



Research article

Examination of information release on return volatility: A market and sectoral analysis[☆]Mason Prasad, Walid Bakry^{*}, Maria Estela Varua

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ABSTRACT

This paper examines the role of information release in explaining the return volatility of the Australian equity market. The study applies proxies of greater accuracy to examine the effect of public and private information on return volatility. Analyst price targets (PTR) and Morningstar stock star ratings (MSR) were used as private information proxies while Australian Securities Exchange (ASX) announcements were used as the public information proxy. Daily data was collected for ASX 200 listed firms for the period 2013 to 2017. Analysis was conducted at both the aggregate market level and the sectoral level. Findings suggest that PTR have the largest effect on return volatility at both levels, with varied effects within each sector. This indicates that investors rely heavily on this information when undertaking investment decisions. In contrast, MSR had a negligible effect, likely due to the lower degree of informational content. Public information had a minor effect on return volatility at both the aggregate market and sectoral levels. These mixed results show that information flow varies depending on the information type (i.e. public or private) with each sector interpreting the same type of information differently. The research findings provide a valuable guide to investors regarding the appropriate information to generate excess returns as well as to hedge against future losses.

1. Introduction

Information plays a vital role in helping investors make investment decisions to improve their portfolio returns. Available information can be classified into two forms: public and private, which vary in their accessibility and informational content. With the vast body of information disseminated across various outlets (e.g. news stories, ASX announcements and analyst recommendations) it is not unexpected that investors may feel overwhelmed, leading to ineffective use of information thus negatively affecting their portfolios. [Vlastakis and Markellos \(2012\)](#) note that investors demand more information when their risk aversion increases, indicating that investors are likely seek out both private and public information to decrease their exposure to volatility. As each investor interprets information differently, it is natural to expect a myriad of reactions as there are variability in investor perceptions instigating stock return volatility. Further, different forms of information (public or private) are expected to initiate diverse levels of volatility partly explained by the differences in the demand for information, the time of release, cost of access and availability. The published literature

indicates that private and public information do not have the same effect on volatility ([Bradley et al., 2014](#); [Kreutzmann, 2010](#); [O'Shea et al., 2008](#); [Nguyen, 2010](#); [Tetlock, 2010](#); [Vega, 2006](#)). This discrepancy can be attributed to their different arrival times, whereby market participants with access to private information make investment decisions before public information holders. Thus, private information holders capitalise on its benefits to generate excess returns, contributing to market volatility. Moreover, there are different degrees of informational content in private and public information, causing varied effects on volatility. If excess volatility is identified, knowledge of the informational effects of private and public information on volatility can guide investors in making their investment decisions. If private information does not cause excess return volatility, investors are less likely to invest in obtaining private information since it does not present an opportunity to generate excess returns or hedge against future capital losses. However, if private information does elicit excess return volatility, this prompts investors to take advantage of this information type by signalling the direction of the stock price. For example, if private information indicates an increase (or decrease) in the stock price, investors can appropriately adjust their

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portfolio asset allocations to generate excess returns (or hedge against potential future capital losses).

Several past studies have attempted to understand the effect of private and public information on return volatility using various proxies to represent each information type. Examples of proxies used are trading volume, news releases, macroeconomic announcements and analyst buy/sell recommendations. However, limitations have also been identified regarding their accuracy that cause either an under- or overestimation of their effect on return volatility. This study aimed to overcome this problem by employing proxies of greater accuracy to gain a better understanding of how private and public information disclosures affect return volatility at both the aggregate market level and the sectoral level. The study is timely because only a limited number of Australian studies have performed comparatively at both the aggregate market and sectoral levels. Since the Australian market operates as a 'two-speed economy', in which some sectors are expected to be higher performing than others, investor expectations of sector performance vary accordingly (Deo et al., 2017). Consequently, some sectors may experience higher volatility than others, partly due to investor responses to information disclosures. It is hoped that the sectoral analysis can help investors better understand the sectoral composition of volatility in their portfolio, thus allowing them to adjust their sectoral exposure to match their risk preferences. Further, this paper informs investors of the similarities and differences in volatility across sectors that are due to private and public information, thereby assisting them in the portfolio diversification process.

2. Literature review

A thorough examination of the literature revealed that the available studies are limited in the way they measure the effect of private information on return volatility in the Australian market. This is partly due to the difficulty in selecting the appropriate proxy to accurately measure private information. Nevertheless, some studies have established a link between private information arrivals and return volatility.¹ However, because of the inconclusive and conflicting results of existing studies, further research is needed to identify more accurate measures of private information. Moreover, multiple studies have also established a relationship between public information and return volatility through proxies such as trading volume and media news releases. The limitations regarding the accuracy of these proxies demonstrate the need for improvements in the current measures of public information.

2.1. Public information proxies

Since Clark (1973) seminal paper on the mixture of distribution hypothesis (MDH), the relationship between trading volume and volatility has been exhaustively tested as the proxy for public information arrivals. For example, Berry and Howe (1994) used trading volume as a proxy for public information and argued that although there was a relationship between public information and trading volume, no link was found between trading volume and volatility in the United States (US) market. However, Kiyamaz and Berument (2003) successfully identified a significant relationship between trading volume and volatility across various international markets. They found that high volatility occurred during periods of low trading volume owing to the reluctance of liquidity traders to trade in periods of high volatility. In contrast to Kiyamaz and Berument (2003), Worthington and Higgs (2008) found that high stock return volatility occurred during periods of higher trading volume for ASX 50 stocks. Tetlock (2010) obtained a similar result. The mixed conclusions of Kiyamaz and Berument (2003), Worthington and Higgs (2008) and Tetlock (2010) could be explained by Andersen (1996), who argued that 34

to 75 per cent of daily trading volume was not attributed to public news release, which may explain the difference among the findings.²

To address the limitations of trading volume as a proxy, various studies have employed financial media headlines to capture specific public information events and their effect on volatility. For example, Edmonds and Kutan (2002) investigated the effect of various types of public macroeconomic news announcements on stock return volatility using the Nikkei 225 index. The results indicated a negative relationship between real gross domestic product announcements and stock return volatility. In contrast, the study found a positive relationship between balance of payment, balance of trade and consumer price index announcements and stock return volatility. Goonatilake and Herath (2007) also found a positive association between the number of public news disclosures and market volatility. Moreover, the authors argued that volatility persisted around the time of the news release but diminished over time. Nonetheless, these studies have limitations because they employed financial media outlets as the proxy for public information. Nguyen (2010) argued that media outlets experience three constraints in measuring public information accurately.³ Further, macroeconomic news announcements may not have the same effect on return volatility at the firm level as they do on an index level.

As a result of these constraints, Kalev et al. (2004) utilised firm-specific ASX announcements as a proxy for public information. Using a GARCH (1,1) model, the study found a positive relationship between firm-specific ASX announcements and stock return volatility. Kalev and Duong (2011) presented similar results, indicating a positive relationship between the number of ASX announcements at a given point in time and stock return volatility. While the abovementioned studies identified the existence and persistence of volatility, they did not attempt to determine the degree to which each *type* of firm-specific announcement affected stock return volatility. Such a distinction is important because each announcement type is likely to have varying effects on volatility based on the level of information content and information sensitivity. The current paper does not discount the usefulness of ASX announcements as they are considered to be highly accurate (Nguyen, 2010). Thus, this paper employs ASX announcements as a proxy for public information. However, unlike previous studies, each ASX company announcement is classified here into different categories of announcement to determine the direct effect of each category on return volatility.

Further, this paper classifies each category of announcement as either a scheduled or an unscheduled announcement. This helps in identifying the association between scheduled/unscheduled announcements and return volatility. DeGennaro and Shrieves (1997) employed such a method by disaggregating public macroeconomic announcements into scheduled and unscheduled news announcements to ascertain their effect on the Japanese Yen and the US dollar. The study found that scheduled news caused larger foreign exchange volatility compared with unscheduled news. Bauwens et al. (2005) also applied this method to EUR/USD currency data and found higher volatility for scheduled announcements. These studies have highlighted that volatility varies depending on the type of public announcement. However, this relationship has only been

² The mixed results may be attributed to the limitations of trading volume as a proxy for public information arrival. Trading volume does not provide insight into the informational content of the disclosures released in the market. This implies that trading volume cannot differentiate between how much of the change in volume is attributed to private and public information, providing mixed results.

