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MODELING AND ESTIMATION OF CUMULATIVE ABNORMAL RETURN USING VECM

Sri Ambarwati[1]
Eka Sudarmaji[2+]
Herlan Masrio[3]
Ismiriati Nasip[4]

[1,2,3]*Fakultas Ekonomi and Bisnis, University of Pancasila, Jalan Srengseng Sawah, Pasar Minggu Jakarta, Indonesia.*
[1]*Email: sriambarwati@univpancasila.ac.id Tel: 081282688334*
[2]*Email: esudarmaji@univpancasila.ac.id Tel: 087884964643*
[3]*Email: herlan@univpancasila.ac.id Tel: 0816946278*
[4]*Bina Nusantara University, Indonesia.*
[4]*Email: ismiriati.nasip@binus.ac.id Tel: 08121085535*


(+ Corresponding author)

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ABSTRACT

This paper examined how firm-level idiosyncratic risk varies over time. It affected initial public offering (IPO) in the presence of pump-and-dump and flipping trends during the early trading of IPO stocks in the Indonesia Stock Exchange. The paper used the IPO data taken from 181 companies during the year 2015-2019. It revisited the relationship between Cumulative Abnormal Return thirty-days (CAR30D) and Cumulative Abnormal Return five-days (CAR5D) and the Characteristics (IPO Floating shares, IPO Fund and Price) and Macroeconomics Condition (Inflation rate). It also used the cointegration analysis and VECM model. The paper found that Both LnFloat and LnPrice had causal evidence in the long-run causality or short-run with Cumulative Abnormal Return thirty days (CAR30D). We also noted that idiosyncratic risk exposure depends on IPO characteristics. It was crucial for firms going public in hot-issue markets, undervalued IPOs, and high idiosyncratic-risk issues. The model suggested that those series should cointegrate firstly. However, the variable of LnIPOFund had causal evidence in the short-run causality only.

Contribution/Originality: This paper expected to fill the gap and confirmed what IPO characteristics and macroeconomics variables were significant and could predict that the IPO categorized into hot-issue markets, undervalued IPOs, and high idiosyncratic-risk issues.

1. INTRODUCTION

The theoretical model's explanation is simple: IPO anomalies generally include underpricing, long-term underperformance, and hot issue/cold issue based on the assumption that the investor is rational, and the average company or underwriter of the stock is not mistaken on IPO share price valuation. Practical explanations that IPO anomalies happened due to price stabilization by companies/underwriters resulted in irrationality/overreaction from investors. Therefore, this research created a model and estimated Cumulative Abnormal Returns for thirty days (CAR30D) and Cumulative Abnormal Returns for five days (CAR5D) to find an explanation of IPO anomalies in Indonesia by using the VECM. The model captured ideas behind IPO stock anomalies offered in the Indonesian capital market.

Phenomena IPO started when the initial return rate of IPO was positive (high) and sometimes unfavorable. The phenomenon was usually related to Phenomena listing stocks in demand/not in demand (Hot/Cold). This IPO initial return rate cycle occurred when some IPO stocks surge significantly due to phenomena underpricing.

However, the movement of IPO stocks would then tend to underperform in the market in its long-term performance. There were always stock price movements that were much worse. The general explanation of underpricing IPO was based on the irrationality and overreaction of investors. Unfortunately, it did not provide an economic reason why they failed to behave rationally and why investors consistently always overreact.

A sample of stock price indexes or composite indexes was taken from companies listed on the Indonesia Stock Exchange. The number of companies that had already conducted an IPO was obtained from the Indonesia Stock Exchange. It consists of primary-board and emerging-board between January 2015 and December 2019. The authors selected several external and internal variables as two naturally different variables. VECM's econometric methodology was used to test the AR=0 hypothesis for each IPO share already listed on IDX.

Authors combined company returns, calculated using the average abnormal return: AARt = (1/N) Σi ARi,t, and the average abnormal return, used AARt = (1/N) Σi ARi,t and the average abnormal return, used $AR_{jt} = R_{jt} - \overline{R}_j$ d. While some companies' CAR or Cumulative Abnormal Return values, used formulas (AAR) - Average abnormal return or $AAR_t = \frac{\sum_{j=1}^{N} AR_{jt}}{N}$ cumulative abnormal return (CAR) $CAR_{T_1,T_2} = \frac{\sum_{j=1}^{N}\sum_{t=T_1}^{T_2} AR_{jt}}{N}$.

Meanwhile, the Initial Return (IR) calculation on the first day of listing used IR = (LnR_{ij}/LnR_{ijt-1}). IPOs with oversupply or high demand got a positive initial return on a positive average, while oversupply, IPOs experienced negative initial returns. A good proxy for oversupply was the level of oversupply and trading volume on the secondary market; the more significant the oversupply, the greater the total shares bought and sold immediately on the secondary market. The empirical literature had shown that macroeconomic factors and the frequency of IPOs were in a relationship. Therefore, we presented the following hypothesis: we wanted to test that the VECM might explain the relationship between endogenous factors or the company's characteristics. The exogen factors or 'Macroeconomic' factors with the thirty-day Cumulative Abnormal Return (CAR30D) and the five-day Cumulative Abnormal Return (CAR5D) were examined.

