Global Business and Management Research: An International Journal
Vol. 16, No. 4 (2024)

Assessing Asymmetrical Sentiment Effects and Firm Characteristics on Saudi Stock Returns

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Abstract
Purpose: This study assesses the potential asymmetrical effects of market sentiment on Saudi stock returns and the impact of firm characteristics on the sentiment-return nexus.
Design/methodology/approach: We used five sentiment proxies to create a unified sentiment proxy. Regression was used to detect the influence of sentiment on stock returns (January 2004-December 2017). Asymmetric shock to sentiment is tested using TGARCH models, while impulse response functions (IRFs) analyze the shock responses of sentiment proxies on stock returns.
Findings: This study shows that sentiment significantly impacts the Saudi market, with trade volume and moving averages as key proxies, while IPOs are less relevant. Firm characteristics have an unclear role in sentiment-return relationships, and both noise and smart traders shape market sentiment. While the market is inefficient, as sentiment strongly influences returns, there is insufficient evidence of the asymmetric effect of sentiment changes. Institutional investors often struggle to counter sentiment-driven trading, leading to persistent inefficiency.
Research limitations/implications: This study did not consider the impacts of COVID-19, where structural breaks occurred, which may mis-justify the inconsistent behavior of both institutional and individual investors.
Practical implications: Strong presence of individual or retail investors, weak monitoring authority, and the deep-rooted existence of a collectivistic society have contributed to the unstable behavior and widespread influence of sentiment in the Saudi market. Investors should consider "sentiment" factor to the Fama-French models. It is also better to use two individual factors, past moving average and market liquidity, in these models.
Originality/value: This is a pioneering study that assesses the asymmetrical effects of market sentiment on Saudi stock returns and the impact of firm characteristics on the sentiment-return nexus using a specially constructed unified sentiment index.

Keywords: Saudi stocks, emerging markets, investor sentiment, asymmetric sentiment effect, the TGARCH models.

Classification: Research paper

Introduction
An efficient market is one in which the prices of financial assets completely reflect all available relevant information. As such, stock prices are supposed to follow a random path in which they

move randomly in response to new information. This process makes the stock prices unpredictable. However, financial markets are often fueled by emotion,[1] and one of the recent ways to justify the market efficiency is to assess market sentiment[2] and its relationship with stock returns (e.g., Dash and Maitra, 2018; Guo et al., 2017; Chowdhury et al., 2014). The term "sentiment" refers to whether market participants possess highly positive or negative emotions, and findings from decision science research suggest that sentiment (both positive and negative) results in overly extreme views (Bower, 1991).

Investors' overall psychological perceptions of financial stock markets can be defined as their sentiment. Baker and Wurgler (2007) explain market sentiment as investors' beliefs about future cash flows, which cannot be justified by the current evidence they have in their hands. Many researchers believe that sentiment should be considered a vital market-wide, non-diversifiable phenomenon (Stambaugh et al., 2012). Thus, the role of sentiment in stock markets cannot be ignored. More importantly, reading the mood of the market allows investors to capitalize on changes in investment direction.

Nevertheless, market sentiment behavior varies across regions. Studies show that there are differences in perception (Ishii et al., 2009), reasoning (Buchtel and Norenzayan, 2008), and modes of thinking (Nisbett and Masuda, 2003) between Asian and Western investors. According to Hassan et al. (2003), emerging and frontier markets exhibit low liquidity, high presence of infrequent trading, strong participation of less-informed individual investors, limited access to reliable information, and substantial volatility in stock returns. Baker and Wurgler (2006) report that young firms, extreme growth firms, small firms, and non-dividend-paying firms are more susceptible to sentiments because there is a lack of information about such firms. Thus, sentiment may play a significant role in asset pricing if the market is young or emerging. This is supported by recent literature that shows that sentiment in emerging and frontier markets is very high (Chowdhury et al., 2014). While these markets provide new investment opportunities for portfolio diversification, it is obvious that potential foreign investors do not want to prey on the illogical behaviors of less- or uninformed traders.

Such concerns offer a good opportunity to explore the market sentiment-stock returns nexus in the Saudi market, the largest stock market in the Arab world. Although recent works on market sentiment have been growing, the US$ 451 billion Saudi market has failed to attract comprehensive studies from international scholars. Most past studies on the Saudi market were related to either the effect of Ramadan (Wasiuzzaman, 2017; Bialkowski et al., 2012) or oil prices, probably because of the primary dependency of these economies on fossil fuel exports. Until recently, the minimal access of international investors to the Saudi market is among the important possible reasons for the lack of attention in the literature.

Policymakers realize that the Saudi market cannot develop without foreign investment. The recent partial opening of Saudi equities to foreign investment and partial permission for short selling are crucial steps toward financial liberalization. The Saudi stock market joined the FTSE Russell

[1] Share prices may not match company's book value if investors are biased due the presence of sentiment in the market. Sentiment can be influenced by all manner of things prevailing in the market.
[2] Financial market sentiment is the overall accumulation of the mood of financial markets and the general feeling among traders, e.g., being optimistic or pessimistic about the market at present or in the future.

Emerging Market Index in March 2019 and the MSCI Emerging Market in June 2019. As the market has become more open to foreign investment, cross-border investors seek thorough information to explore it. Their interest depends on how liberal, open, and understandable the market is. In particular, the behavioral aspects of any regional market are of strong interest mainly because of the presence of retail traders. Presently, the Saudi market is dominated by 83.63% less-informed retail investors among local investors (Tadaul.com), and approximately 91% of trades are generated by retail traders (Chowdhury et al., 2015). This phenomenon contributes to the likelihood of sentiment-based trading.

According to a recent Bloomberg report, the Saudi market has underperformed so far in 2024 in comparison to other emerging markets for the first time since the pandemic, with the TASI trailing the MSCI index by nearly 6% this year. This underperformance is due to low oil prices and regional conflicts (Bloomberg 2024). Saudi Arabia has undergone a significant transformation to reduce oil dependence, which is the main objective of Vision 2030. The latest IMF report indicates that non-oil growth has accelerated since 2021, averaging 4.8% in 2022, and is expected to remain close to 5% by 2023, driven by strong domestic demand such as private non-oil investments (IMF, 2023). Of course, the Saudi stock market has to play a considerable role in this regard.

Considering the issues mentioned above, this study is specifically designed to (i) identify the influence of market sentiment and relevant proxies, (ii) determine the effect of firm characteristics (e.g., size, BV/MV ratio, volatility) on the returns-sentiment nexus, (iii) identify the potential asymmetric impact of sentiment on stock returns concerning positive or negative shocks to sentiment, and (iv) assess the shock response of stock returns to sentiment over time.

Various methods have been applied for analysis. First, we consider monthly macroeconomic data and individual firms' returns (January 2004-December 2017) to compile the portfolio returns unexplained by relevant systematic risk that comes from macroeconomic risk factors. Residual return portfolios are then constructed by focusing on firm characteristics. We used five sentiment proxies to create a unified sentiment proxy. Panel regression was used to detect the influence of sentiment on stock returns. Asymmetric shock to sentiment is tested using TGARCH models, while impulse response functions (IRFs) analyze the shock responses of sentiment proxies on stock market returns.

This study is expected to fill the research gap in market sentiment in Saudi Arabia, where retail investors are the main players. This study offers new insights into the existing literature. These findings provide a practical guide for investor sentiment responses and risk preferences. Appropriate handling of sentiment by both authorities and investors would prevent another episode of a stock market disaster that occurred in 2006; specifically, the market may become less susceptible to sentiment by providing an appropriate database whenever necessary. A quantifiable measure of sentiment, such as the Trader's Index (TRIN), can provide real-time sentiment information to market traders and help regulators make appropriate and timely policy interventions. Thus, local, regional, and foreign investors would feel more confident in investing in these markets, attracting more foreign capital in the future.

The remainder of this paper is organized as follows. Section 2 discusses previous studies on sentiment in emerging and mature markets. Section 3 provides information on the data and methodology, and Section 4 discusses the results. Section 5 concludes the paper with policy implications.

Literature Review

Classical finance theory states that investors are rational and invest to maximize their wealth. According to this theory, sentiment is irrelevant because people's illogical feelings and expectations about the market should not influence stock prices. Fisher and Statman (2000) provided two critical reasons for studying sentiment. First, they inform us about the systematic biases in investors' stock market predictions. Second, they show us possible opportunities to earn abnormal returns by deploying trading rules.

Some earlier theoretical studies on the impact of sentiment on stock returns may be worth noting. Considering the psychological influence on human beings, Barberis et al. (1997) provided a theoretical framework for how investors underreact and overreact systematically when making financial decisions. They also provide empirical evidence to support their theoretical predictions. Tversky and Kahneman (1974) provided the importance of behavioral heuristics in making investment decisions. Hirshleifer et al. (2001) also showed theoretically that investors' rational behavior is often subsumed by their psychological state, creating biases in financial decisions.

De Long et al. (1990), in the traditional finance theory, point out that noise traders can create additional risk in the form of the unpredictability of their beliefs. Schmeling (2007) showed that noisy traders create sentiment, which creates a situation in which arbitrage becomes difficult. Schmeling (2009) confirmed similar findings for 18 industrialized countries. Dumas et al. (2005) confirmed that rational investors cannot eliminate the effect of sentiment in the short term. In addition, Baker and Wurgler (2006) found that when market sentiment is high (low), relatively riskier stocks of small, young, volatile, unprofitable, non-dividend-paying, high-growth, and distressed firms provide significantly low (high) risk-adjusted future returns. In their following paper, Baker and Wurgler (2007) reconfirmed the previous conclusion by showing that difficult-to-arbitrage firms are the most likely ones to be susceptible to market sentiment, providing opportunities for abnormal returns. Stambaugh et al. (2012) showed that where short selling is restricted, overpricing is hard to be eliminated through arbitrage; as a result, optimistic investors' perceptions influence subsequent stock prices.

