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Domestic and Foreign Investor Dynamics in Indonesian Stock Exchange: Evidence from 10 Years High-Frequency Data

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This study analyses price impact, herding behaviour, and feedback trading of domestic and foreign investors in Indonesia Stock Exchange (IDX) by employing vector autoregressive models using high-frequency transaction data in the period of 2008 – 2017. We find that domestic investors impact return negatively whereas foreign investors have no impact to return. In terms of herding behavior, domestic and foreign investors herd to themselves strongly. Domestic investors reverse-herd to foreign investors in the short-term (1 day) but no consistent pattern in the opposite direction. Regarding feedback trading, both domestic and foreign investors are contrarian in the big and medium cap portfolios but employ momentum strategy in the small cap portfolio. We also find that, in the crisis period, price impact is more pronounced in terms of economic and statistical significance. On the other hand, evidence of herding behavior and feedback trading decreases in market downturns, although with the same patterns overall.

Keyword: *domestic investors; foreign investors; price impact; herding behavior; feedback trading; intraday data; vector autoregressive*

JEL Classification: G10, G20, G40

Introduction

There are three important aspects of investor behavior worth investigating: price impact, herding behavior, and feedback trading. First, price impact is defined as the impact of trading activity of investors to the market return. Classical finance approach believes that prices reflect information fully, with a consequence of there is no investment strategy that will be profitable in the long term. Nevertheless, even under the assumption that efficient market hypothesis (EMH) holds, investor trading is expected to impact prices, otherwise prices can not reflect available information. Second, herding behavior is shown by the trading activity of certain group of investors impacting the trading activity of other group of investors. The study of herding behavior has also been linked to the topic of efficient market hypothesis in the sense that if investors trade not based on real information and herd to other investors instead, the price might not rationally reflect the true value of a stock. Therefore, its existence might stand in opposition with the theory of efficient market hypothesis. Third, feedback trading is the act of trading following past performance or return of stock. When investors buy past winners (losers) or sell past losers (winners), they are known as performing positive (negative) feedback or momentum (contrarian) trading. Being studied intensively in the financial research, this behav-

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ior sparks a debate regarding whether trading based on past performance is considered as a rational behavior; Carhart (1997) includes momentum factor as a risk factor while Fama and French (2015) do not.

This paper focuses on the distinction of the behaviors of domestic and foreign investors in Indonesia, one of the fastest growing emerging markets. According to Frankel (1996), domestic and foreign investors might have different expectations regarding the future of the economy, possibly arising from asymmetric information. As a consequence, their trading behaviors could differ from one another (Bowe & Domuta, 2004; Grinblatt & Keloharju, 2000; Iihara, Kato, & Tokunaga, 2001; Tayde & Rao, 2011; Yao, Ma, & He, 2014). Grouping them together as one type of investor might hinder us from gaining important insights. Another explanation to explain their difference in trading behavior is that they might have different information. This is shown by the researchers that compare their performance, which many show that domestic investors obtain higher profits than foreign investors (Agarwal, Faircloth, Liu, & Rhee, 2009; Choe, Kho, & Stulz, 2005; Dvořák, 2005).

We contribute to the literature by adding trade direction in the construction of trading imbalance in the analysis. Many research (Dorn, Huberman, & Sengmueller, 2008; Griffin, Harris, & Topaloglu, 2003; Ng & Wu, 2007) construct trading imbalance as a measure of trading activity by calculating the difference between buying and selling volume/value scaled by some common measures. However, there is no information regarding trading direction is incorporated in the construction of the trading imbalance measure, even though many regard trade directions are essential in capturing trade information, for example in testing asymmetric information (Hasbrouck, 1988) or calculating trading imbalances in testing market breakdowns (Blume, MacKinlay, & Terker, 1989). Trade direction is also important because the information contained in different direction might differ (Ahn, Kang, & Ryu, 2010; Lee, 1992). Because not many data providers are able to provide such information, Lee and Ready (1991) develops a method to approximate the trade direction from trade and quote data. Fortunately, our data contain both order and transaction number, making it possible to exactly determine whether a trade is buyer- or seller-initiated, eliminating the needs for approximation.

This study is relevant for the following reason. Knowing that foreign and domestic investors might have different expectations and information, we want to investigate their behavior using analysis that contains trade direction which, to the best of our knowledge, has never been studied before in Indonesia. This is useful for both policymakers and investors to identify what type of investors are impacting the market and/or influencing other investors and what strategy they implement. Finally, we also add more depth to our analysis by investigating the behaviors specifically in the period of crisis. Many researches have shown that investors show different behaviors in the period of downturns (Zhou & Lai, 2009). This is highly relevant because it is a period when the systemic risks are high and often influences the economy quite adversely, therefore the importance.

Literature Review

In Indonesia, there is not much study that use intraday data yet. Most research still use daily data due to the availability and lower cost. Nevertheless, there are already some research that incorporate such data in Indonesia. Among the first ones is Bonser-Neal, Linnan, and Neal (1999) who use intraday data to estimate trading/transaction costs and analysing price impact in Indonesian stock market. Another research that use high-frequency data is undertaken by Comerton-Forde (1999) that investigates the impact of market opening procedures to the stock market efficiency by comparing the opening rules in Jakarta and Australia. There is also a research by Dvořák (2005) and Agarwal et al. (2009) that use transaction data in comparing the profits of foreign and domestic investors. However, those researches only use relatively small sample which is around 1-2 years. Finally, a research by Arroisi (2019) also use intraday data in calculating market interconnectedness with realized volatility as the inputs in constructing the measure and trading imbalances.

Previous studies show that foreign and domestic investors have different kind of information which lead to their difference in performance. Dvořák (2005) compares the performance of domestic and foreign investor in Jakarta Stock Exchange (JSX, now Indonesia Stock Exchange or IDX) and find that domestic investors obtain higher profits than the foreign counterparts in the short-term. The conventional wisdom is that this superior performance might be due to an advantage from local information. Using different sample from another market, Choe et al. (2005) find similar results that domestic investors perform better than foreign investors. They explain this stylized fact using different approach and conclude that the reason for the underperformance of foreign investors is that they trade at bad times. Agarwal et al. (2009) examines both hypothesis using JSX as sample and instead conclude that the explanation of the inferior performance of foreign investors is due to overly aggressive trading.

In terms of price impact, Brennan and Cao (1997) find that in the U.S. and several emerging markets, foreign investment has positive impact on the stock market return. Similar evidences are given by Bekaert, Harvey, and Lumsdaine (2002) who find that, in emerging markets, foreign capital flows impact stock return in the short term, even though the permanent effect is without significant magnitude. This is also supported by Bonser-Neal et al. (1999) who find that foreign investors have greater price impact than domestic investors. One particular event that is often related to the impact of foreign investors' trading impact to stock prices is market liberalization. Henry (2000) shows that liberalization on the stock market, permission for foreign investors to participate in a country's capital market, positively correlate with higher stock market return. This is supported by Jeon and Moffett (2010) who study the impact of trading by foreign investors in Korea in pre- and post-liberalization. They use yearly stock ownership as a proxy of trading activity and find that there is a positive relationship between foreign ownership and stock return and the relationship is even stronger after liberalization. They also show that the relationship can be explained by both (1) the positive impact of trading to stock return and (2) a result of feedback trading by investors. Finally, recent evidence from Vietnam adds to the literature that foreign purchases are associated with future short-term return (Vo, 2017).

Foreign and domestic investors are known to have different behaviors in terms of herding. Bowe and Domuta (2004), using the sample around Indonesian 1997 Financial Crisis, find that both types of investor herd, with foreign investors show more herding. Foreign investors also herd more when the crisis starts. However, this research only uses daily data. In other region, Garg, Mitra, and Kumar (2016) find that foreign institutional investors in India perform herding in both buying and selling by using LSV measure of Lakonishok, Shleifer, and Vishny (1992), again, with only low-frequency data. On the other hand, using monthly data from Tokyo Stock Exchange, Iihara et al. (2001) show that, in fact, domestic investors are more likely to herd and foreign investors trade based on information, quite contrary to other research. Interestingly, Yao et al. (2014) suggest that there is no substantial difference in domestic and foreign investors in Chinese stock market in their herding, even in the period of extreme price changes, especially after market liberalization.