2. LITERATURE REVIEW

In recent years, IPO research had also occurred and increased with the taking of capital market research in several developing countries such as China (Chang, Chen, Chi, & Young, 2008; Chen & Kao, 2006; Mok & Hui, 1998; Tian, 2011), India (Bansal & Khanna, 2012; Deb & Mishra, 2009), New Zealand (Vos & Cheung, 1992), Bangladesh (Islam, Ali, & Ahmad, 2010), Indonesia (Indriani & Marlia, 2013; Manurung, Juwono, & Siswanti, 2019; Manurung & Manurung, 2019) and more. The launch of new IPO capital markets such as REIT and Listed Property Trust (LPT) had also become very popular to discuss in the literature (Bairagi & Dimovski, 2011; Chen & Lu, 2006; Dimovski, 2010) in it about Phenomena 'flipping' (Bayley, Lee, & Walter, 2006; Dimovski, 2010) There was a link between idiosyncratic risk and IPO return rates. The idiosyncratic risk was often used to measure information asymmetry (Campbell & Taksler, 2003). Some empirical studies (Beaulieu & Bouden, 2020; Fu, 2009) found a positive relationship between volatility and idiosyncratic risk. The authors argued that investors need high premiums to hold idiosyncratic risky stocks. However, Arena, Haggard, and Yan (2008) and Ang, Hodrick, Xing, and Zhang (2006) showed negative relationships in their findings. Ang et al. (2006) explained pricing that stocks with high idiosyncratic risks were more sensitive to market volatility risks, thus lowering the return rate. Vidal-García, Vidal, and Nguyen (2016) also highlighted the importance of idiosyncratic risk factors in determining IPO performance in European markets. Therefore, they noted that more portfolios (especially in Spain and the Netherlands) contained positively idiosyncratic risks, whereas all portfolios were very damaging in the UK. Beaulieu and Bouden (2020) found that idiosyncratic risk at the firm level positively affected the IPO's return in the case of the IPO. This paper investigated whether IPO-specific risks were essential in IPO pricing, given the high asymmetry of information occurring within the first 30 days of stock IPO trading.

3. METHOD & DATA

The authors built a model Vector Error Correction (VECM). VECM was used to estimate and predict the future value of potential cumulative abnormal returns (CAR) on IPO stocks. VAR & VECM served to analyze the innovative structure of the IPO model. Based on this VECM model, the authors tried to prove and identify dynamic relationships of endogenous and exogen variables within the IPO model.

First, several testing stages checked the root unit to see the behavior of time series economic data. It could be seen as the initial step in constructing a time series model, whether the data used stationary or not, which could be achieved using the dickey-fuller augmented test (Dickey & Fuller, 1979) Secondly, test the cointegration and causality of granger temporal were using the maximum probability approach of Johansen (1988); lastly, the third stage included replacing VECM and testing its exogenity variables. The process of forming VECM could be seen in Figure 1.

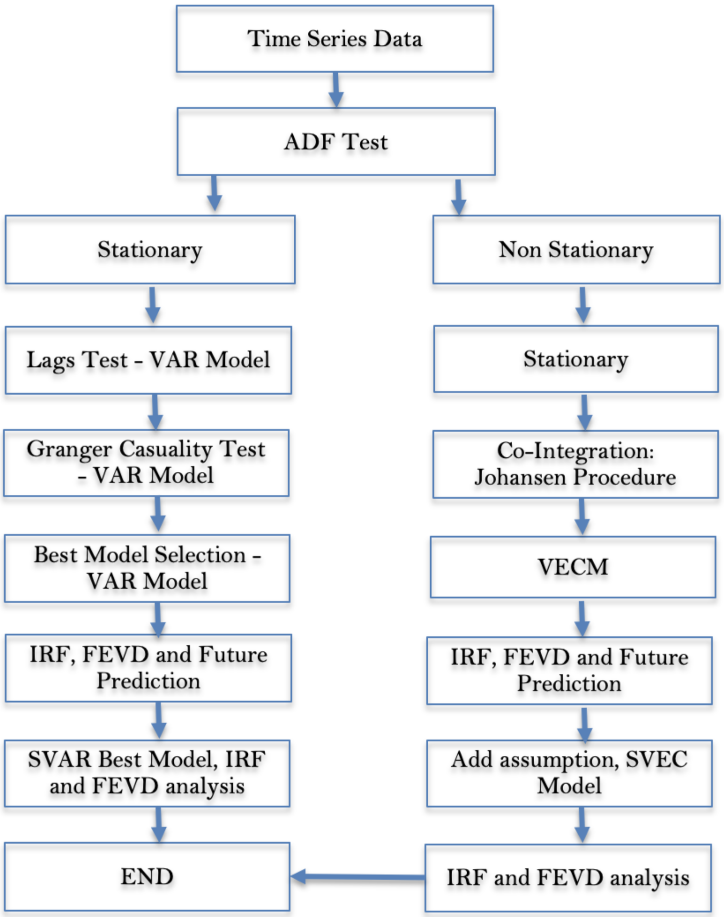

Figure-1. Var and VECM model correction process.

The VAR model explained the endogenous alteration of past data with other endogenous. VAR model parameters predicted using Ordinary Least Square (OLS) or the smallest square method. In general, the VAR model for k-variables, i.e., each equation was an equation with one of the other variables and a deterministic trend component. A common form, VAR(p) with endogenous k-variable $y_t = (y_{1t}, ..., y_{et})$ can be written, Equation 1.

$$y_t = A_0 + \sum_{i=1}^{p} \mathbf{A}_{it-I} + u_t, \; t = 0, \pm 1, \pm 2, \ldots \qquad (1)$$

with A_i, $i = 1,\ldots,p$ is a dimensional coefficient matrix (k x k), u_t is k-dimensional white-noise with $E(u_t\, u_t)' = \Sigma u$ the definitive white-noise. For in-sample, observations could be written in linear form.