Several studies on emerging markets have claimed that sentiment does presence. For example, Chi et al. (2012) and Liu et al. (2011) considered the direct and indirect impact of sentiment on the Taiwanese stock market, and their findings suggest that extreme sentiment indicators play a critical role in explaining stock returns. Anusakumar et al. (2012) indicated the presence of sentiment in the Asian emerging market. Their results are valid across firms irrespective of size, trading volume, sample period, and alternative proxies. Rehman (2013) provided evidence that Karachi – a market that retail investors dominate – is impacted by market sentiment. Recent studies have reported the presence of sentiment in the Indian stock market (e.g., Jana, 2016; Dash and Maitra, 2018). Likewise, Debata et al. (2018) claimed that the sentiments of both domestic and foreign investors impact emerging stock market liquidity. However, emerging and mature markets differ in their sophistication, history, depth, and institutional and regulatory frameworks. Therefore, the impact of sentiment may vary in these markets. Kling and Gao (2008) showed that institutional investor sentiment fails to predict future stock returns, but that previous stock returns influence sentiment.

Zhang and Yang's (2009) findings showed that changes in investor sentiment are a systematic factor in forming future stock prices. By contrast, Guo et al. (2017) revealed that investor sentiment is not always useful in predicting Chinese stock prices. Empirical evidence on the effect of sentiment on emerging markets remains inconclusive.

On the other hand, due to the dominance of uninformed retail traders in Saudi Arabia and the above-mentioned findings of the presence of sentiment in both emerging and mature markets, it is plausible that sentiment is present in Saudi Arabia. However, limited sentiment-related research has been conducted in the Saudi market. At this point, research related to behavioral finance is worth discussing. Past literature indicates a possible sentiment-related bias in the Saudi market. Bialkowski et al. (2012) showed that Ramadan has a significant positive impact on sentiment in 14 Muslim economies, and stock returns during the month of Ramadan are much higher and less volatile than those in other months of the year. This optimism affects investor sentiment and decisions, leading to price runups. Seyyed et al. (2005) had also reported a similar effect of the holy month of Ramadan on stock returns in the Saudi stock market. Wasiuzzaman (2017), on the other hand, focused on the issue of religious anomalies, particularly the impact of the Hajj effect on the returns and volatility of the Saudi stock market. He reports that volatility was significantly higher during the Hajj period. Abbes and Abdelhédi-Zouch (2015) investigated whether celebrated Islamic hajj can affect the performance of the Saudi stock market through its impact on investor sentiment. They show that the sentiment of Islamic investors is significantly higher after the Hajj pilgrimage than before this religious occasion. In other vein, Chowdhury et al. (2015) showed a notable first-order autocorrelation of returns for the Saudi stock market. In another study, Chowdhury et al. (2017) reported a strong positive autocorrelation in the returns of individual stocks, size portfolios, and market portfolios. The last two are almost always more prominent than the first one. Altuwaijri (2016) investigated the relationship between market sentiment and stock returns in the Saudi market. He concluded that when investors are in a good (bad) mood, their investment decisions are optimistic (pessimistic), which means that investors' moods and stock prices have a direct relationship.

While extensive research shows that sentiment impacts stock markets globally, there is a notable literature gap in studying sentiment in the Saudi market. Limited research, primarily focused on religious events like Ramadan and Hajj, suggests a sentiment-related bias in Saudi Arabia. However, further investigation is needed to fully understand the role of firm characteristics, the broader impact of investor sentiment and its potential asymmetric effect on the Saudi stock market.

Data and Methodology

The study period spans January 2004 to December 2017, encompassing 168 months of updated financial and sentiment series (indirect). Macroeconomic data, such as industrial production, consumer price index, interest rates, and Brent crude oil prices, are used to find residual returns for firms. Firm size, volatility, and market-to-book value ratio were used to capture the effects of firm characteristics. All data were sourced from International Financial Statistics and Investing.com.

There are two broad types of sentiment measure: direct and indirect. Investor surveys are direct measures of market sentiment. According to Baker and Wurgler (2006), direct measures for sentiment may be biased, and investors' opinions in surveys may be inconsistent with their own investment behavior. In addition, it is difficult to collect direct sentiment for emerging markets within a reasonable period. In Saudi Arabia, short selling has been partially allowed (since late 2017), and mutual fund information is confidential, but analyst recommendations are not popular. Therefore, this study cannot use popular sentiment indicators related to short-selling media and mutual funds; instead, both individual sentiment proxies and unified sentiment proxies were used in the analysis.

Following Baker et al. (2004) and Baker and Wurgler (2007), we deploy five individual sentiment proxies that include the number of IPOs, average trading volume (*VOL*), aggregate market turnover (*TURN*), moving average ratio (*MA*), and the Trading Index, $TRIN_t = \frac{DECVOL_t / DEC_t}{ADVVOL_t / ADV_t}$. *TRIN* < 1 indicates a bullish period, while *TRIN* > 1 indicates a bearish period. *DECVOL*, *DEC*, *ADVVOL*, and *ADV* indicate declining volume, declining stock, advancing volume, and advancing stock, respectively. A unified sentiment proxy is then constructed through Principal Component Analysis (PCA hereafter) to tackle the possible multicollinearity problem among the five sentiment proxies (Baker and Wurgler, 2006).

Sentiment Models

Since changes in macroeconomic variables affect the systematic risk of a stock, residual return series are created by regressing individual firm returns on macroeconomic variables. The regression model is

$$R_{it} = \alpha_0 + \alpha_1 IP_t + \alpha_2 IP_{t-1} + \alpha_3 INF_t + \alpha_4 INF_{t-1} + \alpha_5 INT_t + \alpha_6 INT_{t-1} + \alpha_7 OIL_t + \alpha_8 OIL_{t-1} + \varepsilon_{it} \quad (1)$$

where, R_{it} is the return of an individual company *i*; α_0 is the intercept term, *IP*, *INF*, *INT*, and *OIL* indicate monthly percent changes in industrial production, inflation, interest rates, and oil prices, respectively; subscript *t-1* indicates lag of one month from time month *t*; and ε_{it} is the error term (residual return). These error terms indicate a stock's returns, which cannot be predicted by macroeconomic risk, and then ε_{it} is regressed on sentiment variables to detect how sentiment explains macroeconomic risk-adjusted stock returns. The same rules apply to the portfolio returns.

A unified (composite) sentiment index is also constructed to detect the common component in the five sentiment proxies, and incorporates the fact that some variables take longer to reveal the same sentiment (Baker and Wurgler, 2006; Brown and Cliff, 2004). The first principal components of the five proxies and their first lags are estimated. Now, there is a first-stage index with 10 (5 × 2) loadings, one for each of the current and lagged proxies. The regression model to investigate the effect of sentiment on return is

$$R_{\varepsilon,t} = \beta_0 + \beta_1 SENTIMENT_t + \beta_2 SENTIMENT_{t-1} + \epsilon_t \quad (2)$$

where, $R_{\varepsilon,t}$ is the residual portfolio return (portfolio will be based on size, volatility, and market value to book value); *SENTIMENT* is the unified sentiment proxy derived from the PCA discussed above; subscript *t-1* indicates a lag of one month from month *t*; ϵ_t is the error term. If the correlation between the sentiment proxies is low, all proxies are included in the following regression model:

$$R_{\varepsilon,t} = \alpha_0 + \sum_1^5 \alpha_k PROXY_{k,t} + \sum_1^5 \beta_k PROXY_{k,t-1} + \mu_t \quad (3)$$

where *PROXY* may include up to five available sentiment proxies and a one-month lag for each proxy. Different combinations of proxies are used in this study. This shows the importance of each proxy in explaining the residual returns of the portfolios. For a deeper insight into the sentiment-return relationship in the Saudi stock market, we consider both independent variables in regression models, with all the sentiment proxies and with only a unified sentiment proxy.

In addition, the finance literature notes that sentiment may affect firms with different sizes, volatility, MV/BV, and portfolio returns at different magnitudes. For this purpose, size portfolios are constructed from firm-level data on market capitalization. Because of the smaller number of firms, a maximum of four portfolios can be constructed. Then, the regression models given in equations (2) and (3) were used to examine the effect of sentiment on portfolio returns. A similar analysis is performed by sorting firms based on the market-to-book value ratio and volatility.

