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A Study of Stock Price Behavior in Taiwan via Residual Income Valuation Theory and Structural Identification

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This study adopts the methodology introduced by Lee (2006) to analyze stock prices in response to information shocks in six of Taiwan's stock market sectors and present market anomalies utilizing behavioral finance theory. Using the Residual Income Model (RIM) of equity valuation, we specified our empirical model to identify structural fundamental and nonfundamental shocks from reduced-form tangible and intangible news, and we obtained three major results. First, fundamental shock is primarily induced by tangible news and nonfundamental shock by intangible news, suggesting that tangible-oriented RIM can capture the information content of stock prices. Second, impulse response analyses show that investors generally underreact to fundamental shocks and consistently overreact to nonfundamental shocks in the short-run. This finding is compatible with the overconfidence theory of Daniel *et al.* (1998) in behavioral finance literature. Third, information diffusion efficiency in a market appears to depend on the value relevance quality of its tangible information. This is based on our finding that when tangible information constitutes a higher share of a market's fundamental shock, its price converges faster to the long-run equilibrium associated with the shock.

Keywords: Market anomaly; residual income; structural identification; overconfidence; behavioral finance

1. Introduction

Recent capital market research suggests security pricing inefficiencies, also called market anomalies. Many studies have found that stock returns exhibit continuation or momentum, indicating investor underreaction to information releases (Bernard and Thomas, 1990; Hirshleifer *et al.*, 2009). Others have established that long-term stock returns are negatively autocorrelated, suggestive of market overreaction to be corrected by a subsequent price reversal (DeBondt and Thaler, 1985; Daniel and Titman, 2006; Jirasakuldech *et al.*, 2006). These findings imply that asset returns are predictable based on presently available information, violating rational expectations and efficient market assumptions maintained in traditional asset pricing models.

In the search for a theory to accommodate market anomalies, behavioral finance models are proposed to explain pricing behaviors from the perspective of investor psychological biases as opposed to traditional assumptions of efficiency and rationality. For example, Daniel *et al.* (1998) suggested that investors might be overconfident about private signals at the expense of ignoring public information. As a result, prices reflect investors' overreactions to private information and underreactions to public information. Hong and Stein (1999) argued that private information from different sources diffuses slowly throughout the market and causes short-run price underreactions, whereas momentum-chasing strategies made profitable by this short-run underpricing will result in overreaction over a longer horizon.

Using a structural vector moving-average (VMA) modeling approach, this article investigates reaction of stock prices in Taiwan to economic shocks, emphasizing the patterns and lengths of anomalies. In addition, we explore whether existing behavioral finance theory is consistent with or can explain our empirical anomaly results. Specifically, we aim to relate our results to the overconfidence theory developed by Daniel *et al.* (1998), which models two information shocks that exactly match the number of shocks specified in our bivariate model.[1] In comparison, many other behavioral theories address only a single information shock source. As an example, Barberis *et al.* (1998) discussed the ways in which representativeness and conservatism biases may

[1]The recent analysis by Lee (2006) is an example relating time-series price reactions to behavioral theory of market anomalies. He found that Dow Jones and S&P 500 indices overreact to intangible information but underreact to tangible information, a result compatible with the overconfidence hypothesis of Daniel *et al.* (1998). Lin (2005) also documented evidence of investor overconfidence in Taiwan's stock markets.

cause prices to misreact to equity earning shocks. Another theory by Hong and Stein (1999) referred to fundamentals as the single information source.[2]

Our empirical model is based on the Residual Income Model (RIM) of equity valuation used by Jiang and Lee (2005), Lee (2006), Tsay *et al.* (2008) and Higgins (2011). RIM is a distinct valuation theory which postulates that only accounting information, namely book value and residual income, determines equity value. Recent empirical research has found that RIM outperforms other basic valuation theories.[3] Since our study is the first to apply a RIM-based structural VMA method to examine Taiwan's stock market data, our research results will indicate whether RIM is an empirically valid pricing model and whether the underscored accounting information is useful for stock valuation in Taiwan.

The present research has been inspired by that of Lee (2006), which applied structural VMA technique and RIM theory to examine US stock market data. Nevertheless, this study comprises two important aspects. First, most existing research has focused on aggregate stock market price behaviors with little examination of industrial price behavior differences. Unlike those studies, this article examines pricing behaviors in both the composite TAIEX market and major industrial stock sectors in Taiwan. In Taiwan, investors react with higher enthusiasm to news in hot sectors, such as electronics, than to relatively quiet traditional industries. Hence, stock prices in hot sectors are likely to reflect greater overreactions of investors to information shocks compared to traditional sector prices. Another motivation for comparing cross-industry price behaviors is that pricing efficiency differences among sectors have implications for investor risk management and arbitrage activities (e.g., Marshall, 2009; Wang and Xie, 2010).

Second, instead of defining tangible accounting information and market-based intangible news as the sources of stock price fluctuations as Lee (2006) did, we follow the spirit of Lee (1998), Chung and Lee (1998) and Falk and Lee (1998) by specifying stock price variation as the result of permanent fundamental and transitory nonfundamental shocks. In addition, we investigate

[2] Hong and Stein (1999) provided a "unified" theory in the sense that they get both underreaction and overreaction out of just one primitive type of shock: Gradually diffusing news about fundamentals. No other exogenous shocks, such as those to investor sentiment or liquidity trading, are specified.

[3] Jiang and Lee (2005) formally tested the validity of both the dividends discount model (DDM) and RIM, and found that RIM outperforms DDM. Lee (2006) used structural VMA models to compare results based on DDM and RIM, and confirmed that RIM provides better compatibility with Dow Jones and S&P 500 stock index data. Lee (2007) recently found that RIM has better predictability of future stock prices in Taiwan than DDM.

the proportions of reduced-form tangible and intangible news disturbances in structural fundamental and nonfundamental shocks, which involve an analysis rarely undertaken in prior time-series studies.[4] Our *a priori* hypothesis is that tangible news constitutes a greater share, rather than the entirety, of fundamental information, in comparison to intangible news. This is a reasonable hypothesis considering that accounting manipulations and measurement errors may make part of tangible information irrelevant for equity valuation. On the other hand, even though intangible news is susceptible to rumors or behavioral biases, it contributes to fundamental information because financial markets do reveal value relevant private news.

We further define a *relevance* indicator of tangible news by the ratio of fundamental information contributed by tangible relative to intangible news using estimates resulting from structural identification. A high relevance ratio demonstrates that tangible news contributes more to intrinsic equity values. A second tangible news *noise* indicator is defined by the ratio of contribution of tangible news to nonfundamental shocks, relative to intangible news. A high noise ratio indicates that tangible news contains large useless or misleading elements of stock value assessment.

