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Asymmetric effects of investor sentiment on industry stock returns: Panel data evidence

Mei-Ping Chen \textsuperscript{a}, Pei-Fen Chen \textsuperscript{b}, Chien-Chiang Lee \textsuperscript{c,⁎}

\textsuperscript{a} Department of Accounting Information, National Taichung University of Science and Technology, Taiwan
\textsuperscript{b} Department of International Business Studies, National Chi-Nan University, Taiwan
\textsuperscript{c} Department of Finance, National Sun Yat-sen University, Kaohsiung, Taiwan

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\textbf{ABSTRACT}

This article employs a state-of-the-art panel threshold model by allowing for regime intercepts, in order to shed new light on the asymmetric/nonlinear effects of local and global sentiments on expected industry stock returns among 11 Asian countries during the period from 1996 to 2010. Empirical evidence demonstrates that once the regime intercept is included, the asymmetric effects of global sentiment on oil & gas, financials, and health care industry returns become less under optimism, as compared with under pessimism. More critically, the positive (negative) impact of global sentiment above (under) the threshold turns significant, indicating that global optimism leads industry returns to be overvalued, while pessimism leads them to be undervalued. For local market sentiment, our results support that higher local sentiment enhances the returns of basic materials, telecommunications, and utilities industries. The empirical results confirm that the nexus of industry returns and investor sentiments is subject to change between different sentimental intervals.

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1. Introduction

A growing body of research argues that investor sentiment affects stock returns. For instance, the literature addresses initial public offerings (Bradley et al., 2009), liquidity commonality (Choe and Yang, 2010), soccer game results (Palomino et al., 2009), stock split announcement (Kim and Byun, 2010), aviation events (Kaplanski and Levy, 2010), and others that largely sway investor sentiment, and then investor sentiment affects stock returns. Extant studies also confirm that investor sentiment predicts stock
returns (Baker and Wurgler, 2006, 2007; Brown and Cliff, 2005), e.g., when investors are optimistic about the prospects for a specific stock, the stock will sell at a premium, and vice versa.

Most of the related literature of investor sentiment explores how sentiment affects the valuation of stocks in firm-level or aggregated data. Few studies investigated how the firm valuation is affected by investor sentiments in both global and local markets perspectives. Assuming that investors buy more stocks when they are optimistic than when pessimistic, we propose that different degrees of investor sentiment affect the valuation of specific industries. Additionally, investors may fully account for the relevant conditions within local and global equity markets when implementing industry-based investment strategies. Existing research studies are scant in the area of a nonlinear/asymmetric relationship between investor sentiment and expected industry returns for Asian economies with industry-level analysis, and this study looks to fill this gap.

There have been some studies that deal with the relationship between stock returns and investor sentiments based on the panel data context (Schmeling, 2009). In a panel framework, the number of available observations greatly increases when examining the relationship of return-sentiments, and as a result, more informative data can be obtained. Therefore, panel-based investigations can help benefit statistical power and overcome the low power problem. Our quantitative local sentiment indices follow 11 Asian stock markets’ degree of liquidity. We employ a global sentiment index through the liquidity of the world equity index. Based on the predictive regression model, we estimate panel fixed-effect regressions, in which the sentiment effect relies on industry-based data across 11 markets. For individual investors, knowledge of the relative sensitivities of industry stock returns to global and local sentiments would be of great benefit for risk management purposes.

As De Groot and Verschoor (2002) who explored the behavior of Asian stock markets, we focus on Asian economies because these markets are much less liquid than the developed market. Consequently, it is restricted to implement arbitrage trading strategies. Therefore, the returns for Asian markets are subject to investor sentiment more than developed markets. Previous studies related to stock returns and investor sentiment have focused on single country, such as Simpson and Ramcharnder (Australia, 2002); Chelley-Steeley and Siganos (UK, 2004); Tsuji (Japan, 2006), and Arquette et al. (China, 2008). To the authors’ best knowledge, this is the first research to address countries within the relationship between regional and global sentiment and stock returns using the panel data framework.

Baker et al. (2012) apply a linear regression model to construct investor sentiment indices for six major stock markets as a global index. They find that investor sentiment plays a significant role in international market volatility. Using a panel fixed-effect model, Bathia and Bredin (in press) examine the relationship between investor sentiment and G7 stock market returns. Easaw and Ghoshray (2008) employ threshold models and find asymmetric behavior and a cyclical nature of consumer sentiment in the U.S. and UK. Marcucci and Quaglianriello (2009) point out that panel threshold regression models allow different regime effects which are identified by the endogenous threshold value. Based on the above-mentioned literature, our paper applies the nonlinear panel threshold models with and without regime intercept in order to analyze the asymmetric relationship between industry returns and investor sentiment. Assuming that linear relationships may hinder some critical features of stock market riskiness, we seek empirical evidence for the asymmetric behavior of various industry returns across different sentiment regimes.

This paper presents some new features that are not necessarily shared by existing studies. First, we offer a first attempt to examine how industry returns are affected by both global and local market sentiments. Baker et al. (2012) find that both global and local sentiments contain distinctly and statistically significant predictive power, and global sentiment is marginally more important than local sentiment. Chang et al. (2011) confirm that global sentiment explains future returns of global portfolios via a proxy global sentiment through a U.S. investor sentiment index. Baker et al. (2012) decompose the six total sentiment indices into a single global index and six local indices. Unlike prior sentiment studies which applied indices composed by regional single economy, the present article uses the world indices.

Second, mounting evidence suggests that the relationship between sentiment and stock returns is more complex. In particular, the marginal impact of sentiment on returns may differ for high- and low-sentiment regimes (optimism and pessimism). McMillan (2003) and Lee and Chiu (2012) show that financial markets

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1 Brooks (2002) pinpoints that we can address a broader range of issues and tackles more complex problems with panel data than would be possible with pure time-series or pure cross-sectional data alone.
may be characterized by nonlinear behavior resulting from the presence of market frictions, transaction costs, and the interaction between informed and “noise” traders. The prospect theory can account for the asymmetric behavior in which individuals derive values from gains and losses with respect to a reference point, and individuals' value functions are asymmetric in gains and in losses (Kahneman and Tversky, 1979; Lee and Zeng, 2011). Empirically, Ding et al. (2004) and Zhang and Semmler (2009) apply the prospect theory on asset pricing. Their study finds that stock returns react much stronger to optimism, but less to pessimism, implying the presence of investor loss aversion whereby they are reluctant to realize their losses. Some studies also find the importance of threshold effects in the financial field, e.g., Ivanov et al. (2011), Chang and Su (2010), Lee and Chiu (2012), and Chang and Lee (2012). We employ Hansen’s (1999) panel threshold model without a regime intercept and a modified version of this with a regime intercept introduced by Bick (2010) to explore the sentiment–industry returns' linkage. This allows us to estimate the threshold levels and the nonlinear impact of sentiment on industry returns in the various regimes.

Third, the investor sentiment approach that we establish in this study is distinct from previous ones. Baker and Wurgler (2007) explore which stocks are most affected by sentiment. Kaplanski and Levy (2010) discuss which industries are most affected by aviation disasters. Schmeling (2009) examines what kind of country is most influenced by sentiment. Anderson et al. (2010) find that after an information technology (IT) bubble, investors shifted their capital to non-cyclical consumer goods, financials, resources, utilities, and smaller bubble sectors. Dissimilarly, we are targeting the linkage between industry returns and sentiment. Therefore, industry returns are directly used in our measurement, rather than aggregate or portfolio returns. Our paper adds to the current literature on simple stylish investment.