³ The first constraint is that media information is not centrally released, which could result in prior trading occurring any point before it is released in central exchanges (including post-trading sessions and the pre-open trading period). Second, the information is not time-stamped, thereby preventing the ability to accurately measure volatility after the specific announcement. Last, the information may not be directly sourced from the company, thus causing the accuracy of the news announcements to be questionable (Nguyen, 2010).

¹ These studies placed great emphasis on analyst buy/sell recommendations and trading volume as proxies for private information signals, yielding an array of varying results.

examined for announcements at the macroeconomic level. Currently, no studies exist that have applied this disaggregation method at the firm level in the Australian equity market.

2.2. Private information proxies

Easley and O'Hara (1987) developed one of the first measures of private information, known as the probability of informed trading (PIN) model. Their findings indicated that large trades (block trades), in comparison with small trades, were made during times in which no public information was released, resulting in a subsequent price increase. The larger trade size during these periods highlighted the existence of informed trading, indicating that some market participants had access to more superior information than others. The PIN model successfully captured block trades by identifying abnormal returns generated within large capitalisation stocks since they consisted of clear block trades.⁴ The authors argued that order imbalances could partially explain the block trades, although this was not conclusively proven in the study. Tissaoui and Aloui (2014) empirically tested the relationship between block trades and order imbalances and its resulting effect on return volatility. A positive relationship was found between order imbalance and return volatility caused by abnormal returns generated during times of no public information release, indicating that private information was being utilised by blockholders. Brockman and Yan (2009) found that blockholders had a greater advantage because the cost of acquiring private information remained fixed, but that the information could be used to generate higher returns through making large trades. This resulted in an increase in the probability of informed trading as well as the firm-specific volatility.

Following Clark (1973) MDH model, Boussaidi (2013) employed trading volume as a proxy for private information to investigate the relationship between private signals and stock return volatility in the Tunis stock market. More specifically, he investigated whether overconfident investors overreact to private signals in the market and trade excessively (thereby increasing trading volume), causing price deviation and excess volatility. The results indicated a positive correlation between high trading volume and return volatility when no public announcements took place. However, this relationship was true for only one-third of the stocks in the sample. Manganeli (2005) explained that this was because the relationship between volume and volatility exists only in frequently traded stocks, presenting a problem when modelling volatility for infrequently traded stocks. Boussaidi (2013) trading volume proxy was also unable to capture the effect of private information on return volatility after unscheduled announcements.⁵

Bradley et al. (2014) used Thomson Reuters' Institutional Brokers Estimate System (I/B/E/S) estimates to analyse the informational content of analysts' buy/sell and upgrade/downgrade recommendations and their effect on abnormal returns. Their study found that downgrades result in larger negative abnormal returns compared with the positive abnormal returns for upgrades. The authors argued that upgrades in analyst recommendations resulted in large stock price increases at the start of the trading day. This suggests that investors who have access to

⁴ Brockman and Yan (2009) argued that the shortcoming of the PIN model is its inability to capture the potential of small capitalisation stocks to generate abnormal returns because they do not consist of clear block trades owing to their size. Thus, the model is unable to capture the effect of private information on abnormal returns generated by informed traders on small capitalisation stocks, and, consequently, volatility.

⁵ Boussaidi (2013) study did not capture unscheduled announcements because it established the start of the 'private information period' one month after each public announcement. However, this approach is only plausible for announcements that are scheduled in nature and occur only once a month. Further, most stocks consist of scheduled and unscheduled announcements thus making it near impossible to predetermine the 'private information period' for unscheduled announcements. This is due to the frequency of disclosure for each stock being unpredictable.

analyst recommendations react during the pre-opening period, generating abnormal returns once the market opens. Such a result highlights investors' beliefs that analysts have access to valuable private information not available to other market participants. Other studies have presented similar results, discovering that this holds true from anywhere between 2 hours and one month after the announcement (Barber et al., 1998; Green, 2006; Womack, 1996). The excess returns generated imply that there is potential for private information to influence volatility. The limitation of qualitative buy/sell and upgrade/downgrade recommendations is that they can cause analysts to herd, which strengthens the credibility of their own recommendation. The results of Jegadeesh and Kim (2009) and Desai et al. (2000) highlighted the existence of the herding phenomenon among analysts.⁶ PTR not only significantly minimise this potential for herding but also contain more informational content. This renders PTR an appropriate alternative to use as a private information proxy.

Bolster et al. (2016) and Bolster et al. (2017) utilised MSR to examine the nature and effect of individual stock ratings on abnormal returns. They found that when a stock rating was upgraded (downgraded), it experienced positive (negative) abnormal returns. Further, their results indicated that the abnormal return appeared to have lasted 30 days, implying that MSR may have contained private information. To date, these studies have examined the relationship between Morningstar's individual stock ratings and abnormal returns. However, no study so far has examined the extent to which the change (upgrade/downgrade) in MSR, as a proxy for private information, affects return volatility. MSR is deemed to be an appropriate proxy for private information because the ratings are not publicly available, which allows only investors with access to this information to capitalise on their potential benefits. Moreover, the persistence of abnormal returns for 30 days after the rating disclosure may indicate investors' belief that Morningstar analysts have access to superior information compared with other market participants.

3. Data

This study utilised stocks listed on the ASX 200 index, consisting of the largest 200 stocks by market capitalisation. The study employed daily data spanning the period 2 January 2013 to 29 December 2017. Stocks that were delisted during the period or did not have associated price targets or Morningstar ratings were excluded, leaving a total of 127 stocks remaining in the sample. Stocks were classified into sectors in accordance with the Global Industry Classification Standards (GICS). The daily closing stock prices for each company were obtained from the Thomson Reuters Eikon database. Each company provided 1,264 observations per year with a total of 160,528 observations across 127 companies for the entire study period. A total of 42,115 ASX announcement disclosures were recorded during the study period.

PTR were obtained from the Thomson Reuters Eikon database while MSR was obtained from the Morningstar Direct database. ASX announcements were gathered from the Morningstar DatAnalysis Premium database for each stock during the study period. ASX announcements represented all the public information disclosures explored in the study. Each ASX announcement was categorised into its respective ASX

⁶ The drawback of herding is that it results in a biased recommendation, which may not necessarily be provided by analysts' own individual interpretation of a company's fundamentals. These limitations are less prominent with PTR, since analysts are required to provide an exact dollar amount that the stock is forecasted to reach. As each brokerage firm has different levels of market information and operates on different assumptions as their counterparts, it would be difficult to reach the same price target.

Table 1. List of ASX announcements.

Variable	Announcement Type	Scheduled/Unscheduled Announcement
TO	Takeover	Unscheduled
SD	Shareholder details	Unscheduled
PER	Period report	Scheduled
QAR	Quarterly activity report	Scheduled
QCFR	Quarterly cash flow report	Scheduled
IC	Issued capital	Unscheduled
AAD	Asset acquisition and disposal	Unscheduled
NOM	Notice of meeting	Unscheduled
DA	Dividend	Scheduled
SEA	Stock exchange announcement	Unscheduled
PR	Progress report	Scheduled
CAD	Company administration	Unscheduled
NOC	Notice of call	Unscheduled
OT	Other	Unscheduled
CA	Chairman's address	Scheduled
LTS	Letter to shareholders	Scheduled
ASXQ	Australian securities exchange query	Unscheduled
WSP	Warrants and structured products	Unscheduled
CTE	Commitments test entity quarterly report	Scheduled

announcement type⁷ and was further classified as either a scheduled or unscheduled announcement.⁸ See Table 1.

Table 2 provides a summary of the descriptive statistics for the return, volatility, PTR and MSR for each of the panel sectors. The statistics reveal that all sectors provided a positive mean for the return variable across the study period, with the highest recorded by the Information Technology sector. The Information Technology sector also produced the lowest variability, measured by the standard deviation, for both PTR and MSR. This indicates that the Information Technology sector is an attractive sector to investors as it provides the highest return and the lowest risk.

4. Method

Based on Stărică and Granger (2005), logs were calculated for (1) returns with respect to the daily closing price, (2) PTR and (3) MSR. These are shown below:⁹

$$R_t = \text{Log Stock Returns} = \ln\left(\frac{Price_t}{Price_{t-1}}\right) \tag{1}$$

$$\text{PTR} = \text{Price target changes} = \ln\left(\frac{Target Price_t}{Target Price_{t-1}}\right) \tag{2}$$

$$\text{MSR} = \text{Morningstar stock star ratings changes} = \ln\left(\frac{Stock Star Rating_t}{Stock Star Rating_{t-1}}\right) \tag{3}$$

⁷ There were 19 announcement types based on the ASX's continuous disclosure requirements (ASX Listing Rule 3.1).

