Systematic Risk in Emerging Markets: a High-Frequency Approach

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Abstract

The study investigates how systematic, continuous, and discrete (jump) risk can explain the equity returns in Southeast Asia markets. Using the latest econometric techniques and a high-frequency dataset, I construct two high-frequency betas associated with intraday continuous and discontinuous risk premia. To improve consistency, I employ several statistical robustness levels and multiple frequencies (one minutes, five minutes, ten minutes, and thirty minutes). The findings show that both continuous and discontinuous risk premia are significant and positive in Indonesia, and these results are consistent for lower frequency data samples. Furthermore, the study reveals that diffusive and jump risk premia have different impacts in other countries, but the results are not consistent for lower frequency samples.

Resiko Sistematis di Pasar Berkembang: sebuah Pendekatan Frekuensi Tinggi

Abstrak

Penelitian ini menginvestigasi bagaimana systematic risk yang terdiri dari continuous dan jump risk dapat menjelaskan return saham di pasar Asia Tenggara. Menggunakan teknik ekonometri terbaru dengan data frekuensi tinggi, penulis menghitung dua beta frekuensi tinggi yang berhubungan dengan continuous dan discontinuous risk premium. Untuk meningkatkan konsistensi, penulis menggunakan beberapa statistikal robustness level dan beberapa frekuensi. Temuan menunjukkan bahwa continuous dan discontinuous risk premium positif dan signifikan di pasar saham di Indonesia, dan hasil ini konsisten untuk frekuensi yang lebih rendah. Selanjutnya, penelitian ini menunjukkan bahwa diffusive dan jump risk premium memiliki dampak yang berbeda pada pasar saham negara lain, namun temuan tersebut tidak konsisten untuk frekuensi yang lebih rendah.

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INTRODUCTION

One of the most popular topics in finance is how to determine systematic risk factor models. In asset pricing, systematic risk is estimated using monthly cross-sectional data that require a long-time horizon. Furthermore, the central concept of asset pricing is that only systematic risk or beta should be priced. For instance, in the equilibrium state, systematic risk is the only factor that explains the expected return; as a result, the anomalies condition will not hold in this state. However, to achieve the equilibrium condition with no anomalies takes 167 years (Lundblad, 2007).

The research paper from Fama and Macbeth (1973) generally supported the Capital Asset Pricing Model (CAPM), and the market betas present a satisfactory explanation of the cross-section of expected returns. For this reason, the systematic risk factor represents one of the cornerstones in finance. On the other hand, in the perspective of market microstructure, asset prices are determined by two critical unobservable components which are component involve equilibrium prices that reflect demand and supply and the other is microstructure noise. Hence, the concept of beta in the high-frequency environment is the factor loading of asset returns and market returns.

The development of econometric models in market microstructure field has grown exponentially. Moreover, the availability to analyze a large dimensional data has exploded and provided us with a variety of tools to estimate. As a result, the advantages of using high-frequency data to estimate systematic risk is that it only requires short time horizons, such as one month or three months.

The factor model of asset pricing in market microstructure can be viewed as the linear function of discrete factor model which pervade to academic field such as constructing portfolio asset, optimizing portfolio assets, as well as risk management. Within this framework, the state of equilibrium is a non-diversifiable risk as approached by the factor loading, and it should

be priced. Todorov and Bollerslev (2010) developed an empirical model to disentangle the systematic risk into discontinuous, or jump, and continuous beta. They find that betas discontinuous are priced higher than the expected continuous components. Another research reveals how macroeconomic shock affect discontinuous price movements significantly rather than continuous (Andersen et al., 2007). Their research findings imply that beta discontinuous will be priced higher in asset pricing when the macroeconomic shock is significant. Lee and Mykland (2012) explained how characterizing jump and the continuous process could improve the asset pricing models.

Given this background, I set a general asset pricing framework into two betas: a continuous beta reflecting smooth intraday co-movements with the market and a jump beta associated with intraday price discontinuities, or jump, along the trading days. The motivation for disentangling the betas is from Todorov and Bollerslev (2010) who reported the idea of dynamic jump and continuous betas that help in explaining the cross-section of expected stock returns.

