the upside return partition is $\eta_u = 0.06$, and is not significant either (with $t$ statistic 0.23). Therefore HK investors treat signs of previous HK market returns indifferently before the recent financial crisis.

2. For the US market (Table 4): conclusion is quite similar. US investors do not treat signs of previous returns seriously ($\eta_d$ and $\eta_u$ in this case are not significant as well) as shown.

Therefore, evidence between 2001 and 2007 in both markets shows dramatic difference from that in Low’s (2004) paper. Low supports the hypothesis that fear increases more rapidly in case prices fall two days in a row, while empirical evidence does not exhibit such pattern in the booming period (ends in July 2007) after the dot.com bubble bursts which caused US recession until November 2001.

Moreover, if we extend the time horizon from the financial crisis until now, we find zero slope for consecutive market gains ($\eta^{++} = 0.19 (1.02)$) in HK.
and can hence be defined accordingly. To test the significance of the slope differences given previous gains/losses in the two partitions, we stack the vectors as

$$
\begin{align*}
\begin{bmatrix}
\gamma_t^- \\
\gamma_t^+
\end{bmatrix} &= \begin{bmatrix}
\alpha^- + \eta_t^-
\end{bmatrix} + \begin{bmatrix}
\alpha^+ + \eta_t^+
\end{bmatrix} + \eta_t \\
\begin{bmatrix}
\gamma_t'^- \\
\gamma_t'^+
\end{bmatrix} &= \begin{bmatrix}
\alpha'^- + \eta_t'^-
\end{bmatrix} + \begin{bmatrix}
\alpha'^+ + \eta_t'^+
\end{bmatrix} + \eta_t'
\end{align*}
$$

where, $\alpha^-$ and $\alpha'^-$ denote the constants of model $C$ and $D$; $\alpha_A$ denotes the differences of constants ($\alpha^- - \alpha^-$) in model $A$ and $C$; $\alpha_B$ denotes the differences of constants ($\alpha'^- - \alpha'^-$) in model $B$ and $D$; $\eta_t^-$ denotes the slope of model $C$; $\eta_t'^-$ denotes the slope in model $D$. $\eta_{tA}$ is the differences of the slopes ($\eta_t^+ - \eta_t^-$) in model $A$ and $C$; $\eta_{tB}$ denotes the differences of the slopes ($\eta_t'^+ - \eta_t'^-$) in model $A$ and $C$. 

### Table 3

**Two-partition Conditional Asymmetric Regressions (without Quadratic Terms): HK Data Set**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Previous loss</th>
<th>Previous gain</th>
<th>Auxiliary regressions/tests of slope differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$A$</td>
<td>$A'$</td>
<td>$B$</td>
</tr>
<tr>
<td>$r^+$</td>
<td>-2.51*</td>
<td>-2.45*</td>
<td>-0.64*</td>
</tr>
<tr>
<td></td>
<td>(-5.51)</td>
<td>(-6.05)</td>
<td></td>
</tr>
<tr>
<td>$r^-$</td>
<td>-0.58*</td>
<td>-0.59*</td>
<td>-2.65*</td>
</tr>
<tr>
<td></td>
<td>(-2.91)</td>
<td>(-3.74)</td>
<td></td>
</tr>
<tr>
<td>$\alpha^+$</td>
<td>-0.71</td>
<td>-0.66</td>
<td>-0.99*</td>
</tr>
<tr>
<td></td>
<td>(-3.09)</td>
<td>(-1.30)</td>
<td></td>
</tr>
<tr>
<td>$\alpha_t$</td>
<td>-0.00</td>
<td>-0.46</td>
<td>-0.30</td>
</tr>
<tr>
<td>$\alpha_t'$</td>
<td>-0.71</td>
<td>-0.66</td>
<td>-0.99*</td>
</tr>
<tr>
<td>$\eta_t^-$</td>
<td>-2.65</td>
<td>-2.15</td>
<td>-3.22*</td>
</tr>
<tr>
<td></td>
<td>(-12.90)</td>
<td>(-8.88)</td>
<td></td>
</tr>
<tr>
<td>$\eta_t'^-$</td>
<td>0.14</td>
<td>-0.30</td>
<td>-0.30</td>
</tr>
<tr>
<td>$\eta_{tA}$</td>
<td>0.28</td>
<td>0.39</td>
<td>0.04</td>
</tr>
</tbody>
</table>