⁸ Scheduled announcements are defined as those that are 'periodic' and unscheduled announcements are those that are 'non-periodic' in nature (Mudalige et al., 2016).

⁹ The augmented Dickey-Fuller (ADF) and Phillips Perron (PP) tests were performed for each stock's closing price, PTR and MSR. Both tests indicated non-stationarity of the data. The first difference was taken, which subsequently confirmed the stationarity of the variables. Although the results of these tests are not reported in the paper itself, the results can be supplied by the authors on request.

4.1. Estimation of asymmetric volatility of individual stocks

Prior to the estimation of the asymmetric volatility, the optimal lag length for each stock's return was ascertained based on the lowest value from the following information criteria: Final Prediction Error information criterion, Akaike information criterion (AIC), Bayesian information criterion (BIC), Hannan-Quinn information criterion and Schwarz/Bayesian information criterion. E-GARCH, GJR-GARCH and APGARCH models were then estimated for each stock using maximum likelihood estimation (MLE) with a Gaussian (normal) distribution. Models that did not achieve a MLE using the Gaussian distribution were estimated under the Student's t-distribution (i.e. lower peak and fatter tails). If the model did not achieve an MLE under the Student's t-distribution, the generalised error distribution was specified, which is commonly used when the distribution contains non-normal errors.

Bollerslev (1986) GARCH (p,q) model was introduced to deal with the large lag structure required by the ARCH model to capture the dynamic behaviour of conditional variance. However, because the GARCH (1,1) model cannot capture the leverage effect, it was not an appropriate model to estimate return volatility for stocks. Therefore, the following asymmetric models were employed in this study: E-GARCH, GJR-GARCH and APGARCH¹⁰. These asymmetric models relax the non-negative constraints on parameters, although they differ in their methods of accommodating the leverage effect (i.e. asymmetry) based on their assumptions. Since it cannot be assumed that the volatility of each stock will behave identically in response to private and public information, more than one asymmetric model was applied. Additionally, employing multiple asymmetric models ensures that the estimation of return volatility is more reliable and hence robust (Kreinvovich et al., 2017).

Based on the associated leverage effect benefits, the following asymmetric GARCH models were employed and specified as follows.

4.2. E-GARCH model

Nelson (1991) proposed the E-GARCH model to rectify the limitations of the standard GARCH model, thereby capturing the leverage effect. The E-GARCH model is specified as follows:

$$\ln(h_t) = \alpha_0 + \beta \ln(h_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}^2}} + \alpha_1 \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] \tag{4}$$

where:

- h_t is the conditional stock return volatility at interval t
- α_0 is the intercept for the variance
- β is the coefficient for the natural logged GARCH term, which measures the magnitude and persistence of volatility
- $\ln(h_{t-1})$ is the logged GARCH term
- $\gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$ is the size of the asymmetric volatility. The sign of γ determines whether volatility is positive or negative and the value of γ determines the size of the shock (Brooks, 2014) and:

$\left[\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right]$ is the parameter capturing the absolute value of the previous period volatility shocks (this replaces the ARCH term).

¹⁰ In order to model the dynamics of volatility and time-varying risk premia, various asymmetric GARCH modelling was applied. Tests were carried out to ascertain the best asymmetric GARCH type model to be applied for each stock. Following Lashgari and Ahmadi (2014) the Hausman test was carried out to test for the problem of endogeneity through ascertaining the appropriateness of a fixed or random effects model. Based on the results, the model did not suffer from endogeneity.

Table 2. Descriptive statistics.

Sector	Variable	Number of Stocks	Mean	Standard Deviation	Skewness	Kurtosis	Obs.
Consumer Discretionary	Return	18	0.0000673	0.0184676	-0.9005753	28.4643	22,752
	Volatility		0.0000673	0.0184676	-0.8905730	28.5007	
	PTR		0.0004000	0.0107958	8.0684100	413.2820	
	MSR		0.0000052	0.0733617	-0.0063933	63.5391	
Consumer Staples	Return	7	0.0002257	0.0178178	-0.6778761	25.8297	8,848
	Volatility		0.0001235	0.0178112	-0.7033866	25.7918	
	PTR		0.0002141	0.0094747	1.9285300	232.3947	
	MSR		-0.0001375	0.0674750	0.5780013	67.7186	
Energy	Return	8	0.0004104	0.0245339	-0.0419588	11.7155	10,112
	Volatility		0.0004104	0.0245339	0.0006081	11.6959	
	PTR		-0.0002128	0.0083259	-2.4656140	171.9436	
	MSR		-0.0003247	0.0711119	-0.2829785	62.6485	
Financials	Return	19	0.0004340	0.0151098	-0.5612626	11.6348	24,016
	Volatility		-0.0000010	0.0151223	-0.5748406	11.5926	
	PTR		0.0004532	0.0050494	1.9719970	116.8178	
	MSR		-0.0001007	0.0482187	0.1310799	71.4758	
Health Care	Return	10	0.0005425	0.0193602	-7.4610870	290.4957	12,640
	Volatility		-0.0000513	0.0193569	-7.4284840	289.7961	
	PTR		0.0005447	0.0074860	-5.9651430	273.5259	
	MSR		0.0001190	0.0637708	0.3452860	55.7230	
Industrials	Return	14	0.0003709	0.0198342	-1.4457920	48.1850	17,696
	Volatility		0.0000144	0.0198328	-1.4324630	48.2664	
	PTR		0.0003658	0.0078523	0.2679940	256.9431	
	MSR		-0.0002646	0.0719443	-0.2352123	53.9823	
Information Technology	Return	5	0.0006661	0.0162931	-0.0291646	7.2371	6,320
	Volatility		0.0000111	0.0162903	-0.0385354	7.2608	
	PTR		0.0007233	0.0007233	5.8820070	100.9194	
	MSR		0.0007233	0.0007233	0.7032923	67.6024	
Materials	Return	23	0.0002802	0.0219777	-0.1252618	11.3004	29,072
	Volatility		0.0000520	0.0219763	-0.1177762	11.3156	
	PTR		0.0002432	0.0064721	2.1725330	98.0588	
	MSR		-0.0002699	0.0762443	-0.1580465	60.1607	
Real Estate	Return	15	0.0003438	0.0128239	0.0009799	5.9680	18,960
	Volatility		-0.0000343	0.0128231	-0.0063388	5.9669	
	PTR		0.0003575	0.0037558	8.0519920	202.4118	
	MSR		-0.0001187	0.0494165	-0.0803129	66.9731	
Telecommunications Services	Return	4	0.0003137	0.0165979	-0.1660377	28.4631	5,056
	Volatility		-0.0000778	0.0165972	-0.1699227	28.4544	
	PTR		0.0003459	0.0073430	2.8010380	121.6617	
	MSR		0.0000802	0.0718024	0.4747489	53.1471	
Utilities	Return	4	0.0003661	0.0121846	-0.1668716	5.0181	5,056
	Volatility		0.0001164	0.0121859	-0.1671390	5.0165	
	PTR		0.0004113	0.0031531	7.0662900	119.1726	
	MSR		-0.0002406	0.0528048	-0.2550396	72.0186	

4.3. GJR-GARCH model

Glosten et al. (1993) GJR-GARCH model, which is sometimes referred to as Zakonian (1994) threshold GARCH (TGARCH) model, introduced another approach to capture asymmetric effects by including an additional term in the equation. The GJR-GARCH model is as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q (\alpha_i \varepsilon_{t-i}^2 + \delta \varepsilon_{t-i}^2 d_{t-i}) + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \tag{5}$$

where:

- σ_t^2 is the conditional forecasted variance in time t
- α_0 is a constant
- $\alpha_1 \varepsilon_{t-1}^2$ is the GARCH term capturing the symmetric volatility

$\delta \varepsilon_{t-i}^2 d_{t-i}$ accounts for the effect that different past shocks have on the current conditional variance (asymmetry term)

$\beta_j \sigma_{t-j}^2$ is a parameter that captures the persistence of volatility

d_{t-i} is a dummy variable $d_{t-i} = 1$ if $\varepsilon_{t-i} < 0$ (bad news) and $d_{t-i} = 0$ if $\varepsilon_{t-i} > 0$ (good news)

4.4. APGARCH model

Ding et al. (1993) employed the asymmetric power GARCH (APGARCH) model to capture the leverage effect. This model nests as many as seven other ARCH extensions as special cases, such as ARCH (Engle, 1982), GARCH (Bollerslev, 1986), Taylor (1986)/Schwert (1990) GARCH, GJR-GARCH (Glosten et al., 1993), TGARCH (Zakonian, 1994), NARCH (Higgins and Bera, 1992) and Log-ARCH (Geweke, 1986; Pentula, 1986). The model is expressed as follows:

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^q \alpha_i (|\epsilon_{t-i}| - \gamma \epsilon_{t-i})^\delta + \sum_{j=1}^p \beta_j \sigma_{t-j}^\delta \tag{6}$$

where:

σ_t^δ is the conditional standard deviation
 α_0 is a constant
 α_i is the GARCH term that captures the symmetric volatility
 $\gamma \epsilon_{t-i}$ is a parameter that accommodates the leverage effect. If $\gamma > 0$, then past negative shocks have a large effect on current volatility relative to past positive shocks (Hentschel, 1995).