I investigate these dynamic betas and their power in explaining expected of individual equity returns in emerging markets. However, empirical investigations should not be interpreted as a formal test of the Capital Asset Pricing Model (CAPM). Instead, the purpose is to examine that market risk with different degrees of jumpiness are priced differently than that of continuous risk factor. To illustrate the practical usefulness of the procedures that disentangle beta into its jump and continuous components, I estimate separate continuous and jump betas concerning an aggregate market portfolio in Southeast Asia countries.

This paper makes some novelties. First, I use emerging markets in our sample. Most research papers on the jump and continuous processes are on developed countries that in which all relevant information is fully reflected in the stock price. However, the result is different when emerging countries are used, such as Indonesia, Thailand, Malaysia, and Singapore.

Secondly, some statistical robustness and several frequencies (1, 5, 10, and 30 minutes) are used to improve consistency and prevent estimation from being affected by noise issues. Third, I use a recent econometrics model to disentangle the total variance into the jump and continuous variances. Several proxies exist to estimate continuous volatility, namely, bipower variation (BP*)* (Barndorff-Nielsen & Shephard, 2006) and realized outlyingness weighted variation (rowvar) (Boudt et al., 2011).

According to recent papers, several drawbacks exist when using bipower variation as a proxy for continuous volatility (Boudt et al., 2011; Bajgrowicz et al., 2016). First, the univariate version of the bipower variation is in some cases also robust to infinite activity jumps (Barndorff-Nielsen & Shephard, 2006). However, in finite samples, jumps induce an upward bias in the bipower variation, mainly if jumps affect two or more contiguous returns (Andersen et al., 2007; Bormetti et al., 2015; Pelger, 2020). Second, in a multivariate setting, the bipower variation is not an entirely satisfactory covolatility estimator because it is not affine equivariant and not always positive semidefinite. A final practical disadvantage is that the implied realized correlation estimate given by the ratio of the realized bipower co-variation of two assets and the square root of the products of the univariate realized bipower variation does not always lie between -1 and 1. Adopting emerging countries to measure private information using a jump process causes several biases given market conditions; therefore, I use the realized outlyingness weighted variation-called *rowvar*-model to capture price movements during trading days.

The remainder of this paper is organized as follows. Section 2 introduces the modelling framework and our dataset. In Section 3, I explain our findings and discuss our empirical results. Section 4 concludes the paper.

Quadratic Variation Theory

Quadratic variation (QV) is a measure of variance for high-frequency data, where *Yt* is the

value of the risky asset yield. The size of the variance is as follows:

$$[Y]_t = \mathrm{p}-\lim_{n\to\infty} \sum_{j=0}^{n-1} \left(Y_{t_{j+1}} - Y_{t_j}\right)^2$$

(1)

According to Barndorff-Nielsen and Shephard (2006), for any sequence of $t_0 = 0 < t_1 < .... < t_n = t$, with the subscript $j\{t_{j+1} - t_j\} = 0$ and the value of n close to infinity (∞), it is well known that the model becomes as follows:

$$\begin{aligned}[Y]_t &= [M^c]_t + \sum_{0 \le s \le t} \Delta Y_s^2 \\ &= [M^c]_t + [Y^d]_t,\end{aligned}$$

(2)

The process in equation (2) shows that QV is the aggregation of M^c and $\Delta\mathbf{Y}$, where M^c is a continuous process and $\Delta\mathbf{Y}$ is the jump component. This tells us that I could disaggregate QV into each component and then test for the jump by asking the value of the rest of QV minus M^c. The continuous process using the bipower variation in equation (3) is from Barndorff-Nielsen and Shephard (2006), and a statistical test is conducted to test the existence of jumps in the data. The significance level of this statistical test was set at 99%, and a jump is detected if the threshold value exceeds the t-stat.

$$\mu_1^{-2} \sum_{j=2}^{1/\Delta} |r_{t+j\Delta,\Delta}| |r_{t+(j-1)\Delta,\Delta}|$$

(3)

Disentangling Realized Volatility

To decompose realized volatility into each continuous and discontinuous component, I consider the continuous-jump diffusion process model $dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t)$, where $p(t)$ is a log price at time t, $\mu(t)$ is a continuous variation process, $\sigma(t)$ is a strictly positive stochastic volatility process with a continuous sample path and has well-defined limits, $W(t)$ is a standard Brownian motion, $q(t)$ is a pure jump levy process, and $\kappa(t)$ is jump size. Total volatility in high-frequency trading known as realized

volatility, popularized by Andersen et al. (2003) is the sum of intraday squared returns, that is, $RV_{\Delta(t)} = \Sigma_{(t)} r_{\Delta(t)}^2$, where $r_\Delta(t) = log\,(pt) - log\,(pt-_\Delta)$ is a sample Δ of the period return. It also follows the QV rule that $RV_{\Delta(t)}$ is the summation of continuous volatility and jump volatility, $RV_{\Delta(t)} = \sigma(t)dW(t) + \kappa(t)dq(t)$. Thus, the difference between realized volatility and continuous volatility is jump volatility.