**Notes:** Prime superscript denotes the data set used is after August 2007. The two-partition asymmetric regressions of %VHSI on contemporaneous $r_t$ (HSI return) are: $A$: %VHSI$^-_t = \alpha^- + \eta^- _t$; $B$: %VHSI$^+_t = \alpha^+ + \eta^+_t$; $C$: %VHSI$^-_t = \alpha^- + \eta^- _t$; $D$: %VHSI$^+_t = \alpha^+ + \eta^+_t$, where %VHSI$^-_t$ and %VHSI$^+_t$ are %VHSI and $r_t$ in days when $r_{t-1} < 0$ and $r_t < 0$; %VHSI$^-_t$ and %VHSI$^+_t$ are %VHSI and $r_t$ when $r_{t-1} < 0$ and $r_t > 0$; %VHSI$^-_t$, %VHSI$^+_t$, %VHSI$^-_t$ and %VHSI$^+_t$ can hence be defined accordingly. To test the significance of the slope differences given previous gains/losses in the two partitions. We stack the vectors as

$$\begin{bmatrix}
\gamma_t^- \\
\gamma_t^+
\end{bmatrix} = \begin{bmatrix}
\alpha^- + \eta_t^-
\end{bmatrix} + \begin{bmatrix}
\alpha^+ + \eta_t^+
\end{bmatrix} + \eta_t \\
\begin{bmatrix}
\gamma_t'^- \\
\gamma_t'^+
\end{bmatrix} = \begin{bmatrix}
\alpha'^- + \eta_t'^-
\end{bmatrix} + \begin{bmatrix}
\alpha'^+ + \eta_t'^+
\end{bmatrix} + \eta_t'
$$

and

$$R^2 = 0.24, 0.46, 0.02, 0.07, 0.32, 0.30, 0.02, 0.05, 0.28, 0.39, 0.04, 0.08$$
## Table 4
### Two-partition Conditional Symmetric Regressions (without Quadratic Terms): US Data Set

<table>
<thead>
<tr>
<th>Variable</th>
<th>Previous loss</th>
<th>Previous gain</th>
<th>Auxiliary regressions/tests of slope differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$A$</td>
<td>$A'$</td>
<td>$B$</td>
</tr>
<tr>
<td>$r^{++}$</td>
<td>-4.40*</td>
<td>-2.94*</td>
<td>-2.25*</td>
</tr>
<tr>
<td></td>
<td>(-13.30)</td>
<td>(-9.60)</td>
<td></td>
</tr>
<tr>
<td>$r^{--}$</td>
<td>-4.24*</td>
<td>-3.43*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-15.20)</td>
<td>(-15.70)</td>
<td></td>
</tr>
<tr>
<td>$r^{-+}$</td>
<td>-2.62*</td>
<td>-2.12*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-12.20)</td>
<td>(-13.60)</td>
<td></td>
</tr>
<tr>
<td>$r^{+ -}$</td>
<td>-1.04</td>
<td>-1.34</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(1.99)</td>
<td></td>
</tr>
<tr>
<td>$\alpha^{+}$</td>
<td>0.30</td>
<td>0.36</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.00)</td>
<td>(0.77)</td>
<td></td>
</tr>
<tr>
<td>$\alpha^{-}$</td>
<td>-0.15</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.32)</td>
<td>(1.31)</td>
<td></td>
</tr>
<tr>
<td>$\alpha_{d1}$</td>
<td>0.16</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.37)</td>
<td>(1.35)</td>
<td></td>
</tr>
<tr>
<td>$\eta^{+}$</td>
<td>-0.37</td>
<td>-0.84*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.18)</td>
<td>(-2.83)</td>
<td></td>
</tr>
<tr>
<td>$\eta^{-}$</td>
<td>-0.38</td>
<td>-0.34</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.19)</td>
<td>(-0.75)</td>
<td></td>
</tr>
<tr>
<td>$\eta_{d1}$</td>
<td>-0.25</td>
<td>-1.28</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-10.00)</td>
<td>(-5.00)</td>
<td></td>
</tr>
<tr>
<td>$\eta_{d2}$</td>
<td>-4.24</td>
<td>-3.43</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-14.00)</td>
<td>(-14.10)</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.35</td>
<td>0.38</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(1.99)</td>
<td>(6.21)</td>
</tr>
</tbody>
</table>

**Notes:** Prime superscript denotes the data set used is after August 2007. The two-partition asymmetric regressions of $%VIX_t$ on contemporaneous $r_t$ (SPX return) are: 

- **A**: $%VIX_t = \alpha^- + \eta^- \epsilon^-; 
- **B**: $%VIX_t = \alpha^- + \eta^- \epsilon^-; 
- **C**: $%VIX_t = \alpha^- + \eta^- \epsilon^-; 
- **D**: $%VIX_t = \alpha^- + \eta^- \epsilon^-; 

where $\alpha^-$ and $\alpha^+$ denote the constants of model $C$ and $D$; $\alpha_{d1}$ denotes the differences of constants ($\alpha^- - \alpha^-$) in model $A$ and $C$; $\alpha_{d2}$ denotes the differences of constants ($\alpha^- - \alpha^-$) in model $B$ and $D$; $\eta^-$ denotes the slope of model $C$; $\eta^+$ denotes the slope in model $D$. $\eta_{d1}$ is the differences of the slopes ($\eta^- - \eta^-$) in model $A$ and $C$; $\eta_{d2}$ denotes the differences of the slopes ($\eta^- - \eta^+$) in model $A$ and $C$. 