Sentiment, Returns Volatility, and Asymmetric Effect

In an emerging market like Saudi Arabia, sentiment traders are mostly naive and inexperienced and may not be able to judge risk properly, which leads to a sub-optimal risk-return (mean-variance) relationship. Investors are likely to behave differently conditional on sentiment. For instance, investors are reluctant about risk in high-sentiment periods but are more sensitive to risk in low-sentiment periods. Along this line, Brooks (2014) argues that information arrivals cause price changes in bunches rather than smoothly over time, creating volatility clustering in the return series. He argues that a negative shock to a financial asset is likely to cause its volatility to rise more than a positive shock of the same magnitude. Similarly, the effect of a negative sentiment shock on stock returns differs from that of a positive shock on stock returns. Yu and Yuan (2011) suggest that investor sentiment has a dramatic effect on the mean-variance relationship when asymmetric GARCH models are applied. Following Glosten et al. (1993), a T-GARCH (1,1) is constructed as:

$$\mu_t = \theta_0 + \theta_1 h_{t-1} + \theta_2 \Delta SI_t + \varepsilon_t \quad (4a)$$

and

$$h_t = \gamma_0 + \gamma_1 \varepsilon^2{}_{t-1} + \gamma_2 \varepsilon^2{}_{t-1} I_{t-t} + \gamma_3 h_{t-1} + \gamma_4 (\Delta SI_{t-1})^2 D_{t-1} + \gamma_5 (\Delta SI_{t-1})^2 (1 - D_{t-1}) \quad (4b)$$

where h_t is the conditional standard deviation, μ_t is the conditional mean return, θ_0 is the intercept term in the mean equation, γ_0 is the intercept term in the volatility equation, $\varepsilon^2{}_{t-1}$is the error term with one month-lag, $\gamma_2$is the asymmetric effect of volatility change, I_{t-t}=1 if ε_{t-1}<1 and 0 otherwise, ΔSI_t is the change in sentiment index, D_{t-1} is a dummy variable so that $D_{t-1} = 0$ if ΔSI_{t-1}< 0 and D_{t-1} = 1 if ΔSI_{t-1}> 0, and *t*-1 indicates a lag of one month. Coefficients θ_2, $\gamma_4$and $\gamma_5$indicate how sentiment affects mean return and if there is any asymmetric effect of sentiment on conditional volatility. For example, a significant γ_5 would mean that a negative shock to sentiment provides more shocks on conditional volatility than a positive shock does. A significant θ_2 would indicate how changes in sentiment affect returns in the presence of an asymmetric effect of volatility.

Dynamic Response of Returns to Innovations in Sentiment

So far, we have not tested how returns are dynamically related to sentiment proxies and how the effect of sentiment travels through the systems of regressions. The Impulse Response Function (IRF) derived from Vector Autoregression (VAR) is able to show how dependent variables react to a shock to each of the independent variables. We have five variables. Thus, 25 IRF charts are there. To save space, we only report the effect on returns of the market and two extreme portfolios (such as the lowest and the highest or the smallest and the largest) with respect to a shock to respective proxies. We need to run separate VAR when we use a unified sentiment proxy (*USNT*) as the only variable (in addition to returns). We assume that the effects of proxy take a maximum of 12 months to adjust into returns, and hence, the lag length is 12 in the IRF.

Empirical Findings and Discussion

Table 1 provides the correlation between every pair of sentiment proxies used in the paper. Proxies include five individual proxies – *TRIN*, *MA*, *VOL*, *TURN*, and *IPO* – and a unified proxy derived from principal component analysis. For this reason, the correlation between unified proxies and other proxies is very high. Among proxies, the highest correlation is 0.37 between *MA* and *VOL*. This level of correlation is not high yet not negligible either. The correlation between the *USNT* and other proxies is high, which implies that the unified sentiment proxy is able to extract most of the information embedded in individual proxies.

Table 2 shows the descriptive statistics of monthly returns of the market, size-sorted, MV/BV-sorted, and volatility-sorted portfolios. There are 13 return series (market and firm-characteristics-based portfolios). One problematic fact about this market is that it does not show a clear relationship between risk and returns. Thus, the basic notion of the positive relationship between risk and return is violated to some extent for this market. For example, the stocks with the lowest volatility give the highest return among all the volatility-sorted portfolios. Then, the kurtosis and skewness statistics indicate that the returns series of this market may not satisfy the assumption of normal distribution. Financial time series data often do not follow a normal distribution. Extreme values in the data may be a reason for such a phenomenon. According to Brooks (pg 210, 2014), it is better to stick to the ordinary least squares method for estimation even if the normality assumption in data is violated. Skewness and kurtosis are not usually too big, and some moderate violation of normality assumption is expected to be tolerable. Nonetheless, GARCH models have been used in the later part of this chapter, which can handle some of the non-normality problems related to ARCH effects in financial data (Brooks, pg 214, 2014).

Table 3 shows the effect of sentiment proxies on the equal-weighted returns of the Saudi market. Model 1 considers all the proxies except the unified proxy except *USNT* and its lags. This model's adjusted R^2 of 0.33 is the highest, suggesting that it explains the most among all the nine models. Residual *TRIN*, *VOL*, *MA*, and lagged *VOL* significantly explain the residual market returns. Model 2 exhibits the result of contemporaneous proxies, and model 3 exhibits lagged proxies. Respective adjusted R^2 shows that the effect of sentiment is primarily contemporaneous, and lagged sentiment does not play any role.

Model 4 to Model 9 use only individual proxies and their one-month lags. Throughout the paper, models and proxies are arranged in the same order in Table 3 to Table 6. Among all these six models (from models 4 through 9), individual proxy *VOL* and its one-month lag – represented by model 5 – are the most important contributors to predicting market returns. However, as suggested by individual regressions, sentiment proxies – *TRIN*, *VOL*, and *MA* – contribute significantly to predict residual market returns. Of all, model 9 – the model with only unified sentiment – explains about 18% of the market return variability, indicating that unified sentiment can explain returns reasonably well. However, the higher adjusted R^2 of other models implies that more sentiment can be captured if a larger model is used. The effect of *IPO* and *TURN* on returns is absent, as shown by individual models. If the process of initial public offering takes too long due to administrative and regulatory requirements, then it may not impact market returns.

Table 4, on the other hand, shows the effect of firm size on the sentiment-return relationship. Results for the largest firms are somewhat different from those for the overall market discussed above. As demonstrated by adjusted R^2s, the most effective model is the first one, comprised of all the proxies. *USNT* significantly captures sentiment and its impact on the returns of size-portfolios, but much of the returns remains unexplained.

The change of sign for coefficients of sentiment proxies and their one-month lags suggests that the effect of sentiment on stock returns is probably transient. This may happen when a market is dominated by less-informed individual investors, and initial overreaction and subsequent correction happen systematically. As far as a single proxy is concerned in these models, *VOL* and its lag appear to be the most important indicator of market sentiment with adjusted R^2 with a range of 0.19-0.29. This is true for all size-portfolios (Table 4, Panels A-D).

There is no noticeable pattern of change in the performance of models when results for size-portfolios are juxtaposed. If model 1 is the benchmark between the smallest- and the largest-size portfolios, sentiment slightly explains returns better for the former. Similarly, between small- and large-size portfolios, sentiment also explains returns better for the former. Thus, overall, sentiment has a slightly stronger impact on smaller-size portfolios. This finding indicates that investors in the Saudi market are probably less informed about small firms. This phenomenon may make them more inclined toward sentiment-biased trading decisions with respect to small firms. On the other hand, large firms are less affected by market sentiment, probably due to their transparent financial practices and more intense investor following.

Results in Table 5 suggest that model 1 performs the best among all the models for all the MV/BV-sorted portfolios. Interestingly, *TRIN* in model 1 does not capture market sentiment in the current period, but it exerts strong impact in the next period. *TURN* and *IPO* are unable to explain returns of these portfolios. Like before, although unified sentiment significantly impacts all these portfolio returns, other proxies can add considerably more to sentiment.

Based on model 1, the impact of MV/BV on the sentiment-return relationship is not very clear because the effect of sentiment does not change monotonously with MV/BV-sorted portfolios. However, from an overall perspective, a high MV/BV portfolio shows slightly less sensitivity to sentiment than a low MV/BV portfolio. Relatively high MV/BV indicates stronger confidence from investors as they reward the firm by offering higher prices, which eventually results in a higher ratio. Thus, investors in these firms are expected to show less dependence on market sentiment. Interestingly, as shown by models 2 and 3 in all the panels of Table 5, these portfolios are more sensitive to lagged than current sentiment. This result suggests a delayed response to sentiment changes, indicating the inefficiency of the overall Saudi market. However, based on model 1, current effects cannot be neglected because it has a much larger adjusted R^2 than that for model 2 (current variables) and/or model 3 (lagged variables). Finally, for all the MV/BV portfolios, *VOL* is the best proxy to capture sentiment because it has the highest adjusted R^2 in every case (from 0.20 to 0.29).

Table 6 shows the results for volatility-sorted portfolios, and the results are similar to the other two sorted portfolios, where model 1 performs the best among all the models. Interestingly, *TRIN* in all the models does not capture market sentiment, while its lag does it so strongly. *MA*, *TURN*, and *IPO* fail to show any impact on the returns of these portfolios. Just like the MV/BV-sorted portfolios discussed above, *USNT* cannot completely capture all the effects of sentiment variables. That is, other proxies can provide additional information to sentiment. It is supported by the fact that a larger model, such as model 1, has a much higher adjusted R^2 (that is, 0.32 in model 1 vs. 0.16 in model 9). Finally, for all the volatility-sorted portfolios, *VOL* is the best individual proxy to capture sentiment because it has the highest adjusted R^2 in every case (from 0.21 through 0.25 in all the panels of Table 6).

Like before, the impact of volatility on the sentiment-return relationship cannot be clearly perceived. However, overall, a high volatility-portfolio shows slightly more sensitivity to sentiment than a low volatility-portfolio does. High volatility of returns of a firm indicates lower confidence and higher divergence of investor beliefs, which may lead them to rely less on fundamental information and more on market sentiment.

Table 7 presents the results of T-GARCH regression to find the impact of sentiment in the presence of dynamic conditional volatility and the nature of sentiment effect in the case of a positive and negative shock to changes in sentiment. The most important coefficients are θ_1, θ_2, γ_4, and γ_5, which discuss the effect of conditional volatility on returns, the effect of changes in sentiment on returns, the effect of positive changes in sentiment, and the effect of negative changes in sentiment, respectively. All the individual proxies except *IPO* have been considered. *IPO* is dropped due to its negligible impact on returns for this market.