Several proxies can be used to estimate continuous volatility, namely, bipower variation (*BP)* from Barndorff-Nielsen and Shephard (2006) and realized outlyingness weighted variation (*rowvar*) from Boudt et al. (2009). According to recent papers, such as Boudt et al. (2009) and Bajgrowicz et al. (2016), several drawbacks exist when using bipower variation as a proxy for continuous volatility. First, Barndorff-Nielsen and Shephard (2006) showed that the univariate version of the bipower variation is in some cases also robust to infinite activity jumps. However, in finite samples, jumps induce an upward bias in the bipower variation, especially if jumps affect two or more contiguous returns. Second, in a multivariate setting, the bipower variation is not a completely satisfactory covolatility estimator because it is not affine equivariant and not always positive semi-definite. A final practical disadvantage is that the implied realized correlation estimate given by the ratio of the realized bipower co-variation of two assets and the square root of the products of the univariate realized bipower variation does not always lie between -1 and 1. Therefore, in this paper, I use *rowvar* to avoid these drawbacks in our results.

Realized Outlyingness Weighted Variation (ROWVAR) and Econometrics Model of Betas

Rowvar is an alternative to the bipower variation that has none of the aforementioned shortcomings. It is defined as the classical realized variance applied to weighted, instead of raw, high-frequency returns. We downweight returns with a large local outlyingness, and state that a return is a local outlier if it has an extreme value relative to its neighboring returns. Returns affected by jumps have a large local outlyingness and, thus, receive a lower weight.

$$ROWVAR = c_w\Sigma_{i=0}^{[\frac{1}{\Delta}]} w(di\Delta)ri,\Delta r'i,\Delta \tag{4}$$

where c_w is correction factor for the *rowvar* model to avoid bias and spurious jump detection and w is weighted for the *rowvar* model for specific intraday returns that consisted of hard and soft rejections. We apply hard rejection instead of soft rejection for our *rowvar* model to earn very tight criteria.

$$w_{HR}(z) = \begin{cases} 1 & \text{if } z \leq k \\ 0 & \text{otherwise,} \end{cases} \tag{5}$$

$$w_{SR}(z) = \min\{1, k/z\}, \tag{6}$$

The traditional method for estimating beta is a rolling linear regression using monthly returns, as Fama and Macbeth (1973) discussed in their study. In equation (7), beta is a loading factor from *ri* (individual return) and *rm* (market return). Beta can be calculated by dividing the process of the co-movement, covariance of return for the individual and the market, and the variance for the market.

$$E(r_i - r_f) = \alpha_i + \beta_i(r_m - r_f) + \varepsilon_{i,t}$$
$$i = 1,......, N.$$
$$\hat{\beta} = \frac{\sum(x_t - \bar{x})(y_t - \bar{y})}{\sum(x_t - \bar{x})^2}$$
$$\beta_i^c = \frac{[p_i^c, p_0^c]_{(0,T]}}{[p_0^c, p_0^c]_{(0,T]}},$$
$$\beta_i^d = sign\left\{\sum_{s\leq T} sign\{\Delta p_{is}\Delta p_{0s}\}|\Delta p_{is}\Delta p_{0s}|^\tau\right\} \tag{7}$$

Engle (2014) proposed an econometric model for time-varying betas called the Dynamic Conditional Beta (DCB). This model allows beta to vary across time even using low fre-

quency data. The advantages of using the DCB model to calculate beta are more robust and precise than the classic beta model. The structural form (8) shows that the DCB can be calculated using multivariate GARCH, where H_{xx} is the conditional variance of the stock market and H_{xy} is the covariance of individual stock and market returns.