Finally, the threshold level determined by the local and global sentiments delineates the sample into different regimes instead of using an arbitrary zero as a cutoff point. Hence, if the nonlinear relationships between investor sentiment and industry returns can gain powerful support, then these outcomes will be beneficial for financial analysis. We find notable differences between the results obtained from global and local market sentiments. Regarding global sentiment for oil & gas (OIL), financials (FIN), and health care (HEA) returns, once the regime intercept is included and when global sentiments are optimistic, the positive impact of sentiment on industry returns becomes significant. For the local sentiment–returns nexus, some of the younger, speculative industries, such as HEA, FIN, and Technology (TECH), fit a linear model better, compared with a nonlinear model. By focusing on nonlinear model, the results herein support that optimistic local sentiment enhances the returns of basic materials (MATS), telecommunications (TELE), and utilities (UTIL) industries.

The remainder of this paper is separated into six sections. The next section reviews the existing literature. Section 3 describes the data and variables used in this study. Section 4 outlines the methodology. Section 5 discusses the results. Section 6 provides the conclusion.

2 Kaplanski and Levy (2010) conclude that, with the increased anxiety following disasters which reduce the demand for risky assets, this in turn affects stock prices.
specific stocks or countries are impacted differently by sentiment. For instance, Baker and Wurgler (2006, 2007) declare that speculative stocks are more sensitive to investor sentiment. Schmeling (2009) reveals that the impact of sentiment on stock returns is higher for countries which have less market integrity and which are culturally more prone to herd-like behavior and overreaction. In contrast, our study focuses on how industries are affected by the local market and global sentiments for 11 Asian markets. Fig. 1 portrays our research concept.

Baker and Wurgler (2006, 2007) determine that when investor sentiment is low, subsequent returns are much higher for low capitalized, smaller, young, highly volatile, unprofitable, non-dividend-paying, speculative companies with extreme growth potential or distressed stocks. When sentiment is high, such categories of stock earn relatively low subsequent returns. By contrast, “bond-like” and safer stocks are less driven by sentiment. The value of a firm with a long earnings history, tangible assets, and stable dividends is much less subjective, and thus its stock is likely to be less affected by fluctuations in the propensity to speculate (Baker and Wurgler, 2006).³ Fink et al. (2010) affirm that young firms explain most of the spike

³ Baker and Wurgler (2006) state that sentiment is defined by a higher demand for more speculative securities.
in volatility, rather than firm size, profitability, or asset tangibility, which all show little evidence of any abnormal volatility.

Our main motivation for this research angle is to see whether young, unprofitable, or experiencing extreme growth industries (such as TECH, TELE, and HEA)\textsuperscript{4} are more affected by investor sentiment, since such industries are difficult to value, making biases more insidious and misestimated. Likewise, are conventional industries, e.g. UTIL and OIL,\textsuperscript{5} which possess bond-like and safer features, less affected by sentiment? If yes, then we can deduce that more speculative industry returns should co-move more with sentiment changes.

\textit{Baker et al. (2012)}\textsuperscript{4} find that during the global financial crash of 2007–2008, the MSCI World Index of developed markets fell about 50%, emerging markets fell 66%, while the Chinese local market index dropped 71%. Such large crashes may be explained by less catastrophic (and perhaps greater) declines in global returns where capital flows and market contagion represent the mechanism by which global sentiment develops and propagates. In other words, a crash sways differently between countries and areas. \textit{Baker et al.'s (2012)} findings validate that both global and local sentiments play a role in cross-sectional returns, yet they contain distinct and statistically solid predictive power. \textit{Brown et al. (2002)} explore that there are both foreign and domestic sentiment factors in Japan, suggesting that it is important to account for the significance of investor sentiment outside the domestic country. \textit{Chang et al. (2011)} demonstrate that the global sentiment impact tends to be further strengthened when local sentiment is high. Hence, our paper considers both global and local sentiments and is able to gather comprehensive sentiment evidence that spans diverse industries in Asian countries.

\textit{Baker and Wurgler (2006)} investigate which stocks are most affected by sentiment using panel regressions. \textit{Kaplanski and Levy (2010)} utilize regression to study which industries are most affected by aviation disasters. Utilizing panel regressions, \textit{Schmeling (2009)} demonstrates what type of country is most influenced by sentiment. While the vast majority of existing works examine stock returns’ predictability in a linear model, there is increasing evidence that stock returns may be better characterized by a model that allows for nonlinearity (\textit{Abhyankar et al., 1997; McMillan, 2003}). \textit{Chung et al. (2011)} challenge the common assumption made that investors consistently deal with uncertainty. \textit{McMillan (2003)} validates that, due to the interaction of noise and arbitrage traders, stock returns are inherently nonlinear, whereby market reactions differ between small and large returns. Yet, most related studies do not take asymmetric effects of investor sentiment into account.

Considering nonlinear relationships and by using the Markov-switching model, \textit{Chung et al. (2011)} state that the regime-switching feature on stock returns may cause a problem in identifying the source of returns’ predictability. Alternatively, \textit{Gray (1996), Maheu and McCurdy (2000), Perez-Quiros and Timmermann (2000), Ang and Chen (2002), and Guidolin and Timmermann (2008)} argue that expected returns, volatilities, and correlations of stock returns vary with regimes. In this study, we first begin our

\textsuperscript{4} TECH, TELE, and HEA represent industry group of technology, telecommunications, and health care respectively. Please refer to Section 3 for data description.

\textsuperscript{5} UTIL and OIL represent industry group of utilities, and oil & gas respectively. Please refer to Section 3 for data description.
analysis with a linear panel regression of sentiment on industry returns with country-specific fixed effects. Second, we employ the heteroskedasticity-consistent Lagrange multiplier (LM) of Hansen (1999) to test the null hypothesis of the linear assumption. Third and finally, examining the relevance of sentiment thresholds for industry returns by applying a modified Hansen’s version of the panel threshold model introduced by Bick (2010) enables us to estimate the threshold levels and the marginal impact of sentiments on returns in the regime.

Hansen (1999) implements the panel threshold regression model to investigate for threshold effects and to search for two or more regimes endogenously. Based on the prospect theory, our paper assumes that there is a reference point of sentiment and uses the panel threshold model to estimate the impact of sentiment on industry returns. We take up the panel threshold model to examine whether there exists a threshold effect between sentiment and industry returns, to search for regimes endogenously, and then to estimate the effects of different sentiment regimes on industry returns.

3. Data and variables

Our empirical analysis employs a panel dataset of 11 selected Asian countries. They are China, Hong Kong (HK), India, Indonesia, Japan, South Korea, Malaysia, the Philippines, Singapore, Taiwan, and Thailand. Using monthly data from 1996 to 2010, our sample time span contains the 1996 HK Provisional Legislature election during the transition from British to Chinese administration governance, the 1997–1998 Asian financial crisis, the 2001 oil price spike, the 2003 SARS outbreak and Iraq War, and the 2007–2008 U.S. subprime crisis and global financial crisis. The data used in this research are local market sentiments, global sentiment, industry returns, and control variables taken fromDataStream.6

3.1. Independent variables – investor sentiment

We ideally want to measure global and each country investors’ views toward the future prospects of their respective markets. Economists are suspicious of individual survey data, as there is a potential gap between how people respond to a survey and how they actually behave (Baker and Wurgler, 2007). As such, we use turnover by volume in local stock markets and global markets to proxy local and global investor sentiments, respectively. Scheinkman and Xiong (2003) indicate that trading volume reveals underlying differences of opinion. Baker and Stein (2004) explain why the turnover ratio as a degree of liquidity in the market can measure investor sentiment, since high liquidity denotes that stocks are overvalued, and vice versa. Scheinkman and Xiong (2003), Baker and Stein (2004), and Baker and Wurgler (2007) also use turnover as a measure of liquidity.