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(Model $D'$ of Table 3), which leads to a significant slope difference conditional on different signs of previous market returns (see the coefficient of $\eta_{d2} = -0.78$ with $t$ statistic $-3.19$). Evidence (Table 4) also justifies a similar significance for its US counterpart ($\eta_{d2} = -0.84$ ($-2.83$)) but no flat slope in the upside conditional on lagged gains.

To sum up, slope differences in the downside are all statistically insignificant in each market whatever the previous market condition is (also regardless of the financial crisis). But the sentiment towards previous gains/losses in the upside does shift: investors start to be far less exuberant if the market closed two gains in a row after August 2007. In other words, after the onset of the financial crisis, people tend to believe looming corrections are more likely following a rise but not otherwise, nor vice versa.

Results from our study are, therefore, in direct contrast to the conclusion by Low (2004), which shows accelerated concerns among investors in the USA when the market is down two days in a row. However, our evidence shows updated results using recent data sets: investors always treat past gains and losses equally in the downside. Specifically, two losses in a row does not significantly raise the risk perception (the $\%VIX$) any faster than a single contemporaneous loss. And this is true in both HK and the USA over the whole period that we consider. It can only be justified that consecutive gains lowers the risk perception a lot less after August 2007. It hence shows that after the recent financial crisis started, investors cared much more about consecutive gains than otherwise.

A column of graphs on the left of Fig. 3\(^9\) show the OLS-fitted lines generated from regressions in Table 3, while the leftmost column of Fig. 4 depicts their US counterparts. There apparently exist a dramatic change in slopes in the very bottom graph of Fig. 4: the dashed line shows a much flatter tendency in the upside, while in the downside, slope changes are not serious in either Fig. 3 or Fig. 4.

### 5.2 A Reclined S-curve?

The term 'reclined S-curve' is used by many recent publications to describe a concave feature in the upside while convexity in the downside. Intuitively, it implies a dramatic fear resides in losses yet exuberance in gains. Such features are of instant practical meanings yet hard to be justified in the presence of outliers. Nonetheless, as long as we want a complete picture of the behavior changes to both sides of returns we must put extreme values into consideration since they can be very informative, and this is also one of the arguments in Low (2004).

We hence model the partitional risk–return relationship conditional on previous market conditions (gain or loss) with an extra quadratic term

\(^9\)Figures 3 and 4 include six graphs each. The first rows of graphs are results of the merged data sets (2001–10) which are only for description purpose and not discussed in this paper.
respectively to capture non-linearities. These partitional models are reported in equations (5)–(8). Graphs of the fitted quadratic curves are summarized on the right-hand side of Figs 3 and 4. Both groups of figures are of the following order: the first graph uses the merged data set; the second uses the data set before the break; the one at the bottom uses the post-break data set (data set after August 2007).

The partitional models\textsuperscript{10} are

\begin{enumerate}
\item \%\(y_t^-\) denotes the innovation of risk perception \%\(VIX\), within the lagged downside-return \((r_{t-1})\) partition and being negative; \(r_t^-\) stands for a further market loss in this partition.
\item \%\(y_t^+\) denotes the innovation of risk perception \%\(VIX\), within the lagged downside-return \((r_{t-1})\) partition and being positive; \(r_t^+\) stands for a market gain in this partition.
\item \%\(y_t^-\) denotes the innovation of risk perception \%\(VIX\), within the lagged upside-return \((r_{t+1})\) partition and being negative; \(r_t^-\) stands for the market loss in this partition.
\item \%\(y_t^+\) denotes the innovation of risk perception \%\(VIX\), within the lagged upside-return \((r_{t+1})\) partition and being positive; \(r_t^+\) stands for a market gain in this partition.
\end{enumerate}

\textsuperscript{10}The partitional models\textsuperscript{10} are

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\[ (A): \%y_t^- = \alpha^- + \eta_1^- r_t^- + \eta_2^- (r_t^-)^2 \] (5)

\[ (B): \%y_t^+ = \alpha^+ + \eta_1^+ r_t^+ + \eta_2^+ (r_t^+)^2 \] (6)

\[ (C): \%y_t^{++} = \alpha^{++} + \eta_1^{++} r_t^{++} + \eta_2^{++} (r_t^{++})^2 \] (7)

\[ (D): \%y_t^{++} = \alpha^{++} + \eta_1^{++} r_t^{++} + \eta_2^{++} (r_t^{++})^2 \] (8)

denotes the innovation of risk perception \%VIX, within the lagged upside-return \((r_t^+)^2\) partition and being positive; \(r_t^{++}\) stands for a further market gain in this partition. Notation variations of \(\alpha, \eta_1, \eta_2\) stands for corresponding coefficients in each regression.
Empirical results are presented in Table 5. Corresponding graphs of these (quadratic) fittings are summarized on the right-hand side of Figs 3 and 4, where solid lines (broken lines) depict the fittings conditional on negative (positive) one-day lagged market return.