δ is the varying exponent. If a large negative shock is followed by another negative shock, the APGARCH model will account for this by estimating current volatility to be higher in the previous period—this causes volatility clustering—and

$\beta_j \sigma_{t-j}^\delta$ is a parameter that captures the persistence of volatility.

Following the estimation of all models, the best fitting model was chosen based on the lowest AIC and BIC value (Hamadu and Ibiwoye, 2010; Ding, 2011).¹¹ Asymmetric volatility was estimated for each stock by employing either the E-GARCH, GJR-GARCH or APGARCH models, depending on the optimal lag length.¹² The results indicated that across all sectors, the Student's t-distribution APGARCH model fitted the largest number of stocks.

4.5. Panel data regression

The panel regression analysis¹³ facilitated the verification of the following hypotheses using private (PTR and MSR) and public information proxies (ASX announcements¹⁴):

H_0 : MSR, PTR and ASX announcements for all stocks across the market and in the respective GICS sectors are not statistically significant in explaining the change in return volatility in the panel.

H_1 : PTR for at least one of the stocks across the market is positively associated with changes in return volatility in the panel.

H_2 : PTR for at least one of the stocks in each GICS sector is positively associated with changes in return volatility in the panel.

H_3 : MSR for at least one of the stocks across the market is positively associated with changes in return volatility in the panel.

H_4 : MSR for at least one of the stocks in each GICS sector is positively associated with changes in return volatility in the panel.

H_5 : ASX announcements for at least one of the stocks across the market are positively associated with changes in return volatility in the panel.

H_6 : ASX announcements for at least one of the stocks in each GICS sector are positively associated with changes in return volatility in the panel.

Mathematically, the model is specified as follows:

¹¹ Strictly adhering to the AIC and BIC selection criteria is important because simply selecting a model based on the highest number of significant parameters results in ‘data-snooping bias’ (Lo and MacKinlay, 1990).

¹² Three hundred and eighty-one asymmetric GARCH models were estimated across the sample of 127 stocks (three asymmetric models per stock).

¹³ Multicollinearity was tested using the correlation matrix, which calculates the correlation coefficient between each independent variable. A commonly followed correlation coefficient of 0.80 was applied (Brooks, 2014). A correlation coefficient produced by the correlation matrix that is greater than 0.80 would indicate multicollinearity. If multicollinearity is identified, judgement is made to remove one of the conflicting variables from the panel regression.

¹⁴ All public information proxies (ASX announcements) were represented as a dummy variable with a value of 1 if an announcement occurred and 0 otherwise.

$$h_{i,t} = c_{i,t} + \beta_1 PTR_{i,t} + \beta_2 MSR_{i,t} + \beta_3 TO_{i,t} + \beta_4 SD_{i,t} + \beta_5 PER_{i,t} + \beta_6 QAR_{i,t} + \beta_7 QCFR_{i,t} + \beta_8 IC_{i,t} + \beta_9 AAD_{i,t} + \beta_{10} NOM_{i,t} + \beta_{11} SEA_{i,t} + \beta_{12} DA_{i,t} + \beta_{13} PR_{i,t} + \beta_{14} CAD_{i,t} + \beta_{15} NOC_{i,t} + \beta_{16} OT_{i,t} + \beta_{17} CA_{i,t} + \beta_{18} LTS_{i,t} + \beta_{19} ASXQ_{i,t} + \beta_{20} WSP_{i,t} + \beta_{21} CTE_{i,t} + e_{i,t} \tag{7}$$

where:

$h_{i,t}$ = return volatility of firm i , in time t
 $c_{i,t}$ = intercept i.e. minimum return volatility of firm i , in time t , when changes in explanatory variables are zero
 $PTR_{i,t}$ = change in price target for each panel of stocks within the GICS sector at time t
 $MSR_{i,t}$ = change in Morningstar stock star rating for the panel of stocks within the GICS sector at time t
 $TO_{i,t}$ = takeover/scheme announcement of firm i , in time t
 $SD_{i,t}$ = shareholder details announcement of firm i , in time t
 $PER_{i,t}$ = periodic report announcement of firm i , in time t
 $QAR_{i,t}$ = quarterly activity report announcement of firm i , in time t
 $QCFR_{i,t}$ = quarterly cash flow report announcement of firm i , in time t
 $IC_{i,t}$ = issued capital announcement of firm i , in time t
 $AAD_{i,t}$ = asset acquisition and disposal announcement of firm i , in time t
 $NOM_{i,t}$ = notice of meeting announcement of firm i , in time t
 $SEA_{i,t}$ = stock exchange announcement (i.e. market updates and trading halts) of firm i , in time t
 $DA_{i,t}$ = dividend announcement of firm i , in time t
 $PR_{i,t}$ = progress report announcement of firm i , in time t
 $CAD_{i,t}$ = company administration announcement of firm i , in time t
 $NOC_{i,t}$ = notice of call announcement of firm i , in time t
 $OT_{i,t}$ = others announcement of firm i , in time t
 $CA_{i,t}$ = chairpersons's address announcement of firm i , in time t
 $LTS_{i,t}$ = letter to shareholders' announcement of firm i , in time t
 $ASXQ_{i,t}$ = Australian Securities Exchange query announcement of firm i , in time t
 $WSP_{i,t}$ = warrants and structured products announcement of firm i , in time t
 $CTE_{i,t}$ = commitments test entity quarterly report announcement of firm i , in time t
 $e_{i,t}$ = stochastic term (return volatility not captured by the explanatory variables).

The return volatility h_t , denoted as the asymmetric volatility (dependent variable) in the model was represented by the residuals generated from the best fitting models using the asymmetric volatility estimation process. For the aggregate market analysis, the residuals of all stocks were stacked and regressed against PTR, MSR and ASX announcements. For the sectoral analysis, the residuals for each stock were grouped and stacked together into each of their respective GICS sectors and regressed separately for each sector.

5. Results and discussion

A panel data regression analysis was carried out for the aggregate market and each of the GICS sectors. Fixed effects and random effects models were specified and the most appropriate model for each sector was selected using the Hausman specification test.¹⁵ Tables 3 and 4

¹⁵ The Hausman test was performed for the aggregate market and for each of the GICS sectors to test for endogeneity. The test failed to reject the null hypotheses deeming the random effects model the most appropriate for the aggregate market and all the GICS sectors. The non-rejection of the null hypothesis indicates that there was no correlation between the unique errors and the regressors in the model, thus no endogeneity has been identified. We also note that the fixed effect model produced similar coefficients to the random effects model at the same significance level. Therefore, there was minimal potential for bias to occur in the choice between the fixed and random effects model. Although the results of the fixed and random effects model are not reported in the paper itself, the results can be supplied by the authors on request.

Table 3. Panel regression: Aggregate market.

Variable	Coefficient	p-value
PTR	0.3908043	0.000***
MSR	-0.0605708	0.000***
TO	0.0032922	0.004**
SD	-0.0001278	0.458
PER	-0.0005126	0.076*
QAR	-0.0010012	0.315
QCFR	0.0054512	0.227
IC	0.0001631	0.403
AAD	0.0021239	0.000***
NOM	-0.0010797	0.055*
SEA	-0.0072179	0.000***
DA	0.0003346	0.306
PR	-0.0007416	0.012**
CAD	-0.0011175	0.001***
OT	-0.0011146	0.138
CA	0.002502	0.003***
LTS	0.0005387	0.528
ASXQ	0.0014892	0.570
WSP	0.000033	0.952
Constant	-0.0000522	0.284

Notes: ***, **, * imply significance at 1%, 5% and 10%, respectively. NOC and CTE variables were omitted from the results owing to multicollinearity.

summarise the panel regression results for the aggregate market and for each GICS sector based on the random effects model. Overall, all aggregate market and sectoral models (except the Real Estate sector) were highly significant at lag zero. The Real Estate sector was highly significant at lag one. Moreover, each sector had a varied response to volatility with respect to changes in PTR, MSR and ASX announcements.