3.2. Dependent variable – industry returns

To attempt to comprehend individual enterprises in each industry is a little tedious and informative. We suggest that industries should be grouped into a relatively small number of broad categories. We use the Industry Classification Benchmark for the classification. The indices include7: basic materials (MATS), consumer goods (GDS), consumer services (SVS), financials (FIN), health care (HEA), industrials (INDU), oil & gas (OIL), technology (TECH), telecommunications (TEL), and utilities (UTIL). Table 2 lists the components of each major sector. The real effective industry and market indices’ change rates in US dollars are used to indicate the stock returns for each industry. This study uses raw returns for the Financial Times Stock Exchange (FTSE) Global 100 and FTSE 10 industries for 11 Asian countries (e.g., return index for FTSE China basic materials for MATS in China).8 Regarding the Chinese sample, since the Shenzhen stock exchange only accounts for about 20% of the total mainland China stock market capitalization in 2006, the Shanghai market is chosen for empirical analysis.9

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6 As we discuss below, not all the same data items are available in each country sample. Some industries in some countries are not covered during the whole period, such as TECH in Indonesia and UTIL in Taiwan and Singapore due to data unavailability.
7 Industry Classification Benchmark is an industry classification taxonomy developed by Dow Jones and FTSE.
8 FTSE Global 100 is a global multinational benchmark and starts from December 31, 1994 inDataStream database.
9 This research focuses on the more liquid A-shares that were exchanged to domestic residents before December 2002.
3.3. Control variables

Sotomayor and Cadenillas (2009) suggest that market behavior is also affected by long-term macroeconomic conditions that should be included in the market modeling. Baker and Wurgler (2006) also consider that sentiment may capture common business-cycle variations. We specified the macroeconomic factor by including business cycle of an economy as the control variable. Due to the requirement of panel monthly data and availability limitations, we use employment volume for China, HK, Japan, South Korea, Malaysia, Taiwan, and Thailand; unemployment volume for India and Singapore; and exports in US dollars for Indonesia and the Philippines.

Table 3 reports the descriptive statistics and correlations of industry returns (RN), local market sentiment (SE), global sentiment (MS), and a proxy for business cycle (BC). Panel A presents the time-series averages of the cross-sectional means and standard deviations for 10 industries among 11 Asian countries over 180 months from January 1996 to December 2010. Panel B shows the correlations between variables related to sentiments and fundamentals. Table 3 shows that nine of the 10 RNs are significantly positively correlated with SE and significantly negatively correlated with BC, while all of the ten RNs are negatively correlated with MS. Asian SE is negatively related with MS, while considerably positively correlated with BC. The high positive correlations, which are approximately 0.5, between BC and SE indicate a possible feedback effect between the two. The low correlation between SE and MS suggests that two sentimental variables represent the unique feature that is independent from each other.

4. Methodology

This present paper is built on the predictive regression model of Schmeling (2009) and develops a non-dynamic threshold model that allows for nonlinearity in a panel set-up. Rapach and Wohar (2006) point out that structural breaks in the parameters that relate stock returns to state variables can occur for a number of reasons, such as Pesaran and Timmermann (2002) citing major changes in market sentiment

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10 Only RN of HEA is non-significantly negatively related with SE. Only RN of OIL is positively correlated with BC.
### Table 3
Summary statistics, 1996–2010.

#### Panel A. Descriptive statistics

|       | RN | SE | MS | BC |
|-------|----|----|----|----|
| Average | 5.072 | 1.113 | 15.004 | 2.564 |

#### Panel B. Correlation coefficients

| MATS       | GDS       | SVS       | FIN       |
|------------|-----------|-----------|-----------|
| RN         | 1.00      | 1.00      | 1.00      | 1.00      |
| SE         | -0.30***  | 0.05*     | -0.28***  | -0.28***  |
| MS         | -0.26***  | -0.01     | -0.04     | -0.03     |
| BC         | -0.13***  | -0.07**   | -0.11***  | -0.06**   |
| HEA        |           |           |           |           |
| INDU       |           |           |           |           |
| RN         | 1.00      | 1.00      | 1.00      | 1.00      |
| SE         | -0.19***  | -0.02     | -0.04     | -0.03     |
| MS         | -0.49***  | -0.08***  | -0.06**   | -0.05     |
| BC         |           |           |           |           |
| OIL        |           |           |           |           |
| TECH       |           |           |           |           |
| RN         | 1.00      | 1.00      | 1.00      | 1.00      |
| SE         | 0.32***   | 0.05*     | 0.07**    | 0.34***   |
| MS         | -0.29***  | -0.05*    | -0.07**   | -0.32***  |
| BC         | -0.17***  | 0.47***   | -0.08**   | -0.20***  |

Notes: Panel A summarizes the statistics for the variables for 10 industries from 11 Asian countries over 180 months. The 10 industries are: Basic materials (MATS), Consumer goods (GDS), Consumer services (SVS), Financials (FIN), Health care (HEA), Industrials (INDU), Oil & gas (OIL), Technology (TECH), Telecommunications (TELE), and Utilities (UTIL). RN represents the logged industry returns. SE is the logged local market sentiment. MS is the logged global sentiment. BC is the logged macroeconomic factor (business cycle). Panel B reports the correlations of RN, SE, MS, and BC for each industry. *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.
as a possible source of instability in a predictive regression model. We employ a non-dynamic panel threshold model to test the asymmetric effect of investor sentiment on industry returns. However, we do not extend our model to the dynamic threshold model in case of endogenous regressors. We leave this extension of our analysis for future research.

4.1. The linear panel fixed-effect model

In order to investigate investor sentiment effects on future industry returns, we follow Schmeling (2009) to employ the predictive model of investor sentiment and returns, and we begin our analysis with a linear panel fixed-effect model augmented with the impact of both global and local market sentiments on industry returns:

\[ RN_{it+1} = c_i + \eta_1 SE_{it} + \phi_1 MS_{it} + \phi_2 BC_{it} + \varepsilon_{it}, \]

where \( i = 1, \ldots, N; t = 1, \ldots, T; N \) refers to the country number; \( t \) is for time; and \( RN_{it+1} \) denotes the industry stock returns for \( i \) country at time \( t + 1 \). The predictors include local market stock index turnover as a proxy for local market sentiment (\( SE \)), world market index turnover as a proxy for global sentiment (\( MS \)), and an additional macro variable, business cycle (\( BC \)), for different countries; \( \eta_1 \) and \( \phi_1 \) represent the marginal effects of local and global sentiments on industry returns, respectively; and \( \varepsilon_{it} \) is disturbance terms. The parameter \( c_i \) allows for the possibility of country-specific fixed effects.