5.2.1 The HK Market. Based on previous market loss, HK market (Fig. 3, solid curves) consistently shows concave feature in the downside, the coefficients of the quadratic terms are \(-0.38\) and \(-0.10\), respectively. They are all significant under 5 per cent level (see Table 5, model \(A\) and \(A'\)). While the curves in the upside show convexity only before the crisis (model \(B\) and \(B'\)). However, the US market behaves quite differently under the same market condition, which exhibits convexity and then concavity before and after the break date, respectively. Specifically, the US market panel on the right of Table 5 shows coefficients of the quadratic terms are \(0.89\) and \(-0.43\), respectively, and they are statistically significant.

In addition, evidence from the HK market (Table 5) before August 2007 shows a significant worry if the HSI index closes gains two days in a row (convex feature, see the coefficient before \((r^+)^2\) in model \(D\), 0.40 and significant). While on the opposite it shows a dramatic tranquilization (negative coefficient, \(-0.38\), and statistically significant) if the HSI index drops in two consecutive days. After the crisis happens, the tranquilization in the downside persists but consecutive gains no longer put weights on HK market (\(R^2\) of model \(D'\) is close to zero in HK case).

To sum up, It is true that investors in HK market do not perceive too much excessive risk as the market loss continues, and that they are not over-confidence (exuberance) nor too pessimistic (fear) towards HK market conditions. Results as shown so far are of direct contrast to the one argued by Low (2004) which shows the existence of fear and exuberance due to consecutive market losses or gains. The ‘S-curve’ hypothesis is therefore empirically rejected in the HK market.

5.2.2 The US Market. Empirical results using the US data set based on the regressions (5)–(8) are shown graphically in Fig. 4 (on the right-hand side) and the estimations (tests) are listed in Table 5 (the US Market panel). Table 5 clearly lists that before the crisis, US investors show significant fear towards two consecutive market losses: the coefficient before \((r^-)^2\) in model \(A\) is equal to 0.89 with \(t\) statistic 2.33, which implies convexity. But this very coefficient reverts to a significant concave feature, \(-0.43\) with \(t\) statistic \(-4.13\), in model \(A'\), which exhibits somewhat tranquilization towards continuous losses after the break date. In other words, fear in the US financial market due to continuous market losses is somehow alleviated after the crisis starts. And the quadratic term in this case, \((r^+)^2\), becomes insignificant which indicates that the current US market most likely treats continuous gains indifferently.
### Table 5

**Two-partition Conditional Asymmetric Regressions (with Quadratic Terms)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>HK market</th>
<th>US market</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Previous loss</td>
<td>Previous gain</td>
</tr>
<tr>
<td></td>
<td>$A$</td>
<td>$A'$</td>
</tr>
<tr>
<td>$r^{++}$</td>
<td>-1.79*</td>
<td>0.22</td>
</tr>
<tr>
<td>$r^{-}$</td>
<td>-3.62*</td>
<td>-3.28*</td>
</tr>
<tr>
<td>$r^{-}$</td>
<td>-2.52*</td>
<td>-2.28*</td>
</tr>
<tr>
<td>$r^{+}$</td>
<td>0.26</td>
<td>-0.41</td>
</tr>
<tr>
<td>$(r^{-})^2$</td>
<td>0.03</td>
<td>-0.03</td>
</tr>
<tr>
<td>$(r^{+})^2$</td>
<td>-1.31*</td>
<td>-0.02</td>
</tr>
<tr>
<td>$(r^{+})^2$</td>
<td>0.40*</td>
<td>0.00</td>
</tr>
<tr>
<td>Const.</td>
<td>-1.17</td>
<td>-1.95</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.25</td>
<td>0.47</td>
</tr>
</tbody>
</table>

**Notes:** The $t$ statistics are in parentheses. $r_t^{--}$ stands for $r_t$ in days when $r_{t-1} < 0$ and $r_t < 0$; $r_t^{+-}$ stands for $r_t$ when $r_{t-1} < 0$ and $r_t > 0$. $r_t^{++}$ and $r_t^{-+}$ can hence be defined accordingly.
The convexity in the US market (see solid line in Fig. 4, before August 2007) in the downside return partition implies that loss aversion is alleviated in the presence of a previous gain and is enhanced in the presence of a previous loss. This finding is consistent with result derived by Low (2004). However, this study provides no support to the existence any exuberance in the upside as advocated by Low (2004) which uses the data set within the 1990s (well before the dot.com bubble bursts). It is therefore possible that the following crisis (the dot.com bubble starts to burst in 2000) puts permanent influence on investors’ risk perception towards consecutive gains: two gains in a row disturbs the market as well as two loss (see the convexity in model $D$ of Table 5). It is hence plausible that US investors are ever since inclined to speculate a third loss after two consecutive falls as well as correction after two consecutive gains. This is partly consistent with the ‘gambler’s fallacy’ effect by Tversky and Kahneman (1974).