In summary, various behavioral finance researchers have proposed that stock price overreaction and underreaction arise from investor cognitive and behavioral biases. We apply the methodology introduced by Lee (2006) to analyze stock prices in response to fundamental and nonfundamental information shocks in Taiwan, and present market anomalies utilizing behavioral finance theory. In addition, we compare the whole listed and five industrial sector stocks in terms of price anomaly types and length of misreaction to judge pricing efficiencies. The empirical structural VMA model is specified based on RIM theory. The empirical results may help shed light on whether tangible-oriented RIM is a viable valuation theory. The proportion of reduced-form tangible and intangible innovations in fundamental and nonfundamental shocks is also explored in order to assess the value relevance quality of tangible information. We used quarterly data collected over an eleven-year period and suggested that price anomaly phenomena are

[4] According to Daniel and Titman (2006) and Lee (2006), tangible information is about a firm's performance that can be concretely observed in its accounting statements. Intangible information refers to non-accounting performance measures, which primarily reflect future corporate performance expectations. Furthermore, Lee (2006) observed that the terminology of tangible and intangible information is related to a behavioral finance interpretation, whereas that of fundamental and non-fundamental information is based on conventional valuation model-based interpretation.

prevalent in the markets because prices take time to incorporate fundamental information while nonfundamental shocks exert considerable influence on short-term price movements.

Our first major result confirmed that fundamental information comprises tangible accounting information rather than intangible market information. Conversely, nonfundamental shock was associated with intangible rather than tangible accounting news, with the exception of the cement industry. This result provides evidence that the valuation variables incorporated into the RIM can capture the information content of Taiwan's stock prices, supporting RIM as a viable theory for stock valuation in Taiwan. The aggregate and plastics-chemistry markets showed the highest share of tangible news in composing fundamental shocks, indicating their accounting information is the most value relevant among the six markets. Moreover, these two markets also showed the lowest share of tangible information in nonfundamental shocks, proving that their accounting numbers are the least noisy. On the other hand, the cement industry showed the least relevant and most noisy tangible information among the markets studied.

Second, utilizing impulse response functions (IRF), the five industrial sectors generally showed short-term price underreactions to fundamental shocks while the aggregate market result was less definite. Regarding nonfundamental shocks, an overreaction was observed across all six markets. Forecast error variance decomposition (FEVD) similarly showed that nonfundamental shocks generally dominate fundamental shocks in explaining short-term price variations. This is evident in the IRF and FEVD analyses and thus suggests that investors tend to overreact to nonfundamental shocks and underreact to fundamental information in the short-term. In view of the previously described correspondence between tangible and fundamental and between intangible and nonfundamental, the overall observed behavior is consistent with the overconfidence hypothesis of Daniel *et al.* (1998) wherein investors overreact to private news while underestimating the precision of public information. That is, investors who overestimate intangible private news tend to overreact to nonfundamental shocks. When investors underestimate the precision of tangible public information, they are also effectively underreacting to fundamental shocks composed primarily of tangible signals.

Lastly, we found that the aggregate market exhibits the fastest convergence toward the long-run equilibrium followed by the plastics-chemistry market after a shock hits. This suggests that the two markets have pricing mechanisms of the highest efficiency. In contrast, the cement industry has the slowest long-term price adjustments, indicating the lowest pricing efficiency

among the six sectors. We noticed that the two fastest adjusting markets are the ones that offer the most relevant and least noisy tangible information, whereas the least efficient cement market is the one offering the least relevant and most noisy tangible information. Consequently, we conjecture that pricing efficiency in a market may depend upon the quality of its tangible information in terms of high relevance and low noise. Higher quality of tangible information is likely to speed up the price convergence in a market. The cross-market pricing efficiency findings also have practical implications in formulating investment or arbitrage strategies, because investors can target their trades at the sectors taking longer to converge to fundamental equilibrium.

The remainder of this paper is organized as follows. Section 2 offers a brief review of the research literature on market anomalies, behavioral finance theory, and basic valuation models. Section 3 describes research methodology, Sec. 4 introduces the data and presents the results, and Sec. 5 concludes the paper.

2. Background Discussions

This article investigates changes in Taiwan's stock prices in response to structural shocks. This section briefly reviews the empirical findings and methods used to study market anomaly followed by three behavioral finance theories proposed to explain anomalies. It ends with a discussion of basic valuation models, including our choice of RIM.

2.1. *Market anomaly evidence and approach*

Efficient Market Hypothesis (EMH) proposes that risky asset prices can fully reflect relevant information about intrinsic values in a timely manner. Under the strong form of an EMH, no arbitrage opportunity exists that allows investors to earn excess risk-adjusted returns. Nevertheless, numerous studies have found results that reject the non-profitable prediction for rationally efficient markets. Williams (1956) observed that biased perceptions of investors could cause price overreactions, which will recede only gradually through offset trading. DeBondt and Thaler (1985) documented a long-term market reversal resulting from a negative association of three and five-year returns with future returns. Recently, Daniel and Titman (2006) showed that five-year stock returns are negatively associated with future returns over time spans of up to twelve months. On the other hand, Lo and MacKinlay (1988) examined weekly returns of NYSE stocks and found positive serial

correlations over short time horizons, a result indicative of price momentum, which can be interpreted as price underreaction to news. Price underreaction has also been found in other studies, including those by Bernard and Thomas (1990), Gaa (2008) and Hirshleifer *et al.* (2009).

Regarding modeling approach, the above-mentioned momentum and reversal anomalies are inferred mainly from stock return correlations measured over non-overlapping periods of various lengths. One potential drawback of this correlation approach is its inability to identify what the economic shocks are that might cause the correlations. The other weakness is that a few correlations, possibly calculated over arbitrarily chosen time intervals, cannot capture complete price response patterns over a continuous time horizon. In contrast to a correlation measure, an impulse response function in the time-series method framework can reflect the entire picture of price responses on a time line, as evident in the analytical IRF employed by Daniel *et al.* (1998). They demonstrated that a momentum anomaly, or positive return autocorrelation, is consistent with investor's *overreaction* to nonfundamental private shocks. However, when using the correlation approach, such positive return correlation is often interpreted as price *underreaction*. We decided to utilize time-series vector autoregression (VAR) model, which is conducive to an IRF analysis and has been applied extensively to stock price research in the past (e.g., Lee, 1998, 2006; Liu and Wang, 2001).

2.2. *Behavioral interpretation of time-series results*

In response to empirical findings that are incompatible with the assumptions of investor rationality and EMH, behavioral finance theories are proposed to investigate the investors' psychological biases. Prominent behavioral theories, including those developed by Daniel *et al.* (1998), Barberis *et al.* (1998) and Hong and Stein (1999), have been used to explain price anomalies.