4.2. The sentiment–return nexus of panel threshold models without regime intercepts

Next, we specify the model with respect to the nonlinear relationship between stock returns and market sentiment. Hansen (1999) proposes an estimation and inference strategy for panels with individual specific effects and observations. The equations of interest have two potential threshold values \( \gamma \) and \( \gamma' \), which are unknown ex ante but can be estimated. Here, \( SE_{it}(MS_{it}) \leq \gamma \) (\( \gamma' \)) denotes that local sentiment (global sentiment) is pessimistic, whereas all the other ones are optimistic. Once the threshold \( \gamma \) (\( \gamma' \)) is estimated for the data, the extent of sentiment (\( SE(MS) \)) determines which of the two regimes a country belongs to. Moreover, the marginal impacts of sentiment are regime specific.

Despite a number of econometric difficulties associated with predictive regression models (Kirby, 1997; Nelson and Kim, 1993), the consensus appears to be that stock returns contain a considerable predictable component (Campbell, 2000).
Eq. (2) tests local market sentiment on industry returns, and Eq. (3) examines global sentiment on industry returns.

\[
RN_{it+1} = \alpha_i + \beta_1 SE_{it} I(SE_{it} \leq \gamma) + \beta_2 SE_{it} I(SE_{it} > \gamma) + \varphi_1 MS_t + \varphi_2 BC_{it} + \epsilon_{it}
\]

(2)

\[
RN_{it+1} = \alpha'_i + \beta'_1 MS_{it} I(MS_{it} \leq \gamma') + \beta'_2 MS_{it} I(MS_{it} > \gamma') + \varphi'_1 SE_{it} + \varphi'_2 BC_{it} + \epsilon_{it},
\]

(3)

where \( I(\cdot) \) is the indicator function, and the threshold variable \( SE_{it} \) \((MS_t)\) divides the observations into two ‘regimes’ distinguished by differing regression slopes \( \beta_1 \) \((\beta'_1) \) and \( \beta_2 \) \((\beta'_2) \). Coefficients \( \beta_1 \) \((\beta'_1) \) and \( \beta_1 \) \((\beta'_1) \) denote the respective marginal effect of sentiment on industry returns in the low \((\) high\) sentiment regime, i.e., when sentiment is below \((\) above\) the estimated threshold value. For instance, parameter \( \beta_1 \) \((\beta'_1) \) is the change in returns related to sentiment levels below the threshold. As such, a positive value indicates that as sentiment moves towards the threshold value, the returns tend to increase. More specifically, a positive \( \beta_2 \) \((\beta'_2) \) means that periods of higher investor optimism tend to be followed by higher returns for the industry. The dependent variable \( RN_{it+1} \) is future industry returns for country \( i \) at time \( t+1 \). The threshold parameter \( \gamma \) \((\gamma') \), which is the threshold value of sentiment level at time \( t \) and for industry \( i \), needs to be estimated as well. The individual specific effects are eliminated using the standard fixed-effects transformation, implying for the identification of \( \beta_1 \) \((\beta'_1) \) and \( \beta_2 \) \((\beta'_2) \) that the elements of \( SE_{it} \) \((MS_t)\) are neither time-invariant nor add up to a vector of one. We follow the structure of Bick (2010) to consider investor sentiment as the main resource of asymmetry, and thus parameters \( \varphi_1(\varphi'_1) \) and \( \varphi_2(\varphi'_2) \) are not allowed to change with the threshold. The benefit from such a model establishment is to clarify the impact of the threshold variable on the return–sentiment nexus.

### 4.3. The sentiment–return nexus of panel threshold models with regime intercepts

Given the observed sentiment differentials across countries \((\text{S.D.}=2.56)\), an additional feature of the panel threshold models \((4)\) and \((5)\) is that it generalizes the original set-up in Hansen (1999) by allowing for regime-dependent intercepts \( \delta_{i1} \) and \( \delta'_{i1} \). According to Bick (2010), ignoring intercepts can lead to biased estimates of both the thresholds and the corresponding marginal impacts. The latter case applies to regime intercepts, which are usually included in each regime in threshold models for pure cross-sectional or time-series contexts. Even in the presence of fixed effects, it is possible to control for differences in the regime intercepts by including them in all but one regime as in the following extension of the panel threshold model with regime intercept.

\[
RN_{it+1} = \alpha_i + \beta_1 SE_{it} I(SE_{it} \leq \gamma) + \delta_{i1} I(SE_{it} \leq \gamma) + \beta_2 SE_{it} I(SE_{it} > \gamma) + \varphi_1 MS_t + \varphi_2 BC_{it} + \epsilon_{it}
\]

(4)

\[
RN_{it+1} = \alpha'_i + \beta'_1 MS_{it} I(MS_{it} \leq \gamma') + \delta'_{i1} I(MS_{it} \leq \gamma') + \beta'_2 MS_{it} I(MS_{it} > \gamma') + \varphi'_1 SE_{it} + \varphi'_2 BC_{it} + \epsilon_{it},
\]

(5)

The dependent variable is the expected industry returns. Local and global sentiments \((SE \text{ and } MS)\) are both threshold variables and regime dependent regressors. In addition, estimating Eqs. \((4)\) and \((5)\) in the presence of regime intercepts in the data generating process results in a bias proportional to \( \delta_{i1} \) and \( \delta'_{i1} \), because the orthogonality of the regressors is not preserved anymore.

### 5. Empirical results

#### 5.1. The linear panel fixed-effect model results

Table 4 reports the empirical results for the linear model \((\text{Eq. (1)})\). There is a positive and statistically significant relationship between the industry returns and local sentiment. Interestingly, only TECH returns present an insignificant negative relationship with local sentiment, which is consistent with Baker and Wurgler’s (2006) finding that sentiment is negatively related with subsequent returns for stocks that are considered highly speculative. We notice that the TECH-and-sentiment negative relationship occurs also for our global sentiment and business cycle analyses. However, the other nine industries display solid
positive relations with local sentiment. The empirical results show a parallelism with Baker et al. (2012) in that optimism leads stocks to be overvalued, while pessimism leads them to be undervalued from the impact of local sentiment.

Regarding global sentiment, eight out of ten industry returns are significantly and negatively related with global sentiment, except for HEA being positively related, and OIL shows no notable positive relationship with global sentiment. The findings suggest that expected industry returns react diversely to local and global sentiments. Specifically, the results show that from the predictive relation, greater global market optimism lowers future industry returns. More exceptionally, local and global sentiments positively sway HEA, which is consistent with prior studies arguing that HEA is the next mainstream industry with fortunes to be made, and Asian economies are rushing to establish themselves as a major player here and to become a prime target for foreign investment.12 Global sentiment shows no significant positive effect for OIL, which is consistent with our inference that conventional industries possessing bond-like and safer features are less affected by sentiment.

It is worth noting that one of the most possibly important sources of the correlation between current shock to stock returns and the shock to sentiment is the business cycle fluctuation. After controlling for economic fundamentals, the residual from Eq. (1) is expected to be a purely irrational element in sentiment, uncorrelated with shocks to industry returns. However, the limitations of Eq. (1) are that heterogeneous effects in different sentiment regimes cannot be analyzed. The plausible nonlinearity in investor sentiment impact on expected industry returns and the asymmetry between high- and low-sentiments also cannot be taken into account and may generate bias. Hence, the next two subsections discuss the results of asymmetric sentiment–return nexuses.