$$y_t \mid x_t, \mathbb{F}_{t-1} \sim N\left(\mu_{y,t} + H_{yx,t}H_{xx,t}^{-1}\left(x_t - \mu_{x,t}\right), H_{yy,t} - H_{yx,t}H_{xx,t}^{-1}H_{xy,t}\right)$$

$$\beta_t = H_{xx,t}^{-1}H_{xy,t} \qquad (8)$$

In the market microstructure model, the theoretical framework essentially encompasses all discrete-time one-factor models, whereas the diffusive risk is captured by the variance of Brownian motion, explicitly allowing for time-varying stochastic volatility. The systematic jump risk is determined by the Poisson measure and the jump size of the function, which allows for both time-varying jump intensities and jump sizes. Consistent with the extended discrete-time model from equations (9) to (11), the continuous-time representation also explicitly allows for different sensitivities to the systematic diffusive and jump risk, captured by βc and βd.

$$dp_i(t) = \alpha_{it}dt + \beta_i^c \sigma_t dW_t + \int \beta_i^d x\,\mu\,(dt,\,dx) + \sigma_t dW + \int x\,\mu\,(dt,\,dx) \qquad (9)$$

$$\hat{\beta}_t^{(d,i)} = \sqrt{\frac{\sum_{s=t-l}^{t-1}\sum_{\tau=1}^{n}\left(r_{s:\tau}^{(i)}r_{s:\tau}^{(0)}\right)^2}{\sum_{s=t-l}^{t-1}\sum_{\tau=1}^{n}\left(r_{s:\tau}^{(0)}\right)^4}} \qquad (10)$$

$$\hat{\beta}_t^{(c,i)} = \frac{\sum_{s=t-l}^{t-1}\sum_{\tau=1}^{n}\left[(r_{s:\tau}^{(i)}+r_{s:\tau}^{(0)})^2\mathbf{1}_{\{|r_{s:\tau}^{(i)}+r_{s:\tau}^{(0)}|\leq k_{s,\tau}^{(i+0)}\}} - (r_{s:\tau}^{(i)}-r_{s:\tau}^{(0)})^2\mathbf{1}_{\{|r_{s:\tau}^{(i)}-r_{s:\tau}^{(0)}|\leq k_{s,\tau}^{(i-0)}\}}\right]}{4\sum_{s=t-l}^{t-1}\sum_{\tau=1}^{n}(r_{s:\tau}^{(0)})^2\mathbf{1}_{\{|r_{s:\tau}^{(0)}|\leq k_{s,\tau}^{(0)}\}}},$$

$$(11)$$

METHOD

Refresh Time, Data Cleaning, and Synchronization

Non-synchronous trading delivers fresh (trade or quote) prices at irregularly spaced times that differ across stocks. Dealing with non-synchronous trading has been an active area of research in financial econometrics are a crucial feature of estimating covariances in financial econometrics as recognized at least since (Epps, 1979) because they induce cross-autocorrelation among asset price returns. The number of observations in the *i-th* asset up to time t is written as the counting process N(i)(t) and the times at which trades are made as *t(i)* 1, *t(i)* 2,... Then, the refresh time is defined, which is key to the construction of multivariate realized kernels. Harris et al. (2002) used this time scale in a cointegration study of price discovery, and Merton (1976) used the same concept in the context of realized covariances.

I use two refresh time processes from Barndorff-Nielsen et al. (2011) which are removing and assigning. The removing process omits the anonymous data that have more than one volume or one transaction price and that are traded outside market trading hours. The assigning process used to identify trade and volume direction and seller initiated or buyer initiated from our intraday data.

Robust Estimation of Intraday Periodicity

Intraday volatility is unique because it has a U-shaped pattern in trading sessions. This pattern can be explained by having the highest intraday volatility in the opening and the closing sessions, while having the lowest value in the lunch break session. This volatility behavior leads to a bias estimation for continuous and jump volatility because jump volatility is high at the opening and closing, but has no value during the lunch break. To ensure that the jump estimation model is robust from the periodicity problem, I apply high-frequency filtering from Boudt et al. (2011b) using the median absolute deviation (MAD) from the value of 1.486, such that Median $[y_i - \text{median}\ j,\ y_j]$:

$$\hat{f}_{t,i}^{\text{MAD}} = \frac{\text{MAD}_{t,i}}{\sqrt{\frac{1}{M}\sum_{j=1}^{M}\text{MAD}_{t,j}^2}}. \qquad (12)$$