The central theme of Daniel *et al.* (1998) theory is that investors are overconfident about private signals and ignore public information. As a result, price reflects an investor's overreaction to private information and their underreaction to public information. If investor's overconfidence is influenced by investor's biased self-attribution, then an overreaction to private information may intensify, showing price momentum with an eventual reversal, which results in a hump-shaped response curve. In contrast, an overreaction that is consistently correcting will show a slide-shaped response curve subsiding toward the long-run response level. Concurrently, the theory of Barberis *et al.* (1998) suggests that conservatism could cause investors who

face information events with weak consistency to underreact, setting off a short-term momentum. In contrast, when investors receive a consistent series of information, they suffer from representativeness bias and tend to overreact, which leads to an eventual price reversal.[5] Hong and Stein (1999) argued that gradually diffusing private information might give rise to short-term price underreaction to this information, whereas momentum-chasing strategies made profitable by short-term price underreactions will result in an overreaction over longer time span. The resulting price response pattern also shows a hump-shaped curve.

One criticism of behavioral theories is that a theory may be vague in terms of the specific kind of information associated with a psychological bias. For instance, Barberis *et al.* (1998) categorized the information in their model as either good or bad without specifying its exact content.[6] Thus, conservatism and representativeness should influence investor sentiment in the face of various types of information. The overconfidence hypothesis of Daniel *et al.* (1998) may also be applicable to other orthogonal pairs of economic shocks, even though it originally designated a public-private pair of information shocks. Along this line, Daniel and Titman (2006) referred to the overconfidence theory to interpret stock price behaviors in response to a tangible−intangible pair of information. Similarly, Lee (2006) suggested that reactions of the Dow Jones and S&P 500 indices to tangible and intangible shocks are compatible with the overconfidence theory.

Despite plenty of existing research on fundamental versus nonfundamental shock effects (e.g., Allen and Yang, 2004; Binswanger, 2004; Black *et al.*, 2003; Chung and Lee, 1998; Falk and Lee, 1998; Jean Louis and Eldomiaty, 2010; Lee, 1998), few have been analyzed in relation to behavioral finance theory.[7] We suggest that the behavioral theory of Daniel *et al.* (1998) is appropriate to interpret our work, which classifies stock market shock sources as fundamental and nonfundamental. Specifically, we claim that overconfident investors who overestimate private information are likely to overreact to nonfundamental shocks comprised mainly of intangible news, whereas

[5] An empirical implication of Barberis *et al.* (1998) is that one can obtain auxiliary proxies for information strength and consistency to measure the effect of representativeness and conservatism, respectively. This "proxy approach" is frequently performed in cross-sectional regression analysis but is much less frequently found in time-series analysis models.

[6] Chang (2007) indicated that even though the specific information Barberis *et al.* (1998) modeled originates from earnings announcements, their model itself does not distinguish between different types of information.

[7] Zhong *et al.* (2003) is an exception in that they did refer to both Daniel *et al.* (1998) and Hong and Stein (1999) to explain US stock price deviations from the fundamental values.

investors underestimating tangible public information tend to underreact to fundamental tangible information.

2.3. *Basic valuation theory*

Dividend discount model (DDM) is most prominent among parsimonious valuation theories, and it is included in most finance textbooks. A competing model, which takes a distant second place, is the earnings capitalization model (ECM) (Miller and Modigliani, 1961; Miller and Rock, 1985). However, ECM has attracted much attention from practitioners because future corporate earnings can be forecasted with greater ease compared to dividends that are subject to corporate discretion.[8] Nevertheless, dividends and earnings series are independently useful in measuring shareholder cash flows; therefore, modeling both factors simultaneously will increase valuation accuracy. Lee (1996, 1998) adopted this approach to compare the relative roles of dividends and earnings in stock valuation.

The valuation theory of our choice based on residual income model is algebraically equivalent to DDM but appears to use solely accounting numbers in valuation. RIM was an early concept traceable back to Preinreich (1938) and later elaborated by Edwards and Bell (1961) and Peasnell (1981, 1982). However, the model has begun winning popularity in valuation research only after Ohlson (1991, 1995) and Feltham and Ohlson (1995) designed a linear and flexibly adaptable specification for RIM.

On the empirical validity of the models, prior research indicated that RIM has better valuation implications than DDM (Penman and Sougiannis, 1998; Dechow *et al.*, 1999). In a more recent comparison of the value relevance between RIM and the earnings capitalization model, Ashbaugh and Olsson (2002) and Ndubizu and Sanchez (2006) found that RIM outperforms ECM.

In terms of research data structure, most studies were conducted using cross-sectional or panel company data. Few studies, e.g., Jiang and Lee (2005) and Lee (2006), used multivariate time-series methods with longitudinal data to compare the valuation performance of the models. Both these articles investigated the DJIA and S&P 500 markets and concluded that RIM has better compatibility with the aggregate stock market data than DDM. In another study on Taiwan's industrial stock sectors, Lee (2007) applied panel cointegration tests and found that RIM forecasted stock prices more

[8]Empirical valuation research that focuses on earnings figures includes Crowder and Wohar (1998) and Liu and Wang (2001).

accurately than DDM. These documented advantages of RIM have motivated this study to set up a VAR and VMA based on RIM theory.

3. Research Methodology

3.1. *Residual income model*

RIM postulates that book value along with present value of all future residual income streams determines fair stock price according to

$$P_t = B_t + \sum_{i=1}^{\infty} \beta^i E_t[\mathrm{RI}_{t+i}]. \tag{1}$$

Residual income is defined by

$$\mathrm{RI}_t = X_t - rB_{t-1}, \tag{2}$$

where RI equals earnings X_t minus beginning-of-period book value B_{t-1} times the rate of equity required return r. This in turn is assumed to be equal to the discount rate for present value calculation, i.e., $\beta = (1 + r)^{-1}$.

Campbell and Shiller (1987) asserted that DDM contains, although implicitly, a long-term equilibrium relation between price and dividends. Applying the same principle to RIM, Jiang and Lee (2005) set up a cointegrating spread among price, book value, and residual income, denoted by

$$S_t = P_t - B_t - \theta \mathrm{RI}_t, \tag{3}$$

where $\theta = r^{-1}$. With Eq. (3) defined as above, Eq. (1) can be rewritten as

$$S_t = (1 + \theta) \sum_{i=1}^{\infty} \beta^i E_t[\Delta \mathrm{RI}_{t+i}]. \tag{4}$$

This alternative RIM expression confirms that the spread S_t reflects a stationary cointegration relation because the RHS terms in Eq. (4) will add up to a stationary value, given each $\Delta \mathrm{RI}_{t+i}$ is stationary. Lee *et al.* (1999), Jiang and Lee (2005), and Lee (2006) have upheld similar cointegrations among price, book value, and residual income.