5.2. Local sentiment–return nexus of panel threshold models

Tables 5 and 6 present the local sentiment–return results for both specifications, i.e. without and with regime intercepts, respectively. Both tables show that the null hypothesis of no threshold for MATS, GDS, SVS, TELE, and UTIL industries can be rejected at the 10% significance level, while the presence of one threshold cannot be rejected for the others. The results in the above five industries indicate a clear

| Industry | MATS | GDS | SVS | FIN | HEA |
|----------|------|-----|-----|-----|-----|
| \( \eta_1 \) | 0.146** | 0.284** | 0.064** | 0.143** | 0.249** |
| (0.016) | (0.017) | (0.018) | (0.017) | (0.012) |
| \( \phi_1 \) | -0.061** | -0.183** | -0.110** | -0.155** | 0.048** |
| (0.011) | (0.016) | (0.011) | (0.012) | (0.012) |
| \( \phi_2 \) | -0.038** | -0.041** | 0.017** | -0.038** | -0.038** |
| (0.006) | (0.004) | (0.006) | (0.004) | (0.004) |
| Adj. \( R^2 \) | 0.370 | 0.670 | 0.475 | 0.757 | 0.343 |

| Industry | INDU | OIL | TECH | TELE | UTIL |
|----------|------|-----|------|------|------|
| \( \eta_1 \) | 0.172** | 0.319** | -0.036 | 0.352** | 0.248** |
| (0.016) | (0.021) | (0.035) | (0.019) | (0.015) |
| \( \phi_1 \) | -0.163** | 0.022 | -0.096** | -0.167** | -0.118** |
| (0.013) | (0.023) | (0.014) | (0.019) | (0.008) |
| \( \phi_2 \) | -0.058** | 0.124** | -0.482** | 0.082** | 0.539** |
| (0.002) | (0.015) | (0.077) | (0.014) | (0.063) |
| Adj. \( R^2 \) | 0.650 | 0.549 | 0.513 | 0.532 | 0.816 |

Notes: The table reports the panel fixed-effect regressions’ estimates and the results of coefficient estimates for ten industries: \( RN_{it+1} = \eta_1 + \eta_1S_{Eit} + \phi_1M_{Sit} + \phi_2B_{Cit} + \epsilon_{it} \). The sample periods include monthly data from 1996–2010. \( RN \) represents the logged industry returns. \( S_{E} \) is the logged local market sentiment. \( M_{S} \) is the logged global sentiment. \( B_{C} \) is the logged macroeconomic factor, or business cycle. Robust standard errors are in parentheses. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

12 Source: Taiwan–Industry from www.nationsencyclopedia.com.
rejection of a linear relation between sentiment and industry returns in favor of a single-threshold model. By contrast, FIN, HEA, INDU, OIL, and TECH are fitted for linear models. Specifically, the null hypothesis of no sentiment threshold in the equation can be rejected at the 5% significance level, while the hypothesis of a single threshold cannot be rejected. Thus, it is not necessary to conduct the hypothesis of a double threshold. In Table 5 (Table 6), γ is 16.5 (16.1) for MATS in the without (with) regime model. Observations larger than 16.5 (16.1) represent when local investor sentiment is optimistic, whereas smaller than 16.5 (16.1) shows pessimism.

Inclusion of a regime intercept decreases the threshold estimates of MATS from 16.5% to 16.1%, and TELE from 15.4% to 15.2%, while inclusion of a regime intercept increases the threshold estimates of SVS from 12.9% to 13% and UTIL from 9.4% to 13.5%, whereas that for GDS remains unchanged. The most

### Table 5
Local sentiment thresholds and industry returns (no regime intercepts model), 1996–2010.

| Industry | MATS | GDS | SVS | FIN | HEA |
|----------|------|-----|-----|-----|-----|
| **Test for the number of thresholds (p-value)** | | | | | |
| $H_0$: No threshold | 0.093 | 0.066 | 0.040 | 0.413 | 0.513 |
| $H_0$: At most one threshold | 0.852 | 0.451 | 0.400 | 0.897 | 0.550 |
| **γ** | 16.513 | 15.979 | 12.9816 | | |
| Estimated threshold country [time] | HK | HK | Korea | | |
| [2007/04] | [1996/08] | [1996/06] | | |

**Impact of regime-dependent regressors**

| $\beta_1$ | 0.182** | 0.123** | 0.382** |
|-----------|---------|---------|---------|
| (0.011) | (0.009) | (0.019) | |

| $\beta_2$ | 0.219** | 0.156** | 0.285** |
|-----------|---------|---------|---------|
| (0.009) | (0.008) | (0.012) | |

**Impact of regime-independent regressors**

| $\phi_1$ | −0.157** | −0.147** | −0.131** |
|----------|---------|---------|---------|
| (0.009) | (0.007) | (0.006) | |

| $\phi_2$ | −0.123** | −0.168** | −0.188** |
|----------|---------|---------|---------|
| (0.006) | (0.004) | (0.003) | |

| Industry | INDU | OIL | TECH | TELE | UTIL |
|----------|------|-----|------|------|------|
| **Test for the number of thresholds (p-value)** | | | | | |
| $H_0$: No threshold | 0.458 | 0.337 | 0.687 | 0.002 | 0.073 |
| $H_0$: At most one threshold | 0.406 | 0.488 | 0.346 | 0.311 | 0.549 |
| **γ** | 15.427 | 9.432 | | |
| Estimated threshold country [time] | HK | Malaysia | | |
| [1999/03] | [2002/07] | | | |

**Impact of regime-dependent regressors**

| $\beta_1$ | 0.083** | 0.042** |
|-----------|---------|---------|
| (0.009) | (0.018) | |

| $\beta_2$ | 0.126** | 0.665** |
|-----------|---------|---------|
| (0.008) | (0.009) | |

**Impact of regime-independent regressors**

| $\phi_1$ | −0.101** | −0.053** |
|----------|---------|---------|
| (0.005) | (0.009) | |

| $\phi_2$ | −0.071** | −0.006 |
|----------|---------|--------|
| (0.004) | (0.009) | |

Notes: The table presents the local sentiment-return results for without regime intercept models. Coefficient estimates: $RN_{it+1} = \alpha_i + \beta_1 SE_{it}(SE_{it} \leq \gamma) + \beta_2 SE_{it}(SE_{it} > \gamma) + \phi_1 MS_t + \phi_2 BC_t + \epsilon_{it}$.

Figures following null hypothesis are p-values. The bold-face characters represent significant in 10% level. Robust standard errors are in parentheses. The sample periods include monthly data from 1996–2010. RN represents the logged industry returns. SE is the logged local market sentiment. MS is the logged global sentiment. BC is the logged macroeconomic factor (business cycle). ** and * indicate statistical significance at the 5% and 10% levels, respectively. The threshold variable is local market sentiment. Each regime has to contain at least 5% of all observations. 1000 bootstrap replications are used to obtain the p-values to test for the number of thresholds. By construction, the confidence intervals for the threshold estimates can be highly asymmetric.

rejection of a linear relation between sentiment and industry returns in favor of a single-threshold model. By contrast, FIN, HEA, INDU, OIL, and TECH are fitted for linear models. Specifically, the null hypothesis of no sentiment threshold in the equation can be rejected at the 5% significance level, while the hypothesis of a single threshold cannot be rejected. Thus, it is not necessary to conduct the hypothesis of a double threshold. In Table 5 (Table 6), γ is 16.5 (16.1) for MATS in the without (with) regime model. Observations larger than 16.5 (16.1) represent when local investor sentiment is optimistic, whereas smaller than 16.5 (16.1) shows pessimism.