6 Cross-market Evidence

Different from the focus in Low’s (2004) paper, this study puts weight on a relatively smaller financial market which tracks aggregate performance within Asia–Pacific area. However, given a convenient and advanced international trading platform, it is common for traders located in one country to trade in another. Therefore, hedging and speculative activities across different markets are standard strategies for professional traders. It is now also a common knowledge that volatility (especially consistent and dramatic volatility) can flow from one market to another due to the re-balancing of diversified portfolios. Previous research has documented a shared view on the topic that there exists some contagion from the US spot equity market to other countries. For example, Garefalakis et al. (2011) find evidence suggesting major stock markets, particularly the SPX, positively influence the HK stock market, which is a fact that is attributed to the integration and internationalization of stock markets. Inci et al. (2011) also confirms that there exists contagion from the US spot equity market to that of Germany, Britain, Japan and HK, but no reverse contagion to the USA.

However, past literature does not directly examine the impact from the US benchmark on the risk perception of Asia-Pacific financial market in terms of implied volatility, nor any academic paper to study the Asian version of implied volatility, namely the VHSI. In other words, whether or not the daily returns of the US market shock the risk perception in HK market is still an unsolved question. The difficulty is partly due to the lack of data which can measure the fear gauge. The answer to the cross-market contagion (or the implied volatility spillover) is important to both academics and practitioners because the volatility transmission from one market to another is critical for international portfolio management and portfolio diversification purposes.
We manage to accurately measure this using the VHSI as a forward-looking proxy. The newly released data of the VHSI makes this study possible only recently.

Following the line by Garefalakis et al. (2011) and Inci et al. (2011) it is possible that once the US market goes down, the HK market become volatile as well. Should global traders perceive any risk from downside returns in the USA, their investment strategies in HK would change immediately and thereby will be reflected in the market sentiment. As a result, the aggregate perception of fear or exuberance (extracted from the sentiment index) in HK market would behave differently. We hence look into the possible one-way shockwave from the USA to HK.

6.1 Cross-market Conditions

In order to examine the impact of the cross-market conditions, we use the SPX index as a benchmark of the US equity market. We then regress the percentage change of VHSI on the HSI returns conditional on different signs of SPX returns. Results of estimations and corresponding diagnostic tests are reported in Tables 6 and 7.

Table 6 shows that the linear relationship between the %VHSI and HSI returns stays negative and significant as before. It is however hard, as suggested by the auxiliary tests in Table 6, to find concrete evidence on the (contemporaneous) slope difference\(^\text{11}\) either for the downside or for the upside returns after the financial crisis starts.

Our simple linear models do reveal very mild statistical significance of slope difference (with coefficient 0.58 and only significant under 10 per cent significance level) in the downside before August 2007. Evidence shows that investors in HK market do not care about the previous US market conditions (losses or gains) whenever they happen before or after the crisis starts. Instead, they only feel frustrated on consecutive gains of the HK market alone (as shown in the test result of \(h_{d2}\) in Model II’ of Table 3), and this phenomenon happens only after the financial crisis starts.

We also fit a series of quadratic models to further investigate the fear/exuberance that the HK market may present conditional on previous gains/losses in the USA. Detailed regression results are reported in Table 7. Some important results in this table can be summarized as follows:

(a) Before the financial crisis: conditional on previous gains in the USA, the HK market exhibits significant fear in the downside (see Model C). The coefficient before the quadratic term \((r^{-})^2\) is 0.17 with \(t\) statistic 3.32. Cross-market evidence also indicates significant stress in the upside (see Model D) by observing the (significant) convex profile of the quadratic term \((r^{+})^2\).

\(^\text{11}\)Specifically, the statistical significance of the coefficients \(h_{d1} = (\eta^{-} - \eta^{-})\) and \(h_{d2} = (\eta^{+} - \eta^{+})\) before and after August 2007. (see Table 6)
Table 6
TWO-PARTITION ASYMMETRIC REgressions/Tests of HK DATA CONDITIONal ON US MARKET Performance

<table>
<thead>
<tr>
<th>Variable</th>
<th>Conditional SPX loss</th>
<th>Conditional SPX gain</th>
<th>Auxiliary regressions and tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>A'</td>
<td>B</td>
</tr>
<tr>
<td>r++</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>r-</td>
<td>-2.54</td>
<td></td>
<td>-2.31</td>
</tr>
<tr>
<td></td>
<td>(-12.50)</td>
<td></td>
<td>(-13.70)</td>
</tr>
<tr>
<td>r+</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>r-</td>
<td>-0.64</td>
<td></td>
<td>-0.37</td>
</tr>
<tr>
<td></td>
<td>(-2.11)</td>
<td></td>
<td>(-1.95)</td>
</tr>
<tr>
<td>α++</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>α-</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>αδ</td>
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<td>η++</td>
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</tr>
<tr>
<td>η-</td>
<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Const.</td>
<td>-0.64</td>
<td>-0.57</td>
<td>-0.69</td>
</tr>
<tr>
<td></td>
<td>(-2.46)</td>
<td>(-1.23)</td>
<td>(-2.37)</td>
</tr>
<tr>
<td>R²</td>
<td>0.46</td>
<td>0.45</td>
<td>0.32</td>
</tr>
</tbody>
</table>