Estimating the continuous volatility is sometimes spurious when we use intraday data. To protect our estimation and consistency model from spurious estimations, I include a correction factor, C_w:
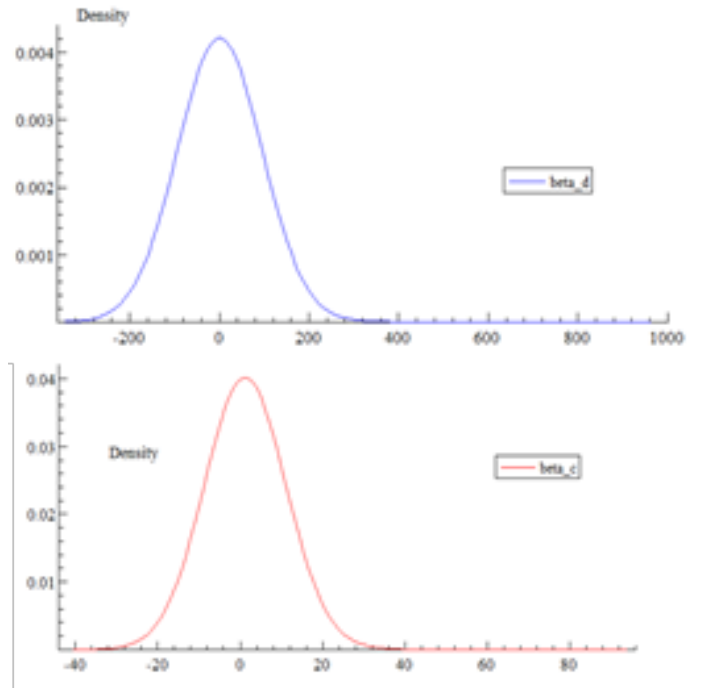
$$Cw = N \frac{E[w(u'u)]}{E[w(u'u)u'u]} \quad (13)$$

29 companies from Singapura, and 28 companies from Thailand. Details on the sample are provided in the Appendix.

RESULT AND DISCUSSION

Estimation Results

The main empirical results are based on continuous and discontinuous betas estimated

Figure 1. The Distribution of Two Betas

Note: Figure 1 displays the kernel density estimation of the unconditional distribution of two betas from 45 stocks in Indonesia using a one-minute sample frequency.

Data

I use trade data from the *Thompson Reuters* database and *Datastream* consisting of four intervals such as 1, 5, 10, and 30 minutes. In addition, I employ four market indexes in Southeast Asia from May 12, 2017 to November 3, 2017. To measure the impact of private information on an individual firm, I used the most liquid firms from Southeast Asian countries. Each country had a different number of most liquid firms, but I used the Thompson Reuters market constituent to determine the most liquid companies in each country from May 12, 2017 to November 3, 2017. Finally, I had 44 companies from Indonesia, 17 companies from Malaysia,

from high-frequency data for each of the individual stocks in the sample. rely on a fixed intraday sampling frequency of 1 minute, 5 minutes, 10 minutes, and 30 minutes to improve consistency and to capture possible temporal variations in systematic risk.

Regarding the estimation results, Figure 1 shows kernel density estimation results from the average value of jump and continuous beta across time and individual firm level. The density of jump betas are higher on the average and more skewed than continuous betas. However, the distribution value of continuous betas are least dispersed than jump betas, and this dispersion indicates to the er-

ror estimation proses when the asset returns move against the market.

In Figure 2, We can see the time series variations of continuous and jump betas for all firms in four countries. The dispersal of jump betas is consistently higher in all countries, as opposed to continuous betas. Furthermore, in the long period, the value of continuous beta closed to zero across individual stocks for all countries. Table 1 indicates the estimation result of the betas using all sample frequencies. When we use a higher frequency, the beta jump value is always more significant than the continuous beta. This result is different when using lower frequency data, for which the value of the beta jump is consistently lower than the continuous beta for the entire sample of companies. A possible explanation for this phenomenon is under research from Alexeev et al. (2017), and Gajurel et al. (2020)which explains that the estimation results at longer time intervals are af-

fected by noise such that the value is different when using lower frequency data.