There are many explanations on why investors exhibit herding behavior. Wermers (1999) synthesizes that there are four theories regarding the reasons why institutional investors herd. These explanations might still be appropriate for investors in general. Firstly, fund managers tend to follow others because of the risk of losing by acting differently than others; therefore, damaging their reputation (Scharfstein & Stein, 1990). Secondly, they seem to herd because they have the same information (Froot, Scharfstein, & Stein, 1992; Hirshleifer, Subrahmanyam, & Titman, 1994). Thirdly, they can gather new information from previous trades by other fund managers (Bikhchandani, Hirshleifer, & Welch, 1992). And lastly, fund managers might

Table 1. Transaction Data Summary

This table presents the summary of the data used in the research. The sample in 2008 – 2010 is directly obtained from Indonesian Stock Exchange (IDX) while the sample in 2011 – 2017 is from third-party, IMQ Multimedia Utama (imq21.com). Overall, there are 2,386 trading days, 554 stocks, 372 million transaction frequency (TF), and 9,600 trillion IDR of transaction value (TV). This table also presents the average daily transaction frequency and value each year and for the whole 10 years.

Year	Trading Days	Stocks Traded	TF (thousand)	Avg. Daily TF (thousand)	TV (trillion IDR)	Avg. Daily TV (trillion IDR)
2008	240	366	12,538.02	52.24	796.55	3.32
2009	238	385	20,635.19	86.70	799.69	3.36
2010	245	394	23,999.43	97.96	883.30	3.61
2011	246	416	26,675.41	108.44	931.82	3.79
2012	245	437	28,713.76	117.20	860.90	3.51
2013	225	456	33,212.82	147.61	1080.65	4.80
2014	242	479	48,678.93	201.15	1096.67	4.53
2015	242	505	51,781.35	213.97	989.63	4.09
2016	236	520	60,749.42	257.41	1123.12	4.76
2017	227	536	65,017.35	286.42	1081.82	4.77
2008 – 2017	2,386	554	372,001.68	155.91	9,644.16	4.04

have the same tendency to avoid assets with particular characteristics, i.e. illiquidity or low riskiness (Falkenstein, 1996).

Foreign and domestic investors are also reported to have different feedback trading behavior. Based on high-frequency data, Grinblatt and Keloharju (2000) find that foreign investors are momentum investors while domestic investors are contrarian investors. Similarly, using high-frequency data from Korean stock exchange, Choe, Kho, and Stulz (1999) find that foreign investors engage in positive feedback trading before the 1997 crisis. In the same country, Kim and Wei (2002) suggest that foreign investors who live outside Korea employ more trend-chasing strategy than foreign investors who live in the country. Research by Tayde and Rao (2011) that implement the methodology of Lakonishok et al. (1992) and Wermers (1999) also find similar results in Indian stock market that foreign institutional investors perform positive feedback trading in various periods. In Indonesia, on the other hand, Bowe and Domuta (2004) do not find evidence of momentum trading by either domestic or foreign investors. They use the sample around 1997 Crisis and find that the trades are not destabilizing prices.

As we have reviewed in the literatures, we only find a handful research that incorporates high-frequency data in the research of price impact, herding behavior, and feedback trading in Indonesia, let alone that also incorporate trade direction in calculating the variables. Given the importance of the topic, this research aims to fill that gap.

Research Methods

Data

The data used in this study include:

1. Transactions of all firms listed in IDX in 2008 – 2017. Sources are directly from IDX for the period of 2008 – 2010 and from IMQ[1] for the period of 2011 – 2017. Information contained in this dataset includes: trade number, order number, trade date, trade time, stock code, board code, price, transaction value in rupiah, buyer and seller code (securities company), and buyer and seller type (domestic or foreign).
2. Daily adjusted (from dividends, stock splits, and new offerings) closing price of all firms listed in IDX in 2008 – 2017 from TICMI[2].
3. Year-end market capitalization in 2007 – 2016 from TICMI.

One feature from the Indonesian stock exchange is that the transaction data include both order and transaction number, making it possible to specifically determine each transaction as buyer- or seller-initiated. As such, we don't need to approximate the trade direction using an algorithm, such as developed by Lee and

[1]IMQ Multimedia Utama, third-party transaction data providers (http://imq21.com)
[2]The Indonesia Capital Market Institute, primary market data providers (http://ticmi.co.id)

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Table 2. Domestic- and Foreign-initiated Transaction Frequency and Value

This table presents the frequency (TF) and value (TV) of domestic- and foreign-initiated transactions in 2008 – 2017. Overall, in the span of 10 years, 72.71% of all transactions is initiated by domestic investors and 27.29% is initiated by foreign investors. Regarding the transaction value, domestic investors account for 64.48% of total value and foreign investors for 35.52%.

Year	TF (thousand)		TV (trillion IDR)	
	Domestic-initiated	Foreign-initiated	Domestic-initiated	Foreign-initiated
2008	11,001.30	1,536.72	596.92	199.63
	87.74%	12.26%	74.94%	25.06%
2009	18,551.71	2,083.47	631.05	168.64
	89.90%	10.10%	78.91%	21.09%
2010	20,684.02	3,315.41	614.52	268.78
	86.19%	13.81%	69.57%	30.43%
2011	20,918.83	5,756.58	608.94	322.89
	78.42%	21.58%	65.35%	34.65%
2012	21,603.00	7,110.77	490.70	370.21
	75.24%	24.76%	57.00%	43.00%
2013	22,591.17	10,621.64	627.98	452.67
	68.02%	31.98%	58.11%	41.89%
2014	31,735.10	16,943.84	656.34	440.33
	65.19%	34.81%	59.85%	40.15%
2015	32,615.13	19,166.23	581.28	408.35
	62.99%	37.01%	58.74%	41.26%
2016	41,727.37	19,022.05	689.57	433.56
	68.69%	31.31%	61.40%	38.60%
2017	49,058.01	15,959.35	721.59	360.22
	75.45%	24.55%	66.70%	33.30%
2008 – 2017	270,485.64	101,516.05	6,218.88	3,425.28
	72.71%	27.29%	64.48%	35.52%

Ready (1991). Since the data are huge, we use MATLAB and employ big data methodology (map and reduce) to aggregate the transaction data into daily trading imbalance. However, we need to clean the transaction data before using them in the analysis. We implement the following criteria:

1. The stock is common stock. Other asset types such as warrants (call options) and right issues are excluded.
2. The transaction type is regular transaction. We define regular transaction as transaction within regular trading hours (09.30 – 16.00 for 2008 – 2012 and 09.00 – 16.00 for 2013 – 2017). Other transaction types are excluded.
3. The stocks have at least 2 transactions per day.
4. The stocks have available market capitalization data at the end of each year.
5. The stocks have both daily return data from TICMI and transaction data from IDX.

After implementing the cleaning criteria, our sample consists of 372 million transactions of 554 stocks over 2,386 days. We present the summary of transaction data after cleaning in Table 1. We also present the comparison of transaction frequency and value of foreign and domestic investors in Table 2. As we can see, the proportion of foreign transaction frequency and value is becoming higher over the years. It strengthens the importance of this study since foreign investors can no longer be neglected due to its significant presence.

Methodology

To fulfill our objectives, we implement vector autoregressive (VAR) model, as what is carried out by Griffin et al. (2003). VAR model allows us to analyze the price impact, herding behavior, and feedback trading simultaneously. To achieve that, we use portfolio return, foreign trading imbalance, and domestic trading imbalance as the variables in the model. The evidence of price impact will be shown by lagged foreign/domestic trading imbalance explaining portfolio return. Herding behavior is demonstrated by the ability of lagged foreign/domestic trading imbalance to explain foreign/domestic trading imbalance. Finally, feedback trading is happening when lagged returns are significant in predicting foreign/domestic trad-

Table 3. Trading Data Example for Illustration

Trade No.	Stock	Price	Volume	Value	Buyer	Seller	Initiator
1	ABCD	5	300	1500	Foreign	Domestic	Buy
2	ABCD	5.1	200	1020	Foreign	Foreign	Buy
3	ABCD	4.9	500	2450	Domestic	Domestic	Sell
4	ABCD	4.8	400	1920	Domestic	Foreign	Sell

ing imbalance. Besides that, VAR model also provides versatility to control for other lagged variables, including the dependent variable's lagged values. This is useful to make sure that the significance is not raised by omitted variables.

Unlike Griffin et al. (2003) and Ng and Wu (2007), we do our analysis in the portfolio-level instead of individual stocks because we also want to analyze specific behavior in certain characteristics of stocks which is often achieved by creating portfolios. Since size of the stocks matter for investors and often act as an investing consideration (Fama & French, 1993) and that investor behavior might differ depending on the size of the stocks (Lakonishok et al., 1992), we determine our portfolios based on size, more specifically market capitalization. All stocks are sorted based on year-end market capitalization to decide which portfolio they will be included into in the following year. Stocks that are equal or below 30% percentile are considered as small, above 30% and equal or below 70% are considered as medium, and the rest are considered as big. This method of sorting is also done by Lakonishok et al. (1992) and Fama and French (1993), although they divide the sample into five quintiles.