The conditional volatility of *VOL* has an impact on the equal-weighted market returns. The coefficient of volume volatility has a negative impact on returns. Except for *TURN*, θ_2 – the coefficient for the change in sentiment proxy in the mean equation – is strongly significant. The effect of sentiment is also evident in the presence of volatility and in the first difference of sentiment (ΔS_t). The GARCH models use change in sentiment rather than just sentiment. Therefore, the strong presence of sentiment is supported in both cases. Coefficients γ_4 and γ_5 show that there is no conclusive evidence of a difference in effect with respect to positive and negative sentiment changes on stock returns. In fact, both *TRIN* and *VOL* have significant impact on returns regardless of signs of shocks.

Figure 1 to Figure 4 exhibit the IRF of the market and firm-characteristics-sorted portfolios with respect to shock in sentiments. Besides the market portfolio, only the lowest- and highest- MV/BV, lowest- and highest-volatility, and smallest- and largest-size portfolios are considered. Figure 1 gives the impulse function for the market portfolio returns with respect to shock to *USNT* and five proxies. Figure 1(a) uses *USNT* as the only proxy, and it does not seem to capture the combined effect of all the proxies very well. In Figure 1(b), apart from own returns, *MA*, *TRIN*, and *IPO* have relatively stronger initial effects on the market, and the effect eventually dies away within approximately six months.

Figure 2 shows impulse response for size portfolios. Figure 2(a) and Figure 2(c) show similar responses to a shock to *USNT*. The initial impact of sentiment shock is bigger for the smallest *USNT* size portfolio, compared to that for the largest counterpart. Figure 2(b) for the largest and Figure 2(d) for the smallest firms show the response to a shock to five proxies, which are very similar, and both portfolios take similar time to absorb the shock to sentiment. As exhibited in Figure 3, for the lowest volatility portfolio, the initial impact of sentiment is slightly stronger than that for the highest volatility portfolio. The response is similar when a shock to *USNT* is considered. Figure 4 shows that the highest MV/BV portfolio responds slightly strongly to shocks to all the sentiment proxies except turnover, although the absorbing time for both cases is about the same. This phenomenon is also confirmed when *USNT* shock is taken into account.

Findings from IRF give some indication of the impact of innovations in sentiment on portfolio returns. IRF finds slightly more responses of lowest volatility and highest MV/BV portfolios with respect to sentiment shocks. Finally, the unified sentiment seems to slightly capture the variations in individual proxies.

Policy Implications

Overall, results show that sentiment has a strong impact on this market. The most important sentiment proxies in this market to capture sentiment are the moving average and volume of trade, but not the IPOs. The reason could be the lapse of time between the occurrence of market sentiment and the approval to go public due to the absence of shelf registration. The unified market sentiment proxy is always able to significantly detect sentiment. However, usually the inclusion of other proxies in the models can capture sentiment even more.

In addition, the impact of firm characteristics on the sentiment-return relationship is unclear. In the notion of efficiency, Saudi market is inefficient since sentiment significantly explains returns. Interestingly, the investigation of asymmetric effect of sentiment on this market also provides inconclusive evidence. Results show the effects of equal magnitude of both positive and negative, sentiment shocks.

The findings suggest that noise traders and smart traders contribute to the sentiment of the Saudi market. When institutional investors are unable to take smart decisions, the behavior of both types of investors – institutional and individual – are almost indifferent. This may happen when smart investors cannot take risks due to the risk created by noise traders through sentiment-driven trading. Arbitragers can actively trade in the short run to take advantage of market inefficiency, which will drive any possibility of abnormal profits in the long run. Foreign investors with hot money may be able to take advantage of sentiment-based trading strategies to optimize their global profits. In other words, arbitragers may find difficulty to go against individual investors and such an illogical phenomenon is likely to persist.

In general, regardless of their trading strategies, the findings of this paper should help all actual and potential foreign investors to better understand these markets. Moreover, it is noteworthy that the participation of foreign investors is important for these markets to achieve more informational efficiency in the long run. The findings also lead to the possible adoption of effective policies by market monitoring agencies to construct real-time sentiment to improve market efficiency in the long run. Most importantly, policymakers and regulators will be able to set up mechanisms to identify market disorders (such as excessive sentiment) and intervene for corrections before the situation gets out of hand.

Conclusion and Suggestions

The study examines the impact of sentiment on Saudi stock returns. This paper considers the monthly macroeconomic data and individual firms' returns to find the portfolio returns unexplained by the relevant systematic risk that comes from macroeconomic risk factors. Residual return portfolios are then constructed by focusing on firm characteristics. We used five sentiment proxies to create a unified sentiment proxy. Ordinary least squares regression is used to detect the influence of sentiment on the returns. An asymmetric shock-to-sentiment test is conducted using TGARCH models. Finally, the impulse response function shows how the shocks to sentiment proxies affect stock market returns.

Findings of the study imply that sentiment significantly impacts the Saudi market, with trade volume and moving averages as key proxies, while IPOs are less relevant. Firm characteristics have an unclear role in sentiment-return relationships, and both noise and smart traders shape market sentiment. In a nutshell, the absence of analyst recommendations, the strong presence of individual or retail investors, weak monitoring authority, and the deep-rooted existence of a collectivistic society have contributed to the unstable behavior and widespread influence of sentiment in the Saudi market. It is suggested that investors add a " sentiment " factor to the Fama-French type 3-factor or Carhart type 4-factor models. Based on the results, it is better to use two individual factors – past moving average and market liquidity – in those models. For simplicity, at least, a unified proxy using PCA should be able to improve the performance of asset pricing models to explain the returns of the Saudi market.

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References

Abbes, M. B. and Abdelhédi-Zouch M. (2015). Does Hajj pilgrimage affect the Islamic investor sentiment? *Research in International Business and Finance*, 35 (C), 138–152.

Altuwaijri, B. (2016). Investors' Sentiment and the Stock Market Behavior: An Empirical Analysis of the Saudi Stock Market. *Available at SSRN 2889708*.

Anusakumar, S., Ali, R. and Wooi, H. C. (2012). *Momentum and investor sentiment: Evidence from Asian stock markets*. 7th Annual Conference on Asia-Pacific Financial Markets, South Korea.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61* (4), 1645–1680.

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives, 21*(2), 129–151.

Baker, M. and Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets*, *7*(3), 271–299.

Barberis, N., Shleifer, A. and Vishny, R. W. A. (1997). A Model of investor sentiment. *NBER Working Paper No. w5926*.
Available https://ssrn.com/abstract=225707.

Bower, G. H. (1991). Mood congruity of social judgments. *Emotion and Social Judgments*, 31–53.

Brown, G. W. and Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, *11*(1), 1–27.

Buchtel, E. E. and Norenzayan, A. (2008). Which should you use, intuition or logic? Cultural differences in injunctive norms about reasoning. *Asian Journal of Social Psychology*, *11*(4), 264–273.

Chi, L., Zhuang, X. and Song, D. (2012). Investor sentiment in the Chinese stock market: An empirical analysis. *Applied Economics Letters*, *19*(4), 345–348.

Chowdhury, S. S. H., Rahman, M. A. and Sadique, M. S. (2015). Behavior of stock return autocorrelation in the GCC stock markets. *Global Business Review, 16*(5), 737–746.

Chowdhury, S. S. H., Sharmin, R., & Rahman, A. (2014). Effect of sentiment on the Bangladesh stock market returns. *Available at SSRN 2416223*.

Chowdhury, S. S H., Rahman, M. A. and Sadique, M. S. (2017). Stock return autocorrelation, day of the week and volatility: An empirical investigation on the Saudi Arabian stock market. *Review of Accounting and Finance*, 16(2), 218–238.

Dash, S. R., & Maitra, D. (2018). Does sentiment matter for stock returns? Evidence from Indian stock market using wavelet approach. *Finance Research Letters*, *26*, 32-39.

Debata, B., Dash, S. R., & Mahakud, J. (2018). Investor sentiment and emerging stock market liquidity. *Finance Research Letters*, *26*, 15-31.

De Long, J. B., Shleifer, A., Summers, L. G. and Waldman, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703–738.

Dumas, B., Kurshev, A. and Uppal, R. (2005). What can rational investors do about excessive volatility and sentiment fluctuations? Working paper, London Business School.

Elbahrawy, F. (2024). Saudi Stocks Trail Emerging Peers for First Time Since Pandemic. Available https://www.bloomberg.com/news/articles/2024-05-21/saudi-stocks-trail-emerging-peers-for-first-time-since-pandemic

Fisher, K. L. and Statman, M. (2000). Cognitive biases in market forecasts. *Journal of Portfolio Management*, *27*(1), 72–81.

Guo, K., Sun, Y. and Qian, X. (2017). Can investor sentiment be used to predict the stock price? Dynamic analysis based on China stock market. *Physica A: Statistical Mechanics and its Applications,* 469, 390–396.

Hassan, K. M., Al-Sultan, W. S. and Al-Saleem, J. A. (2003). Stock market efficiency in the Gulf Cooperation Council countries (GCC): The case of Kuwait Stock Exchange. *Scientific Journal of Administrative Development*, *1*(1), 1–21.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *AFA 2001 New Orleans Meetings*, Available at SSRN: https://ssrn.com/abstract=265132.

Ishii, K., Tsukasaki, T. and Kitayama, S. (2009). Culture and visual perception: Does perceptual inference depend on culture? *Japanese Psychological Research*, *51*(2), 103–109.