3.2. *VAR and VMA representations*

In a bivariate VAR set up based on RIM, Lee (2006) redefined the spread in Eq. (3) to reflect the relation between stock price and a modified residual income, $\mathrm{MRI}_t = B_t + \theta \mathrm{RI}_t$, as shown by

$$S_t = P_t - \mathrm{MRI}_t = P_t - (B_t + \theta \mathrm{RI}_t). \tag{5}$$

Lee then grouped the first-differenced MRI and S_t into a bivariate VAR

$$\begin{bmatrix} \Delta\text{MRI}_t \\ S_t \end{bmatrix} = \begin{bmatrix} \text{A}_{11}(\text{L}) & \text{A}_{12}(\text{L}) \\ \text{A}_{21}(\text{L}) & \text{A}_{22}(\text{L}) \end{bmatrix} \begin{bmatrix} \Delta\text{MRI}_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^{\text{T}} \\ e_t^{\text{IT}} \end{bmatrix}, \tag{6}$$

where $\text{A}_{ij}(\text{L})$ are polynomials in the lag operator L of order k for $i, j = 1, 2$. We denote the first disturbance term as e^{T} to give it a tangible innovation interpretation, as its dependent variable, ΔMRI, comprises information from accounting records. The second disturbance term e^{IT} represents intangible news originating from the market that drives a wedge between stock price and the level indicated by MRI, according to Eq. (5). The two disturbances are correlated, as market assessment and accounting performance measures tend to move together over business cycles.

Inverting the VAR in Eq. (6) yields the bivariate vector moving average (VMA) representation, $z_t = \text{R}(\text{L})e_t$, shown explicitly as

$$\begin{bmatrix} \Delta\text{MRI}_t \\ S_t \end{bmatrix} = \begin{bmatrix} \text{R}_{11}(\text{L}) & \text{R}_{12}(\text{L}) \\ \text{R}_{21}(\text{L}) & \text{R}_{22}(\text{L}) \end{bmatrix} \begin{bmatrix} e_t^{\text{T}} \\ e_t^{\text{IT}} \end{bmatrix}, \tag{7}$$

where $\text{R}_{ij}(\text{L})$ contains the reduced-form IRFs associated with tangible and intangible innovations. To facilitate economic interpretations, we use an identification scheme to obtain a structural VMA that provides the IRFs with respect to orthogonal structural shocks. Following Lee (1998) and Chung and Lee (1998), we assume that this structural VMA consists of fundamental ε_t^{f} and nonfundamental ε_t^{n} shock components, as shown in

$$\begin{bmatrix} \Delta\text{MRI}_t \\ S_t \end{bmatrix} = \begin{bmatrix} C_{11}(\text{L}) & C_{12}(\text{L}) \\ C_{21}(\text{L}) & C_{22}(\text{L}) \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\text{f}} \\ \varepsilon_t^{\text{n}} \end{bmatrix} \tag{8}$$

or compactly as $z_t = C(\text{L})\varepsilon_t$, which supplies the IRFs for S_t and ΔMRI with respect to the structural shocks.

3.3. *Structural VMA identification*

To identify the structural VMA from the reduced-form $z_t = \text{R}(\text{L})e_t$, we need four equations to solve four elements in a 2×2 matrix B in the relation

$$\varepsilon_t = Be_t. \tag{9}$$

Then we can obtain the structural VMA according to

$$C(\text{L}) = \text{R}(\text{L})B^{-1}. \tag{10}$$

To this end, the 2×2 symmetric covariance matrix

$$I \equiv E(\varepsilon_t \varepsilon_t') = BE(e_t e_t')B' \equiv B\Sigma B', \tag{11}$$

provides three restrictive equations to identify matrix B.

An additional restriction for structural identification comes from our assumption that MRI is affected in the long-run only by the fundamental shock while nonfundamental shock affects MRI only in the short-run. This assumption is characterized by a zero long-term effect of $\varepsilon_{\mathrm{f}}^{\mathrm{n}}$ on ΔMRI,

$$C_{12}(1) = 0 \quad \text{or} \quad \sum_{k=0}^{\infty} C_{12}^{k} = 0, \tag{12}$$

which restricts the long-term VMA representation, $z_t = C(1)\varepsilon_t$, to be

$$\begin{bmatrix} \Delta\mathrm{MRI}_t \\ S_t \end{bmatrix} = \begin{bmatrix} C_{11}(1) & 0 \\ C_{21}(1) & C_{22}(1) \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\mathrm{f}} \\ \varepsilon_t^{\mathrm{n}} \end{bmatrix}. \tag{13}$$

The long-run version of Eq. (10),

$$C(1)B = \mathrm{R}(1), \tag{14}$$

now provides the fourth equation required for exact identification of matrix B. Upon completing the identification, we then follow Lee (2006) by using the stock price equation

$$P_t = \mathrm{MRI}_t + S_t \tag{15}$$

to obtain the impulse responses of stock price to structural shocks, followed by performing price forecast-error variance decompositions.

3.4. *Composition of structural shocks by reduced-form news*

An original analysis in this research involves the examination of elements in matrix B to shed light on how fundamental and nonfundamental shocks relate to tangible and intangible innovations. To show this, display Eq. (9) explicitly as

$$\begin{bmatrix} \varepsilon_t^{\mathrm{f}} \\ \varepsilon_t^{\mathrm{n}} \end{bmatrix} = \begin{bmatrix} b_{\mathrm{f,T}} & b_{\mathrm{f,IT}} \\ b_{\mathrm{n,T}} & b_{\mathrm{n,IT}} \end{bmatrix} \begin{bmatrix} e_t^{\mathrm{T}} \\ e_t^{\mathrm{IT}} \end{bmatrix}. \tag{16}$$

A nonzero $b_{\mathrm{n,T}}$ obtained means that tangible information contains noise content irrelevant to fundamental valuations. Such nonfundamental elements within tangible news may arise from accounting manipulations or deficiencies in measurement techniques. The upper-right element $b_{\mathrm{f,IT}}$ is also likely nonzero, as stock markets do play a role in disseminating value relevant private news.

To facilitate the analysis, we define a ratio $|b_{\mathrm{f,T}}/b_{\mathrm{f,IT}}|$ to indicate the value relevance of tangible information. A high relevance ratio means that tangible news is highly relevant and contributes more to the fundamental information compared to intangible private news. A second noise ratio defined by $|b_{\mathrm{n,T}}/b_{\mathrm{n,IT}}|$ measures the proportion of nonfundamental noise contributed by tangible news relative to intangible news. Higher noise ratio suggests noisier tangible information, resulting in larger tangible-related mispricing in the market.