**Notes:** The t statistics are in parentheses. Similar footnotes to Table 7, only to replace \( \delta_{ACNAC} \) with \( \delta_{SPX} \).
After the onset of the financial crisis: the downside fear is persistent, while the stress disappears entirely. It is also surprising that previous US losses do not translate into any fear or exuberance in HK market (by noticing the insignificant quadratic terms, \((r^-)^2\) and \((r^+)^2\)). On the contrary, HK investors seem to care much more about the previous US gains, which in effect ‘export’ fear to the downside while stress to the upside in HK. Our results also provide additional empirical evidence that the 2008 financial crisis does affect the aggregate sentiment spillovers (at least US towards HK market) by noticing the upside-return subsample conditional on positive US market returns is no longer considered stressful (nor show any tendency) after the crisis (from Model \(D\) to Model \(D'\) in Table 7).

If we compare these results with Table 5, we do see some interesting findings: first, because the HK market alone shows no evidence of fear or exuberance whatsoever, then it is true that the only scary thing in term of financial disturbance to the HK investors is the combined message of a HK market fall and a previous US rise. Second, although HK investors do not consider previous US losses as an acceleration of the perceived risk (nor the
alleviation of that), they do consistently put positive views on consecutive HK losses as some sign of looming market correction (see the concavity profile of Model A and A’ in Table 5 for HK market).

To sum up, the cross-market analysis reveals some interesting findings: fear is exotic for HK market and it is only fueled by previous US gain and current domestic loss together; foreign loss combined with the next-day HSI drop does not translate into fear (or even stress) at all. This result is in direct contradiction to the case of US market where two consecutive downside returns induce fear dramatically. It is true that a gain in the SPX index preceding a loss in the HSI generates deep fear in HK. Nevertheless, evidence from HK market, US market and the cross-market all agrees on the plausible conclusion that the crisis wipes out the concerns over consecutive gains, which disturb markets before the crisis.

6.2 Implied Volatility Transmission

Apart from the conditional asymmetric analysis, people also tend to ask the following question: when investors perceive risk in the USA, do they also perceive risk in HK market? The prerequisite of the answer is the availability of the implied volatility data sets for both markets. The released VHSI index also makes this study possible.

We adopt a simple vector autoregressive (VAR) framework to consider the possible implied volatility flow from one market to another. The VAR system consists of four endogenous variables, and allows one known break date. The one-period, four-dimensional VAR model is

\[
\begin{pmatrix}
    r_{t}^{\text{SPX}} \\
r_{t}^{\text{HSI}} \\
\%VIX_{t} \\
\%VHSI_{t}
\end{pmatrix} = A_{0} + A_{1}
\begin{pmatrix}
    r_{t-1}^{\text{SPX}} \\
r_{t-1}^{\text{HSI}} \\
\%VIX_{t-1} \\
\%VHSI_{t-1}
\end{pmatrix} + \ldots + A_{j}
\begin{pmatrix}
    r_{t-j}^{\text{SPX}} \\
r_{t-j}^{\text{HSI}} \\
\%VIX_{t-j} \\
\%VHSI_{t-j}
\end{pmatrix} + \xi_{t} \quad (9)
\]

in which \(A_{0}\) is a 4 \times 1 vector standing for the constant terms of each equation, and \(A_{j}\) stands for the \(j\)th coefficient matrix (4 \times 4) corresponding to the lagged independent vectors. The variables \(r_{t}^{\text{SPX}}\) and \(r_{t}^{\text{HSI}}\) represent index return in the US and HK, respectively, while the \(\%VIX\) and \(\%VHSI\), stand for the percentage changes of the implied volatilities in each market as defined. The optimal lag number of the model (9) is determined by Schwarz information criterion as in the pioneer work by Schwarz (1978). The Granger causality results of the VAR model\(^{12}\) are reported in Table 8.

Within the VAR system (9), Column A (results before crisis) of Table 8 clearly shows a significant Granger causality from the innovations of the VIX

\(^{12}\)As all variables in the VAR system (innovations of risk perceptions and returns) have been heavily documented about their stationarity (first-order differenced). Therefore, this study does not particularly report the augmented Dickey–Fuller unit root test for each variable. Test results as well as the estimation of the VAR models can be obtained from the author.
and the SPX returns towards the innovations of the VHSI (%VHSI) and HSI returns but not vice versa. Therefore, evidence in this section is partly consistent with Inci et al. (2011) which confirms the existence of contagion from the US equity market to that of HK, but no reverse contagion to the USA. This suggests that when investors perceive risk in the US market (volatile VIX), they transmit this sentiment to the HK market through the channel of %VIX—%VHSI as well as SPX return—%VHSI. Hence, within our simple VAR framework, traders may directly predict both the HSI returns and the %VHSI using lagged US counterparts.