$Y = X\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, with matrix covariance

$$\mathbf{Y} = \begin{bmatrix} z \\ z \\ \vdots \\ z \end{bmatrix}_{n \times 1}, \quad \mathbf{X} = \begin{bmatrix} 1 & z_{(1-1)} & z_{(1-2)} & \cdots & z_{(1-p)} \\ 1 & z_{(2-1)} & z_{(2-2)} & & z_{(2-p)} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & z_{(n-1)} & z_{(n-2)} & \cdots & z_{(n-p)} \end{bmatrix}_{n \times (p+1)}, \quad \beta = \begin{bmatrix} \alpha_0 \\ \varphi_1 \\ \varphi_2 \\ \vdots \\ \varphi_p \end{bmatrix}_{(p+1) \times 1} \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

The best order selection criteria used four criteria to select the best order (p) using final prediction error (FPE), Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ), Schwarz Information Criterion (SIC). The vector error correction model was used to analyze multivariate time series data that was not stationer. The VAR model that had a linear cointegration relationship would be the VECM model, which could be written, Equation 2.

$$\Delta y_t = \alpha\beta^T y_{t-1} + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{p-1}\Delta y_{t-p+1} + U_t\ 0,\ \Gamma_i = -(I - A_1 - \ldots A_t) \quad (2)$$

The α and β had dimensions N x r, where N was the number of variables, and r was the cointegration degree. The degree of cointegration indicated some long-term relationship between the changes y_t of the model we create. Hence, cointegration was the main requirement of using VECM, where the degree of cointegration was determined using the Johansen Test. Short-term and long-term restrictions occurred in VAR and VECM models. Short-term restriction occurred if one variable could not immediately respond to changes or shocks in another variable. While long-term restriction occurred when there was a cointegration or long-term relationship between the variables used.

At the end of modeling, IRF and PEVD would be analyzed and reviewed. The final results, along with the best models, whether stationer or stationer, could be used as a reference in forecasting IPO events. Step in the Johansen test, namely:

H0: there was r, where r = 0.1,... k-1 cointegration equation, no cointegration or long-term relationship between variables.

H1: there was a cointegration equation, a cointegration, or a long-term relationship between variables.

Trace tests were used, where the test criteria were rejected H0 if the trace test statistical value was more than the critical value of Mackinnon-Hang-Michelis. The authors used Akaike's information criteria for optimum lag (p) selection, better known as the Akaike Information Criterion (AIC). Where the AIC was defined as follows: $AIC(p) = \log\det(\Sigma u\,(p)) + \frac{2Pk^{\wedge}2}{T}$, with $(\Sigma u\,(p)) = T^{-1} \sum_{t=1}^{T} \hat{U}_t\ \hat{U}_t$, where T was the sample size, and k was the number of endogenous variables. Value of p* that minimizes the criteria of information in intervals of 1, P_{max} to be observed or selected.

4. RESULT

There were 181 companies listed on the mainboard and development board for 2015-2019 on Indonesia Stock Exchange. The IPO funds rose, amounting to 129.51 trillion rupiahs or equivalent USD 8.93 billion (1usd=IDR 14,500), see Table 1.

Table-1. Number of IPO Companies, Acquisition Fund and Number of Shares.

Description	2015	2016	2017	2018	2019	Total
IPO Funds (Bio IDR)	7,324.6	11,424.7	34,318.8	61,657.2	14,786.6	129,511.9
Shares Float (Million)	23,950.1	24,817.5	9,439.0	168,454.0	39,745.5	266,406.1
Companies	17	15	36	58	55	181

Table-2. Descriptive Statistic.

Description	N	Minimum	Maximum	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
1st Initial Return	181	-1.8	1.7	0.326	0.0291	0.3910
CAR-5Days	181	-0.8	2.1	0.546	0.0417	0.5616
CAR-30Days	181	-0.8	2.6	0.385	0.0432	0.5809

The descriptive statistical test resulted in the values of Initial Return (IR), Cumulative Abnormal Return five-days (CA5D). Cumulative Abnormal Return thirty-days (CA30D) in Table 2 above showed an average of 0.326, 0.546, and 0.385 with maximum data distribution of 2.60. It also showed a minimum of -1.80, -0.08 -0.08 with standard deviations of 0.0291, 0.0417, and 0.0432 for IR, CA5D, and CA30D. We concluded that for all IPO shares, the average CA5D than IR and CA30D. Hence we claimed that under-pricing performed on the Indonesia stock exchange provided that the lowest minimum value existed in the IR variable. At the same time, the highest limit found in the CA30D due to the Buy & Hold practices, Sudarmaji, Ambarwati, Hubbansyah, and Shinta (2020).

Based on empirical studies by Sudarmaji et al. (2020) this article revealed that underpricing strategy led to Pump-and-Dump & Flipping strategy occurred on the Indonesia Stock Exchange. The underpricing strategy could be written in the following ways:

$$CA30D_{it} = \alpha_1 + \beta_1 CA5D_{it} + \beta_2 InflationR_{it} + \beta_3 LnIPOFund_{it} + \beta_4 lnPrice_{it} + \beta_5 lnFloat_{it} + \varepsilon_{it}$$

Where CA30D represented an abnormal cumulative return of thirties days. CA5D was a cumulative return of five days. Inflation was an inflation rate. LnIPOFund showed the amount of fundraising at IPO. LnPrice was the IPO stock price, and LnFloat showed the total number of shares floating in the IPO; subscript i (i = 1, . . ., N) and t (t = 1, . . ., T) indicated, respectively, individual IPO shares and periods. The lower IPO prices, lower IPO fundraising, a small number of floating IPO stocks traded, and an increase in inflation were expected to increase five days' cumulative return. In the end, it prompted an abnormal cumulative thirty days. On the other hand, the higher IPO prices, the large number of floating IPO shares traded, and the high inflation rate were expected to decrease to an abnormal cumulative return rate in the next thirty days.

4.1. Unit Roots Test

The most common and widely used test for stationary data tests was the Dickey-Fuller Augmented test criteria (ADF test). This test had the following equations presented.

$$\Delta Y_{it} = {}_{1+2}\alpha + {}_{2}\rho Y_{it-1+ik} + {}_{ik}\sum_{k=1}^{p} \delta \Delta Y_{it-k+\varepsilon} \quad \varepsilon_{it}; = 1 = 1, 2, 3, ..., N; t = 1, 2, 3, ... T$$

Where: ΔY_t was the first difference from Y; = α_1, as a constant value or intercept. ρ_2 was the regression coefficient for trends; was the regression coefficient for Y lag; was a regression coefficient for Y lag differences; lag-difference; ε was a term of error; p was lag, and t was the time.