According to Griffin et al. (2003) and Ng and Wu (2007), trading imbalances are the appropriate representation of trading activity, which is required to achieve our purposes. Having said that, this research uses a measure built on the measure by Ng and Wu (2007) instead of Griffin et al. (2003) because it uses currency value instead of number of shares, ensuring that the measure matches what investors often have in mind when investing which is the currency value. A slight improvement that we implement is that we classify every trade into their respective direction, either buyer-initiated or seller-initiated. Therefore, we define the imbalance as the difference between buyer-initiated transaction value and seller-initiated transaction value. To clarify this distinction, we will use the analogy from Griffin et al. (2003). Suppose there are only three categories of investor in a market: market maker, institutions, and individuals. When market maker has zero net transaction in a day, net buying of institutional investors will be completely offset by net selling of individuals. Therefore, when there is no market maker and every trade is identified, correlation between institutions' and individuals' imbalances is perfectly negative 1. In our case, however, the difference between buyer-initiated and seller-initiated transaction value of foreign investors will not necessarily be completely offset by that of domestic investors. To explain this more clearly, see illustration below.

Suppose there are four transactions in a day as described in Table 3. The measure of Griffin et al. (2003) will produce the value as follow:

- Buy – sell volume of foreigners: (300 + 200) – (200 + 400) = –100
- Buy – sell volume of locals: (500 + 400) – (300 + 500) = 100

The measure of Ng and Wu (2007) will produce the value as follow:

- Buy – sell value of foreigners: (1500 + 1020) – (1020 + 1920) = –420
- Buy – sell value of locals: (2450 + 1920) – (1500 + 2450) = 420

In contrast, our measure will produce the value as follow:

- Buyer-initiated – seller-initiated value of foreigners: (1500 + 1020) – (1920) = 600
- Buyer-initiated – seller-initiated value of locals: (0) – (2450) = –2450

We argue that our measure is superior to both Griffin et al. (2003) and Ng and Wu (2007) in the sense that we incorporate trade direction in our measure. As we can see, even though all buying trades are from foreign investors, the measure of Griffin et al. (2003) and Ng and Wu (2007) cannot capture that information and give negative sign (indicating more selling activities) instead. Another thing to highlight is that we don't have the same problem as in Griffin et al. (2003) that needs to drop the individual trading imbalance in the VAR due to high correlation with institutional trading imbalance. Our measure simply does not have that properties. Nevertheless, we will calculate the average of cross-sectional correlation between foreign and domestic trading imbalance both in stock-level and portfolio-level to make sure that the problem of correlation is minimal.

To be more specific, we calculate foreign and domestic trading imbalances following these equations:

$$TOT_t = \sum_{i=1}^{N_t}\sum_{ib=1}^{Nbf_t} valBF_{ib,i,t} + \sum_{i=1}^{N_t}\sum_{is=1}^{Nsf_t} valSF_{ib,i,t} + \sum_{i=1}^{N_t}\sum_{ib=1}^{Nbd_t} valBD_{ib,i,t} + \sum_{i=1}^{N_t}\sum_{is=1}^{Nsd_t} valSD_{is,i,t} \quad (1)$$

$$FOR_{p,t} = \frac{\sum_{i=1}^{N_{p,t}}\sum_{ib=1}^{Nbf_t} valBF_{ib,i,t} - \sum_{i=1}^{N_t}\sum_{is=1}^{Nsf_t} valSF_{is,i,t}}{TOT_t} \quad (2)$$

$$DOM_{p,t} = \frac{\sum_{i=1}^{N_{p,t}}\sum_{ib=1}^{Nbd_t} valBD_{ib,i,t} - \sum_{i=1}^{N_t}\sum_{is=1}^{Nsd_t} valSD_{is,i,t}}{TOT_t} \quad (3)$$

where TOT_t is total trading value at day t, $FOR_{p,t}$ is portfolio p's trading imbalance of foreign investors, $DOM_{p,t}$ is portfolio p's trading imbalance of domestic investors, $valBF_{ib,i,t}$ is rupiah value of ib-th foreign buyer-initiated transaction of stock i, $valSF_{is,i,t}$ is rupiah value of is-th foreign seller-initiated transaction of stock i, $valBD_{ib,i,t}$ is rupiah value of ib-th domestic buyer-initiated transaction of stock i, $valSD_{is,i,t}$ is rupiah value of is-th domestic seller-initiated transaction of stock i, Nbf_t is total number of foreign buyer-initiated transaction, Nsf_t is total number of foreign seller-initiated transaction, Nbd_t is total number of domestic buyer-initiated transaction, Nsd_t is total number of domestic seller-initiated transaction, and $N_{p,t}$ is total number of stocks in portfolio p, and N_t is total number of stocks in the market.

As we mentioned previously, we expect that the problem of correlation is minimal due to how our measure of trading imbalance is constructed. After calculation, we get the average cross-sectional correlation of daily *DOM* with daily *DOM* both at portfolio-level and individual-level are -4.65% and -8.96%, respectively. As such, we will implement tri-variate (instead of bi-variate) model of daily VAR. Our final variable in the VAR is portfolio return. We first calculate daily log return of each stock. Then, daily portfolio log return is constructed as weighted average of daily log return of stocks included in a particular portfolio (all, big, medium, or small) with the weight calculated based on market capitalization.

In order to remove the common market-wide effect, we adjust the three variables by subtracting them with their respective value-weighted averages. Finally, the three variables will be standardized by their own time-series to help interpretation. As such, the VAR model is specified below:

$$RET_t = \alpha + \sum_{i=1}^{k}\beta_{1,i}RET_{t-i} + \sum_{i=1}^{k}\beta_{2,i}FOR_{t-i} + \sum_{i=1}^{k}\beta_{3,i}DOM_{t-i} + \varepsilon_{RET,t} \quad (4)$$

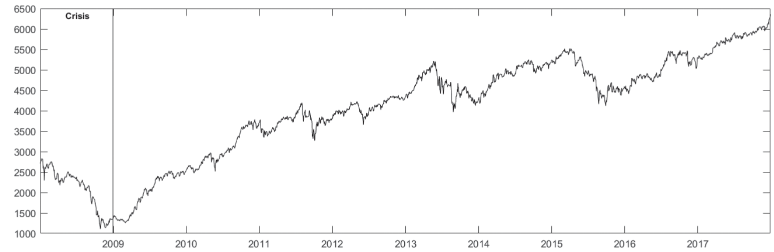
$$FOR_t = \alpha + \sum_{i=1}^{k}\beta_{1,i}RET_{t-i} + \sum_{i=1}^{k}\beta_{2,i}FOR_{t-i} + \sum_{i=1}^{k}\beta_{3,i}DOM_{t-i} + \varepsilon_{FOR,t} \quad (5)$$

$$DOM_t = \alpha + \sum_{i=1}^{k}\beta_{1,i}RET_{t-i} + \sum_{i=1}^{k}\beta_{2,i}FOR_{t-i} + \sum_{i=1}^{k}\beta_{3,i}DOM_{t-i} + \varepsilon_{DOM,t} \quad (6)$$

where RET_t is the adjusted and standardized portfolio log return at time t, FOR_t is adjusted and standardized foreign trading imbalance at time t, DOM_t is the adjusted and standardized domestic trading imbalance at time t, and k is the lag of the VAR system.

In this research, we use two different time periods. The first one includes all days available which is January 2nd, 2008 – December 29th, 2017 or 2,386 days. The second one only includes the crisis period. We use January 2nd, 2008 – December 30th, 2008 as our sample of crisis period with a total of 240 days. This determination of crisis period is based on the common fact of 2008 Global Financial Crisis.

Figure 1. Indonesian Composite Index (JKSE), 2008 – 2017



Although it is not based on formal test, we believe it is still appropriate, observing that market index (JKSE) experience an extreme drawdown during this period; JKSE decreased by 1,376.10 points or a staggering -49.62% return, as we shown in Figure 1. This indicates a strong evidence of a crisis.

To estimate the VAR model, we use least square estimation instead of maximum likelihood estimation in order to get a robust estimation with less strict assumption regarding the distribution of the error. All variables in the VAR model must be stationary or not have unit-root. If they are not stationary or have unit root, the estimation will produce spurious inference since the relationship is driven by the trend, not the true relationship. As such, we ensure that all our variables are stationary by implementing Augmented Dickey Fuller test developed by Dickey and Fuller (1979). Another requirement for VAR model to produce acceptable results is regarding the error term. Error terms from regular, plain vanilla VAR has to be homoscedastic with no autocorrelation in order to get legitimate inference. However, financial data usually produce error terms that are heteroskedastic with autocorrelation. To account for this, we use adjusted standard error developed by Newey and West (1987) and Hansen and Hodrick (1980). Lag of Newey-West (NW) standard error is calculated using the function[3] specified in the paper while lag of Hansen-Hodrick (HH) standard error is calculated as 2/3 of the NW lag. In dealing with financial data, these two methods of calculating adjusted error is common among researchers, for example Cochrane and Piazzesi (2005).