Inclusion of a regime intercept decreases the threshold estimates of MATS from 16.5% to 16.1% and TELE from 15.4% to 15.2%, while inclusion of a regime intercept increases the threshold estimates of SVS from 12.9% to 13% and UTIL from 9.4% to 13.5%, whereas that for GDS remains unchanged. The most
notable point is that, in absence of a regime intercept, local sentiments, both when investors are optimistic and pessimistic, all have a significantly positive effect on returns at the 5% significant level. Conversely, Table 6 shows that, pessimistic sentiment has a significantly positive effect on returns. However, in case of optimistic sentiment, GDS industry shows positive effect but not statistically significant. To sum up, the asymmetric effects of local sentiment on expected industry returns exist but vary across industries. In addition, the asymmetric constant term, \( \delta_1 \), is significantly positive except in GDS industry. This indicates

| Industry | MATS | GDS | SVS | FIN | HEA |
|----------|------|-----|-----|-----|-----|
| Test for the number of thresholds (p-value) | H0: No threshold | 0.009 | 0.066 | 0.058 | 0.521 | 0.297 |
| H0: At most one threshold | 0.919 | 0.451 | 0.178 | 0.713 | 0.130 |
| \( \gamma \) | 16.141 | 15.979 | 13.000 |
| Estimated threshold country [time] | HK [2003/01] | HK [1996/08] | Philippines [2003/01] |

Impact of regime-dependent regressors

| Industry | MATS | GDS | SVS | FIN | HEA |
|----------|------|-----|-----|-----|-----|
| Impact of regime-dependent regressors | \( \beta_1 \) | 0.164** | 0.133** | 0.337** |
| | \( \delta_1 \) | 4.878** | -1.894** | 0.877** |
| | \( \beta_2 \) | 0.489** | 0.053 | 0.321** |
| Impact of regime-independent regressors | \( \gamma_1 \) | -0.154** | -0.152** | -0.128** |
| | \( \gamma_2 \) | -0.121** | -0.170** | -0.184** |
| Industry | INDU | OIL | TECH | TELE | UTIL |
| Test for the number of thresholds (p-value) | H0: No threshold | 0.513 | 0.441 | 0.810 | 0.003 | 0.049 |
| H0: At most one threshold | 0.565 | 0.352 | 0.410 |
| \( \gamma \) | 15.253 | 13.551 |
| Estimated threshold country [time] | Philippines [2008/01] | Taiwan [1997/10] |

Impact of regime-dependent regressors

| Industry | MATS | GDS | SVS | FIN | HEA |
|----------|------|-----|-----|-----|-----|
| Impact of regime-dependent regressors | \( \beta_1 \) | 0.062** | 0.011 |
| | \( \delta_1 \) | 2.092** | 7.699** |
| | \( \beta_2 \) | 0.235** | 0.661** |
| Impact of regime-independent regressors | \( \gamma_1 \) | -0.097** | -0.055** |
| | \( \gamma_2 \) | -0.069** | 0.004 |

Notes: The table presents the local sentiment-return results for the with regime intercept models. Coefficient estimates: \( RN_{it+1} = \alpha_i + \beta_1SE_i(\text{SE}_{it} \leq \gamma) + \delta_1I(\text{SE}_{it} \leq \gamma) + \beta_2SE_i(\text{SE}_{it} > \gamma) + \phi_1MS_i + \phi_2BC_i + \epsilon_{it} \).

Figures following null hypothesis are p-values. The bold-face characters represent significant in 10% level. Robust standard errors are in parentheses. The sample periods include monthly data from 1996–2010. RN represents the logged industry returns. SE is the logged local market sentiment. MS is the logged global sentiment. BC is the logged macroeconomic factor (business cycle). ** and * indicate statistical significance at the 5% and 10% levels, respectively. The threshold variable is local market sentiment. Each regime has to contain at least 5% of all observations. 1000 bootstrap replications are used to obtain the p-values to test for the number of thresholds. By construction, the confidence intervals for the threshold estimates can be highly asymmetric.
the presence of intercept asymmetry when market sentiment is considered. Our results are similar to Baker and Wurgler (2006, 2007) whereby diverse stocks react differently to investor sentiment.

This study used the panel threshold model to estimate the threshold value in which the threshold country and time can be uncovered. In doing so, we can provide the economic meanings and interpretations of the panel threshold model. In the past two decades, the Asian financial community has experienced some of the most devastating financial crises and disasters in modern history. Shortly after recovering from the 1997–1998 Asian financial crisis, the region was hit by SARS (Severe Acute Respiratory Syndrome) in 2002–2003, followed by the 2006–2007 subprime crisis, and then the 2007–2010 global financial crisis. With our model specification, we can reveal a country and a time spot for that country which the threshold value is located.

In Table 5, industries MATS, GDS, and TELE have HK as the threshold country. Korea and Malaysia are the threshold country for sector SVS and UTIL respectively. The threshold time is located in Apr. 2007, Aug. 1996, and Mar. 1999 for HK, Jun. 1996 for Korea, and Jul. 2002 for Malaysia. The MATS sector that is switched by HK in the middle of 2007 could be the pre-reaction of the US subprime crisis. Moreover, our finding suggests that the HK Provisional Legislature election, held in 1996 during the transition from British to Chinese administrations' governing of HK, signifies that this event has a largely negative influence on the GDS sector. After HK was incorporated into China, the huge resources certainly will change the sector of GDS.

In Table 6, allowing for an intercept asymmetry, industry MATS and GDS have HK as the threshold country. Philippines is the threshold country for industry SVS and TELE, and Taiwan for UTIL. The threshold time is located in (according to the order of industry) Jan. 2003, Aug. 1996, Jan. 2003, Jan. 2008 and Oct. 1997 respectively. Note that during 1997, Taiwan was hit by a strain of Foot-and-Mouth disease, and the Asian financial crisis took place in 1997 as well, indicating that the UTIL industry was largely influenced by these events. We further notice that in January 2003 MATS in Hong Kong and the SVS in the Philippines are influenced by local market sentiment that may be rooted in SARS spreading throughout Asia. In particular, the SVS sector contributes to more than half of the Philippines overall economic output. Sector TELE is switched by Philippine's market sentiment in Jan. 2008. This indicates the worldwide influence of the global financial crisis.

5.3. Global sentiment–return nexus of panel threshold models

Tables 7 and 8 show the estimated sentiment threshold of global sentiment on expected industry returns for models without and with regime intercepts, respectively. Among the 10 industries in Asia, only TECH and UTIL industries fit the linear models. For the other eight industries, the null hypothesis of no threshold can be rejected at the 5% significance level. Since the hypothesis of one threshold cannot be rejected we adopt the one threshold model. The estimated global sentiment threshold and the marginal effects of global sentiment on returns strongly suggest the prevailing sentiment importance for analysts and investors. The threshold values range from 16.3% to 19.9% across the eight sectors. However, in Table 8, the threshold estimate of OIL decreased from 19.9% to 18.3%, HEA increased from 16.3% to 16.5%, and the estimates for the remaining sectors remain unchanged.

In the absence of a regime intercept sentiment, regardless if the global sentiment is below or above the threshold, global sentiment, for most cases, positively significantly influences future industries returns; and only SVS and OIL are negatively influenced by global sentiment both below and above the global sentiment threshold. However, in the presence of a regime intercept, we do observe reversed adjustments on several industries. For industries of FIN, HEA, INDU (but not significant), and OIL, global sentiments negatively affect the stock returns when the market is pessimistic and turned positively when optimistic. This is consistent with the finding by Brown and Cliff (2005), Kumar and Lee (2006), and Baker and Wurgler (2006, 2007), in which optimism leads stocks to be overvalued before a stock price crash and pessimism leads them to be undervalued thereafter. For industries MATS, GDS and TELE, the adjustment in pessimistic and optimistic regimes are both positive although the latter two industries show significant impact in optimistic regime only. In addition, except for MATS and TELE, the other six regime intercepts $\delta^1_{1}$

13 Southeast Asia’s export growth slowed dramatically in the spring of 1996, deteriorating the current accounts of countries in the region.
are significant at the 5% level, indicating that the regime intercept is present in the return–global sentiment nexus.