4. Empirical Result and Analysis

4.1. *Preliminary analysis*

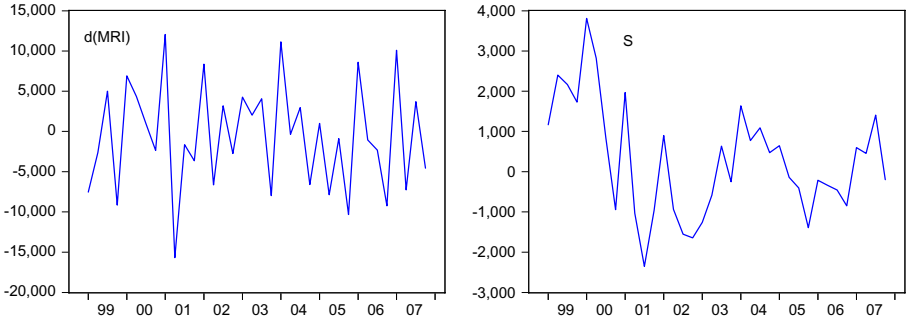
4.1.1. *Data description*

This paper investigates temporal stock price responses by estimating bivariate VARs based on RIM. Previous research that has adopted a similar setup (e.g., Lee, 2006) used aggregate stock market data as samples. To broaden the application range for this design, we use both industrial sector and aggregate stock market data collected in Taiwan. Five important industries are selected for study based on their high trading volume rankings, which are electronics, finance, plastics-chemistry, electric machinery, and cement. The data was collected between 1998:Q3 and 2008:Q2, supplying 240 data points.

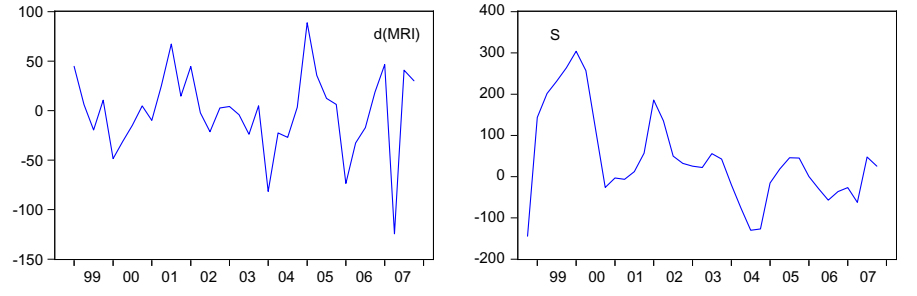
Calculation of MRI and the spread ($S_t = P_t - \mathrm{MRI}_t$) requires four raw data series: Stock price, earnings, book value, and cost of equity/discount rate (r). The prices examined for the six markets reflected the Taiwan composite stock index (TAIEX) and the respective industrial sector stock indices. Since no earnings (E) and book value (B) data series associated with the six stock indices are directly available, we computed the earnings data by dividing an index P by an index price-to-earnings (P/E) ratio. Likewise, we obtained the book value data by dividing an index P by an index price-to-book (P/B) ratio. The Taiwan Stock Exchange (TWSE) contains P/B and P/E data going back to the third quarter of 1998. We then apply Eqs. (2) and (3) to calculate MRI, with the cost of equity/discount rate proxied by the average of commercial paper rates during the sample period.

4.1.2. *Unit root tests*

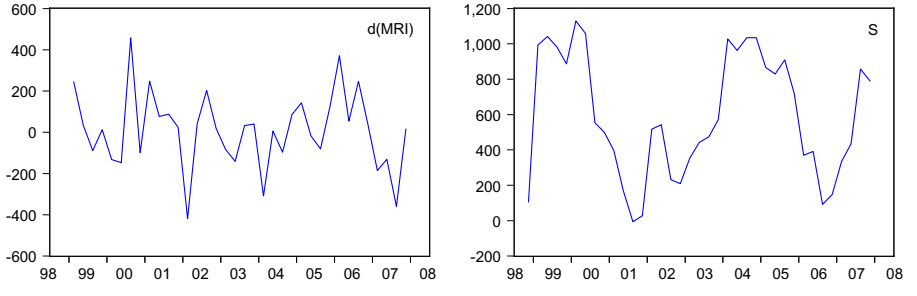
The empirical analysis begins by verifying whether the VAR variables, $\Delta\mathrm{MRI}_t$ and S_t, are both stationary, to assure that a spurious regression that Granger and Newbold (1974) specified would not be an issue for our bivariate VARs. We implemented unit root tests using both Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) test methods. To determine whether



(a) Aggregate market data



(b) Electronics industry data



(c) Finance industry data

Fig. 1. Modified residual income ΔMRI_t and spread S_t series of aggregate stocks and two industries in Taiwan over the period 1998Q3−2008Q2.

a time trend is present in the series and whether a constant term needs to be included in test regression, we first plotted the data series in Fig. 1 for visual screening.[9] We then compared the regressions with and without a constant before choosing a final test regression. Test results in Table 1 suggest that

[9]In Fig. 1, we only show the data series of Taiwan's aggregate market, electronics, and finance industries to save space. We will provide plots for the other industries upon request by readers.

Table 1. Augmented Dickey–Fuller and Phillips–Perron unit root test results.

	Level MRI			First Diff. MRI			Level Spread		
Industry	ADF	PP	Model Lag Length	ADF	PP	Model Lag Length	ADF	PP	Model Lag Length
Aggregate	0.348	1.831	1	-10.358^{***}	-10.655^{***}	1	-3.093^{***}	-3.033^{***}	2
	(0.780)	(0.982)		(0.000)	(0.000)		(0.003)	(0.003)	
Electronics	−0.120	−0.137	1	-5.475^{**}	-5.474^{**}	1	-2.843^{***}	-2.650^{***}	1
	(0.123)	(0.134)		(0.000)	(0.000)		(0.005)	(0.009)	
Finance	−1.423	−1.478	3	-5.831^{***}	-5.831^{***}	3	-3.236^{**}	-2.809^{*}	4
	(0.142)	(0.128)		(0.000)	(0.000)		(0.027)	(0.067)	
Electric machinery	−1.101	−1.101	5	-2.201^{**}	-4.649^{***}	5	-4.171^{**}	−2.457	9
	(0.241)	(0.241)		(0.029)	(0.000)		(0.015)	(0.136)	
Plastics-chemistry	4.011	−3.598	1	-1.915^{**}	-3.401^{***}	1	-4.548^{***}	-4.746^{***}	3
	(0.999)	(0.999)		(0.054)	(0.001)		(0.000)	(0.000)	
Cement	−0.295	−0.042	1	-6.609^{***}	-11.475^{***}	1	17.271^{***}	−0.715	17
	(0.572)	(0.689)		(0.000)	(0.000)		(0.000)	(0.399)	

Note: *, **, *** indicate significant test statistics at the 10%, 5%, 1% levels, respectively to reject the null hypothesis of a unit root. The appropriate lag length is determined by the AIC and SBC criteria.