To determine the lag of the VAR model, we implement one of the most widely used penalized likelihood criterions: Bayesian information criterion developed by Schwarz (1978), which is also known as Schwarz information criterion and abbreviated as SBIC. The appropriate model, according to the criterion, is the one that produces the lowest value of SBIC. We check the possibility until 10 days (2 trading weeks) of lag. The suggested lag from the test is then used as consideration to determine the appropriate lag for the model. However, we do not always use the suggested lag from the test at face value. After all, many researchers even determine the lag of a VAR model without any formal test, for example Dorn et al. (2008) and Griffin et al. (2003). Finally, to check whether joint lagged variables are useful in predicting another variable, we implement Granger causality test (Granger, 1969). Keep in mind that Granger causality is actually a test of precedence rather than true causality.

Results and Discussions

Descriptive Statistics

Descriptive statistics of several important variables is presented in Table 4. In Panel A, we show descriptive statistics of unadjusted daily log return. Daily log returns of big and medium stocks have relatively the same mean value at around 0.01% and median value at around 0.06% – 0.08%. The striking difference between mean and median value of big and medium stocks indicates an asymmetric distribution with negative skewness. In contrast, mean and median of daily log return in small stocks are relatively similar at 0.03% and 0.04%, respec-

[3]Newey and West (1987) specify the function to determine the lag as: $lag = floor(T^{1/4})$, where *floor* is floor function and T is number of observations (in this case 2,386 days for the all sample and 240 days for the crisis period).

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Table 4. Descriptive Statistics of Unadjusted Variables

This table presents the descriptive statistics of the variables used in the research for the sample of all, big cap, medium cap, and small cap stocks in 2,386 days of observation. Panel A presents the descriptive statistics of unadjusted daily log return (before subtracted by its averages) of each portfolio. The descriptive statistics in Panel B and Panel C is for daily buyer- (NB) and seller-initiated transaction frequency (NS) in thousand, Panel D and Panel E is for daily buyer- (VB) and seller-initiated transaction value (VS) in billion IDR, Panel F is for daily average transaction value (VA = (VB+VS)/(NB+NS)) in million IDR, and Panel G is for unadjusted daily trading imbalances (U_IMB = $(VB–VS)/(VB_{FOR}+VS_{FOR}+VB_{DOM}+VS_{DOM})$) of each portfolio and of both domestic (DOM) and foreign (FOR) investor type.

Statistic	All Stocks		Big Cap Stocks		Medium Cap Stocks		Small Cap Stocks	
Panel A: Unadjusted daily log return								
Mean	0.01%		0.01%		0.01%		0.03%	
Median	0.08%		0.08%		0.06%		0.04%	
StDev	1.32%		1.37%		0.71%		0.57%	
Statistic	DOM	FOR	DOM	FOR	DOM	FOR	DOM	FOR
Panel B: Daily buyer-initiated transaction frequency (NB) in thousand								
Mean	66.43	21.59	35.76	20.26	21.55	1.22	9.12	0.11
Median	61.42	18.14	31.54	16.75	18.94	0.88	5.43	0.04
StDev	35.04	16.98	16.83	16.06	15.37	1.30	10.55	0.27
Panel C: Daily seller-initiated transaction frequency (NS) in thousand								
Mean	51.74	16.16	34.80	15.23	13.16	0.87	3.78	0.06
Median	46.21	10.16	31.28	9.50	10.86	0.60	2.67	0.02
StDev	26.02	14.54	16.00	13.84	9.74	0.88	3.69	0.15
Panel D: Daily buyer-initiated transaction value (VB) in billion IDR								
Mean	1,424.27	736.63	1,182.58	720.77	209.44	15.24	32.25	0.61
Median	1,359.18	676.50	1,111.68	661.30	190.94	11.16	19.93	0.17
StDev	571.69	424.81	488.54	415.30	151.48	16.20	38.46	1.60
Panel E: Daily seller-initiated transaction value (VS) in billion IDR								
Mean	1,270.09	610.99	1,101.16	597.43	151.15	13.07	17.78	0.49
Median	1,201.20	557.62	1,023.01	545.09	124.23	9.49	12.25	0.18
StDev	519.97	363.24	468.92	355.07	118.96	13.13	19.60	1.20
Panel F: Daily average transaction value (VA) in million IDR								
Mean	22.80	35.70	32.37	37.14	10.39	13.52	3.88	6.84
Median	23.79	43.61	33.98	45.96	10.57	13.95	3.97	6.05
StDev	17.88	25.00	29.17	25.77	10.77	13.41	4.08	6.60
Panel G: Unadjusted daily trading imbalance (U_IMB)								
Mean	5.94%	0.71%	4.75%	0.71%	14.05%	0.67%	18.29%	0.50%
Median	6.50%	0.90%	5.27%	0.91%	14.35%	0.51%	15.31%	0.03%
StDev	8.44%	6.84%	8.37%	7.51%	14.81%	2.73%	27.82%	4.55%

tively. Higher returns in small stocks, compared to medium and big stocks, is also an indication of the existence of size premium in Indonesian stock market, as what is argued by Fama and French (1993) in many countries, although in this research we use daily return instead of monthly return. Looking at the standard deviation, big stocks are the most volatile whereas the small stocks are the least volatile. This is quite surprising, since small stocks are usually known as the most volatile group of stocks.

Furthermore, Panel B and C present the number of buyer- and seller-initiated daily transaction frequency, respectively. Overall, domestic investors are the major players in Indonesian capital market. Mean and median of daily buyer-initiated transaction frequency of locals in all stocks are more than three times the foreign investors' values. The difference is even more striking in the seller-initiated transaction frequency. If we look into the size-based portfolios, we can see that foreign investors are mostly trading in big stocks and almost non-existent in small stocks. In Panel D and E, we present the daily buyer- and seller-initiated transaction value in rupiah, respectively. The pattern from before still continues, although the difference between domestic and foreign investors is smaller. The lesser difference could be explained by the higher daily average transaction value of foreign investors, as shown in Panel F. In short, while domestic investors trade more frequently each day, foreign investors trades with higher value.

The last panel in Table 4 shows the unadjusted foreign and domestic trading imbalances. Trading imbalance above (below) zero means there are more buyer- (seller-) initiated

Figure 2. Adjusted, Standardized Portfolio Return, Foreign Imbalance, and Domestic Imbalance in Big, Medium, and Small Cap Stocks

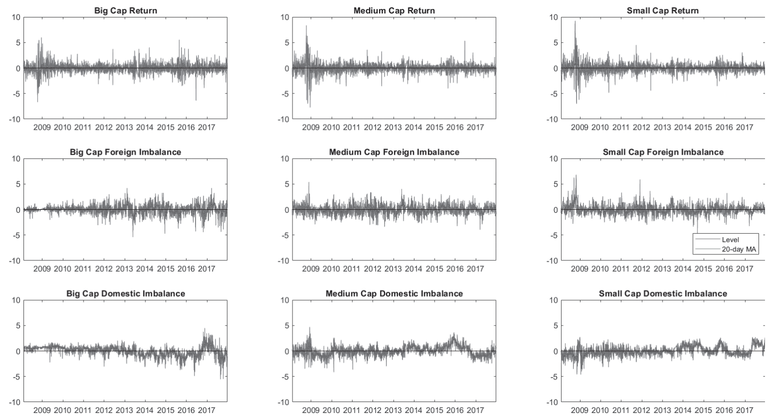

Table 5. Descriptive Statistics of Adjusted Variables

This table presents the descriptive statistics of the variables used in the VAR model for big cap, medium cap, and small cap stocks in 2,386 days of observation. Panel A and B present the descriptive statistics of adjusted, unstandardized daily log return and adjusted, standardized daily log return of each portfolio. Panel C and D present the descriptive statistics of adjusted, unstandardized daily trading imbalance and adjusted, standardized daily trading imbalance of each portfolio for both domestic (DOM) and foreign (FOR) investors.