Fama-MacBeth Cross-Sectional Regression

Numerous empirical research papers have related the cross-sectional variations in equity returns to betas and other firm characteristics. In the standard CAPM, the control variables such as; SMB, HML, MoM, reversal factor, and idiosyncratic factor. I do not include these variables in the model because of a lack of data and technical analysis support. Thus, I focus on the cross-sectional variation of stock returns based on high-frequency betas.

In the previous sections, we empirically showed that beta jumps are high in Southeast Asia. In this section, we present the risk premia on individual asset ret+urns using the Fama-Macbeth regression (Fama & Macbeth, 1973). The continuous beta (βc) represents the factor loading or sensitivity of individual asset returns
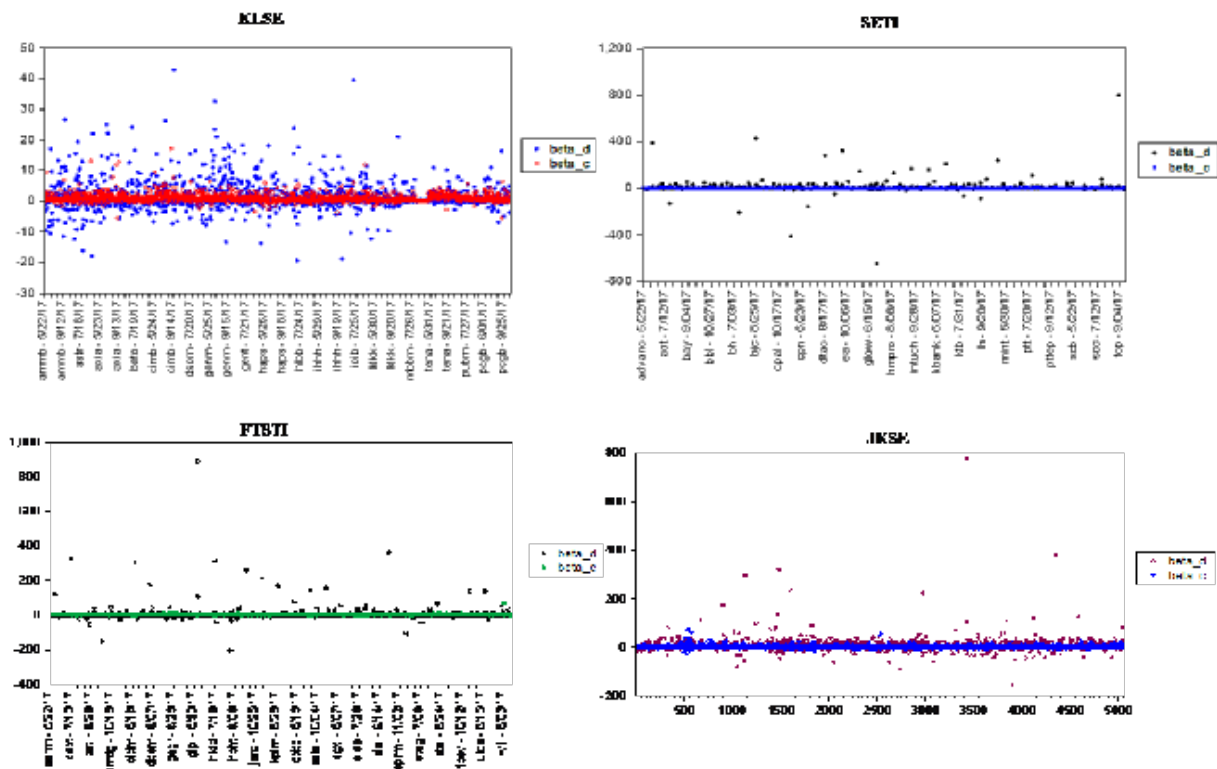

Figure 2. Scatter Plots of Two Betas

Note : Figure 2 displays time series plots of continuous and discontinuous betas for individual sample stocks from Southeast Asian countries.