5.1. Aggregate market analysis

Table 3 presents the results of the aggregate market analysis. It shows that the PTR has a positive ($\beta_1 = 0.39$) relationship to Australian market return volatility. This implies that market participants may have access to this private information proxy when undertaking an investment decision. Conversely, MSR shows a negative effect ($\beta_2 = -0.06$) on aggregate market volatility. While the effect of MSR may not be as large, the relationship is nonetheless interesting because it highlights the varied reactions of investors to different types of private information proxies. Table 3 also reports the results of the public information proxy, that is, ASX announcements. The results indicate that only some ASX announcements have a statistically significant effect on the aggregate market return volatility, none of which are substantial when compared with private information proxies. Thus, with respect to the specified hypotheses, the null hypothesis is rejected because each information proxy was found to be statistically significant. H_1 and H_2 are accepted since a positive association was found between PTR and return volatility. However, H_3 and H_4 are rejected since a negative association was found between MSR and return volatility. With respect to ASX announcement, H_5 and H_6 are rejected for some announcements and accepted for other announcements, since some show a positive relationship and others show a negative relationship to return volatility. The detailed results are presented in Table 3.

5.2. Sectoral analysis

As previously mentioned, the Australian economy operates as a 'two-speed economy', with some sectors growing more rapidly than others, resulting in some sectors experiencing higher volatility than others (Deo et al., 2017). This implies that some sectors might experience differing

degrees of informational efficiency. As shown in Figure 1, the returns for each sector indicated different degrees of volatility over time, shown by the large clustering of returns in some sectors compared with others. Since each sector has its own individual characteristics, it was expected that private and public information would have a different effect on return volatility across each sector. Therefore, a sectoral analysis provided insight into the information determinants of each sector and their effect on return volatility. Moreover, the highly significant outcome for PTR and MSR within the aggregate market provided an impetus to explore their effect on a sectoral basis.

5.2.1. Private information and return volatility

The results of the sectoral panel regressions are presented in Table 4. They reveal that the significance level and the direction of the relationship was the same as the aggregate market analysis. Thus, each private information proxy may either positively or negatively affect the return volatility of stocks within the sectors. This finding highlights the importance of the fact that not all types of private information are treated equally by investors and do not play the same role in every sector. Since these private information proxies do affect the return volatility of ASX 200 firms, investors can capitalise on them to generate excess portfolio returns. To describe the effect of PTR and MSR on sectoral return volatility better, the following classifications have been used: 'large effect' (0.76 to 1), 'moderate effect' (0.32 to 0.75) and 'small effect' (0.01 to 0.31). A common method of grouping results is to define the lower (upper) bound of results as any value one standard deviation below (above) the mean (DeJong et al., 1992). However, for this study the midrange was substituted in place of the mean as the true centre of the data.¹⁶ Detailed results are presented in Table 5.

5.2.1.1. Analyst price targets and volatility. The Health Care sector exhibited a positive and substantial relationship (0.92) between PTR and sectoral return volatility. In comparison with all other sectors, PTR has had the largest effect on sectoral return volatility in this sector. A possible explanation for this is that the sector generated the highest 5-year average return (2013–2017) of 14.55% and a 1-year return in 2017 of 20.83%. Harrison (2019) noted that this increase in return has occurred because the Health Care sector is currently in the growth phase of its life cycle. Thus, investors are likely to have an optimistic outlook on the future performance of stocks within this sector and may employ price targets to improve their chances of generating excess returns. The results further reveal that a decrease in PTR substantially reduces return volatility (-0.92). This indicates that despite the cut in PTR, investors do not partake in panic selling and maintain an optimistic outlook regarding the sector's future performance.

PTR in the Industrials, Consumer Staples, Information Technology (IT) and Materials sectors exhibited a moderate effect on sectoral return volatility. The result for the Consumer Staples sector is rather surprising because this sector produced a 5-year return of only 6.97%, yet investors still had a moderate reliance on PTR. However, it is noted that during the study period, this sector experienced significant growth, producing negative returns of -4.46% in 2014 to 18.38% in 2017. PTR in the

¹⁶ The mean should provide an indication of the centre of the data, however it is affected by extreme values. Thus, this method is only possible for normally distributed data. As volatility is leptokurtic in nature, this paper substitutes 'midrange' in place of the 'mean' to represent the true centre. The midrange is calculated as the sum of the highest value and the lowest value, divided by 2. This allows for determination of the midpoint for the specific coefficients in this study. The upper and lower bound specification method remains the same as previous studies, that is, 1 standard deviation above or below. Thus, the 'large effect' is specified as any value above 1 standard deviation away from the midrange of 0.53, calculated as 0.75. The 'small effect' is specified as any value below 1 standard deviation away from the midrange of 0.53, calculated as 0.32. The 'moderate effect' is specified as any value between the 'large effect' and 'small effect' range.

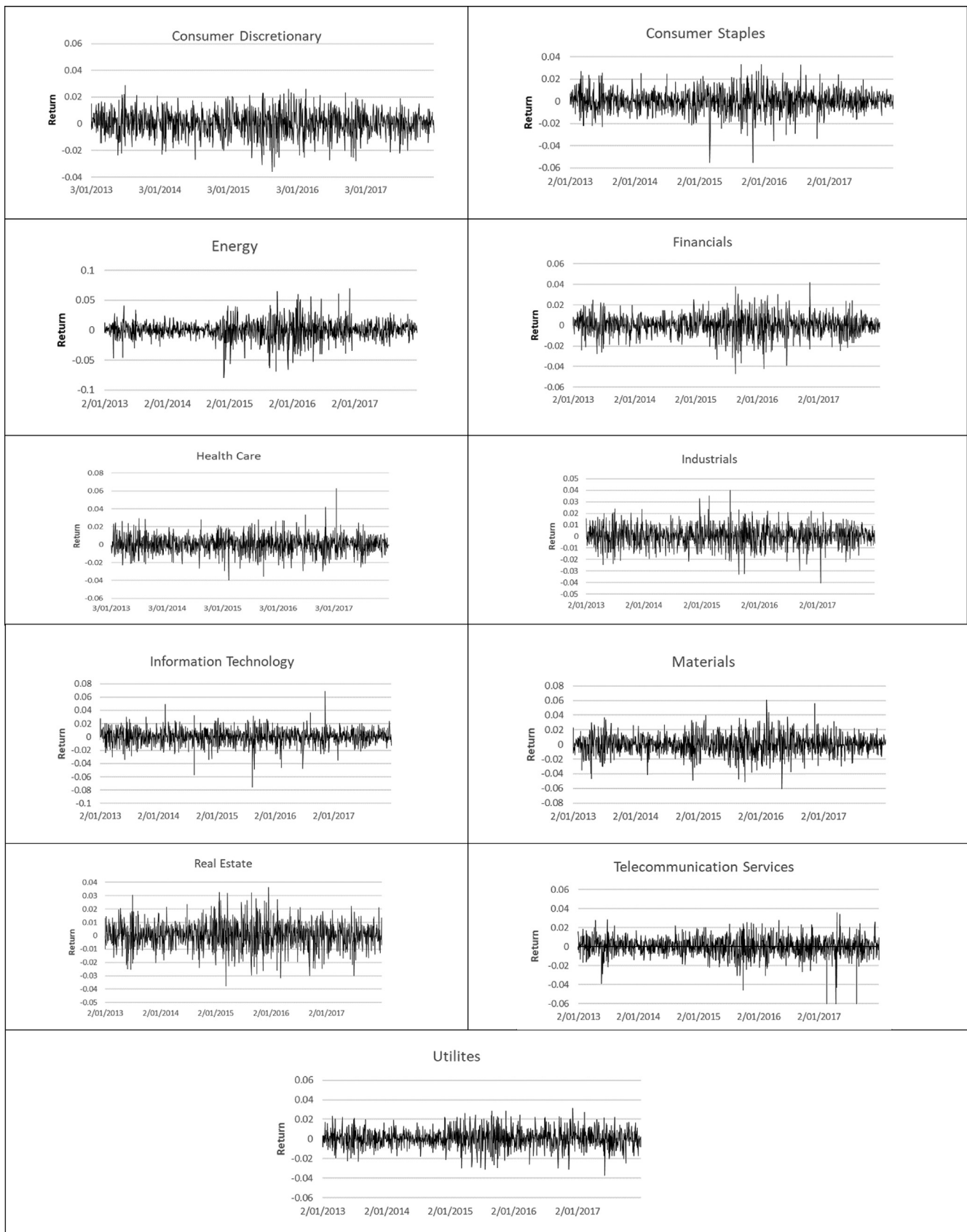


Figure 1. ASX 200 individual GICS sector index returns.