Table-3. Individual Unit-Root analysis of InflationR, LnPrice, LnIPOFund and LnFloat

Augmented Dickey-Fuller test statistic		CA30D		CA5D		InflationR		LnPrice		LnIPOFund		LnFloat	
		t-Stat	Prob.*	t-Stat	Prob.*	t-Stat	Prob.*	t-Stat	Prob.*	t-Stat	Prob.*	t-Stat	Prob.*
		-12.21	0.00	-13.42	0.00	-15.01	0.00	-14.21	0.00	-15.01	0.00	-13.88	0.00
Test critical values:	1% level	-3.47		-3.47		-3.47		-3.47		-3.47		-3.47	
	5% level	-2.88		-2.88		-2.88		-2.88		-2.88		-2.88	
	10% level	-2.58		-2.58		-2.58		-2.58		-2.58		-2.58	

The test results of Table 3 above showed that overall, the CA30D and CA5D variables show stationary in the level value. Meanwhile, inflation, LnIPOFund, LnPrice, and lnFloat showed stationary in the first difference, with statistical test scores smaller than critical scores on the ADF of 0.01. Based on autoregressive reverse root data and characteristic polynomial roots, the authors concluded that the VECM model formed in a stable state since all the roots were inside the circle unit see Figure 2.

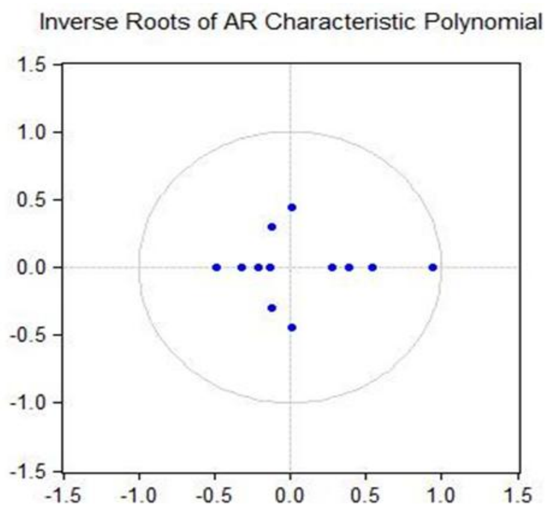

Figure-2. Inverse Roots of AR.

4.2. Optimal Lag Selection

The optimal lag length was two based on Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). Table 4.

Table-4. VAR Lag Order Selection for InflationR, LnPrice, LnIPOFund and LnFloat

Lag	LogL	LR	FPE	AIC	SC	HQ
1	409.361	NA	0.000	-4.316	-3.660139*	-4.050109*
2	448.134	72.16641*	5.22e-10*	-4.348369*	-3.036	-3.816
3	469.084	37.541	0.000	-4.174	-2.206	-3.376
4	491.691	38.942	0.000	-4.020	-1395	-2.955
5	511.561	32.848	0.000	-3.833	-0.552	-2.502
6	527.157	24.702	0.000	-3.597	0.340	-2.000
7	551.994	37.613	0.000	-3.468	1.125	-1.605
8	571.371	28.002	0.000	-3.276	1.973	-1.146

4.3. Johansen Cointegration Test

The integration analysis findings used Johansen's maximum likelihood method using maximum eigenvalue and trace statistics were listed in Table 5. Both produce evidence to refute the null hypothesis that vectors for vector integration at an actual 5 percent rate.

Table-5. Cointegration Test.

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized		**Trace**	**0,05**	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.358515	268.4658	95.75366	0.00
At most 1 *	0.313162	189.4393	69.81889	0.00
At most 2 *	0.226732	122.5724	47.85613	0.00
At most 3 *	0.208252	76.80324	29.79707	0.00
At most 4 *	0.15403	35.23798	15.49471	0.00
At most 5 *	0.030228	5.463616	3.841466	0.02
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				
Hypothesized		Max-Eigen	0,05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.358515	79.02651	40.07757	0.00
At most 1 *	0.313162	66.86693	33.87687	0.00
At most 2 *	0.226732	45.76917	27.58434	0.00
At most 3 *	0.208252	41.56526	21.13162	0.00
At most 4 *	0.15403	29.77436	14.2646	0.00
At most 5 *	0.030228	5.463616	3.841466	0.02

Note: * denotes rejection of the hypothesis at the 0.05 level.
**MacKinnon-Haug-Michelis (1999) p-values.

4.4. Vector Error Correction Model

Based on these results, the short-term relationship existed between CA50D and IPO prices, lower IPO funds, and the floating number of IPOs in terms of Pump-and-Dump & Flipping Strategies on the Indonesia Stock Exchange in 2015-2019, see Table 6

Table-6. The short-run causality from VECM estimates result.

CA5D(-1)	**InflationR(-1)**	**LnFloat(-1)**	**LnIPOFund(-1)**	**LnPrice(-1)**
-0,011	56.194	0.447	-0.585	1.774
-0,266	-35.789	-0.223	-0.187	-0.241
[-0.04014]	[1.57017]	[2.00574]	[-3.12333]	[7.34775]

Variable LnFloat and LnPrice influenced positively on Pump-and-Dump & Flipping Strategy (CA30D). It meant that a change in the stock (float) and the price change would cause the pump-and-dump & flipping strategy to occur by 0.447 percent and 1,774 percent. Meanwhile, on the variable amount of funds to be raised in an IPO or IPOFund negative influenced on the Pump-and-Dump & Flipping Strategy (CA30D), in other words, a null hypothesis was accepted. It meant that if there were a change in the amount of money to be raised (LnIPOFund) would cause the possibility of the Pump-and-Dump & Flipping Strategy to drop by -0.585 percent. The exact process was repeated in other models to test the short-term causality between past slowdowns in inflation (inflation) and rising share prices in five trading days (CA5D). For variable inflation (inflation) and share price increased within five trading days (CA5D), there was no short-term link to the Pump-and-Dump & Flipping (CA30D) Strategy. Statistically, (inflation) and the increase in the share price in CA5D had a probability value of Chi-square, which was <0.05; thus, the null hypothesis was accepted. It meant that there was no short-term causality between (inflation) and the increase in the share price in five trading days (CA5D) and the Pump-and-Dump & Flipping Strategy (CA30D).