Jana, S. (2016). Effect of investors' sentiment on Indian stock market. *Global Business Review*, *17*(5), 1240–1248.

Kling, G. and Gao, L. (2008). Chinese institutional investors' sentiment. *Journal of International Financial Markets, Institutions and Money*, *18*(4), 374–387.

Liu, H. H., Wu, C. C. and Su, Y. K. (2011). The role of extreme investor sentiment on stock and futures market returns and volatilities in Taiwan. *British Journal of Politics and International Relations*, *11*(1), 504–551.

Mati, A. and Rehman, S. (2023). Saudi Arabia's Economy Grows as it Diversifies Available https://www.imf.org/en/News/Articles/2023/09/28/cf-saudi-arabias-economy-grows-as-it-diversifies

Nisbett, R. E. and Masuda, T. (2003). Culture and point of view. *Proceedings of the National Academy of Sciences*, *100*(19), 11163–11170.

Rehman, U. M. (2013). Investor's sentiment and stock market volatility: An empirical evidence from emerging stock market. *Pakistan Journal of Commerce and Social Sciences*, 7(1), 80–90.

Schmeling, M. (2007). Institutional and individual sentiment: Smart money and noise trader risk? *International Journal of Forecasting*, *23*(1), 127–145.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance*, *16*(3), 394–408.

Seyyed, F. J., Abraham, A. and Al-Hajji, M. (2005). Seasonality in stock returns and volatility: The Ramadan effect. *Research in International Business and Finance*, *19*(3), 374–383.

Stambaugh, R. F., Yu, J. and Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104 (2), 288–302.

Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, 185 (4157), 1124–1131.

Wasiuzzaman, S. (2017). Religious anomalies in Islamic stock markets: The Hajj effect in Saudi Arabia. *Journal of Asset Management*, *18*(3), 157–162.

Zhang, Q. and Yang, S., (2009). Noise trading, investor sentiment, volatility, and stock returns. *Systems Engineering-Theory and Practice*, *29*(3) 40–47.

APPENDICES

Appendix A: List of tables of correlation and descriptive statistics

Table 1 Correlation matrix of Saudi Arabia sentiment proxies

Variables	*TRIN*	*VOL*	*TURN*	*MA*	*IPO*	*USNT*
TRIN	1					
VOL	-0.004	1				
TURN	-0.033	0.040	1			
MA	-0.027	0.368	-0.001	1		
IPO	0.010	0.020	0.006	0.265	1	
USNT	0.029	0.784	0.142	0.753	0.390	1

Table 2. Descriptive statistics of market, size-, MV/BV-, and volatility-sorted portfolios returns in Saudi Arabia stock market

Market return	Market return	Largest size	Large size	Small size	Smallest size	Highest MV/BV	High MV/BV	Low MV/BV	Lowest MV/BV	Highest volatility	High volatility	Low volatility	Lowest volatility
Mean	0.33	0.25	0.19	0.37	0.65	-0.26	0.26	0.82	0.77	-0.41	0.45	0.70	0.60
Median	1.27	0.94	0.76	0.97	0.74	-0.42	1.03	1.66	1.35	0.43	1.49	0.82	0.78
Std. Dev.	9.68	7.00	10.25	10.36	14.08	10.16	8.81	9.94	10.76	12.02	10.60	9.62	8.18
Kurtosis	5.11	2.61	5.75	5.62	5.43	6.50	3.19	2.71	7.02	6.84	6.26	4.44	2.22
Skewness	-1.21	-0.79	-1.20	-1.02	-1.16	-1.37	-0.88	-0.52	-1.33	-1.37	-1.27	-0.84	-0.42
Range	75.94	49.91	83.59	81.82	108.00	82.77	61.44	64.85	90.71	100.76	87.80	73.24	54.99
Minimum	-44.11	-30.39	-46.41	-47.57	-69.91	-53.59	-30.58	-35.84	-53.15	-62.24	-49.22	-39.98	-28.24
Maximum	31.83	19.54	37.13	34.27	38.12	29.19	30.83	29.00	37.58	38.53	38.59	33.26	26.74
Observations (monthly)	166	166	166	166	166	166	166	166	166	166	166	166	166

Appendix B: List of tables of effect of market characteristics on the sentiment-return relationship

Table 3. Impact of sentiment on the market portfolio returns

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	0.37	(0.60)	0.30	(0.43)	0.29	(0.38)	0.28	(0.38)	0.40	(0.62)	0.29	(0.38)	0.28	(0.39)	0.28	(0.38)	0.37	(0.53)
TRIN	-1.51^{***}	(-2.71)	-1.53^{**}	(-2.50)			-1.61^{**}	(-2.43)										
VOL	11.32^{***}	(6.62)	3.48^{***}	(2.89)					13.13^{***}	(8.02)								
TURN	0.01	(0.26)	0.03	(0.57)							0.061	(1.03)						
MA	0.30^{***}	(2.75)	0.34^{***}	(3.08)									0.55^{***}	(4.88)				
IPO	0.07	(0.36)	-0.09	(-0.40)											0.14	(0.58)		
LTRIN	0.27	(0.49)			0.21	(0.32)	0.16	(0.24)										
LVOL	-9.68^{***}	(-5.58)			-0.28	(-0.21)			-10.85^{***}	(-6.49)								
LTURN	-0.03	(-0.54)			-0.03	(-0.53)					-0.054	(-0.91)						
LMA	-0.13	(-1.11)			-0.04	(-0.30)							-0.24^{**}	(-2.11)				
LIPO	0.34	(1.64)			0.39	(1.58)									0.38	(1.59)		
USNT																	4.53^{***}	(6.05)
LUSNT																	-2.75^{***}	(-3.64)
Obser.	165		166		165		165		165		165		165		165		165	
Adj. R^2	0.33		0.16		-0.01		0.02		0.28		-0.00		0.12		0.01		0.18	

Note: ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. *t*-statistics are reported in parentheses just below respective coefficients. Twelve different combinations of sentiment proxies are considered in this table, which are represented by model numbers. The sentiment proxies *TRIN*, *VOL*, *TURN*, *MA*, and *IPO* are estimated from Trading Index, aggregate trading volume, aggregate market turnover, moving average, and initial public offer by debut firms each month, respectively. "L" has been used before proxies to indicate one-month lag. *USNT* and *LUSNT* are unified sentiment proxies created from individual sentiment proxies (*TRIN*, *VOL*, *TURN*, *MA*, *IPO*, and their one-month lag).

Table 4. Effect of size portfolios on the sentiment-return relationship

Panel A. largest-size portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	0.27	(0.56)	0.23	(0.45)	0.22	(0.39)	0.21	(0.39)	0.28	(0.56)	0.21	(0.38)	0.21	(0.40)	0.21	(0.38)	0.26	(0.51)
TRIN	-1.06^{**}	(-2.46)	-1.09^{**}	(-2.37)			-1.15^{**}	(-2.40)										
VOL	6.86^{***}	(5.15)	2.14^{**}	(2.38)					7.93^{***}	(6.30)								
TURN	0.01	(0.16)	0.02	(0.41)							0.04	(0.84)						
MA	0.17^{**}	(1.99)	0.18^{**}	(2.14)									0.33^{***}	(3.95)				
IPO	0.16	(1.01)	0.05	(0.27)											0.17	(0.98)		
LTRIN	-0.18	(-0.42)			-0.22	(-0.44)	-0.25	(-0.52)										
LVOL	-5.71^{***}	(-4.25)			-0.08	(-0.08)			-6.59^{***}	(-5.16)								
LTURN	-0.02	(-0.45)			-0.02	(-0.48)					-0.03	(-0.76)						
LMA	-0.13	(-1.44)			-0.06	(-0.73)							-0.17^{**}	(-2.06)				
LIPO	0.28^{*}	(1.76)			0.30^{*}	(1.70)									0.27	(1.61)		
USNT																	2.86^{***}	(5.15)
LUSNT																	-1.74^{***}	(-3.11)
Obser.	165		166		165		165		165		165		165		165		165	
Adj. R^2	0.23		0.10		-0.01		0.02		0.19		-0.01		0.08		0.01		0.13	

Table 4 continued

Panel B**.** large-size portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	0.19	(0.28)	0.15	(0.20)	0.12	(0.15)	0.11	(0.14)	0.21	(0.30)	0.11	(0.14)	0.10	(0.14)	0.11	(0.14)	0.19	(0.26)
TRIN	-1.43**	(-2.28)	-1.43**	(-2.14)			-1.52**	(-2.16)										
VOL	10.02***	(5.18)	2.61**	(1.99)					11.77***	(6.42)								
TURN	0.026	(0.47)	0.03	(0.55)							0.07	(1.11)						
MA	0.28**	(2.31)	0.32***	(2.67)									0.52***	(4.32)				
IPO	0.29	(1.23)	0.130	(0.53)											0.34	(1.38)		
LTRIN	-0.01	(-0.01)			-0.07	(-0.09)	-0.11	(-0.15)										
LVOL	-9.07***	(-4.65)			-0.86	(-0.61)			-10.20***	(-5.48)								
LTURN	-0.05	(-0.87)			-0.045	(-0.77)					-0.07	(-1.17)						
LMA	-0.13	(-1.00)			-0.01	(-0.09)							-0.23*	(-1.86)				
LIPO	0.31	(1.34)			0.33	(1.28)									0.34	(1.37)		
USNT																	4.45***	(5.54)
LUSNT																	-2.86***	(-3.53)
Obser.	165		166		165		165		165		165		165		165		165	
Adj. R^2	0.24		0.12		-0.01		0.02		0.20		-0.01		0.09		0.01		0.15	