Table 1. Betas Microstructure - Full Sample

	SETI		KLSE		JKSE		FTSTI	
	β^d	β^c	β^d	β^c	β^d	β^c	β^d	β^c
1 minute								
Mean	1.22	1.01	1.15	.94	1.5	1.32	1.35	1.3
Standard deviation	25.82	1.14	4.19	1.31	17.02	2.82	22.05	1.97
Skewness	6.88	2.08	2.5	3.27	24.61	7.98	24.41	12.19
Kurtosis	487.89	12.31	19.98	30.18	958.93	158.65	859.05	371.2
5 minutes								
Mean	.48	1.61	.9	1.85	.45	2.14	.4	2.03
Standard deviation	9.77	2.35	3.64	3.62	14.42	37.54	4.68	2.77
Skewness	23.15	2.67	3.94	2.02	-4.97	-67.8	18.1	2.71
Kurtosis	865.63	26.84	37.11	35.02	1114.2	4746.3	468.2	16.7
10 minutes								
Mean	.2	2.33	.49	2.49	.21	3.29	.35	2.85
Standard deviation	3.24	4.27	4.74	2.27	9.91	14.81	4.34	4.58
Skewness	-0.15	2.99	3.15	3.28	-8.14	11.54	14.95	2.67
Kurtosis	227.94	45.69	25.45	26.8	615.71	261.99	305.29	18.73
30 minutes								
Mean	.25	6.47	.15	3.78	.25	2.93	.1	4.93
Standard deviation	2.99	30.36	1.11	10.57	4.23	35.28	1.15	10.99
Skewness	4.67	8.71	6.95	4.25	9.66	-54.33	26.6	3.68
Kurtosis	111.7	129.52	89.55	37.47	323.59	3559.5	1046.35	40.1

Note : Table 1 shows the beta estimations from all sample frequencies across the countries. The beta value is a loading factor that implies co-movement between individual assets and market returns.

from all continuous information. The jump beta (βd) represents the sensitivity of individual asset returns from discontinuous information, such as macroeconomic announcements or private information. Once we retrieve the value of both betas, we then use equation 15 to estimate γ using the Fama-Macbeth regression method When γ^d is positive and significant, this implies that discontinuous information is priced.

$$dp_i(t) = \alpha_{i,t} + g^c \beta^c_{i,t} + g^d \beta^d_{i,t} + e_{i,t} \qquad (14)$$

Table 2 shows the results of the Fama-Macbeth regression. The values of βc and βc are from the disentangling process in equation 12. γ^c is the risk premia associated with variations in continuous information content and γ^d is the risk premia associated with discrete

information content. The regressions indicate that the t-statistics of the two betas are positively and consistently significant in Indonesia for all sample frequencies. This result implies the positive relationship between the expected equity returns and continuous and jump betas. This relationship monotonically increases when investors hold portfolios with high betas jump or continuos, they will gain a higher return. In contrast, the regression results in Thailand consistently show that only the discontinuous beta is positively and consistently significant at all sample frequencies. Consequently, Investors in the Thailand Stock Exchange will gain a higher return when holding a portfolio with higher jump betas.

The regression results show that there is not consistent result for both continuous and

Table 2. Fama - Macbeth Regression Results – Full Sample Frequencies

	α	g^c	g^d	Adjusted R2
Panel A : 1 minute frequency				
klse	-.001	.001***	.000***	.136
	(-1.753)	(-4.54)	(-5.88)	
jkse	-.002***	.001***	.000***	.241
	(-5.43)	(-5.83)	(-3.17)	
ftsti	-.011***	.009***	.000***	.472
	(-31.852)	(-5.03)	(-3.87)	
seti	0	.002***	.000***	.157
	(-1.062)	(-6.72)	(-3.67)	
Panel B : 5 minute frequency				
klse	-.01***	0	0	.19
	(-13.1)	-.9	-.03	
jkse	.00***	.00***	.00***	.4
	-26.4	(-21.10)	(-47.8)	
ftsti	.00**	.01***	.00***	.54
	(-1.34)	-2.58	(-1.70)	
seti	.00***	.00***	.00***	.25
	(-5.85)	(-7.51)	(-7.94)	
Panel C : 10 minute frequency				
klse	-.01***	.00***	.00**	.24
	(-12)	(-4.15)	(-1.77)	
jkse	.00***	.00***	.00**	.97
	(-31.7)	(-2.54)	(-1.76)	
ftsti	.00***	.00***	0	.23
	(-3.28)	(-6.48)	(-.63)	
seti	.00***	.00***	.00***	.38
	(-3.74)	(-5.51)	(-4.08)	
Panel D : 30 minute frequency				
klse	-.01***	.00***	0	.22
	(-39.40)	(-3.73)	(-.59)	
jkse	.00***	.00***	.00***	.95
	-11	(-4.90)	(-5.84)	
ftsti	.00***	0	.00**	.28
	-18.9	-7.87	(-1.73)	
seti	.00***	0	.00***	.2
	(-2.51)	-.65	-2.95	