Empirical evidence also shows that HK market becomes contagious after August 2007. Therefore, results from Inci et al. (2011) are not necessarily correct. Our study suggests that the HK implied volatility does matter just recently: when investors perceive risk in the Asia-Pacific, they also transmit this sentiment to the USA (as shown in EQ3 and EQ4 in Column B).

### 6.3 Broader Market Conditions

Low (2004) further shows that the US investors share an effect called ‘keep up with the Joneses’, which means traders behave as if they are benchmarking the performance of the S&P100 relative to the rest of the investment universe. When the S&P100 performs worse than the broader market, the option traders experience a sharper perception of risk. Conversely, when the S&P100 performs better than the broader market, their perception of risk is alleviated.
Using his methodology, we examine whether or not HK traders are influenced by a similar effect. We choose the AlphaShares New China All Cap Index (ACNAC) as the proxy for the broader market. The index comprises the comprehensive performance of large, mid- and small capitalization Chinese companies currently trading on the HK or New York stock exchanges and available to international investors. We form two subsamples by conditioning the original sample on the signs of the contemporaneous difference between ACNAC returns \( r_{\text{ACNAC}} \) and Hang Seng returns \( r_{\text{HSI}} \).

Table 9 reports the results. The slope in the downside return partition is \(-1.96\) for the \( r_{\text{ACNAC}} \geq r_{\text{HSI}} \) subsample and \(-2.60\) for the \( r_{\text{ACNAC}} < r_{\text{HSI}} \) subsample. The difference (0.65) is statistically significant (see Table 9, Model I coefficient \( \eta_{hl} \)). Unlike the case reported in Low’s paper (\( \eta^- < \eta^+ < 0 \)), Chinese traders behave inversely: investors’ risk perception is significantly alleviated when the broader market is outperforming the Hang Seng Index (\( \eta^- < \eta^- < 0 \)) and this matters only after the financial crisis.

The slope in the upside return partition is \(-0.46\) for the \( r_{\text{ACNAC}} \geq r_{\text{HSI}} \) subsample and \(-0.85\) for the \( r_{\text{ACNAC}} < r_{\text{HSI}} \) subsample. The difference of 0.39 is not statistically significant (see Table 9, Model II coefficient \( \eta_{ul} \)). And this is true regardless of the crisis. Therefore, different from what US traders behave, HK traders simply ignore the broader market conditions when Hang Seng is going up. This suggests when daily Hang Seng returns are positive, the broader market conditions will impose no impact on traders’ risk perception.

7 Leverage Hypothesis

It is also possible to examine the non-behavioral hypothesis that leverage explains the risk–return relation. To test the leverage effect, we sort constituent stocks in the Hang Seng Index independently by previous year-end financial leverage (TD/ME) and operating leverage (PPE/sales). Within each leverage category, the top 50 per cent form the high-leverage portfolio and the bottom 50 per cent form the low-leverage portfolio. We use the same methodology of HSI to calculate the returns of all portfolios. Because the weights HSI constituent shares hold do not vary so much, the base weights of the two portfolios are nearly the same. As a result, the returns of the low- and high-leverage portfolios within each leverage category sum to the returns of the HSI.

Empirical study in this paper suggest that high-leverage stocks do not have a more sensitive (steeper) risk–return relation relative to low-leverage stocks. Financial and operating leverages fail to support the leverage hypothesis in the downside partition. More generally, within each portfolio, the slope in the downside partition is more negative than the corresponding slope in the upside partition. Such within-portfolio differences in slopes further
### Table 9
**Two-partition Asymmetric Regressions/Tests Conditional on Broader Market Performance (ACNAC)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Conditional higher return</th>
<th>Conditional lower return</th>
<th>Auxiliary regressions and tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>A'</td>
<td>B</td>
</tr>
<tr>
<td>$r^{++}$</td>
<td>-3.95</td>
<td>-1.96</td>
<td>(-7.04)</td>
</tr>
<tr>
<td>$r^{--}$</td>
<td>-0.46</td>
<td>-0.25</td>
<td>(-1.11)</td>
</tr>
<tr>
<td>$\alpha^+$</td>
<td>-1.70</td>
<td>-1.10</td>
<td>(-7.04)</td>
</tr>
<tr>
<td>$\alpha^-$</td>
<td>-1.80</td>
<td>-1.32</td>
<td>(-3.05)</td>
</tr>
<tr>
<td>$\eta^{++}$</td>
<td>-0.86</td>
<td>-0.68</td>
<td>(-1.15)</td>
</tr>
<tr>
<td>$\eta^{--}$</td>
<td>-0.28</td>
<td>-0.26</td>
<td>0.31</td>
</tr>
<tr>
<td>Const.</td>
<td>-0.15</td>
<td>-0.15</td>
<td>-0.15</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.82</td>
<td>0.82</td>
<td>0.82</td>
</tr>
</tbody>
</table>