Panel C. small-size portfolios

Const.	0.41	(0.61)	0.34	(0.45)	0.32	(0.39)	0.31	(0.39)	0.43	(0.64)	0.31	(0.39)	0.31	(0.39)	0.31	(0.38)	0.39	(0.53)
TRIN	-1.41**	(-2.32)	-1.39**	(-2.07)			-1.46**	(-2.05)										
VOL	12.86***	(6.82)	4.01***	(3.05)					14.12***	(8.03)								
TURN	0.02	(0.28)	0.020	(0.37)							0.07	(1.01)						
MA	0.20*	(1.70)	0.27**	(2.22)									0.49***	(3.94)				
IPO	0.013	(0.06)	-0.14	(-0.58)											0.04	(0.15)		
LTRIN	0.29	(0.47)			0.22	(0.31)	0.19	(0.26)										
LVOL	-10.92***	(-5.74)			-0.40	(-0.28)			-11.75***	(-6.59)								
LTURN	-0.05	(-0.95)			-0.05	(-0.90)					-0.08	(-1.25)						
LMA	-0.09	(-0.69)			-0.05	(-0.36)							-0.23*	(-1.90)				
LIPO	0.23	(1.00)			0.32	(1.20)									0.29	(1.15)		
USNT																	4.48***	(5.50)
LUSNT																	-2.83***	(-3.46)
Obser.	165		166		165		165		165		165		165		165		165	
Adj. R^2	0.29		0.12		-0.02		0.01		0.28		-0.00		0.08		-0.00		0.15	

Table 4 continued

Panel D. smallest-size portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	0.67	(0.72)	0.59	(0.60)	0.57	(0.51)	0.57	(0.53)	0.71	(0.73)	0.58	(0.52)	0.56	(0.54)	0.58	(0.52)	0.68	(0.68)
TRIN	-2.62***	(-3.14)	-2.62***	(-2.98)			-2.71***	(-2.84)										
VOL	14.1***	(5.50)	4.63***	(2.69)					17.02***	(6.83)								
TURN	0.02	(0.31)	0.036	(0.50)							0.08	(0.94)						
MA	0.511***	(3.14)	0.59***	(3.70)									0.83***	(5.08)				
IPO	-0.13	(-0.43)	-0.30	(-0.94)											0.06	(0.18)		
LTRIN	1.04	(1.26)			1.03	(1.04)	0.90	(0.95)										
LVOL	-11.71***	(-4.52)			0.22	(0.11)			-13.03***	(-5.15)								
LTURN	-0.04	(-0.53)			-0.04	(-0.48)					-0.07	(-0.85)						
LMA	-0.08	(-0.46)			0.05	(0.27)							-0.28*	(-1.72)				
LIPO	0.16	(0.53)			0.25	(0.69)									0.28	(0.81)		
USNT																	6.29***	(5.74)
LUSNT																	-3.48***	(-3.15)
Obser.	165		166		165		165		165		165		165		165		165	
Adj. R^2	0.29		0.19		-0.02		0.04		0.21		-0.01		0.13		-0.01		0.16	

Note: ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. *t*-statistics are reported in parentheses just below respective coefficients. Twelve different combinations of sentiment proxies are considered in this table, which are represented by model numbers. The sentiment proxies *TRIN*, *VOL*, *TURN*, *MA*, and *IPO* are estimated from Trading Index, aggregate trading volume, aggregate market turnover, moving average, and initial public offer by debut firms each month, respectively. “L” has been used before proxies to indicate one-month lag. *USNT* and *LUSNT* are unified sentiment proxies created from individual sentiment proxies (*TRIN*, *VOL*, *TURN*, *MA*, *IPO*, and their one-month lag).

Table 5. Effect of MV/BV portfolios on the sentiment-return relationship

Panel A. highest MV/BV portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	-9.09	(-0.95)	-24.78**	(-2.37)	1.74	(0.17)	3.75***	(3.21)	-9.30	(-1.00)	-0.31	(-0.37)	-0.40	(-0.43)	-0.65	(-0.75)	-0.25	(-0.33)
TRIN	-0.53	(-1.37)	-0.78*	(-1.79)			-0.70*	(-1.71)										
VOL	10.86***	(6.23)	2.18**	(2.42)					11.66***	(6.61)								
TURN	0.00	(0.33)	0.00	(0.54)							0.00	(0.78)						
MA	0.08	(0.76)	-0.06	(-0.53)									0.05	(0.44)				
IPO	0.02	(0.08)	0.10	(0.39)											0.20	(0.84)		
LTRIN	-1.71***	(-4.51)			-1.92***	(-4.57)	-1.92***	(-4.72)										
LVOL	-9.82***	(-5.45)			0.10	(0.11)			-10.89***	(-6.15)								
LTURN	-0.00	(-0.63)			-0.00	(-0.75)					-0.00	(-0.88)						
LMA	-0.00	(-0.01)			-0.03	(-0.24)							-0.04	(-0.29)				
LIPO	-0.15	(-0.69)			0.03	(0.12)									0.11	(0.44)		
USNT																	4.43***	(4.32)
LUSNT																	-3.75***	(-3.64)
Obser.	164		165		164		165		165		165		164		165		165	
Adj. R^2	0.27		0.02		0.094		0.12		0.20		-0.01		-0.01		-0.01		0.09	

Table 5 continued

Panel B. high MV/BV portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	-10.79	(-1.31)	-24.68***	(-2.78)	-0.50	(-0.06)	3.35***	(3.29)	-11.34	(-1.44)	0.15	(0.21)	-0.021	(-0.03)	-0.28	(-0.38)	0.23	(0.37)
TRIN	-0.42	(-1.27)	-0.60	(-1.63)			-0.54	(-1.52)										
VOL	9.70***	(6.47)	2.19***	(2.85)					10.41***	(6.94)								
TURN	0.00	(0.47)	0.00	(0.67)							0.00	(0.94)						
MA	0.03	(0.31)	-0.07	(-0.78)									0.022	(0.21)				
IPO	0.14	(0.73)	0.21	(1.00)											0.30	(1.46)		
LTRIN	-1.31***	(-4.00)			-1.52***	(-4.14)	-1.51***	(-4.25)										
LVOL	-8.55***	(-5.52)			0.26	(0.34)			-9.43***	(-6.25)								
LTURN	-0.00	(-0.62)			-0.00	(-0.68)					-0.00	(-0.92)						
LMA	0.035	(0.36)			0.01	(0.05)							0.02	(0.15)				
LIPO	-0.13	(-0.66)			0.04	(0.20)									0.12	(0.60)		
USNT																	4.35***	(5.03)
LUSNT																	-3.44***	(-3.96)
Obser.	164		165		164		165		165		165		164		165		165	
Adj. R^2	0.27		0.04		0.07		0.10		0.22		0.01		-0.01		-0.00		0.13	

Panel C. low MV/BV portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	-14.01	(-1.58)	-34.74***	(-3.47)	-0.50	(-0.05)	4.58***	(3.98)	-16.49*	(-1.92)	0.81	(0.99)	0.59	(0.65)	-0.08	(-0.09)	0.90	(1.28)
TRIN	-0.40	(-1.12)	-0.70*	(-1.67)			-0.57	(-1.42)										
VOL	12.33***	(7.66)	3.13***	(3.62)					13.44***	(8.21)								
TURN	0.00	(0.21)	0.00	(0.53)							0.00	(0.72)						
MA	0.00	(0.02)	-0.13	(-1.25)									-0.04	(-0.33)				
IPO	0.09	(0.42)	0.17	(0.71)											0.27	(1.18)		
LTRIN	-1.53***	(-4.37)			-1.79***	(-4.42)	-1.86***	(-4.64)										
LVOL	-10.85***	(-6.53)			0.32	(0.38)			-11.97***									
LTURN	-0.00	(-0.64)			-0.00	(-0.83)					-0.00	(-0.81)						
LMA	0.06	(0.59)			-0.01	(-0.05							0.09	(0.73)				
LIPO	0.25	(1.23)			0.48**	(2.06)									0.57**	(2.46)		
USNT																	5.96***	(6.26)
LUSNT																	-4.83***	(-5.06)
Obser.	164		165		164		165		165		165		164		165		165	
Adj. R^2	0.36		0.06		0.12		0.12		0.29		-0.01		-0.01		0.03		0.19	

Table 5 continued

Panel D. lowest MV/BV portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const	-17.41*	(-1.78)	-33.85***	(-3.08)	-5.79	(-0.57)	4.83***	(4.01)	-18.28*	(-1.86)	0.71	(0.81)	0.40	(0.41)	0.20	(0.22)	0.83	(1.08)
TRIN	-0.13	(-0.34)	-0.23	(-0.51)			-0.12	(-0.29)										
VOL	11.09***	(6.26)	2.98***	(3.14)					12.31***	(6.59)								
TURN	0.00	(0.40)	0.00	(0.63)							0.00	(0.75)						
MA	0.018	(0.16)	-0.09	(-0.79)									-0.01	(-0.10)				
IPO	0.01	(0.04)	0.12	(0.45)											0.22	(0.85)		
LTRIN	-2.30***	(-5.97)			-2.54***	(-6.00)	-2.51***	(-5.99)										
LVOL	-9.24***	(-5.05)			0.88	(01.00)			-10.69***	(-5.69)								
LTURN	-0.00	(-0.47)			-0.00	(-0.57)					-0.00	(-0.70)						
LMA	0.07	(0.57)			0.00	(0.04)							0.07	(0.55)				
LIPO	-0.07	(-0.32)			0.13	(0.54)									0.29	(1.15)		
USNT																	5.92***	(5.65)
LUSNT																	-4.85***	(-4.61)
Obser.	164		165		164		165		165		165		164		165		165	
Adj. R^2	0.32		0.03		0.17		0.17		0.20		-0.01		-0.01		0.00		0.16	

Note: ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. *t*-statistics are reported in parentheses just below respective coefficients. Twelve different combinations of sentiment proxies are considered in this table, which are represented by model numbers. The sentiment proxies *TRIN*, *VOL*, *TURN*, *MA*, and *IPO* are estimated from TRading Index, aggregate trading volume, aggregate market turnover, moving average, and initial public offer by debut firms each month, respectively. "L" has been used before proxies to indicate one--month lag. *USNT* and *LUSNT* are unified sentiment proxies created from individual sentiment proxies (*TRIN*, *VOL*, *TURN*, *MA*, *IPO*, and their one-month lag).