Note : *** significant at 99%, ** significant at 95%, * significant at 90%

jump risk premia in stock market in Malaysia and Singapore. For one minute frequency, Malaysia and Singapore experienced positive and significant in both jumps and continuous risk premia. But, jump and continuous risk premia are not significant for five minutes frequency in Malaysia while Singapore only experience insignificant jump risk premia in ten minutes frequency.

The explanation of jumps in our findings is more likely to reflect the surprise or sudden information instead of the continuous process. The sudden news or shocks most of the time is unexpected information such as macro announcements as well as private information which is permeated discretely in the price formation. Our findings are supported by Aït-Sahalia and Xiu (2016), and Bollerslev et al. (2016) empirically find that jump components are strongly associated with macroeconomic announcements.

The discrete process or jump in asset price is associated with discrete information arrival, such as private information (Merton, 1976). Easley et al. (1996) and Easley et al. (2008) used the discrete process to calculate private information in capital markets. On the other hand, Merton (1976) and French and Roll (1986) explain that the continuous process in the price formation is related to public information which is incorporated to price continuously. He argued that within public news release traders could not obtain abnormal return because the news has already reflected into the price. This type of news is well-known information that traders easily obtain and is reflected smoothly and continuously in the price while private and macro announcements are surprised shocks reflected discretely or discontinuously in the price.

CONCLUSION AND RECOMMENDATION

The factor models of discrete-time are a well-known model in asset pricing to disentangle the diffusive and discrete price movements. I realize this separation process has a real effect in emerging markets. The separation of risk premia

for jumps and continuous might have different impacts across individual asset returns in emerging markets with different sample frequencies.

Motivated by the theoretical frameworks, I empirically investigate whether the market's diffusive and jump risks are priced differently in the cross-section of expected stock returns. My empirical investigations rely on a novel high-frequency dataset for a broad cross-section of individual stocks together with new econometric techniques for separately estimating continuous and discontinuous betas. The second novelty is that I realized that most papers on high-frequency data used developed countries, whereas I used data from emerging countries, which have different characteristics from developed countries.

The empirical results show that continuous and discrete (jump) betas have a significant impact on asset returns in Indonesia, and the results hold for all frequencies. In contrast, the findings reveal that continuous betas do not have the same results as jump betas when the sample frequencies decrease in other countries. I find that individual asset returns in Malaysia and Singapore have the same results for both jump and continuous betas that are not consistent. Finally, the individual asset returns in Thailand are positively significant for jump betas, and the results are consistent for all sample frequencies.

The findings of this paper have direct managerial implications for investment strategies as there are risk factors, namely jump and continuous risk, which explained the individual stock returns. Secondly, the high-frequency investors who trade intraday can choose stocks with higher beta jump to curb the higher return

The fundamental theoretical setup for cross-sectional variations in asset pricing is deliberately very general. The differences in the premia of continuous and discontinuous risk are possibly influenced by the behavioural effect of traders or the information content of continuous and discontinuous price movements. The behavioural effect could be transitory and does not affect the fundamental asset value. However, the information contained might differ because it brings the arrival of information that could permanently affect fundamental asset values. The information contents of diffusive, or continuous, and jump risk would be fascinating to investigate. Secondly, the research from Alexeev et al. (2019) shows that jumps and continuous betas in the United States market have asymmetric impact on portofolio performance. The results are expected to be different in emerging markets; hence it has still wide opened research to be investigated.

Another concern for improving this research in the future is the effect of macroeconomic announcements news on a set price. With the significant jumps estimation in the high-frequency environment have a potential relationship with the scheduled of the macroeconomic news release. Related to this, Bollerslev et al. (2016) and Zhou and Zhu (2019) investigate the macroeconomic announcement news and high-frequency betas in the US stock market. They found that the macroeconomic announcement days confound with beta jumps estimation. However, this research in emerging markets as best our knowledge is still rare. Hence, I leave this topic for future research.

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