Statistic	Big Cap Stocks		Medium Cap Stocks		Small Cap Stocks	
Panel A: Adjusted, unstandardized daily log return						
Mean	0.0002%		0.0025%		0.0185%	
Median	-0.0006%		0.0083%		0.0018%	
StDev	0.0536%		0.8922%		1.1252%	
Panel B: Adjusted, standardized daily log return						
Mean	0.0000		0.0000		0.0000	
Median	-0.0150		0.0066		-0.0148	
StDev	1.0000		1.0000		1.0000	
Statistic	DOM	FOR	DOM	FOR	DOM	FOR
Panel C: Adjusted, unstandardized daily trading imbalance						
Mean	-1.19%	0.01%	8.11%	-0.04%	12.35%	-0.21%
Median	-0.98%	0.01%	8.10%	-0.10%	9.82%	-0.71%
StDev	1.54%	0.82%	12.35%	6.82%	25.84%	8.12%
Panel D: Adjusted, standardized daily trading imbalance						
Mean	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.14	-0.00	-0.00	-0.01	-0.10	-0.06
StDev	1.00	1.00	1.00	1.00	1.00	1.00

transaction values than seller- (buyer-) initiated transaction values, in rupiah. We can see that domestic investors have higher mean and median value of trading imbalance in all portfolios. It shows that, generally, domestic investors tend to buy more than foreign investors, although both tend to buy more than sell, as shown by positive trading imbalances. Comparing between portfolios, small stocks have the highest trading imbalance, followed by medium and big stocks. It shows that in small stocks, investors tend to buy rather than sell. In terms of volatility of trading imbalance, locals vary more than foreigners, showing that local investors significantly change their tendency to buy or sell on a daily basis. We then present the adjusted and standardized value of portfolio return and trading imbalances in Table 5 and plot the values in Figure 2.

Stationarity and Lag Selection

As the requirement of the VAR model, we have to make sure that all variables are stationary to prevent spurious inferences. It turns out that all our variables are indeed stationary, as we present in Table 6. Then, the next step is the determination of lag for the VAR models. In general, it is common to directly determine how many lagged days are appropriate based on

Table 6. Results of Augmented Dickey Fuller Tests of Stationarity

This table presents the results, Z(t), of stationarity test using augmented Dickey-Fuller test, with null hypothesis of there is unit-root. We report the results of each portfolio (big, medium, and small cap stocks) and of each variable (adjusted, standardized portfolio return, RET, foreign trading imbalance, FOR, and domestic trading imbalance, DOM). Significance at 5% and 1% is shown with ** and ***, respectively.

Portfolio	Variables			5% Critical Value	1% Critical Value
	RET	FOR	DOM		
Panel A: All Sample, 2008 – 2017 (2,386 obs.)					
Big cap stocks	-19.079***	-18.316***	-12.243***		
Medium cap stocks	-13.478***	-23.806***	-13.519***	-3.412	-3.963
Small cap stocks	-13.855 ***	-11.833***	-13.603***		
Panel B: Crisis Period, 2008 (240 obs.)					
Big cap stocks	-5.936***	-10.954***	-6.552***		
Medium cap stocks	-5.969***	-7.557***	-7.856***	-3.429	-3.997
Small cap stocks	-5.944***	-3.614**	-6.694***		

Table 7. Determination of Lag for the Models

Panel A presents the lagged days in which the value of Bayesian Information Criterion is minimized. We check until the maximum of 10 days. We have 2 VAR models: models that use all days and models that only use crisis days. For each group of models, there are three different portfolios: big, medium, and small cap stocks. Panel B presents the lags that are actually used in the models.

Portfolio	Observations used in the estimation	
	All days	Crisis period
Panel A: Lagged days with lowest value of Bayesian Information Criterion (days)		
Big stocks	5	1
Medium stocks	6	1
Small stocks	5	1
Panel B: Lagged days to be used in the models (days)		
Big stocks	5	5
Medium stocks	5	5
Small stocks	5	5

mental models. For example, Dorn et al. (2008) and Griffin et al. (2003) determine the lag of their VAR model to be 5 days without any formal tests. However, this research will also use a formal test, which is Bayesian Information Criterion (BIC), as additional consideration. The results of the calculation are presented in Panel A of Table 7. As we can see, the suggested lags of the models that use all days in the sample are different in different portfolios. In contrast, models that use only crisis days have the same and considerably fewer lag (1 day). The fewer lag might be explained by the fact that crisis period only lasts for 240 days whereas all sample consists of 2,368 days. To make the analysis more comparable between portfolios and between two different samples, we determine the lags to be the same. Generally, the higher the lag, the longer the dynamics that can be captured. As such, we determine the lag of our model to be 5-day, or 1 trading week. This is the same with the choice of many researches in microstructure topics such as Dorn et al. (2008) and Griffin et al. (2003) that also use 5-day lag.

Estimation Results

VAR estimates from Equation 4 – 6 using all observations are presented in Table 8. First, we answer our research question regarding price impact. Evidence of price impact is shown by the ability of lagged trading imbalance in predicting return. In big cap portfolio (Panel A), 2-day lag of domestic trading imbalance impacts return negatively and significantly, although at a small economic significance (-0.069). The same pattern also exists in the medium cap portfolio (Panel B) with higher economic significance (-0.111) and slightly higher statistical significance. There is no price impact of domestic investors in the small cap portfolio. In contrast with the impact of locals' trading, foreign investors' trading does not have any impact to subsequent return. This finding is the opposite of research Brennan and Cao (1997) and Bekaert et al. (2002) that show positive impacts of foreign trading to return.

Next, to answer our research question regarding herding behaviour, we will focus on whether lagged domestic and/or foreign trading imbalances are able to predict domestic and/or foreign trading imbalance. As we can see from the table, all five lagged domestic trading imbalances in big cap portfolio (Panel A) predict domestic trading imbalance quite significantly. The economic significance is also high with coefficients of more than 0.1 in all five lagged days. As such, we can conclude that domestic investors generally herd to themselves, in the sense that domestic investors follow previous tendency of buying or selling of domestic investors. This pattern continues to the medium and small cap portfolios. Among the three portfolios, medium stocks produce the most consistent pattern in the 5 lagged days regarding the economic and statistical significance. In small stocks, the coefficient in one day lag is the highest (0.314) compared to other portfolios in different lagged days. It has enormous t-stats of 12.79 (NW) and 13.38 (HH). All in all, domestic investors herd to themselves in all size-based portfolios.

There is also a strong piece of evidence of herding among foreign investors. Lagged trading imbalance of foreign investors positively predict foreign trading imbalance in all portfolios, although with less statistical significance than among domestic investors overall. The strongest predictive power comes from the 1-day lag of big stocks with the coefficient of 0.338 and t-stat of 12.01 (NW) and 11.65 (HH). The predictive power of lagged trading imbalance in all portfolios only last until 2-day lag but emerges again in the 5-day lag. These findings are in line with the study by Yao et al. (2014) who find that the herding behaviour of domestic and foreign investors are not so different.

Interestingly, herding behaviour is not so clear across different types of investors. In big cap portfolio, 1-day domestic trading imbalance significantly predict foreign trading imbalance with positive sign, but 2-day lag domestic trading significantly and negatively predict foreign trading imbalance. In other words, there is no consistent pattern of foreign investor herding to domestic investors. There is no further evidence in the medium and small cap portfolios. Lagged (t-1) foreign trading imbalances significantly predict domestic trading imbalance with negative sign in big, medium, and small portfolio. But, 3-day lag (in big and medium cap portfolio) and 5-day lag (only in big cap portfolio) of foreign imbalance significantly and positively predict domestic imbalances. Again, it shows that there is no consistent pattern of cross-herding using the latest five days, but it is clear that domestic investors reverse-herd foreign investors in the short-term (1 day).

Our third research question is regarding feedback trading which its existence is supported if lagged return explains trading imbalance. In Table 8, we see that domestic investors employ contrarian strategy in big and medium cap portfolios, as shown by negative and significant coefficients of lagged return in predicting domestic trading imbalance. In big cap portfolio, it is significant at t-2 and in medium cap portfolio, it is significant at t-1. Foreign investors also show some evidence of contrarian investing in the medium cap portfolio, with negative and statistically significant coefficient of 2-day lag of return explaining foreign imbalances. Interestingly, both domestic and foreign investors employ momentum investing in the small cap portfolio. This result is in contrast with Grinblatt and Keloharju (2000) who produce the results regarding positive feedback trading of foreign investors and negative feedback trading of domestic investors. We find that both investors have the same pattern of investing instead.

Now, we analyze the same three aspects in the crisis period. The estimation results are presented in Table 9. In terms of price impact, we now have an inconsistent sign across different lag days. In big cap portfolio, we still have negative and significant coefficient of domestic imbalance at 2-day lag with much higher economic significance (-0.772). However, the 4-day lag of the same variable exhibit positive and significant coefficient in explaining return, also with quite high coefficient (0.699). The same pattern also exists in the medium cap portfolio with slightly lower economic significance. This indicates a positive impact of trading but eventually followed by reversal pattern all within 4 days. In small cap portfolio, interestingly, it shows different pattern with positive and sig-

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nificant coefficient at 4-day lag, in contrast with the pattern in the other 2 portfolios. In the crisis period, foreign investors' trading imbalance impacts return positively in the 1-day lag but negatively in the 4-day lag.