**Notes:** The $t$ statistics are in parentheses. These two-partition asymmetric regressions are %VHSI on contemporaneous $r_t$. The models are: $A$: $\%VHSI_t^- = \alpha^- + \eta^- r_t^-; B$: $\%VHSI_t^+ = \alpha^+ + \eta^+ r_t^+$; $C$: $\%VHSI_t^- = \alpha^+ + \eta^- r_t^-; D$: $\%VHSI_t^+ = \alpha^+ + \eta^+ r_t^+$. Here, $\%VHSI_t^-$ and $\%VHSI_t^+$ are $\%VHSI_t$ and $r_t$ in days when $r_t^{ACNAC} \geq \epsilon$, and $r_t < 0; \%VHSI_t^-, r_t^-, \%VHSI_t^+, r_t^+$ can hence be defined accordingly. To test the statistical significance of the slope differences conditional on different broader market conditions (gain or loss) in the two partitions, we stack the vectors as

\[
\begin{align*}
A: \quad \%VHSI_t^- &= \alpha^+ \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \alpha^- \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \eta^- \begin{bmatrix} r_t^- \\ \epsilon \end{bmatrix} + \eta^+ \begin{bmatrix} r_t^+ \\ \epsilon \end{bmatrix} + \eta_0 \begin{bmatrix} \epsilon \\ 0 \end{bmatrix} \\
B: \quad \%VHSI_t^+ &= \alpha^+ \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \alpha^- \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \eta^- \begin{bmatrix} r_t^- \\ \epsilon \end{bmatrix} + \eta^+ \begin{bmatrix} r_t^+ \\ \epsilon \end{bmatrix} + \eta_0 \begin{bmatrix} \epsilon \\ 0 \end{bmatrix} 
\end{align*}
\]

Here, $\alpha^-$ and $\alpha^+$ denote the constants of model $C$ and $D$; $\alpha_A$ denotes the difference of the constants in model $A$ and $C$; $(\alpha^- - \alpha^+)$; $\alpha_{D_2}$ denotes the difference of the constants in model $B$ and $D; (\alpha^+ - \alpha^-)$; $\eta^-$ and $\eta^+$ denote the slope of model $C$ and $D$; $\eta_A$ denotes the difference of the slopes in model $A$ and $C$; $(\eta^- - \eta^+)$; $\eta_{D_2}$ denotes the differences of the slopes of model $A$ and $C$ in model $(\eta^- - \eta^+)$. 

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support the proposition that downside returns exert greater influence than upside returns in the market’s overall perception of risk.\textsuperscript{13}

8 Conclusion

In this paper, we use partitional financial market data to explore potential differences of the risk perception behaviors and possible volatility transmission between the HK and the USA. The newly released Asian counterpart of the CBOE VIX, the VHSI delivers a forward-looking explicit gauge of the risk perception which makes this study possible.

Main results in this paper include the following. 1. We find significant fear in the US financial market if the market closes losses two days in a row, this result is consistent with the study by Low (2004) which argues consecutive negative market returns fuel the aggregate fear. 2. No evidence supports the existence of any exuberance in any market that we consider, which arguably exists when the market closes consecutive gains as in Low’s study. 3. We further prove that result 1 and 2 are not robust to the financial crisis. Specifically, the fear towards consecutive losses in the USA is not persistent after August 2007; instead, investors tend to anticipate correction after consecutive drops. Compared with the results by Low (2004), we hence conclude that after the bust of the dot.com bubble in 2000s, the US market becomes more conservative since there exists no evidence pointing to market exuberance at all (even after consecutive market gains), while stressless towards continuous losses after the recent financial crisis. 4. For the HK market, the contemporaneous market return explains the innovation of the implied volatility less than it does in the USA. 5. We find implied volatility transmits one-way from USA to UK, but reversal exists only after the onset of the financial crisis (after August 2007). The result is partly consistent with Inci et al. (2011) which confirms the existence of contagion from the US spot equity market to that of HK, but no reverse to the USA. Our study reveals that the Asia-Pacific stock performance does matter only recently.

Finally, the combined results of the cross-market analysis indicates that fear is exotic, and the HK market alone does not generate any of it. The fear only exists in the downside and is fueled by previous US gains. Previous US loss combined with the downside HK return does not translate into fear (or even minor stress) at all. This result is in direct contradiction to the case of the US market where two consecutive downside returns induce fear. It is empirically true that a HK market loss against the background of prosperity in the USA is even more scary than altogether losses.

We also find support to the broader market hypothesis but in a different way: compared with the US case, HK investors’ risk perception is significantly alleviated when the broader market outperforms the Hang Seng Index.

\textsuperscript{13}Detailed results are in the authors’ possession. Readers can obtain these through correspondence.
and this matters only after the financial crisis. However, HK investors simply ignore the broader market conditions when the Hang Seng index goes up. This suggests the broader market conditions impose no impact on investors’ risk perception when the HK market closes gains. The financial leverage condition only provides weak explanation to the risk–return relationship.

REFERENCES