MRI_t was nonstationary for all six stock markets. Its first difference, ΔMRI_t, was stationary since the unit-root null hypothesis was rejected at the 0.01 significance level. Thus, we infer that MRI_t is indeed a nonstationary I(1) series. In contrast, S_t is found to be a stationary I(0) series, as the unit-root null is rejected at the 0.01 level across the sectors. According to Eq. (5), the stationary spreads imply that P_t and MRI_t are cointegrated for the Taiwan data.

4.2. *Composition of structural shocks by tangible and intangible news*

Upon identifying the structural VMA, we analyzed matrix B in Eq. (16) to compare the contribution of tangible and intangible innovations to fundamental and nonfundamental shock compositions. As defined, when the tangible news is more relevant, it comprises a greater percentage of fundamental shocks. We conjecture that tangible news contains much more useful valuation information compared to intangible news, irrespective of possible accounting manipulations and measurement errors. On the other hand, when tangible news constitutes a larger share of nonfundamental shocks, the noisier the tangible news becomes. In such cases, noisy tangible news provides ample misleading signals for stock valuations.

The coefficient elements obtained for matrix B are shown in Table 2, along with the measures of tangible *relevance* and *noisiness* for the six markets, both defined in Sec. 3.4. The first two columns show that tangible news unanimously constitutes a higher proportion of fundamental shock compared

Table 2. Tangible/intangible source of structural shocks.

	Fundamental Shock			Nonfundamental Shock		
Market	Tangible News $b_{\text{f,T}}$	Intangible $b_{\text{f,IT}}$	Tangible Relevance	Tangible News $b_{\text{n,T}}$	Intangible $b_{\text{n,IT}}$	Tangible Noisiness
Composite	0.00017	−0.00004	4.25[2]	−0.00016	0.00128	0.13[6]
Electronics	0.0268	−0.0126	2.13	0.0053	0.0182	0.29
Finance	0.0111	0.0066	1.68	0.0057	0.0089	0.064
Electric machinery	0.0059	0.0044	1.34	−0.0013	0.0019	0.68
Plastics-chemistry	0.0644	0.0108	5.96[1]	−0.0041	0.0255	0.16[5]
Cement	0.0138	−0.0117	1.18[6]	0.0520	0.0236	2.20[1]

Note: Tangible relevance is measured by $|b_{\text{f,T}}/b_{\text{f,IT}}|$ and tangible noisiness by $|b_{\text{n,T}}/b_{\text{n,IT}}|$. Superscripts 1, 2, 5 and 6 indicate the cross-market rankings in tangible relevance and noisiness. Tangible and intangible weights are from matrix B in Eq. (16) obtained via structural identification.

to intangible news. The highest $|b_{\mathrm{f,T}}/b_{\mathrm{f,IT}}|$ ratio of 5.96 appears in the plastics-chemistry, followed by a 4.25 for the TAIEX, suggesting that the two markets' tangibles are the most relevant. The lowest ratio of 1.18 for the cement industry makes its tangible information the least relevant across the sectors.

The fourth and fifth columns in Table 2 show that tangible news is generally less important to nonfundamental shock compared to intangible news, as measured by $|b_{\mathrm{n,T}}/b_{\mathrm{n,IT}}|$. The only exception is the cement industry, where the tangible information contributes more to nonfundamental shock compared to the intangible, as its noisiness ratio of 2.20 shown in the sixth column is the only one that is larger than unity. We reason that unrealistically conservative accounting practices that cause intangible news to exert a high influence on stock valuations are most likely to cause the noisier tangible rather than intangible information in the cement industry.[10]

The lowest two noisiness ratios, 0.13 for the aggregate and 0.16 for plastics-chemistry stocks, indicate that they have the least noisy accounting information. However, the aggregate and plastics-chemistry contain the most relevant tangible news, as shown above. This inverse relation between the fundamental relevance and nonfundamental noisiness of tangible news suggests that high relevance and low noisiness may be two sides of the same coin, with either one being sufficiently indicative of tangible information quality.

4.3. *Structural VMA analysis*

4.3.1. *Price reaction to structural shocks*

We first identified the impulse response functions of $\Delta\mathrm{MRI}_t$ and S_t, and subsequently obtained the IRFs of stock prices according to Eq. (15).[11] Figure 2 shows the cumulative impulse responses to structural shocks for Taiwan's aggregate stock index. The fundamental shock produces a strong initial impact high above the long-term response level, followed by a strong reflex sending price far beneath the long-term level and subsequently by repeated and diminishing oscillations, which showed roughly equal occurrences of over- and under-reactions measured against the equilibrium response. This makes the short-run TAIEX mispricing pattern to fundamental

[10] The cement industry has a high proportion of fixed assets on its book, notably aged plants and vast land holdings, and over the past decade, the press has often reported huge discrepancies in the market value of its fixed assets above historical costs.

[11] The $\Delta\mathrm{MRI}_t$ and S_t IRF series and plots are not shown to save space, but are available upon request.

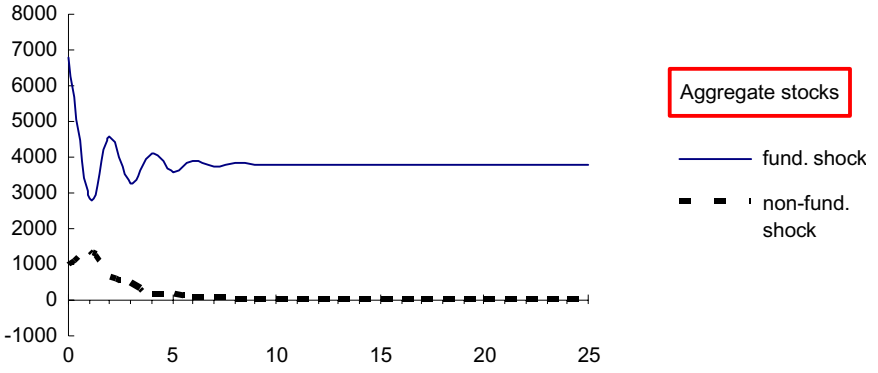


Fig. 2. Cumulative aggregate stock price response to structural shocks.

impulses indefinite. With respect to nonfundamental impulses, the aggregate market showed an unambiguous overreaction pattern over the short-run.

Figure 3 through 7 present prices in response to structural shocks for the five industries. Since the long-term effect of nonfundamental shocks on stock value is zero, any nonzero short-term response to nonfundamental shock is considered a price overreaction, whether positive or negative. Using this criterion, all six market sectors showed a short-term overreaction to non-fundamental shock. Short-term price reaction patterns to fundamental shock differ across the industries. The finance, electric machinery, and cement industries showed a consistent underreaction to fundamental shock in the short-term. In the other two sectors, electronics and plastics-chemistry, stocks showed an initial underreaction to fundamental shocks, followed by a medium-term overreaction and an eventual reversal.