In terms of herding behavior, it is clear that the evidence of herding behavior is smaller in crisis period. There are fewer significant coefficients to predict either domestic or foreign trading imbalances. Despite that, there are still some evidence of herding behavior. Firstly, domestic investors still herd to themselves in all portfolios. Foreign investors still herd to themselves in the medium and small cap portfolio, but reverse-herd in the big cap portfolio. In addition, foreign investors no longer herd nor reverse-herd to locals and reverse-herding of locals to foreign investors in the 1-day lag now only present in the small cap portfolio. This finding is in contrast with by the study of Bowe and Domuta (2004) who find that foreign investors herd more than locals in the crisis.

Interestingly, there is no evidence of both positive and negative feedback trading by foreign investors in the crisis. However, domestic investors are still contrarian in the big and medium cap portfolios. Lagged domestic trading imbalance in big cap portfolio at time t-1 is statistically significant with negative sign, showing negative feedback trading. Lagged domestic trading imbalance at time t-1 and t-5 is also significant with negative sign, an indication of negative feedback trading. This is in line with the result from Bowe and Domuta (2004) who conclude that, in the crisis, both domestic and foreign investors are not momentum traders.

We also conduct Granger causality test to check whether a certain variable indeed comes before another. In other words, it checks whether all lagged variables of a particular variable are useful in predicting another variable. This can act as robustness test of the results from VAR estimates in Table 8 and 9. However, we still need to refer to previous tables to get information regarding the signs or directions, since they are not provided in Granger causality test. As we can see in Table 10, many results from before are confirmed here. Price impacts from domestic investors are stronger in the crisis period than in the all-observation estimation. There are evidence of domestic and foreign investors herding to themselves as well. Cross-herding between domestic and foreign could also be shown in the table, although with no information on whether it is herding or reverse-herding. In the crisis, the F-stats to show herding behavior is smaller in all settings, again, confirming our findings in Table 8 and 9. Table 10 also shows that feedback trading of domestic investors mostly decreases or vanishes when the sample is focused on the market downturns.

Conclusion

Based on their origins, investors could be categorized as domestic or foreign investors. Their behaviour and its impact to the market could differ since they might have different information and/or expectation regarding the future. As such, this study analyses price impact, herding behaviour, and feedback trading of both domestic and foreign investors in Indonesia to have a better understanding of the capital market in Indonesia, one of the fastest growing emerging markets. We use 10 years high-frequency transaction data in the period of 2008 – 2017 as our sample. Vector autoregressive is applied to simultaneously analyse the price impact, herding behaviour, and feedback trading.

First, regarding the price impact, we find that domestic investors impact return negatively whereas foreign investors have no impact to return. Second, in terms of herding behavior, domestic and foreign investors herd to themselves strongly. Domestic investors reverse-herd to foreign investors in the short-term (1 day) but no consistent pattern regarding the opposite direction. Third, regarding feedback trading, both domestic and foreign investors are contrarian in the big and medium cap portfolios but employ momentum strategy in the small cap portfolio. Fourth, we also find that, in the crisis period, price impact is more pronounced. Fifth and finally, evidence of herding behavior and feedback trading decreases in market downturns, although with the same pattern overall.

Table 8. VAR Estimates using All Observations

Using the sample of aggregated intraday data of Indonesian Stock Exchange in 2008 – 2017, this table presents the result of 5-day lag daily VAR estimation (2,385 obs.) with 6-day lag Newey-West (NW) and 4-day lag Hansen-Hodrick (HH) standard error of the following model:

$$RET_t = \alpha + \sum_{i=1}^{5}\beta_{1,i}RET_{t-i} + \sum_{i=1}^{5}\beta_{2,i}FOR_{t-i} + \sum_{i=1}^{5}\beta_{3,i}DOM_{t-i} + \varepsilon_{RET,t}$$

$$FOR_t = \alpha + \sum_{i=1}^{5}\beta_{1,i}RET_{t-i} + \sum_{i=1}^{5}\beta_{2,i}FOR_{t-i} + \sum_{i=1}^{5}\beta_{3,i}DOM_{t-i} + \varepsilon_{FOR,t}$$

$$DOM_t = \alpha + \sum_{i=1}^{5}\beta_{1,i}RET_{t-i} + \sum_{i=1}^{5}\beta_{2,i}FOR_{t-i} + \sum_{i=1}^{5}\beta_{3,i}DOM_{t-i} + \varepsilon_{DOM,t}$$

where RET_t is adjusted, standardized log return of portfolio at time t; FOR_t is adjusted, standardized foreign trading imbalance at time t; and DOM_t is adjusted, standardized domestic trading imbalance at time t. We implement this VAR system for three different portfolios: big, medium, and small cap stocks. T-stat are presented in brackets. Significance at 1% is presented with ***, 5% is presented with **, and 10% is presented with *. Adjusted R^2 is presented at the bottom of the table.

		Dependent Variable								
Independent Variable		Panel A: Big Cap Stocks			Panel B: Medium Cap Stocks			Panel C: Small Cap Stocks		
		RET	FOR	DOM	RET	FOR	DOM	RET	FOR	DOM
	$\beta_{1,1}$	0.091	0.030	-0.023	0.111	0.044	-0.085	0.098	0.079	-0.007
	t (NW)	(2.28)**	(1.82)*	(-1.66)*	(2.05)**	(1.73)*	(-4.74)***	(2.09)**	(3.38)***	(-0.36)
	t (HH)	(2.32)**	(1.78)*	(-1.68)*	(2.14)**	(1.80)*	(-5.23)***	(2.18)**	(3.37)***	(-0.34)
	$\beta_{1,2}$	-0.028	-0.023	-0.043	-0.005	-0.031	-0.035	0.015	0.011	-0.021
	t (NW)	(-0.91)	(-1.39)	(-2.97)***	(-0.13)	(-1.73)*	(-1.20)	(0.35)	(0.47)	(-1.01)
	t (HH)	(-1.22)	(-1.44)	(-2.95)***	(-0.20)	(-2.09)**	(-1.17)	(0.58)	(0.49)	(-1.04)
	$\beta_{1,3}$	-0.037	-0.013	-0.019	-0.047	-0.016	-0.002	-0.088	-0.022	0.048
RET	t (NW)	(-1.35)	(-0.72)	(-1.13)	(-1.29)	(-0.75)	(-0.06)	(-2.65)***	(-0.83)	(2.21)**
	t (HH)	(-1.44)	(-0.72)	(-1.15)	(-1.56)	(-0.83)	(-0.05)	(-3.14)***	(-0.80)	(2.21)**
	$\beta_{1,4}$	-0.032	-0.009	-0.015	-0.030	-0.006	0.001	-0.047	-0.016	-0.005
	t (NW)	(-0.96)	(-0.52)	(-1.03)	(-0.65)	(-0.22)	(0.03)	(-1.22)	(-0.82)	(-0.22)
	t (HH)	(-1.01)	(-0.51)	(-1.04)	(-0.67)	(-0.21)	(0.03)	(-1.29)	(-0.87)	(-0.24)
	$\beta_{1,5}$	-0.048	-0.028	-0.013	-0.012	-0.025	-0.042	-0.036	0.011	0.051
	t (NW)	(-1.25)	(-1.73)*	(-0.93)	(-0.23)	(-1.10)	(-1.65)*	(-0.78)	(0.48)	(2.20)**
	t (HH)	(-1.13)	(-1.69)*	(-0.98)	(-0.20)	(-1.07)	(-1.68)*	(-0.70)	(0.62)	(2.24)**
	$\beta_{2,1}$	0.022	0.338	-0.068	0.019	0.317	-0.055	0.058	0.330	-0.076
	t (NW)	(0.87)	(12.01)***	(-3.14)***	(0.59)	(11.01)***	(-2.48)**	(1.43)	(10.44)***	(-4.09)***
	t (HH)	(0.90)	(11.65)***	(-3.27)***	(0.61)	(11.25)***	(-2.57)**	(1.43)	(10.06)***	(-4.24)***
	$\beta_{2,2}$	-0.021	0.109	-0.019	-0.040	0.087	0.024	-0.021	0.095	0.015
	t (NW)	(-0.89)	(3.76)***	(-0.77)	(-1.37)	(3.12)***	(0.90)	(-0.50)	(3.45)***	(0.72)
	t (HH)	(-0.97)	(3.77)***	(-0.80)	(-1.60)	(3.13)***	(0.91)	(-0.48)	(3.46)***	(0.72)
	$\beta_{2,3}$	-0.025	0.030	0.044	-0.012	0.038	0.054	0.039	0.063	-0.009
FOR	t (NW)	(-1.07)	(0.94)	(2.00)**	(-0.34)	(1.50)	(2.30)**	(1.13)	(1.85)*	(-0.41)
	t (HH)	(-1.12)	(0.91)	(2.08)**	(-0.40)	(1.54)	(2.20)**	(1.18)	(1.81)*	(-0.40)
	$\beta_{2,4}$	-0.021	-0.005	0.000	-0.020	0.008	0.008	-0.021	0.023	0.013
	t (NW)	(-0.73)	(-0.16)	(0.02)	(-0.53)	(0.28)	(0.37)	(-0.65)	(0.89)	(0.53)
	t (HH)	(-0.72)	(-0.16)	(0.02)	(-0.48)	(0.28)	(0.38)	(-0.68)	(0.86)	(0.53)
	$\beta_{2,5}$	0.038	0.104	0.052	-0.003	0.071	0.042	-0.008	0.071	0.011
	t (NW)	(1.45)	(3.81)***	(2.52)**	(-0.11)	(2.88)***	(1.87)*	(-0.21)	(2.96)***	(0.51)
	t (HH)	(1.39)	(3.77)***	(2.50)**	(-0.11)	(2.88)***	(1.82)*	(-0.20)	(2.98)***	(0.50)
	$\beta_{3,1}$	0.043	0.124	0.201	-0.028	0.029	0.255	-0.050	0.002	0.314
	t (NW)	(1.66)*	(4.18)***	(6.97)***	(-0.72)	(1.02)	(11.28)***	(-1.49)	(0.10)	(12.79)***
	t (HH)	(1.69)*	(4.21)***	(6.88)***	(-0.71)	(1.06)	(11.86)***	(-1.44)	(0.10)	(13.38)***
	$\beta_{3,2}$	-0.069	-0.062	0.153	-0.111	-0.025	0.159	-0.043	-0.022	0.173
	t (NW)	(-2.44)**	(-2.08)**	(5.62)***	(-2.55)**	(-0.98)	(6.36)***	(-1.24)	(-0.91)	(6.09)***
	t (HH)	(-2.33)**	(-2.15)**	(5.85)***	(-2.46)**	(-1.00)	(6.64)***	(-1.18)	(-0.90)	(6.37)***
	$\beta_{3,3}$	0.012	-0.037	0.232	0.056	-0.013	0.127	0.004	0.030	0.065
DOM	t (NW)	(0.45)	(-0.99)	(7.17)***	(1.60)	(-0.45)	(3.92)***	(0.11)	(1.14)	(2.01)**
	t (HH)	(0.43)	(-0.96)	(6.64)***	(1.71)*	(-0.45)	(3.68)***	(0.11)	(1.13)	(1.95)*
	$\beta_{3,4}$	-0.004	-0.046	0.115	0.094	0.016	0.118	0.010	-0.008	0.097
	t (NW)	(-0.17)	(-1.58)	(4.30)***	(2.30)**	(0.58)	(5.29)***	(0.30)	(-0.34)	(4.02)***
	t (HH)	(-0.17)	(-1.60)	(4.29)***	(2.14)**	(0.60)	(5.92)***	(0.28)	(-0.35)	(5.13)***
	$\beta_{3,5}$	-0.007	0.053	0.145	-0.012	0.012	0.148	0.005	-0.043	0.168
	t (NW)	(-0.30)	(1.75)*	(5.09)***	(-0.36)	(0.50)	(5.73)***	(0.16)	(-1.79)*	(6.19)***
	t (HH)	(-0.30)	(1.87)*	(5.33)***	(-0.40)	(0.49)	(5.55)***	(0.16)	(-1.76)*	(6.13)***
	α	-0.001	0.000	-0.002	0.001	0.001	0.001	0.001	0.001	0.001
	t (NW)	(-0.03)	(0.00)	(-0.15)	(0.05)	(0.05)	(0.06)	(0.06)	(0.04)	(0.10)
	t (HH)	(-0.03)	(0.00)	(-0.17)	(0.04)	(0.05)	(0.06)	(0.06)	(0.04)	(0.10)
	Adj. R^2 (%)	2.28	19.17	46.97	3.65	15.70	41.76	3.63	23.26	43.51