In Table 7, the results of estimates of six models showed three models had long-term causality, namely the floating number (LnFloat), Cumulative abnormal five days (CA5D), and the IPO price (LnPrice). Meanwhile, three modes did not have long-term causality, namely LnIPOFund, inflation, and CA30D. There was one model in CA5D that had long-term causality in 5% significant long-term causality. Statistically, the first model showed that the ECT coefficient was -0.097, which meant the long-term balanced relationship was valid between the stock's variable IPO floating number (LnFloat) and the CA30D. It implied that -9.70 that imbalance of the previous period shocks reunited a long-term balance in the current period negative for Lnfloat. In other words, there were long-term causality variable IPO floating numbers LnFloat, LnPrice, LnIPOFund, inflation, CA5D, and CA30D. In the second model, there was a negative effect on the previous year's Variable IPO floating number (LnFloat), which showed the coefficient value of −0.905. It meant that the 1% increase in LnFloat reduced CA30D by 90.50%. These findings suggested that an increase in LnFloat would negatively impact CA30D in Indonesia.

Likewise, the third model in the floating number (LnFloat), which has an ECT coefficient of 0.432, meant that there was the validity of the long-term equilibrium relationship between LnFloat and CA30D; this implied that the 43.2% imbalance of the previous period shocks reunited into a long-term balance in the current period positively. In other words, there was long-term causality of LnPrice, LnFloat, LnIPOFund, inflation, CA5D, and CA30D. However, LnFloat-2 and LnPrice-1 indicated that they had a significant effect on the CA30D.

Table-7. The short-run causality from VECM estimates result.

Error Correction:	D(CA30D)	D(CA5D)	D(InflationR)	D(LnFloat)	D(LnIPOFund)	D(LnPrice)
CointEq1	-0.120	-0.097	0.000	0.432	-0.294	-0.905
	-0.078	-0.059	0.000	-0.140	-0.186	-0.117
	[-1.55279]	[-1.65867]	[-1.43697]	[3.07581]	[-1.57851]	[-7.72162]
D(CA30D(-1))	-0.859	-0,009	0.000	0.133	1.501	0.875
	-0.446	-0,337	-0.001	-0.808	-1.073	-0.675
	[-1.92436]	[-0.02770]	[-0.05949]	[0.16465]	[1.39895]	[1.29712]
D(CA30D(-2))	0.042	0.297	0.000	0.015	0.775	0.370
	-0.444	-0.335	-0.001	-0.803	-1.066	-0,671
	[0.09387]	[0.88619]	[0.16843]	[0.01870]	[0.72707]	[0.55196]
D(CA5D(-1))	0.512	-0.439	0.000	-0.570	-1.620	-0.328
	-0.585	-0.442	-0.001	-1.060	-1.407	-0.885
	[0.87489]	[-0.99175]	[0.32261]	[-0.53772]	[-1.15192]	[-0.37029]
D(CA5D(-2))	-0.552	-0.751	0.000	-0.169	-0.803	-0.229
	-0.588	-0.445	-0.001	-1.066	-1.414	-0.890
	[-0.93742]	[-1.68896]	[0.23076]	[-0.15836]	[-0.56759]	[-0.25722]
D(InflationR(-1))	-36.676	-29.238	-0.107	125.889	10.348	-110.921
	-64.850	-49.037	-0.076	-117.464	-155.909	-98.055
	[-0.56556]	[-0.59624]	[-1.39705]	[1.07172]	[0.06637]	[-1.13121]
D(InflationR(-2))	-66.233	-58.043	-0.018	115.326	79.351	-48.277
	-65.230	-49.325	-0.077	-118.154	-156.824	-98.630
	[-1.01538]	[-1.17676]	[-0.23984]	[0.97607]	[0.50599]	[-0.48948]
D(LnFloat(-1))	0.059	0.036	0.000	-0.902	-0.051	0.131

Error Correction:	D(CA30D)	D(CA5D)	D(InflationR)	D(LnFloat)	D(LnIPOFund)	D(LnPrice)
	-0.084	-0.064	0.000	-0.153	-0.203	-0.128
	[0.69979]	[0.56741]	[1.29681]	[-5.90183]	[-0.25036]	[1.03013]
D(LnFloat(-2))	-0.153	-0.118	0.000	-0.435	-0.156	0.079
	-0.082	-0.062	0.000	-0.149	-0.197	-0.124
	[-1.85919]	[-1.90252]	[1.40073]	[-2.92939]	[-0.79260]	[0.63745]
D(LnIPOFund(-1))	-0.086	-0.055	0.000	0.219	-0.555	-0.125
	-0.079	-0.059	0.000	-0.142	-0.189	-0.119
	[-1.08913]	[-0.91723]	[-1.34373]	[1.53508]	[-2.93334]	[-1.05371]
D (LnIPOFund(-2))	0.069	0.058	0.000	0.059	-0.203	-0.045
	-0.074	-0.056	0.000	-0.134	-0.178	-0.112
	[0.93572]	[1.04327]	[-1.45927]	[0.43907]	[-1.14363]	[-0.40698]
D(LnPrice(-1))	0.219	0.167	0.000	-0.617	0.091	0.201
	-0.122	-0.092	0.000	-0.220	-0.292	-0.184
	[1.80026]	[1.81160]	[1.23710]	[-2.79971]	[0.31117]	[1.09538]
D(LnPrice(-2))	-0.049	-0.038	0.000	-0.252	-0.009	0.111
	-0.091	-0.069	0.000	-0.165	-0.219	-0.138
	[-0.53580]	[-0.54924]	[1.13267]	[-1.52735]	[-0.04237]	[0.80159]
C	0.001	-0.001	0.000	0.000	-0.010	-0.011
	-0.047	-0.036	0.000	-0.086	-0.114	-0.071
	[0.01650]	[-0.01474]	[0.04731]	[0.00542]	[-0.09223]	[-0.15659]
R-squared	0.411	0.389	0.066	0.411	0.342	0.539
Adj. R-squared	0,.64	0.341	-0.008	0.364	0.290	0.502