Table 4. Panel regressions: Sectoral analysis.

Information type	Variable	Consumer Discretionary		Consumer Staples		Energy		Financials		Health Care	
		Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Private	PTR	0.1989780	0.000***	0.5027704	0.000***	0.2740791	0.000***	0.4037625	0.000***	0.9191119	0.000***
Private	MSR	-0.0484933	0.000***	-0.0597817	0.000***	-0.0833846	0.000***	-0.0637742	0.000***	-0.0652949	0.000***
Public	TO	0.0021287	0.505	-0.0147927	0.000***	0.0214017	0.000***	0.0080485	0.004***	-0.0421569	0.017**
Public	SD	-0.0009941	0.033**	0.0001779	0.788	0.0006405	0.501	-0.0000152	0.964	0.001111	0.072*
Public	PER	0.0019601	0.038**	-0.0024115	0.055*	0.0013929	0.327	-0.0011112	0.025**	-0.0041344	0.000***
Public	QAR	Omitted owing to multicollinearity		-0.0002407	0.960	0.0003744	0.867	Omitted owing to multicollinearity		Omitted owing to multicollinearity	
Public	QCFR	Omitted owing to multicollinearity		Omitted owing to multicollinearity		-0.0022309	0.925	Omitted owing to multicollinearity		-0.0012593	0.943
Public	IC	0.0004808	0.521	-0.0022881	0.033**	-0.0023156	0.036**	5.05E-07	0.999	0.0000878	0.879
Public	AAD	0.0028383	0.075*	0.0044915	0.032**	0.0011594	0.659	0.0026171	0.065*	-0.002176	0.334
Public	NOM	-0.0011307	0.357	-0.0042285	0.026**	-0.0003448	0.879	-0.0030292	0.009***	-0.0006774	0.700
Public	SEA	-0.0099620	0.002***	-0.0105655	0.030**	0.0032894	0.522	-0.0040715	0.002***	-0.0580985	0.000***
Public	DA	-0.0001837	0.848	-0.0003053	0.822	0.0036902	0.045**	-0.0008612	0.083	0.0024281	0.068*
Public	PR	-0.0018829	0.064*	-0.0014013	0.339	-0.0008077	0.408	-0.0020384	0.014**	0.0004141	0.745
Public	CAD	-0.0022055	0.027**	-0.0011428	0.386	0.0033725	0.093*	0.0004242	0.503	-0.0024007	0.074*
Public	OT	-0.0055339	0.006***	-0.0042113	0.190	0.0010913	0.780	0.0008571	0.577	-0.0065957	0.007***
Public	CA	-0.0012687	0.601	0.0090556	0.009***	0.0049657	0.252	0.0044523	0.011**	0.0026426	0.409
Public	LTS	0.0043764	0.096*	Omitted owing to multicollinearity		-0.0086768	0.093*	-0.0014103	0.311	-0.0031733	0.331
Public	ASXQ	0.0125914	0.020**	0.0232903	0.005***	-0.0124026	0.462	-0.015239	0.011**	-0.0190959	0.065*
Public	WSP	0.0091491	0.510	Omitted owing to multicollinearity		Omitted owing to multicollinearity		Omitted owing to multicollinearity		Omitted owing to multicollinearity	
Public	Constant	-0.0001002	0.523	0.0000914	0.669	0.0002106	0.582	-0.00022	0.111	-0.0002905	0.182
Information type	Variable	Industrials		Information Technology		Materials		Telecommunication Services		Utilities	
		Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Private	PTR	0.5062075	0.000***	0.3665773	0.000***	0.407488	0.000***	0.2450188	0.000***	0.24573	0.000***
Private	MSR	-0.0668747	0.000***	-0.0511617	0.000***	-0.064059	0.000***	-0.0560101	0.000***	-0.049562	0.000***
Public	TO	0.0037234	0.184	0.0065636	0.556	-0.0024151	0.590	0.0208259	0.000***	-0.008817	0.038**
Public	SD	-0.0014838	0.007***	-0.0021625	0.024**	0.0009157	0.055*	-0.0024141	0.068*	0.0014048	0.090*
Public	PER	0.0014175	0.101	-0.0005236	0.751	-0.0011763	0.204	0.0018213	0.174	0.0024673	0.016**
Public	QAR	0.0086282	0.516	-0.0274049	0.082*	0.004479	0.004***	Omitted owing to multicollinearity		Omitted owing to multicollinearity	
Public	QCFR	Omitted owing to multicollinearity		Omitted owing to multicollinearity		0.0087566	0.149	Omitted owing to multicollinearity		Omitted owing to multicollinearity	
Public	IC	0.0015264	0.025**	-0.0019204	0.091*	0.0025202	0.001***	0.0003011	0.801	0.0012556	0.210
Public	AAD	0.0042663	0.009***	0.0053552	0.013**	0.0039596	0.017**	-0.0001203	0.954	0.0074016	0.000***
Public	NOM	-0.0028556	0.104	-0.0016392	0.475	-0.0025879	0.094*	-0.0048718	0.028**	0.0055023	0.016**
Public	SEA	-0.01037	0.001***	-0.0170189	0.037**	-0.0109896	0.002***	-0.032263	0.000***	-0.0158403	0.000***
Public	DA	0.0007989	0.504	0.0056983	0.01**	0.0023509	0.043**	0.0007902	0.697	0.0022102	0.055
Public	PR	0.0021154	0.016**	-0.0002441	0.896	-0.0026039	0.000***	0.0025949	0.05**	-0.0011381	0.238
Public	CAD	-0.0028984	0.013**	0.0046368	0.038**	0.0016084	0.105	-0.0049159	0.001***	0.0011589	0.338
Public	OT	0.0047323	0.061*	0.0034718	0.491	0.004502	0.039**	0.0058987	0.025**	-0.0017698	0.317
Public	CA	-0.0003933	0.879	-0.0012079	0.769	0.0038582	0.092*	0.0014212	0.709	-0.0045745	0.171
Public	LTS	-0.0065943	0.072*	-0.0091033	0.565	-0.0004628	0.891	-0.0102257	0.001***	-0.0000994	0.965
Public	ASXQ	0.0204964	0.009***	Omitted owing to multicollinearity		-0.0006836	0.923	-0.1351829	0.000***	Omitted owing to multicollinearity	
Public	WSP	Omitted owing to multicollinearity		Omitted owing to multicollinearity		Omitted owing to multicollinearity		Omitted owing to multicollinearity		Omitted owing to multicollinearity	
Public	Constant	-0.0002351	0.207	-0.0002485	0.332	-0.0000696	0.680	-0.0002308	0.439	-0.0002111	0.327

Notes: ***, **, * imply significance at 1%, 5% and 10%, respectively. NOC and CTE variables were omitted from the results owing to multicollinearity across all sectors. All sectors were highly significant for PTR and MSR at a lag of zero, except for the Real Estate sector (which was statistically significant at a lag of 1—see Table 6).

Table 5. Private information proxy effect classification.

Sector	Analyst price target (β_1)	Size of the effect
Consumer Discretionary	0.198	Small
Consumer Staples	0.502	Moderate
Energy	0.274	Small
Financials	0.403	Moderate
Health Care	0.919	Large
Industrials	0.506	Moderate
Information Technology	0.366	Moderate
Materials	0.407	Moderate
Real Estate (lag 1)	0.188	Small
Telecommunication Services	0.245	Small
Utilities	0.245	Small
Sector	Morningstar stock star rating (β_2)	Size of the effect
Consumer Discretionary	-0.048	Small
Consumer Staples	-0.059	Small
Energy	-0.083	Small
Financials	-0.063	Small
Health Care	-0.065	Small
Industrials	-0.068	Small
Information Technology	-0.051	Small
Materials	-0.064	Small
Real Estate	-0.045	Small
Telecommunication Services	-0.056	Small
Utilities	-0.049	Small

Notes: The effect of PTR and MSR on sectoral return volatility have been classified as a 'large effect' (0.76–1), 'moderate effect' (0.32–0.75) and 'small effect' (0.01–0.31).