Table 9. VAR Estimates in the Crisis Period

Using the sample of aggregated intraday data of Indonesian Stock Exchange in the crisis period (2008), this table presents the result of 5-day lag daily VAR estimation (235 obs.) with 3-day lag Newey-West (NW) and 2-day lag Hansen-Hodrick (HH) standard error of the following model:

$$RET_t = \alpha + \sum_{i=1}^{5} \beta_{1,i} RET_{t-i} + \sum_{i=1}^{5} \beta_{2,i} FOR_{t-i} + \sum_{i=1}^{5} \beta_{3,i} DOM_{t-i} + \varepsilon_{RET,t}$$

$$FOR_t = \alpha + \sum_{i=1}^{5} \beta_{1,i} RET_{t-i} + \sum_{i=1}^{5} \beta_{2,i} FOR_{t-i} + \sum_{i=1}^{5} \beta_{3,i} DOM_{t-i} + \varepsilon_{FOR,t}$$

$$DOM_t = \alpha + \sum_{i=1}^{5} \beta_{1,i} RET_{t-i} + \sum_{i=1}^{5} \beta_{2,i} FOR_{t-i} + \sum_{i=1}^{5} \beta_{3,i} DOM_{t-i} + \varepsilon_{DOM,t}$$

where RET_t is adjusted, standardized log return of portfolio at time *t*; FOR_t is adjusted, standardized foreign trading imbalance at time *t*; and DOM_t is adjusted, standardized domestic trading imbalance at time *t*. We implement this VAR system for three different portfolios: big, medium, and small cap stocks. T-stat are presented in brackets. Significance at 1% is presented with ***, 5% is presented with **, and 10% is presented with *. Adjusted R^2 is presented at the bottom of the table.