With regard to the threshold time point in Tables 7 and 8, MATS, GDS, FIN, HEA, INDU, and TELE are affected by the Asian financial crisis, which gripped much of Asia beginning in July 1997 and raised fears of a worldwide economic meltdown due to financial contagion during 1997–1998. OIL is affected by the climbing prices of crude oil during the beginning of 2001 and on to their highest levels since the Gulf War. SVE is influenced by the commencement of the Iraq War in 2003 and by SARS in 2002–2003, which spread from Asia and then globally, harming the Asian economies. The empirical results confirm Eun and Shim (1989) in that a substantial amount of interdependence exists among national stock markets. Unexpectedly, the global financial crisis and the U.S. subprime crisis did not show up as a global sentiment threshold for our Asian sample. The subprime crisis in 2007 resulted in major instability in Asian financial markets and then led to the global financial crisis of 2008–2010. As a result, the U.S. subprime and global financial crises only show a

### Table 7
Global sentiment thresholds and industry returns (no regime intercepts model), 1996–2010.

| Industry | MATS | GDS | SVS | FIN | HEA |
|----------|------|-----|-----|-----|-----|
| Test for the number of thresholds | | | | | |
| $H_0$: No threshold | 0.000 | 0.000 | 0.004 | 0.033 | 0.004 |
| $H_0$: At most one threshold | 0.165 | 0.289 | 0.502 | 0.355 | 0.219 |
| Estimated threshold time | 1997/09 | 1998/08 | 2003/09 | 1998/08 | 1997/08 |

#### Impact of regime-dependent regressors

| | $\hat{\beta}_1$ | $\hat{\beta}_2$ |
|----------|-----------------|-----------------|
| $\hat{\gamma}_1$ | 0.167** | 0.087** |
| (0.019) | (0.016) |
| $\hat{\gamma}_2$ | 0.196** | 0.117** |
| (0.018) | (0.014) |

#### Impact of regime-independent regressors

| | $\hat{\phi}_1$ | $\hat{\phi}_2$ |
|----------|-----------------|-----------------|
| $\hat{\phi}_1$ | 0.213** | -0.107** |
| (0.009) | (0.005) |
| $\hat{\phi}_2$ | 0.151** | -0.166** |
| (0.009) | (0.005) |

| Industry | INDU | OIL | TECH | TELE | UTIL |
|----------|------|-----|------|------|------|
| Test for the number of thresholds | | | | | |
| $H_0$: No threshold | 0.003 | 0.002 | 0.601 | 0.003 | 0.261 |
| $H_0$: At most one threshold | 0.217 | 0.195 | 0.503 | 0.103 | 0.640 |
| Estimated threshold time | 1998/08 | 2003/09 | | 1997/09 | |

#### Impact of regime-dependent regressors

| | $\hat{\beta}_1$ | $\hat{\beta}_2$ |
|----------|-----------------|-----------------|
| $\hat{\gamma}_1$ | 0.126** | 0.062** |
| (0.018) | (0.014) |
| $\hat{\gamma}_2$ | -0.299** | -0.255** |
| (0.011) | (0.009) |

#### Impact of regime-independent regressors

| | $\hat{\phi}_1$ | $\hat{\phi}_2$ |
|----------|-----------------|-----------------|
| $\hat{\phi}_1$ | 0.252** | -0.149** |
| (0.003) | (0.013) |
| $\hat{\phi}_2$ | 0.199** | -0.057** |
| (0.016) | (0.013) |

Notes: The tables show the estimated sentiment threshold of global sentiment on expected returns' results without regime intercepts respectively. Coefficient estimates: $\text{RN}_{it+1} = \alpha + \hat{\beta}_1 \text{MS}_{it} (\text{MS}_{t} \leq \hat{\gamma}_1) + \hat{\beta}_2 \text{MS}_{it} (\text{MS}_{t} > \hat{\gamma}_1) + \hat{\phi}_1 \text{SE}_{it} + \hat{\phi}_2 \text{BC}_{it} + \epsilon_{it}$. Figures following null hypothesis are p-values. The bold-face characters represent significance at the 5% and 10% levels, respectively. The threshold variable is global sentiment. Each regime has to contain at least 5% of all observations. 1000 bootstrap replications are used to obtain the p-values to test for the number of thresholds. By construction, the confidence intervals for the threshold estimates can be highly asymmetric.

Figures following null hypothesis are p-values. The bold-face characters represent significance at the 5% and 10% levels, respectively. The threshold variable is global sentiment. Each regime has to contain at least 5% of all observations. 1000 bootstrap replications are used to obtain the p-values to test for the number of thresholds. By construction, the confidence intervals for the threshold estimates can be highly asymmetric.
significant influence on the local sentiment–industry returns nexus, rather than the global sentiment–industry returns nexus.

Two possible reasons for the above findings are as follows. First, our local sentiment follows 11 Asian stock markets’ degree of liquidity. Global sentiment is thus constructed by the liquidity of the world equity index. Our industry return data are from Asia. The components of global sentiment are much more complex than local or regional sentiments. Thus, from the perspective of regional industry data, we do not observe the impact from the global and subprime crises. However, because local sentiment reflects local market reactions quickly, we therefore observe the impacts from the global and subprime crises in the

### Table 8
Global sentiment thresholds and industry returns (regime intercepts model), 1996–2010.

| Industry | MATS | GDS | SVS | FIN | HEA |
|----------|------|-----|-----|-----|-----|
| Test for the number of thresholds (p-value) | | | | | |
| $H_0$: No threshold | **0.000** | **0.002** | **0.017** | **0.040** | **0.006** |
| $H_0$: At most one threshold | 0.046 | 0.173 | 0.322 | 0.241 | 0.037 |
| Estimated threshold time | 1997/09 | 1998/08 | 2003/09 | 1998/08 | 1998/08 |

| Impact of regime-dependent regressors | | | | | |
| $\hat{\gamma}$ | 16.257 | 16.52162 | 19.875 | 16.521 | 16.521 |
| $\hat{\gamma}^*$ | 16.257 | 16.52162 | 19.875 | 16.521 | 16.521 |

| Impact of regime-independent regressors | | | | | |
| $\hat{\beta}_1$ | 0.0753** | 0.064 | $-0.223**$ | $-0.153^*$ | $-0.091^{**}$ |
| (0.086) | (0.068) | (0.008) | (0.084) | (0.046) |
| $\hat{\delta}_1$ | 1.511 | 2.232** | 2.777** | 3.689** | 3.303** |
| (1.376) | (1.103) | (1.196) | (1.337) | (0.756) |
| $\hat{\beta}_2$ | 0.091** | 0.126** | -0.056 | 0.031** | 0.082** |
| (0.016) | (0.014) | (0.057) | (0.014) | (0.011) |

| Industry | INDU | OIL | TECH | TELE | UTIL |
|----------|------|-----|------|------|------|
| Test for the number of thresholds | | | | | |
| $H_0$: No threshold | **0.008** | **0.004** | 0.549 | **0.009** | 0.334 |
| $H_0$: At most one threshold | 0.037 | 0.151 | 0.361 | 0.067 | 0.523 |
| Estimated threshold time | 1998/08 | 2001/03 | 1997/09 | | |

| Impact of regime-dependent regressors | | | | | |
| $\hat{\beta}_1$ | $-0.089$ | $-0.333^{**}$ | | 0.057 | |
| (0.083) | (0.019) | | (0.052) | | |
| $\hat{\delta}_1$ | 0.076** | 0.176** | | 0.024** | |
| (0.014) | (0.031) | | (0.012) | | |

| Impact of regime-independent regressors | | | | | |
| $\hat{\phi}_1$ | 0.254** | 0.200** | | 0.163** | |
| (0.009) | (0.016) | | (0.010) | | |
| $\hat{\phi}_2$ | $-0.150^{**}$ | $-0.058^{**}$ | | $-0.083^{**}$ | |
| (0.002) | (0.012) | | (0.003) | | |