However, LnFloat-2 and LnPrice-1 indicated that it has a significant effect on the CA30D. The third model estimated results in CA5D show a long-term balance between LnPrice, LnFloat, LnIPOFund, inflation, CA30D and CA5D at a significant 5% rate. However, in part, only LnFloat-2 and LnPrice-1 showed an insignificant effect on the CA30D. On the other hand, the fourth, fifth, and sixth models showed no long-term causality of variable LnFloat, LnPrice, LnIPOFund, inflation, CA5D, and CA30D. Statistically, variable LnFloat, LnPrice, LnIPOFund, inflation, CA5D did not affect CA30D.

4.5. Innovative Accounting Approach

4.5.1. Impulse-Response Function

Based on Figure 3 below, the CA30D responded to the CA5D variable shock, inflation, LnFloat, and LnPrice began to surprise with opposing trends, including variables in the LNIPOFund variable. Long-term dynamics response on LnFloat, LnIPOFund, and LnPrice occurred in the 2nd period. Variance decomposition described how many variance errors were predicted from certain effect variables described by innovations resulting from other effect variables in the system for some time.

4.5.2. Variance Decomposition

Variance decomposition described the variance proportion of errors from different impact factors of CO30D on the Indonesia Stock Exchange. It described the relative effect that could explain each variable's contribution to the system variable. Variance decomposition results were presented in Table 8. For CA30D, the LNPrice variable shock was the most significant factor in explaining its variability. Most variables had a surprising account in the third period. Subsequently, we would highlight the most critical shocks that can change each effect that was decomposed. The empirical evidence indicated that 93.68 % of CA30D was due to its innovative shocks. The variable CA5D was mainly affected by CA5D, and the variable LnPrice was 91.866 % and 2.896 %, respectively. At the same time, 2.461 % was CA5D due to its innovator shocks with a standard error of 0.851%. Variable inflation component was mainly affected variable inflation by 84.874 % by its shocks. 94.874 % of the inflation rate was explained by one standard deviation shock in its innovative shocks. Variable inflation component was mainly affected variable inflation by 84.874 % by its shocks. Likewise, the Variable Lnfloat component was mainly affected by its Lnfloat by 82.20 % and the CA5D by 26.43 %. The variable LnIPOFund component was mainly affected by its LnIPOFund by 49.00 % and by the LnFloat by 40.09 %. The variable LnPrice component was mainly affected by its LnPrice by 19.80 %, by the CA30D and LnIPOFund by 44.80 % and 30.76%, respectively.