Independent Variable		Dependent Variable								
		Panel A: Big Cap Stocks			Panel B: Medium Cap Stocks			Panel C: Small Cap Stocks		
		RET	FOR	DOM	RET	FOR	DOM	RET	FOR	DOM
	$\beta_{1,1}$	0.218	0.011	-0.022	0.154	0.003	-0.134	0.129	0.015	-0.018
	t (NW)	(2.06)**	(1.22)	(-2.22)**	(1.52)	(0.07)	(-3.47)***	(1.50)	(0.37)	(-0.46)
	t (HH)	(1.92)*	(1.26)	(-2.29)**	(1.44)	(0.07)	(-3.63)***	(1.43)	(0.44)	(-0.46)
	$\beta_{1,2}$	0.066	0.004	0.007	0.061	0.000	-0.019	0.054	0.052	-0.057
	t (NW)	(0.71)	(0.42)	(0.63)	(0.73)	(-0.01)	(-0.35)	(0.53)	(1.29)	(-1.58)
	t (HH)	(0.74)	(0.44)	(0.64)	(0.83)	(-0.01)	(-0.35)	(0.61)	(1.46)	(-1.71)*
	$\beta_{1,3}$	-0.077	0.000	0.007	-0.076	-0.007	-0.008	-0.139	-0.007	0.027
RET	t (NW)	(-1.12)	(-0.04)	(0.62)	(-1.05)	(-0.20)	(-0.17)	(-2.36)**	(-0.15)	(0.69)
	t (HH)	(-1.63)	(-0.04)	(0.61)	(-1.08)	(-0.19)	(-0.17)	(-2.89)***	(-0.18)	(0.70)
	$\beta_{1,4}$	-0.045	0.012	-0.002	0.007	0.019	0.022	-0.068	-0.031	0.004
	t (NW)	(-0.50)	(1.06)	(-0.17)	(0.08)	(0.48)	(0.76)	(-0.83)	(-0.90)	(0.07)
	t (HH)	(-0.56)	(1.05)	(-0.18)	(0.09)	(0.50)	(0.91)	(-0.86)	(-1.02)	(0.07)
	$\beta_{1,5}$	-0.011	-0.009	-0.015	0.055	-0.007	-0.097	-0.035	0.041	0.068
	t (NW)	(-0.11)	(-1.02)	(-1.57)	(0.59)	(-0.20)	(-2.03)**	(-0.42)	(0.95)	(1.64)
	t (HH)	(-0.11)	(-1.05)	(-1.65)*	(0.61)	(-0.20)	(-1.98)**	(-0.40)	(0.94)	(1.73)*
	$\beta_{2,1}$	0.263	0.140	0.017	0.217	0.220	-0.131	0.432	0.421	-0.092
	t (NW)	(1.08)	(1.56)	(0.20)	(1.58)	(2.38)**	(-1.52)	(2.78)***	(4.41)***	(-2.04)**
	t (HH)	(1.07)	(1.47)	(0.20)	(1.57)	(2.35)**	(-1.45)	(2.62)***	(4.22)***	(-2.17)**
	$\beta_{2,2}$	-0.216	-0.124	-0.023	-0.049	-0.073	0.166	-0.117	0.013	-0.023
	t (NW)	(-0.94)	(-2.06)**	(-0.30)	(-0.33)	(-1.11)	(1.76)*	(-0.96)	(0.15)	(-0.34)
	t (HH)	(-0.90)	(-2.22)**	(-0.28)	(-0.33)	(-1.63)	(1.85)*	(-0.99)	(0.20)	(-0.32)
	$\beta_{2,3}$	0.032	-0.042	-0.125	-0.007	0.073	0.128	0.193	0.199	-0.004
FOR	t (NW)	(0.14)	(-0.67)	(-1.56)	(-0.05)	(0.94)	(1.51)	(1.68)*	(2.16)**	(-0.08)
	t (HH)	(0.13)	(-0.72)	(-1.61)	(-0.04)	(0.88)	(1.54)	(1.77)*	(2.11)**	(-0.08)
	$\beta_{2,4}$	0.036	-0.024	0.055	-0.054	-0.061	-0.076	-0.243	-0.054	0.107
	t (NW)	(0.16)	(-0.33)	(0.69)	(-0.36)	(-0.90)	(-0.95)	(-1.99)**	(-0.69)	(1.62)
	t (HH)	(0.15)	(-0.33)	(0.68)	(-0.34)	(-0.94)	(-1.00)	(-1.81)*	(-0.66)	(1.64)
	$\beta_{2,5}$	-0.181	-0.006	-0.014	-0.232	0.031	-0.023	-0.181	0.038	-0.085
	t (NW)	(-0.89)	(-0.07)	(-0.19)	(-2.07)**	(0.44)	(-0.29)	(-1.32)	(0.56)	(-1.26)
	t (HH)	(-0.93)	(-0.07)	(-0.18)	(-2.47)**	(0.41)	(-0.27)	(-1.23)	(0.57)	(-1.27)
	$\beta_{3,1}$	-0.342	-0.020	0.188	-0.235	-0.121	0.218	-0.070	-0.001	0.296
	t (NW)	(-1.56)	(-0.22)	(2.51)**	(-1.87)*	(-1.64)	(3.47)***	(-0.57)	(-0.02)	(3.80)***
	t (HH)	(-1.71)*	(-0.22)	(2.55)**	(-1.90)*	(-1.77)*	(3.70)***	(-0.61)	(-0.02)	(3.64)***
	$\beta_{3,2}$	-0.772	-0.111	0.006	-0.323	-0.066	0.107	-0.100	-0.089	0.054
	t (NW)	(-2.80)***	(-1.09)	(0.07)	(-2.17)**	(-1.02)	(1.64)	(-0.74)	(-1.22)	(0.60)
	t (HH)	(-2.72)***	(-1.08)	(0.08)	(-2.09)**	(-0.96)	(1.72)*	(-0.71)	(-1.20)	(0.63)
	$\beta_{3,3}$	0.284	0.042	0.261	0.243	-0.015	-0.038	-0.115	0.093	-0.027
DOM	t (NW)	(1.31)	(0.45)	(3.37)***	(1.80)*	(-0.19)	(-0.45)	(-1.05)	(1.23)	(-0.31)
	t (HH)	(1.39)	(0.43)	(3.23)***	(1.81)*	(-0.18)	(-0.44)	(-1.06)	(1.22)	(-0.35)
	$\beta_{3,4}$	0.699	-0.017	-0.014	0.447	0.109	0.036	-0.232	-0.096	0.081
	t (NW)	(2.68)***	(-0.23)	(-0.20)	(3.66)***	(1.61)	(0.48)	(-2.15)**	(-1.27)	(0.96)
	t (HH)	(2.53)**	(-0.25)	(-0.21)	(3.51)***	(1.53)	(0.46)	(-2.65)***	(-1.21)	(0.91)
	$\beta_{3,5}$	0.249	0.017	-0.009	-0.048	0.041	0.072	0.091	-0.072	0.097
	t (NW)	(0.97)	(0.23)	(-0.14)	(-0.38)	(0.64)	(1.03)	(0.67)	(-1.15)	(1.23)
	t (HH)	(0.92)	(0.25)	(-0.16)	(-0.37)	(0.65)	(1.01)	(0.70)	(-1.12)	(1.22)
α		-0.191	0.017	0.320	0.147	0.152	0.051	-0.103	0.099	-0.265
t (NW)		(-0.87)	(0.19)	(4.92)***	(1.44)	(2.46)**	(0.75)	(-0.76)	(1.21)	(-2.13)**
t (HH)		(-0.85)	(0.19)	(5.11)***	(1.49)	(2.40)**	(0.75)	(-0.79)	(1.42)	(-2.04)**
Adj. R^2 (%)		13.35	5.95	15.09	22.10	10.62	21.22	20.29	36.38	20.92

Table 10. Results of Granger Causality Test

This table presents the results (F-stat) of Granger causality test of the VAR models, estimated using both Newey-West (NW) and Hansen-Hodrick (HH) as the standard error, with no causality as the null hypothesis. We conduct the test for three different portfolios: big, medium, and small cap stocks and two different sample: all days (2,386 days) and crisis period (240 days). P-values are presented in brackets. Significance at 1% is presented with ***, 5% is presented with **, and 10% is presented with *.

Granger Cause		Granger Effect								
		Big Cap Stocks			Medium Cap Stocks			Small Cap Stocks		
		RET	FOR	DOM	RET	FOR	DOM	RET	FOR	DOM
		Panel A.1: Big cap stocks & all days			Panel B.1: Medium cap stocks & all days			Panel C.1: Small cap stocks & all days		
RET	F (NW)	2.43**	1.90*	3.07***	1.28	1.51	6.44***	1.78	3.24***	1.71
	Prob.	(0.033)	(0.092)	(0.009)	(0.267)	(0.184)	(0.000)	(0.114)	(0.006)	(0.129)
	F (HH)	3.80***	1.98*	2.95**	2.93**	1.92*	13.48***	-0.68	7.54***	1.67
	Prob.	(0.002)	(0.079)	(0.012)	(0.012)	(0.087)	(0.000)	(1.000)	(0.000)	(0.139)
FOR	F (NW)	1.14	65.37***	4.71***	1.07	59.28***	4.64***	0.72	37.80***	3.58***
	Prob.	(0.339)	(0.000)	(0.000)	(0.374)	(0.000)	(0.000)	(0.606)	(0.000)	(0.003)
	F (HH)	1.15	65.87***	4.89***	1.32	66.56***	4.47***	0.76	35.47***	3.95***
	Prob.	(0.331)	(0.000)	(0.000)	(0.251)	(0.000)	(0.000)	(0.577)	(0.000)	(0.001)
DOM	F (NW)	1.73	4.35***	403.51***	1.93*	0.63	248.03***	2.52**	1.27	288.08***
	Prob.	(0.125)	(0.001)	(0.000)	(0.086)	(0.676)	(0.000)	(0.028)	(0.273)	(0.000)
	F (HH)	1.70	4.42***	596.97***	1.68	0.69	254.52***	2.68**	1.19	297.29***
	Prob.	(0.132)	(0.001)	(0.000)	(0.137)	(0.633)	(0.000)	(0.020)	(0.309)	(0.000)
		Panel A.2: Big cap stocks in crisis			Panel B.2: Medium cap stocks in crisis			Panel C.2: Small cap stocks in crisis		
RET	F (NW)	1.17	0.70	1.64	0.96	0.08	3.82***	1.74	0.72	1.09
	Prob.	(0.326)	(0.626)	(0.151)	(0.442)	(0.995)	(0.002)	(0.126)	(0.612)	(0.367)
	F (HH)	1.40	0.70	2.04*	1.43	0.08	4.47***	-1.29	1.07	0.89
	Prob.	(0.225)	(0.627)	(0.075)	(0.215)	(0.995)	(0.001)	(1.000)	(0.376)	(0.489)
FOR	F (NW)	0.51	1.58	0.55	1.48	2.21*	1.38	3.10**	6.92***	1.53
	Prob.	(0.770)	(0.167)	(0.735)	(0.198)	(0.055)	(0.235)	(0.010)	(0.000)	(0.182)
	F (HH)	0.50	1.71	0.56	2.13*	9.02***	1.38	3.29***	6.07***	1.58
	Prob.	(0.778)	(0.133)	(0.732)	(0.063)	(0.000)	(0.234)	(0.007)	(0.000)	(0.168)
DOM	F (NW)	2.81**	0.30	4.93***	5.50***	1.79	3.57***	2.76**	1.15	3.84***
	Prob.	(0.018)	(0.915)	(0.000)	(0.000)	(0.117)	(0.004)	(0.019)	(0.335)	(0.002)
	F (HH)	2.72**	0.29	4.70***	6.48***	2.81**	5.65***	6.54***	1.11	3.84***
	Prob.	(0.021)	(0.920)	(0.000)	(0.000)	(0.018)	(0.000)	(0.000)	(0.359)	(0.002)

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