Table 6. Effect of volatility portfolios on the sentiment-return relationship

Panel A. highest volatility portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	-13.60	(-1.24)	-32.09**	(-2.60)	-0.34	(-0.03)	4.80***	(3.56)	-12.84	(-1.17)	-0.44	(-0.45)	-0.42	(-0.38)	-1.01	(-0.98)	-0.31	(-0.57)
TRIN	-0.52	(-1.17)	-0.66	(-1.29)			-0.58	(-1.24)										
VOL	12.30***	(6.17)	2.79***	(2.62)					13.89***	(6.65)								
TURN	0.00	(0.38)	0.00	(0.63)							0.00	(0.84)						
MA	0.03	(0.20)	-0.14	(-1.06)									-0.01	(-0.08)				
IPO	0.144	(0.58)	0.24	(0.80)											0.32	(1.13)		
LTRIN	-2.50***	(-5.77)			-2.77***	(-5.77)	-2.76***	(-5.89)										
LVOL	-10.78***	(-5.24)			0.37	(0.37)			-12.83***	(-6.11)								
LTURN	-0.00	(-0.51)			-0.00	(-0.62)					-0.00	(-0.75)						
LMA	-0.01	(-0.10)			-0.06	(-0.48)							-0.01	(-0.08)				
LIPO	-0.08	(-0.32)			0.14	(0.50)									0.25	(0.88)		
USNT																	5.89***	(4.92)
LUSNT																	-5.17***	(-4.31)
Obser.	164		165		164		165		165		165		164		165		165	
Adj. R^2	0.32		0.03		0.16		0.17		0.21		-0.01		-0.01		0.00		0.12	

Table 6 continued

Panel B. high volatility portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	-11.02	(-1.14)	-28.58***	(-2.63)	1.48	(0.14)	4.58***	(3.78)	-10.72	(-1.13)	0.44	(0.50)	0.44	(0.45)	-0.11	(-0.12)	0.51	(0.66)
TRIN	-0.36	(-0.93)	-0.56	(-1.24)			-0.49	(-1.16)										
VOL	12.02***	(6.84)	2.55***	(2.72)					13.13***	(7.29)								
TURN	0.00	(0.08)	0.00	(0.39)							0.00	(0.64)						
MA	0.02	(0.14)	-0.14	(-1.18)									-0.01	(-0.07)				
IPO	0.19	(0.86)	0.27	(1.05)											0.34	(1.34)		
LTRIN	-1.92***	(-5.03)			-2.19***	(-5.07)	-2.18***	(-5.18)										
LVOL	-10.75***	(-5.91)			0.22	(0.24)			-12.17***	(-6.72)								
LTURN	-0.00	(-0.48)			-0.00	(-0.70)					-0.00	(-0.77)						
LMA	-0.00	(-0.01)			-0.05	(-0.42)							-0.01	(-0.11)				
LIPO	-0.13	(-0.58)			0.08	(0.32)									0.16	(0.654)		
USNT																	5.34***	(5.09)
LUSNT																	-4.60***	(-4.36)
Obser.	164		165		164		165		165		165		164		165		165	
Adj. R^2	0.32		0.03		0.12		0.14		0.24		-0.01		-0.01		0.00		0.13	

Panel C. low volatility portfolios

Const.	-16.39*	(-1.82)	-32.78***	(-3.38)	-5.60	(-0.59)	3.89***	(3.48)	-19.57**	(-2.25)	0.60	(0.77)	0.08	(0.09)	0.03	(0.05)	0.71	(1.04)
TRIN	-0.28	(-0.76)	-0.52	(-1.30)			-0.40	(-1.03)										
VOL	10.62***	(6.48)	2.90***	(3.46)					11.29***	(6.85)								
TURN	0.00	(0.65)	0.00	(0.81)							0.00	(0.95)						
MA	0.07	(0.63)	-0.03	(-0.26)									0.04	(0.35)				
IPO	-0.06	(-0.27)	0.045	(0.20)											0.19	(0.86)		
LTRIN	-1.48***	(-4.16)			-1.69***	(-4.28)	-1.70***	(-4.36)										
LVOL	-8.98***	(-5.31)			0.73	(0.88)			-9.57***	(-5.77)								
LTURN	-0.00	(-0.70)			-0.00	(-0.69)					-0.00	(-0.90)						
LMA	0.10	(0.97)			0.06	(0.58)							0.10	(0.87)				
LIPO	0.04	(0.21)			0.23	(1.02)									0.37	(1.64)		
USNT																	5.31***	(5.71)
LUSNT																	-3.95***	(-4.23)
Obser.	164		165		164		165		165		165		164		165		165	
Adj. R^2	0.28		0.05		0.10		0.10		0.22		-0.01		-0.00		0.01		0.16	

Table 6 continued

Panel D. lowest volatility portfolios

Variable	Model1	t-stat	Model2	t-stat	Model3	t-stat	Model4	t-stat	Model5	t-stat	Model6	t-stat	Model7	t-stat	Model8	t-stat	Model9	t-stat
Const.	-10.19	(-1.33)	-25.24***	(-3.04)	0.38	(0.05)	3.30***	(3.43)	-11.93	(-1.64)	0.56	(0.83)	0 .27	(0.36)	0.08	(0.11)	0.62	(1.06)
TRIN	-0.32	(-1.03)	-0.53	(-1.54)			-0.44	(-1.32)										
VOL	9.76***	(7.01)	2.27***	(3.16)					10.29***	(7.45)								
TURN	0.00	(0.27)	0.00	(0.53)							0.00	(0.73)						
MA	0.02	(0.17)	-0.07	(-0.77)									-0.01	(-0.06)				
IPO	0.023	(0.13)	0.10	(0.53)											0.20	(1.02)		
LTRIN	-1.10***	(-3.63)			-1.30***	(-3.80)	-1.33***	(-3.97)										
LVOL	-8.68***	(-6.04)			0.17	(0.24)			-9.22***	(-6.64)								
LTURN	-0.00	(-0.55)			-0.00	(-0.72)					-0.00	(-0.82)						
LMA	0.09	(0.98)			0.04	(0.42)							0.07	(0.72)				
LIPO	-0.01	(-0.08)			0.17	(0.85)									0.25	(1.31)		
USNT																	4.59***	(5.79)
LUSNT																	-3.66***	(-4.60)
Obser.	164		165		164		165		165		165		164		165		165	
Adj. R^2	0.29		0.04		0.07		0.09		0.25		-0.01		-0.01		0.00		0.16	

Note: ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. *t*-statistics are reported in parentheses just below respective coefficients. Twelve different combinations of sentiment proxies are considered in this table, which are represented by model numbers. The sentiment proxies *TRIN*, *VOL*, *TURN*, *MA*, and *IPO* are estimated from TRading Index, aggregate trading volume, aggregate market turnover, moving average, and initial public offer by debut firms each month, respectively. "L" has been used before proxies to indicate one--month lag. *USNT* and *LUSNT* are unified sentiment proxies created from individual sentiment proxies (*TRIN*, *VOL*, *TURN*, *MA*, *IPO*, and their one-month lag).

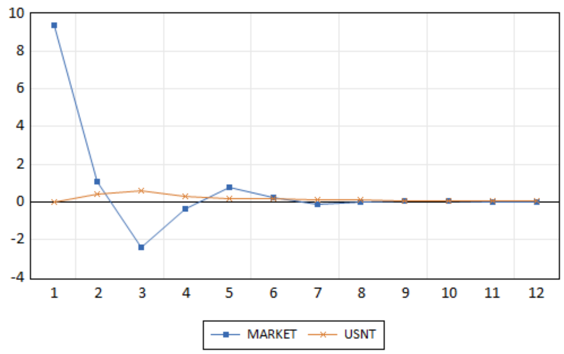
Table 7 Impact of sentiment shock on stock returns in a T-GARCH framework

Coefficients	*TRIN*	*VOL*	*TURN*	*MA*	*USNT*
θ_0	1.148	3.172	2.316	1.042	0.608
	(0.561)	(3.235)***	(0.112)	(0.889)	(0.450)
θ_1	-0.164	-0.394	-0.143	-0.070	-0.013
	(-0.615)	(-2.195)**	(-0.086)	(-0.332)	(-0.052)
θ_2	-0.307	12.533	0.042	0.636	5.197
	(-6.057)***	(9.548)***	(0.492)	(8.444)***	(8.596)***
γ_0	5.812	1.071	60.165	1.046	1.538
	(2.492)**	(1.729)*	(0.850)	(0.984)	(1.447)
γ_1	0.217	0.215	0.067	0.176	0.082
	(1.728)*	(3.276)***	(0.214)	(2.126)**	(0.857)
γ_2	-0.101	-0.233	-0.014	-0.022	0.213
	(-0.836)	(-3.614)***	(0.048)	(-0.219)	(1.477)
γ_3	0.758	0.817	0.572	0.815	0.752
	(9.181)***	(20.719)***	(1.108)	(16.870)***	(9.892)***
γ_4	6.195	-39.289	-0.004	0.148	2.686
	(2.444)**	(-6.289)***	(-0.321)	(1.375)	(0.675)
γ_5	-5.945	97.160	-0.011	-0.022	4.761
	(-4.069)***	(4.482)***	(-0.358)	(-0.475)	(1.440)
LL	-575.702	-541.923	-606.323	-563.822	-553.903

Note: This table reports the coefficients of TGARCH model, described by equations (5.6a) and (5.6b) outlined in chapter five. Every column presents the coefficients of a model that consists of a single sentiment proxy. Here: ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. *t*-statistics are reported in parentheses just below respective coefficients.