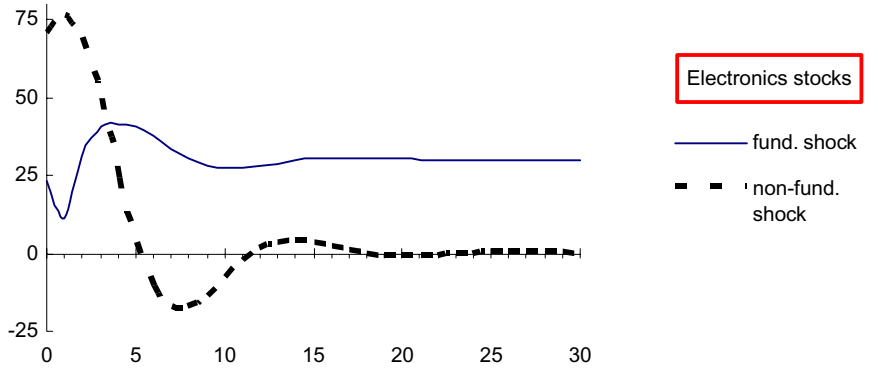


Fig. 3. Cumulative electronics stock price response to structural shocks.

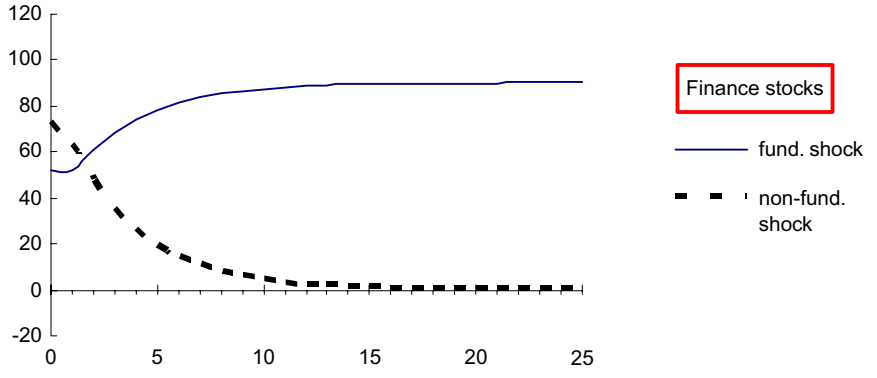


Fig. 4. Cumulative finance stock price response to structural shocks.

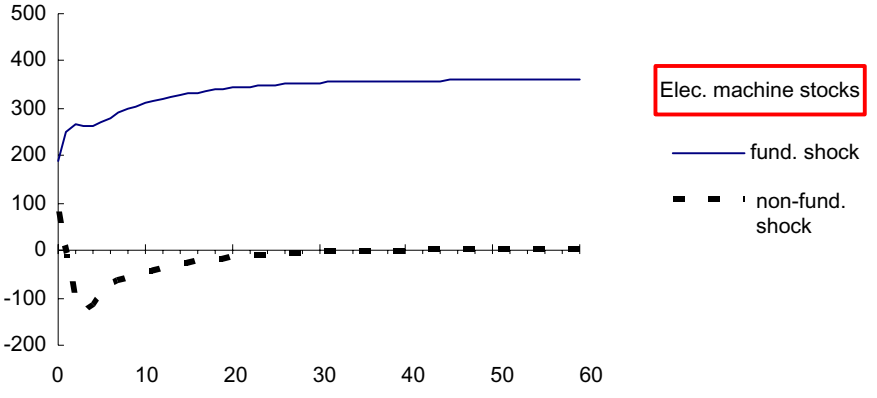


Fig. 5. Cumulative electric machinery stock price response to structural shocks.

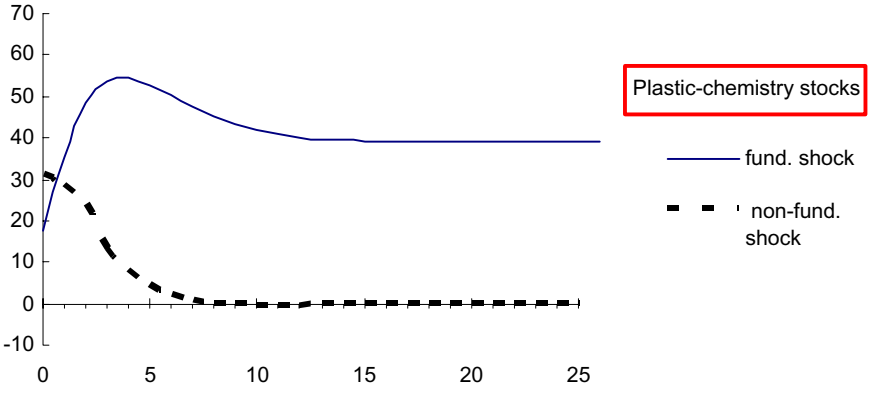


Fig. 6. Cumulative plastics-chemistry stock price response to structural shocks.

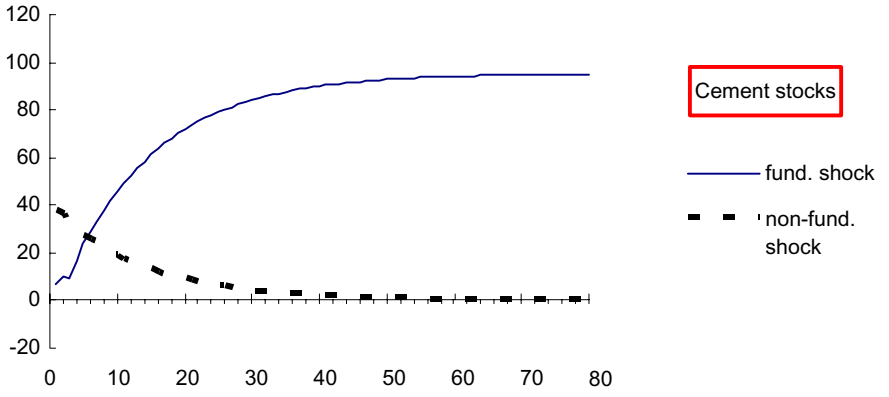


Fig. 7. Cumulative cement stock price response to structural shocks.

In summary, the IRFs of the Taiwan stock markets showed a general underreaction to fundamental shock and a consistent overreaction to nonfundamental shock in the short-term.[12] Since the analysis in Sec. 4.2 indicates that fundamental shock is highly associated with tangible information and that nonfundamental shock is associated with intangible news, our anomalous pricing findings appear consistent with the investor overconfidence theory proposed by Daniel *et al.* (1998). Specifically, overconfident investors who overweigh intangible private information are likely to overreact to nonfundamental shock. When overconfident investors underrate the signals present in public tangible information, they also tend to underreact to fundamental shock.