Materials sector also exhibited a moderate effect on return volatility. Similarly, while this sector produced a 5-year return of only 5.21%, there was significant growth in returns from 2013 (-0.82%) to 2017 (20.63%). Therefore, it appears that investors may be optimistic regarding the long-term growth and performance of this sector, and thus may increase their reliance on price targets over time. Although the IT sector produced one of the highest 5-year returns (13.36%), PTR only had a moderate effect on its sectoral return volatility. This may be partly due to increased performance of the sector for only the most recent period of 2017 of 23.12%. Prior to 2017, the IT sector recorded a decreasing trend in returns from 2013 (24.83%) to 2016 (4.39%). PTR also moderately affected the Industrials sector return volatility. This sector produced a consistent 5-year return of approximately 14%, indicating that investors appear to be quite content with consistently relying on price targets to assist their investment decisions.

PTR in the Financials sector also had a moderate effect on return volatility. This sector produced a 5-year return of 11.71%; however, it recorded a significant drop from 2013 (26.43%) to 2017 (4.92%). These results appear to contradict the relationship identified in all other sectors showing a 'moderate effect' (i.e. Industrials, Consumer Staples, IT and Materials). Although other moderately affected sectors experienced growth in returns during the study period, the Financials sector's returns consistently declined from 2013 (26.43%) to 2017 (4.92%). Despite the decreasing yearly returns in the Financials sector, investors still appeared to rely on PTR. This may be due to a behavioural factor, whereby investors believe that Australian retail banks have a lower chance of bankruptcy based on their 'resilience' during the global financial crisis. This persistent investor belief of resilience is also driven by the fact that the Australian retail banking sector is highly concentrated among the big four banks, thus carrying the 'too big to fail' status. This status has been earned by lower interest rates provided by the Reserve Bank of Australia and financial stimulus provided to these banks by the Australian government. Therefore, although not poised to experience the same growth

rates as significantly affected sectors, namely, Health Care, analysts appear to indicate that the Financials sector will continue to maintain financial stability in the long term.

The Energy, Telecommunications Services, Utilities, Consumer Discretionary and Real Estate sectors exhibited the weakest relationship between PTR and sectoral return volatility. Interestingly, Real Estate was the only sector for which PTR did not have an immediate effect on sectoral return volatility. After further testing, the results, presented in Table 6, indicated that PTR was not statistically significant at a lag of zero but highly significant at a lag of one. This shows that it takes the Real Estate sector one day longer than all other sectors to reflect the effect of PTR on return volatility. The minor increase in sectoral return volatility in the Consumer Discretionary sector seems to be an anomaly since this sector has seen a 5-year return of 10.66% and an 8.32% return in 2017. This may be due to the 'retail recession' that is currently being experienced by consumer goods retailers in Australia. Although, the slight offset of flourishing online retailers has resulted in the consistent return produced by the Consumer Discretionary sector. However, the increase in unemployment rates, fluctuations in real household disposable income and a volatile consumer sentiment index have resulted in mixed results over recent years (IBISWorld, 2019).

The increased concern regarding the future performance of this sector may explain the reluctance of investors to invest in this sector and their associated decreased reliance on PTR. Considering that PTR does not largely influence these sectors, this implies that investors make their investment decisions using private or public information not captured in this study. With respect to the Energy sector, the small effect of PTR may be due to the heavily fluctuating Energy stock prices during the study period. Hence, the sector exhibited poor performance over the study period, generating a 5-year return of 0.64%. This would likely increase investor uncertainty regarding the sector's long-term performance and decrease the usefulness of PTR. Further, the low reliance on price targets in the Telecommunication Services sector may be attributed to its extremely poor

Table 6. Real estate sector panel regression (with lags).

Variable	Real Estate (lag 0)		Real Estate (lag 1)	
	Coefficient	p-value	Coefficient	p-value
PTR	.0053208	0.832	0.1883382	0.000***
MSR	−0.0453835	0.000***	0.0063329	0.154
TO	0.0033013	0.046**	0.0059396	0.118
SD	−0.0011192	0.006***	0.0007249	0.863
PER	0.0016468	0.009***	0.002308	0.086*
QAR	Omitted owing to multicollinearity		Omitted owing to multicollinearity	
QCFR	Omitted owing to multicollinearity		Omitted owing to multicollinearity	
IC	−0.0007968	0.134	0.0013601	0.608
AAD	0.0006656	0.349	0.00189	0.499
NOM	0.0003472	0.705	0.0021399	0.853
SEA	−0.0032692	0.109	0.00606	0.648
DA	−0.0017777	0.002***	0.0015066	0.560
PR	0.00146	0.044**	0.0006882	0.311
CAD	−0.000425	0.582	0.0003969	0.147
OT	0.0062743	0.017**	0.003343	0.491
CA	0.0030634	0.096*	0.0029126	0.702
LTS	0.0007972	0.617	0.0016422	0.345
ASXQ	0.0159984	0.011**	0.0282969	0.011**
WSP	0.0110407	0.870	0.0267935	0.877
Constant	−0.0000888	0.459	0.000151	0.465

performance. The 5-year return of 2.96% was caused by the consistently decreasing returns from 2013 (25.42%) to 2017 (−23.95%). Thus, PTR is redundant and the near negligible effect on sectoral volatility is to be expected. The Utilities sector produced quite volatile yearly returns from 2013 to 2017. This may indicate that investors might not consider investing in this sector to generate excess returns because of the uncertainty of returns with price targets not being useful.

5.2.1.2. Morningstar stock star ratings and volatility. The results of the panel regression are quite interesting for MSR because they reveal that investors interpreted changes to MSR differently from adjustments in PTR. An increase in the PTR was associated with an increase in the sectoral return volatility, which may have been catalysed by the large volume of purchasing. However, consistent with the aggregate market results, the opposite relationship was identified for MSR at the sectoral level. The results demonstrate that an increase in the rating was associated with a decrease in sectoral return volatility. Another interesting observation was the small effect that MSR had on sectoral return volatility. Across all sectors, the effect of MSR upgrades was associated with a decrease in return volatility between 0.048 and 0.083, which is small compared with a range of 0.14 to 0.19 for PTR. Although the effect may not be substantial, the relationship is nonetheless interesting since it highlights the fact that investors have varied reactions to each type of private information proxy. This is presented in Table 4.

MSR had the largest effect on sectoral return volatility in the Energy sector. An upgrade (downgrade) in MSR was associated with a decrease (increase) in sectoral return volatility. These results can be attributed to the extreme volatility of the Energy sector. Owing to the large decline in returns of Energy stocks during 2015 and 2016, followed by the large returns of 35% in 2018, investors appear to be cautious about recent volatility and may exhibit a higher degree of sensitivity to bad news. This uncertainty is likely to be largely driven by the significant decline in oil prices from 2015 to 2016, followed by the subsequent rise in 2017 (Janda, 2016). Thus, the volatility of crude oil prices has directly affected the return of Energy stocks. Hence, investors are not only wary about the volatility of oil prices but are likely to increase their reliance on private information to secure gains and hedge against any potential future losses.

The Industrials sector was the second-largest sector affected by MSR. The findings demonstrate that each upgrade (downgrade) in MSR was associated with a decrease (increase) in sectoral return volatility, closely followed by the Health Care, Materials and Financials sectors. MSR in the remaining sectors exhibited a similar effect on volatility. Sectors that appeared to be the least affected by MSR were Real Estate, Consumer Discretionary and Utilities. This is illustrated in Tables 4 and 6. Interestingly, these sectors were also the least affected by PTR.

The results show that both PTR and MTR were highly significant proxies at the aggregate market and sectoral level. This indicates that investors seek both types of private information in the aforementioned sectors. However, the variation in the size and direction of the relationship for each proxy indicates that investors tend to rely on PTR more than MSR to aid their investment decisions. Although the reason for this cannot be conclusively established, it is likely because PTR provides investors with a higher degree of informational content than does MSR (Huang et al., 2009).