Appendix C: List of figures of market characteristics to innovations using cholesky (d.f. adjusted) factors

(a)



(b)

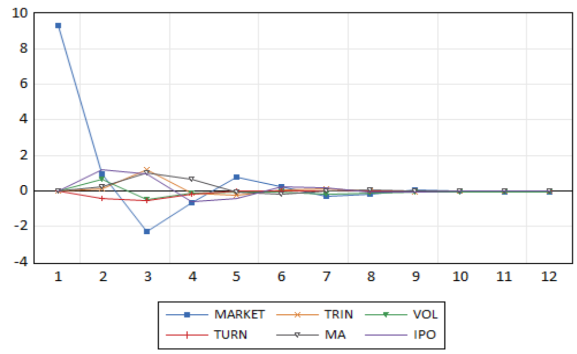
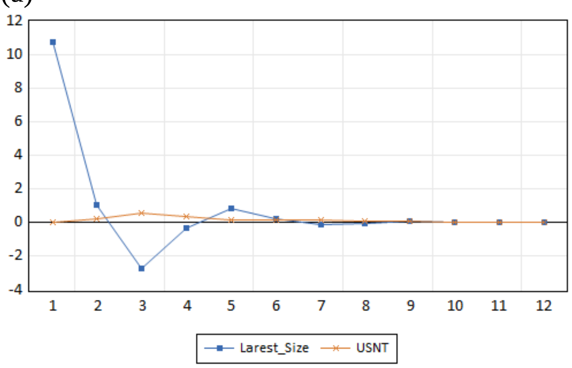
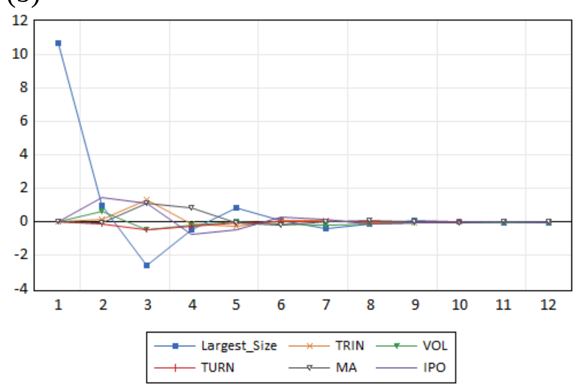


Figure 1: Impulse response of market to innovations using cholesky (d.f. adjusted) factors

(a)



(b)



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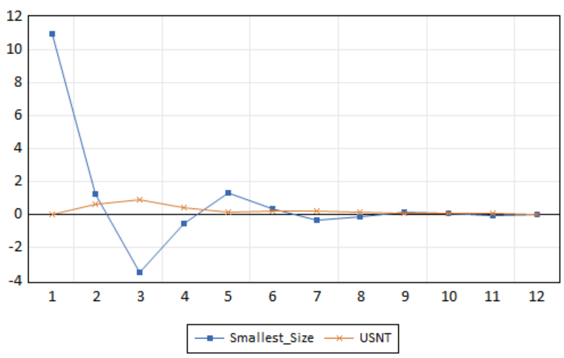


(d)

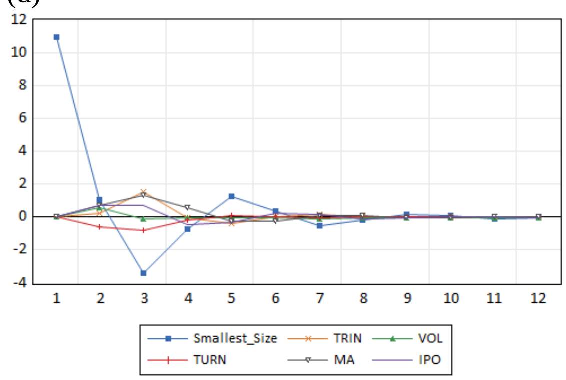
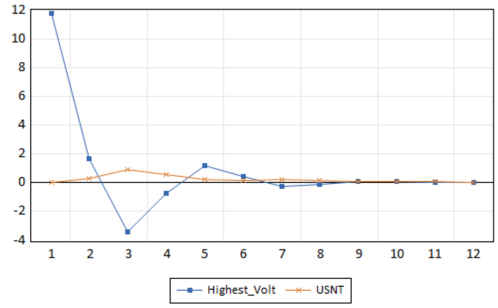
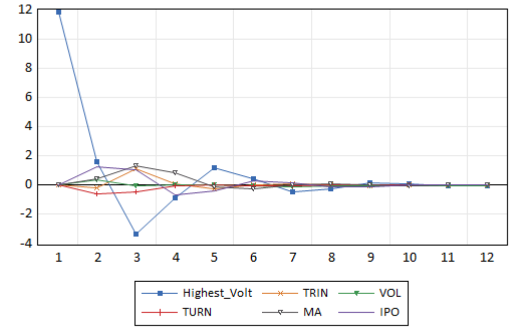


Figure 2: Impulse response of size portfolio to innovations using cholesky (d.f. adjusted) factors

(a)

(b)





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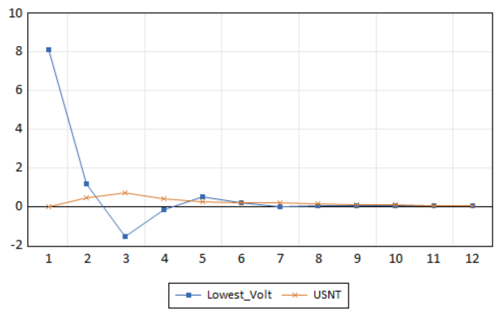
(d)



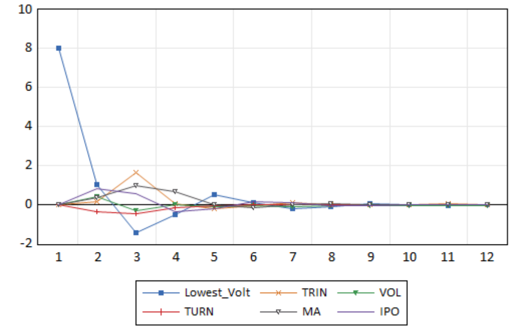
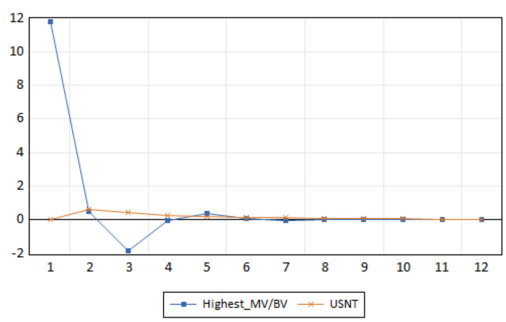
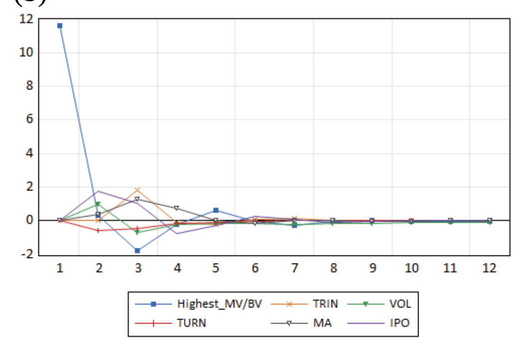


Figure 3: Impulse response of volatility portfolio to innovations using cholesky (d.f. adjusted) factors

(a)

(b)





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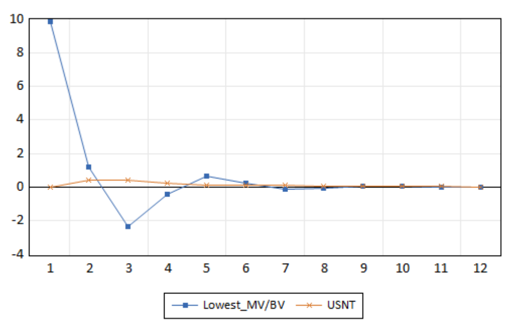
(b)



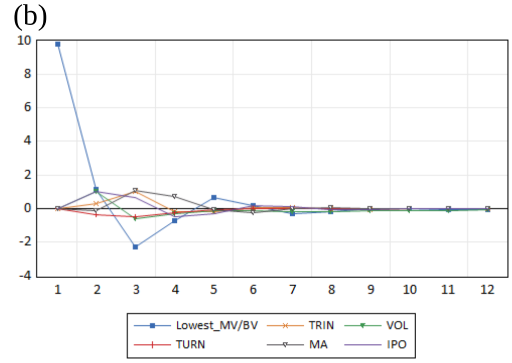


Figure 4: Impulse response of MV/BV portfolio to innovations using cholesky (d.f. adjusted) factors