4.3.2. *Price variation accounted for by structural shocks*

Table 3 presents price forecast-error variance decomposition results for the six markets. For the aggregate market, fundamental shocks explain as much as 91% of the stock price variance upon impact. Fundamental shocks in the electric machinery industry are similarly more important compared to nonfundamental shocks in the short-term, the former explaining 81% of the variance upon impact. Nevertheless, the aggregate and electric machinery decomposition results suggest that their prices are under-influenced by fundamental shock and over-influenced by nonfundamental shock in the short-term, because fundamental shock should explain 100% of price forecast-error

[12]Despite that electronics and plastics-chemistry stocks show medium-run overreaction to fundamental shock in Figs. 3 and 6, initial underreactions to fundamental shock are also factually observed in these two industries. Moreover, short-run underreactions to fundamental shock are unambiguous in the other three industries.

Table 3. Stock price forecast error variance accounted for by structural shocks in the Taiwan stock markets.

	Composite Stocks		Electronics		Finance		Electric Machinery		Plastics-Chemistry		Cement	
Forecast Horizon	ε^{f}	ε^{n}	ε^{f}	ε^{n}	ε^{f}	ε^{n}	ε^{f}	ε^{n}	ε^{f}	ε^{n}	ε^{f}	ε^{n}
1	91.56	8.43	9.66	90.34	33.51	66.49	83.53	16.47	23.34	76.66	3.43	96.57
2	12.58	87.41	2.19	97.81	40.52	59.48	99.86	0.14	57.13	42.87	7.70	92.30
3	93.30	6.69	16.88	83.12	61.68	38.32	87.18	12.82	84.32	15.68	7.81	92.19
4	91.93	8.06	40.11	59.89	78.61	21.39	80.94	19.06	93.96	6.04	23.88	76.12
5	99.38	0.61	73.89	26.11	88.71	11.29	84.29	15.71	97.79	2.21	43.43	56.57
10	99.99	0.01	82.04	17.96	99.54	0.46	96.96	3.04	99.99	0.01	85.43	14.57
20	100.00	0.00	99.94	0.06	100.00	0.00	99.72	0.28	100.00	0.00	98.47	1.53
30	100.00	0.00	100.00	0.00	100.00	0.00	99.97	0.03	100.00	0.00	99.75	0.25
40	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	99.95	0.05
50	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	99.99	0.01
80	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00	100.00	0.00

Note: Stock price FEVDs use the IRFs of stock prices, which in turn are obtained from the IRFs of ΔMRI and S_t using Eq. (15). Notations ε^{f} and ε^{n} represent the fundamental and nonfundamental shocks, respectively.

variances and nonfundamental shock 0% of the variance in the equilibrium. For the remaining four industries, electronics, finance, plastics-chemistry, and cement, nonfundamental shocks account for a higher price variance compared to fundamental shocks early on, but the influence of fundamental shocks overtakes the influence of nonfundamental as forecasting horizon lengthens. The overall FEVD patterns agree with the general IRF result that stock prices underreact to fundamental shock and overreact to nonfundamental shock over the short-term.

4.3.3. *Speed of price adjustment to information*

We suggest judging the pricing efficiency in a market by the speed of information diffusion after a news shock occurs. The speed is measured by time lapsed between a shock occurrence and the eventual price convergence to an equilibrium response level. Pricing efficiency findings obtained for various markets are potentially useful to traders in formulating arbitrary strategies. This is because the longer a market price deviates from the long-term fundamental equilibrium, the more arbitrage opportunities are made available to traders. Table 4 displays the number of quarters lapsed prior to final convergence for the six sectors using the following criterion: Horizon l is the period of convergence if the IRF percentage deviation between horizons ($l-1$, l) and between horizons (l, $l+1$) are both less than 0.001. A manual check is also performed to ensure that any stabilization is not a local occurrence.

For the composite stock market, the oscillating price responses to fundamental shock, illustrated previously in Fig. 2, stabilized in the tenth

Table 4. Number of quarters required for price IRF to reach the long run.

	Response to Fundamental Shock		Response to Nonfundamental Shock	
Stock Market Sector	Quarter of Convergence	Convergence Speed Ranking	Quarter of Convergence	Convergence Speed Ranking
Aggregate	10	1st	8	1st
Electronic	17	4th	21	4th
Finance	16	3rd	16	3rd
Electric machinery	25	5th	33	5th
Plastics-chemistry	15	2nd	10	2nd
Cement	60	6th	51	6th

Note: Convergence speed toward the long run is one measure of information diffusion efficiency. The convergence quarters are obtained using the following criterion: Quarter l is the period of convergence if the percentage deviation of IRFs between horizons ($l-1$, l) and (l, $l+1$) are both smaller than 0.001 and if the stabilization is not local.

quarter. The nonfundamental shock effect converged during the eighth quarter to the long-term. In comparison, the five industrial index responses all took longer to converge than did the TAIEX, ranging from 15 to 66 quarters. Among them, the plastics-chemistry industry showed the fastest price adjustment speed, with fundamental and nonfundamental effects dying down in quarters 15 and 10, respectively. Recall that the aggregate and plastics-chemistry markets shown in Sec. 4.2 include the highest quality tangible news in terms of the highest fundamental relevance and lowest noisiness and show the highest pricing efficiency. On the contrary, the cement industry, previously found to contain the least relevant and most noisy tangible news, showed the slowest price adjustment speed and the lowest pricing efficiency in this study. These results seem to suggest that pricing efficiency and the quality of tangible information may be highly interdependent. That is, a market indicates faster adjustment speeds when the tangible quality is higher and intangible influence on intrinsic value determination is weaker.

5. Conclusion

This article uses a bivariate VMA model specified using RIM theory to examine stock price behavior resulting from fundamental and nonfundamental shocks in six stock markets in Taiwan. Our results support the market anomaly phenomenon, since short-term price responses in all six markets deviate from their equilibrium levels. As RIM indicates that stock price is determined by book value and residual income, our finding that fundamental shocks are primarily induced by tangible accounting information implies that RIM is consistent with the Taiwan stock market data and can model the joint behavior of price and accounting variables. Furthermore, IRF and FEVD analyses showed that nonfundamental shocks are generally more important compared to fundamental shocks in affecting short-term stock price movements. This important role of nonfundamental shocks suggests that investors often temporarily overreact to intangible news, a result consistent with the investor overconfidence theory in literature. Cross-market comparisons show that markets exhibiting the fastest price convergent speed have the best tangible news quality in the form of high fundamental relevance and low nonfundamental noisiness. This finding may have practical implications in that arbitragers can target their trades at the market sectors where price takes longer to converge toward the equilibrium.

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