5.3. Public information and return volatility

Table 4 illustrates the results pertaining to the public information proxy of ASX announcements. Similar to the aggregate market, some ASX announcements had an effect on return volatility across sectors, but the effect was not substantial. ASX Query (ASXQ) announcements in the Telecommunication Services sector was the greatest contributor to sectoral return volatility. The results highlight that ASXQ announcements decreased sectoral return volatility (0.13); however, the effect was not large relative to private information.¹⁷ When a company in the Telecommunication Services sector provides a well-documented response to a significant change in the stock price, there is a decrease in volatility (0.13). This is consistent with Drienko and Sault (2013) findings, where volatility increased in the lead-up to an ASX Query and then decreased after the query had been answered. However, in contrast to the above-mentioned sectors, it was found that for the Consumer Discretionary,

¹⁷ Upon further examination, it was found that these types of announcements specifically refer to the response from companies with 'price queries' from the ASX.

Consumer Staples, Industrials and Real Estate sectors the release of an ASXQ announcement resulted in sectoral return, but the degree to which this type of announcement affected volatility was relatively low, namely, less than 0.03.

No observable pattern emerged with respect to the number or specific types of ASX announcements having the largest effect on sectoral return volatility. Each sector appeared to be associated with a unique set of ASX announcements that affected their sectoral return volatility to varying extents. These results highlight the importance of examining the effect of public information on sectoral return volatility, since one type of announcement in a specific sector may not have the same (or any) effect on volatility in another sector. This was observed for Stock Exchange announcements (SEA) in the Health Care sector relative to other sectors. SEA in the Health Care sector was identified as having the second-largest effect on sectoral return volatility. However, the effects across other sectors were negligible and statistically insignificant for Energy and Real Estate. Additionally, takeover announcements in the Health Care sector had the third largest (negative) effect on sectoral return volatility, which is surprising given that takeover announcements usually cause an increase in volatility (Smith et al., 1997).

5.4. Scheduled and unscheduled ASX announcements

The classification of scheduled and unscheduled announcements is documented in Table 1, and detailed results for each ASX announcement tested as part of the panel regression are exhibited in Tables 3 and 4. The results demonstrate a higher number of statistically significant unscheduled announcements across all sectors in comparison with scheduled announcements. This implies that unscheduled announcements have a larger effect on sectoral return volatility relative to scheduled announcements. This is likely to be because investors who react to an unscheduled announcement for the first time may not have prior insight into the informational content of the announcement.

Additionally, the smaller number of scheduled announcements affecting sectoral return volatility was not unexpected. This could be due to price run-ups (which typically occur when there is a temporary increase in the stock price) in the lead-up to a periodic or scheduled announcement with the price remaining the same or slightly decreasing, post-announcement (Chan, 2003; Heaton and Lucas, 1999). This is attributable to investors anticipating that the contents of announcements will improve their chances of generating excess returns. However, not all scheduled and unscheduled information is expected to cause the same effect on volatility. Bauwens et al. (2005) identified higher volatility in scheduled announcements compared with unscheduled announcements in the pre-announcement period. Interestingly, volatility around macro-economic announcements as documented by Bauwens et al. (2005) provide contrasting behaviour to firm-specific announcements within individual sectors. Although the underlying reason cannot be established here, it may be because the content of scheduled firm-specific announcements in each sector is more predictable than scheduled macro-economic announcements.

6. Policy implications and limitations of the study

6.1. Policy implications

The findings of this research will be of interest to capital market regulators, as it focuses on ways to minimise market volatility due to a specific type of information. During the 2008 Global Financial Crisis, regulators in the United States employed 'circuit breakers' to minimise volatility instigated by panic-selling. Although this was effective in minimising excessive volatility in financial markets, the results of this research indicate that only specific sectors may require circuit breakers rather than the entire market. Specifically, the results indicate that analyst price targets and Morningstar stock star ratings had the largest effect on return volatility of the Health Care, Consumer Staples and

Industrials sectors implying that circuit breakers for these sectors would be appropriate. On the other hand, the effect was minor in the Real Estate and Consumer Discretionary sectors, suggesting that circuit breakers would not be required. Further, results indicate that to minimise shareholder return volatility, regulators may consider imposing circuit breakers for those sectors that exhibit excessive volatility for extended periods even during normal economic conditions.

In addition, the findings imply the possibility of regulators imposing restrictions on the ability of research firms to provide analyst price target recommendations for specific sectors to reduce volatility in the market. For example, this study has evidenced that investor's reliance on analyst price targets in the Health Care sector resulted in the highest return volatility during periods of normal economic conditions (2013–2017). The unchanging reliance on analyst price targets even during a recession, may increase the likelihood of panic selling thus perpetuating return volatility. However, if analysts are prohibited from providing recommendations on stocks within the Health Care sector during the crisis periods only, it may help minimise short-term volatility in the sector.

6.2. Limitations of the study

This study, like many others, does contain some limitations, which could present areas for further research. The following limitations were identified within this study:

1. The stock return volatility in the sample was measured using daily data rather than an intraday basis. Therefore, the study was not able to capture intraday volatility, which literature has shown to be prominent. However, to ensure consistency of data frequency, intraday data could not be used because Morningstar stock star ratings and analyst price targets were only available at the daily frequency.
2. This study has not separated market sensitive from non-sensitive ASX announcements. It is expected that market sensitive announcements would have a larger effect on sectoral return volatility (O'shea et al., 2008). As an example, within the 'dividend' announcements there are various sub-announcements. Thus, a 'dividend alteration' announcement would be classified as market sensitive, while a 'dividend pay date' would be non-sensitive. There is an expectation that both types of sub-announcements would have varying impacts on sectoral return volatility.

7. Conclusions and areas of further research

This study aimed to not only gain insight into how information is interpreted by the market but also improve understanding of the effect of different types of information on return volatility from both an aggregate market and sectoral perspective. The study has several key findings. First, a significant and positive relationship exists between PTR and sectoral return volatility. There is a marked variability in the role that they play in each sector, with the most substantial effect observed in the Health Care sector and the smallest in Real Estate. This result indicates that informational efficiency is not consistent across all sectors; rather, there are varying degrees of efficiency. Further, a positive relationship was identified between sectors producing higher returns in recent years and the increased reliance on PTR. This outcome presents investors with an opportunity to take advantage of PTR in sectors that exhibit higher growth rates in order to generate excess returns. This information would be beneficial to not only individual investors but also to superannuation funds and managed funds. Since superannuation funds and managed funds focus on generating excess returns for their clients, employing price targets may assist in rebalancing their portfolios to specific sectors. Further, since volatility within the Health Care sector is heavily influenced by PTR, this may be of concern for regulators. Within the Australian financial market, regulators have continually implemented measures to increase information transparency and prevent excessive

price fluctuations, yet it appears that the Health Care sector is still exceedingly affected by private information.

The second key result was the observed effect of MSR on sectoral return volatility. The results indicated that MSR was statistically significant, but the size of this effect was small relative to PTR. This indicates that investors do not place heavy reliance on MSR when undertaking investment decisions. This finding may be attributed to the lack of informational content received from these ratings compared with price targets. Nonetheless, it is interesting that investors do not treat each type of private information equally: when PTR increases (decreases), the volatility increases (decreases), but when MSR is upgraded (downgraded), the volatility decreases (increases). Such a finding highlights the fact that investors exhibit more optimism when utilising PTR, whereas investors employing MSR may partake in panic selling when ratings are downgraded.

The third key finding identified the relationship between public information and sectoral return volatility. There are certain ASX announcements that affect sectoral return volatility; however, there is no specific announcement type that was statistically significant across all sectors. Moreover, the findings suggest that unscheduled ASX announcements affect sectoral return volatility to a higher degree than do scheduled announcements, which may partly be due to the unpredictability of the announcements. While the extant literature stresses that scheduled announcements have a larger effect on volatility compared with unscheduled announcements (owing to the former's predictability), our results suggest that the opposite is true.

In general, the results show that investors react to public and private information differently. We recommend that future research could also look at the impact of other private information proxies on return volatility. Further research could consider expanding the current research by using intraday data for other developed markets. Other considerations include utilising other variables that may affect return volatility such as macroeconomic economic variables. Finally, further research could extend the present model by specifying an endogenous dynamic model. Bouchaud (2011) reviewed the erratic dynamics of markets and identified it is to a large extent associated with an endogenous origin, that is, determined by the trading activity itself rather than the rational processing of exogenous news. He argues that the volatility is much too high to only be explained by changed in fundamentals and news releases. Since universal observations and analogies suggest that endogenous dynamics may be a solution to the excess volatility puzzle, further research could specify an endogenous dynamic model.

Declaration

Author contribution statement

W. Bakry and M.E. Varua: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

M. Prasad: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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The authors declare no conflict of interest.

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