Notes: The tables show the estimated sentiment threshold of global sentiment on expected returns’ results with regime intercepts respectively. Coefficient estimates: $RN_{it} = \alpha_i + \beta_1^I MS_i(MS \leq \gamma^I) + \delta_1^I MS_i(MS > \gamma^I) + \beta_2^I SE_i + \delta_2^I BC_i + \epsilon_i$. Figures following null hypothesis are p-values. The bold-face characters represent significance at the 10% level. Robust standard errors are in parentheses. The sample periods include monthly data from 1996–2010. RN represents the logged industry returns. SE is the logged local market sentiment. MS is the logged global sentiment. BC is the logged macroeconomic factor (business cycle). ** and * indicate statistical significance at the 5% and 10% levels, respectively. The threshold variable is global sentiment. Each regime has to contain at least 5% of all observations. 1000 bootstrap replications are used to obtain the p-values to test for the number of thresholds. By construction, the confidence intervals for the threshold estimates can be highly asymmetric.
local sentiment portion. Second, the other possibility is that markets tend to behave as one during great crashes across types of investor, assets, and industry. Hence, markets tend to behave similarly during times of high volatility (Sandoval and Franca, 2012).

To sum up Table 5 through Table 8, we examine the impact or the degree of local market sentiment on industry returns for a wide range of Asian countries at different levels of sentiment. The magnitudes of the impact of SE and MS on industry returns in those two regimes are not the same. Investors act differently during high and low SE and MS. Tables 5 and 6 show that sentiment SE has a significant impact on industry returns in the under and above sentiment thresholds. Note that expected returns react much stronger to optimism, compared with pessimism, indicating the presence of investor loss aversion when they are reluctant to realize their losses. We further observe asymmetry in the impact of sentiment on industry returns, whereby investors are reluctant to realize their losses. Although we do not claim that the prospect theory leads to investors’ reaction on returns, the asymmetry within the impacts of optimism and pessimism on industry returns bears similarity to the reference point and value function of the prospect theory, where gains and losses have an asymmetric impact on the value of a prospect. The results reveal that higher local sentiment enhances the returns of MATS, TELE, and UTIL industries, while higher local sentiment decreases returns for GDS and SVS.

6. Conclusions

Several theoretical models suggest that the interaction from noise and arbitrage traders could result in nonlinear behavior. This paper further provides new evidence on the nonlinear/asymmetric features of local market and global investor sentiments and the diverse impacts of local and global sentiments on expected industry returns. To that aim, we employ recently developed panel threshold models with a generalization of Hansen’s (1999) without regime intercepts and Bick’s (2010) with regime intercept panel threshold models in order to examine a more complex relationship between sentiment and industry returns in a predictive regression model. Allowing for a different change in the sentiment effect might lead to a more realistic view on the sentiment–returns linkage.

Confirming the general consensus in the literature, we find that sentiment enhances future industry returns provided that it exceeds a certain threshold value. The regime intercept is significant in the sentiment–return nexus and affects the results significantly. However, there are significant differences among the 10 industries concerning both the level of the estimated threshold and the impact of sentiment in the various sentiment regimes.

We find notable differences among industries in Asia. For the local sentiment–return nexus, our results reveal that higher local sentiment improves the returns of MATS, SVS, TELE, and UTIL industries. GDS returns are influenced by the August 1996 HK Provisional Legislature election right after the transition from British to Chinese administrations governing HK. During 2003, the MATS in Hong Kong and the SVS in the Philippines are influenced by sentiment that may both be rooted in SARS spreading from Asia globally and then harming Asian economics. During 2008, TELE in the Philippines is influenced by sentiment that may be rooted in the global financial crisis.

For the global sentiment analysis, only TECH and UTIL fit a linear model. For industries of FIN, HEA, INDU (but not significant), and OIL, global sentiments negatively affect the stock returns when the market is pessimistic and turned positively when optimistic. For industries MATS, GDS and TELE, the adjustments in pessimistic and optimistic regimes are both positive although the latter two industries show significant impact in optimistic regime only.

Our main empirical finding is that industry returns are mixed and conditional on the stage of investor sentiments. Generally speaking, our findings are similar to Brown and Cliff (2005), Kumar and Lee (2006), and Baker and Wurgler (2006, 2007) in which when investors are optimistic about the prospects for stocks, the stocks will sell at a premium, and vice versa. Specifically, when sentiment is estimated to be high, industries are attractive to optimists and speculators. Compared with global sentiment, the linkages between local sentiment and future industry returns are mixed. We deem that there are diverse features of firms in an industry; the features of firms may trade off each other, thus obscuring possibly negative connections. The asymmetry in the impact of pessimistic and optimistic sentiments on stock returns bears similarity to the value function of the prospect theory, where gains and losses have an asymmetric impact on stock returns.
This study has several implications. First, the diverse impacts of local and global sentiments on expected industry returns need to be carefully analyzed for international analysts and investors. Second, both investor and entrepreneurial firms should consider the threshold value of sentiment as being interdependent with industry returns when evaluating the timing of sector rotation and investment in order to avoid problems associated with either underinvestment or overinvestment. Therefore, keeping investor sentiment above the threshold has a strong beneficial effect. Third, we provide empirical evidence of the prospect theory from the asymmetric stock return effects of sentiment from the industry perspective. Fourth, the empirical findings confirm the importance of including a regime intercept from a statistical and economical perspective on the relations between sentiment and industry returns. Finally, policy makers or regulatory agents, who want to stabilize equity markets and reduce volatility, should be aware of the certain threshold value of sentiment for a specific industry followed by the potential for irrational exuberance.

This study serves as a basis for future research that tries to analyze the connection between industry sentiment and suggests several potentially useful lines of further research enquiry. First, it would be worthwhile to consider more classifications for the investor sentiment variable so that the findings might be more parsimonious. Second, the empirical set-up of the current study controls for the effect of further variables on industry returns, but does not account for the interrelationships between industries. One example is basic materials in China, which is quite a strong industry that may affect the other related industries in adjacent countries due to supply chain effects. The identification of industries that are interrelated with specific sentiment thresholds in the sentiment–return nexus might provide useful information about the appropriate location and width of a sentiment arbitrage band. Third, there are certainly other factors that influence sector returns, such as institutions (Billmeier and Massa, 2009), currency markets (Fedorova and Saleem, 2010), and market liberalization (Chen and Lu, 2007), and thus future research may include more variables for a better understanding of such important issues. Finally, whether the dynamic panel model explains the industry returns–sentiment nexus better seems worthy of further research. We leave those extensions for the future.

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