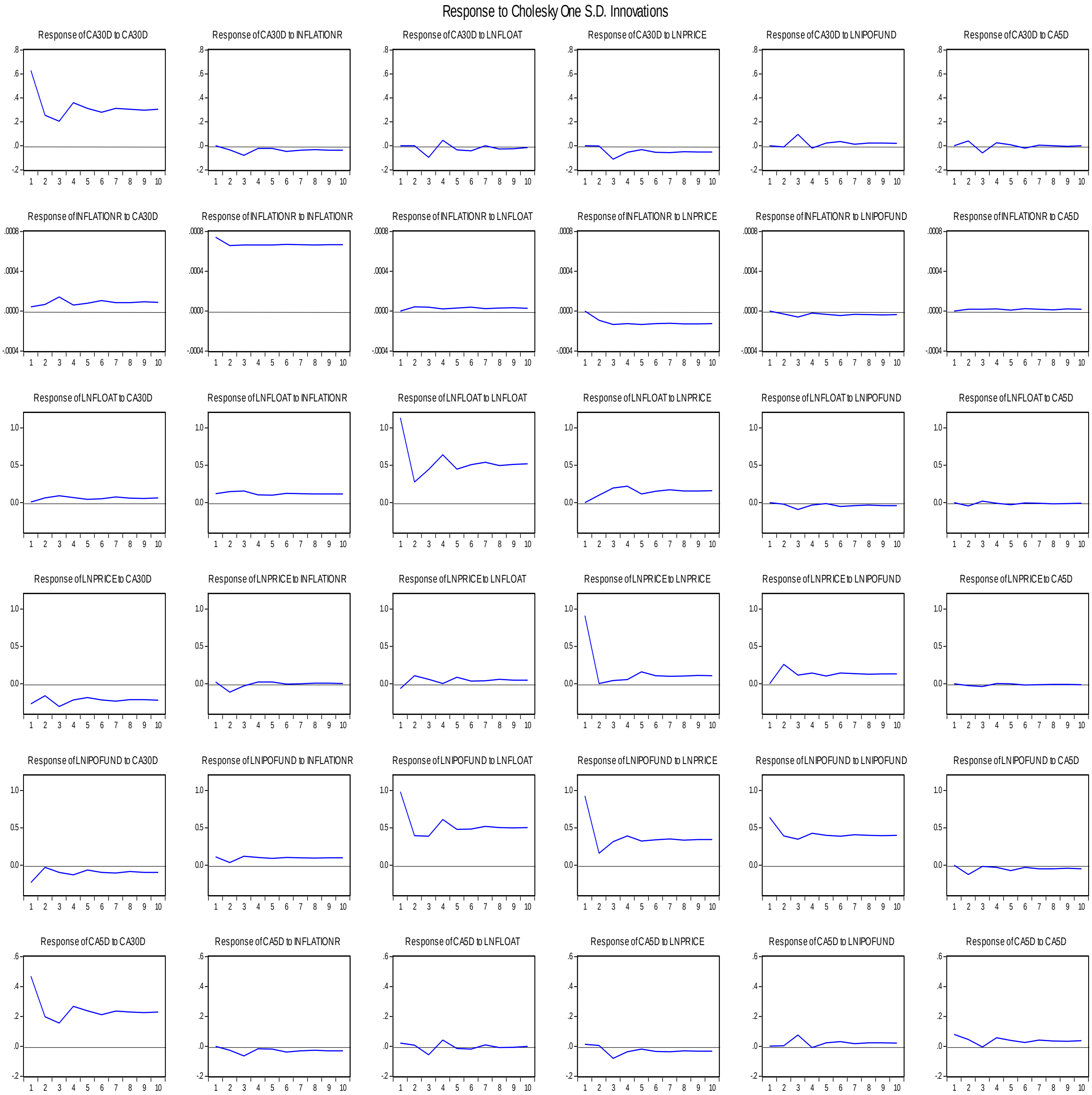

Figure-3. Impulse Responses Variables due to Shocks.

Table-8. CA30D Variance Decomposition.

Variance Decomposition of CA30D:							
Period	**S.E.**	**CA30D**	**CA5D**	**InflationR**	**LnFloat**	**LnIPOFund**	**LnPrice**
1	0.630	100.000	0.000	0.000	0.000	0.000	0.000
2	0.681	99.395	0.314	0.237	0.016	0.036	0.002
3	0.739	92.174	1.978	1.323	0.989	0.160	3.376
4	0.826	92.817	1.680	1.121	1.021	0.619	2.743
5	0.885	93.331	1.466	1.034	1.038	0.566	2.564
6	0.933	93.027	1.470	1.182	1.061	0.554	2.705
7	0.986	93.280	1.315	1.196	0.949	0.645	2.615
8	1.035	93.453	1.213	1.181	0.916	0.647	2.589
9	1.079	93.534	1.145	1.205	0.879	0.656	2.581
10	1.124	93.677	1.064	1.214	0.822	0.675	2.548
Variance Decomposition of CA5D:							
1	0.476	97.009	2.991	0.000	0.000	0.000	0.000
2	0.518	96.457	3.268	0.260	0.010	0.001	0.004
3	0.558	90.658	3.106	1.605	0.843	0.155	3.633
4	0.624	90.807	3.401	1.354	0.862	0.595	2.982
5	0.670	91.376	3.158	1.258	0.864	0.529	2.814
6	0.706	91.302	2.885	1.428	0.886	0.517	2.983
7	0.747	91.454	2.800	1.445	0.791	0.589	2.922
8	0.784	91.647	2.665	1.432	0.759	0.587	2.910
9	0.817	91.766	2.539	1.459	0.729	0.591	2.917
10	0.851	91.887	2.461	1.470	0.682	0.603	2.897
Variance Decomposition of InflationR:							
1	0.001	0.331	0.000	99.668	0.000	0.000	0.000
2	0.001	0.631	0.012	98.237	0.156	0.882	0.082
3	0.001	1.782	0.009	95.857	0.212	2.034	0.107
4	0.001	1.550	0.008	95.753	0.183	2.260	0.246
5	0.002	1.509	0.009	95.466	0.192	2.522	0.302
6	0.002	1.647	0.011	95.151	0.211	2.686	0.294
7	0.002	1.625	0.010	95.109	0.200	2.746	0.309
8	0.002	1.618	0.009	95.017	0.202	2.828	0.326
9	0.002	1.638	0.009	94.918	0.207	2.897	0.331
10	0.002	1.638	0.008	94.874	0.204	2.938	0.338
Variance Decomposition of LnFloat:							
1	1.141	0.002	6.510	1.052	92.435	0.000	0.000
2	1.189	0.275	6.121	2.448	90.365	0.369	0.421
3	1.300	0.720	6.657	3.481	85.835	0.912	2.395
4	1.470	0.773	6.825	3.188	84.407	1.862	2.944
5	1.544	0.776	6.638	3.292	84.366	2.011	2.917
6	1.638	0.784	6.712	3.481	83.699	2.097	3.226
7	1.738	0.868	6.760	3.560	83.079	2.305	3.428
8	1.818	0.889	6.731	3.637	82.740	2.449	3.554
9	1.899	0.895	6.735	3.693	82.471	2.538	3.667
10	1.979	0.921	6.746	3.742	82.202	2.625	3.764
Variance Decomposition of LnIPOFund:							
1	1.514	2.381	7.495	0.526	35.777	53.821	0.000
2	1.626	2.095	6.508	0.498	37.197	51.833	1.870
3	1.742	2.129	6.313	0.892	36.751	51.926	1.989
4	1.941	2.170	6.157	0.997	38.434	50,206	2.037
5	2.068	2.010	5.720	1.070	38.934	50.024	2.243
6	2.189	1.993	5.630	1.177	39.075	49.804	2.321
7	2.317	1.983	5.443	1.225	39.464	49.496	2.390
8	2.431	1.925	5.295	1.269	39.766	49.279	2.466
9	2.539	1.907	5.205	1.318	39.918	49.138	2.514
10	2.645	1.889	5.101	1.350	40.099	49.001	2.560
Variance Decomposition of LnPrice:							
1	0.952	7.993	1.866	0.045	1.175	59.596	29.325
2	1.012	9.635	1.659	1.345	2.175	54.983	30.203

3	1.068	16.937	1.506	1.284	2.321	50.404	27.549
4	1.101	19.864	1.432	1.252	2.184	48.730	26.538
5	1.136	21.376	1.515	1.216	2.515	48.439	24.939
6	1.170	23.577	1.438	1.148	2.451	47.679	23.707
7	1.205	26.006	1.371	1.083	2.397	46.610	22.533
8	1.236	27.670	1.343	1.031	2.466	45.935	21.554
9	1.267	29.232	1.307	0.982	2.453	45.387	20.639
10	1.298	30.765	1.267	0.936	2.436	44.798	19.798

5. CONCLUSIONS

The paper investigated long-term causality between LnFloat, LnPrice, LnIPOFund, inflation, CA5D, and CA30D using VECM-based Granger causality models from 2015-2019. Empirical results showed long-term and short-term causality between variables at significance rates of 1%, 5%, and 10% in Indonesia. The main results for the granger's presence and causality direction were LnFloat, and LnPrice had causal evidence in long-term or short-term causality with Cumulative Abnormal Return thirty days (CAR30D). However, the LnIPOFund had evidence of cause in short-term causality alone. On the other hand, there was no evidence of a cause of variable Inflation and CA5D for long-term causality and short-term causality with Cumulative Abnormal Return thirty days (CAR30D).

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Granger Casualty

Furthermore, to investigated the direction of causality between the cumulative abnormal thirty days (CA30D), the cumulative abnormal five days (CA5D), Inflation (Infaltion), IPO Fund (LnIPOFund), IPO price (lnPrice) and IPO float (lnFloat) in the context of the time-series data. Then the VECM Granger causality equation model can be seen as follows:

Ø

$$\Delta CA30D_t = \alpha_{1t} + \sum^{n-1} \rho_{1t,\,l}\Delta CA5D_{t-1} + \sum^{n-1} \beta_{1t,\,l}\Delta Inflation_{t-1} + \sum^{n-1} \gamma_{1t,\,l}\Delta lnIPOFund_{t-1}$$

$$+ \sum^{n-1} \delta_{1t,\,l}\Delta lnPrice_{t-1} + \sum^{n-1} \text{Ø}_{1t,\,l}\Delta lnFloat_{t-1} + ECT_{t-1} + \varepsilon_{1t} \quad (5)$$

i=1 i=1

$$\Delta CA5D_t = \alpha_{2t} + \sum^{n-1} \rho_{2t,\,l}\Delta CA30D_{t-1} + \sum^{n-1} \beta_{2t,\,l}\Delta Inflation_{t-1} + \sum^{n-1} \gamma_{2t,\,l}\Delta lnIPOFund_{t-1}$$

$$+ \sum^{n-1} \delta_{2t,\,l}\Delta lnPrice_{t-1} + \sum^{n-1} \text{Ø}_{2t,\,l}\Delta lnFloat_{t-1} + ECT_{t-1} + \varepsilon_{2t} \quad (6)$$

i =1 i =1

$$\Delta \ln flation_t = \alpha_{3t} + \sum_{i=1}^{n-1} \rho_{3t,l} \Delta CA30D_{t-1} + \sum_{i=1}^{n-1} \beta_{3t,l} \Delta CA5D_{t-1} + \sum_{i=1}^{n-1} \gamma_{3t,l} \Delta \ln IPOFund_{t-1} + \sum_{i=1}^{n-1} \delta_{3t,l} \Delta \ln Price_{t-1} + \sum_{i=1}^{n-1} \emptyset_{3t,l} \Delta \ln Float_{t-1} + ECT_{t-1} + \varepsilon_{3t.} \quad (7)$$

$$\Delta \ln IPOFund_t = \alpha_{4t} + \sum_{i=1}^{n-1} \rho_{4t,l} \Delta CA30D_{t-1} + \sum_{i=1}^{n-1} \beta_{4t,l} \Delta CA5D_{t-1} + \sum_{i=1}^{n-1} \gamma_{4t,l} \Delta Inflation_{t-1} + \sum_{i=1}^{n-1} \delta_{4t,l} \Delta \ln Price_{t-1} + \sum_{i=1}^{n-1} \emptyset_{4t,l} \Delta \ln Float_{t-1} + ECT_{t-1} + \varepsilon_{4t} \quad (8)$$

$$\Delta \ln Price_t = \alpha_{5t} + \sum_{i=1}^{n-1} \rho_{5t,l} \Delta CA30D_{t-1} + \sum_{i=1}^{n-1} \beta_{5t,l} \Delta CA5D_{t-1} + \sum_{i=1}^{n-1} \gamma_{5t,l} \Delta Inflation_{t-1} + \sum_{i=1}^{n-1} \delta_{5t,l} \Delta \ln IPOFund_{t-1} + \sum_{i=1}^{n-1} \emptyset_{5t,l} \Delta \ln Float_{t-1} + ECT_{t-1} + \varepsilon_{5t.} \quad (9)$$

$$\Delta \ln Float_t = \alpha_{3t} + \sum_{i=1}^{n-1} \rho_{6t,l} \Delta CA30D_{t-1} + \sum_{i=1}^{n-1} \beta_{6t,l} \Delta CA5D_{t-1} + \sum_{i=1}^{n-1} \gamma_{6t,l} \Delta Inflation_{t-1} + \sum_{i=1}^{n-1} \delta_{6t,l} \Delta \ln IPOFund_{t-1} + \sum_{i=1}^{n-1} \emptyset_{6t,l} \Delta \ln Price_{t-1} + ECT_{t-1} + \varepsilon_{6t.} \quad (10)$$

Where t is period (t = 1..., t); l is lag of each variable; ECT is error correction term and ε_{1t}, ε_{2t}, ε_{3t}, ε_{4It}, ε_{5t}, ε_{6t}, is assuming error rates on the model (error term).