Time-Varying Modeling of Systematic Risk: using High-Frequency Characterization of Tehran Stock Exchange

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ABSTRACT

We decompose time-varying beta for stock into beta for continuous systematic risk and beta for discontinuous systematic risk. Brownian motion is assumed as nature of price movements in our modeling. Our empirical research is based on high-frequency data for stocks from Tehran Stock Exchange. Our market portfolio experiences 136 days out of 243 trading days with jumps which is a considerable ratio. Using 1200 monthly (5200 weekly) estimations, 100 stocks for 12 months (52 weeks), 2400 (10400) betas are calculated. No general trend or constancy has been seen in continuous or discrete betas, and no general correlation between them. Existence and importance of both continuous and discrete betas are demonstrated by related tests. Comparing continuous and discrete beta, show that, in addition to greater significance of discrete beta, the estimated jump beta is higher than the continuous beta almost 87% of the time; and on average jump betas are 180% higher than continuous betas. Both greater significance and greater values are resulted for discrete risk premium.

Keywords:

CAPM, jumps, systematic risk, equity risk premium, high frequency data.

1. Introduction

Linear factor models pervade academic asset pricing finance and also form the basis for a wide range of practical portfolio and risk management decisions. Importantly, within this modeling framework, only non-diversifiable risk, as measured by the factor loading(s) [or the sensitivity to the systematic risk factor(s)], should be priced, or carry a risk premium. In other words, the risk of an investment is typically divided into two parts: idiosyncratic risk and systematic risk. Within CAPM [introduced by Sharpe (1964) and Lintner (1965)], as a most popular factor model, co-movement of returns in an individual asset (or portfolio) with the market is quantified and supposed as a systematic risk and the remaining movements of asset’s return is supposed as idiosyncratic risk.

Considering the price process nature is important for return movements and pricing modelling. Brownian motion has been considered as an assumption for price movements in some financial theories since Black-Scholes option pricing model (Black & Scholes, 1973) and Merton’s jump diffusion model (Merton, 1976). So, the price process is known to be the combination of continuous and jump components. Decomposing the price process into a continuous and jump component is consistent with recent evidences, e.g. Andersen, Bollerslev, and Diebold (2007), Dungey, McKenzie, and Smith (2009) and Aït-Sahalia and Jacod (2012).

There is an emerging literature hypothesizing that the CAPM beta may defer for the jump and continuous components of the return, initiated by Todorov and Bollerslev (2010) and extended by Patton and Verardo (2012) and Alexeev, Dungey, and Yao (2017). This paper takes the approach of decomposing the price process (and consequently decomposing return and beta) into a continuous and jump component. So given that asset prices evolve as a combination of Brownian motion with stochastic volatility and a jump process, we examine existence and differences between betas calculated for the continuous and jump components of systematic risk. Unlike the betas routinely calculated for Fama-French factors and other famous factor models, our continuous and jump risk betas have the same scale and are comparable.

Moreover, time-varying beta for individual firms or industries (see (Henkel, Martin, & Nardari, 2011), (Chiarella, Dieci, & He, 2013), (Reeves & Wu, 2013)) and using high-frequency data to construct beta estimation (see (Noureldin, Shephard, & Sheppard, 2012), (Todorov & Bollerslev, 2010), (Patton & Verardo, 2012)) are two other strands of research which are applied in our research approach.

The application in emerging market equities is novel; there is little literature on the high frequency behavior of emerging markets. These few cases are in Chinese markets (Liao, Anderson, & Vahid, 2010; Zhou & Zhu, 2012), in Eastern European markets (Hanousek & Novotný, 2012) and on the stocks of financial sector in India (Sayed, Dungey, & Yao, 2015), while the emerging markets are critically important to the future of the world economy.

Our empirical illustration is based on high-frequency transaction prices for hundred stocks from Tehran Stock Exchange (TSE) over the March 2013 to March 2014 sample period, for a total of 243 active trading days. The data were obtained directly from TSE IT Co. in the form of database (SQL Server) backup and processed and organized by ourselves.

Our market portfolio experiences 136 days out of 243 trading days with jumps that is greater than similar researches on S&P500. This ratio is considerable and may be related to some structural properties and restrictions of TSE. Using 1200 monthly (5200 weekly) regressions, 100 stocks for 12 months (52 weeks), 2400 (10400) betas are calculated. These numerous betas provide our materials for time-series and cross-sectional analysis. General trend or constancy has not been seen in continuous or discrete betas, and in general correlation between them. Existence and importance of both continuous and discrete betas are demonstrated by related tests.

Comparing continuous and discrete beta, show that, in addition to greater significance of discrete beta, the estimated jump beta is higher than the continuous beta almost 87% of the time; and on average jump betas are 180% higher than continuous betas. Calculating risk premia for both jump and continuous component, using cross-sectional regressions of fama-macbeth, demonstrates both greater significance and greater value for risk premium of discrete component of market factor.

The remainder of this paper is organized as follows. Section 2 introduces the modelling framework and the research propositions. Section 3 presents the methodology of this research, estimation techniques, procedure of data processing and parameters value setting. Section 4 describes the empirical analysis of the two beta estimates and their characteristics. Fama and MacBeth (1973) two-stage regressions are used to estimate the risk premia on these two risk components. Section 5 conclude and introduce some further research areas.

2. Literature Review

One factor model may be represented as below:

$$r_i = \alpha_i + \beta_i r_0 + \epsilon_i \ . \quad i = 1. \dots . N \qquad (1)$$

Where:
r_i = returns on the *i-th* asset,
r_0 = returns on the systematic risk factor,
β_i = the *i-th* asset's return sensitivity to systematic risk factor,
ϵ_i = the idiosyncratic risk (assumed to be uncorrelated with r_0).

The most popular one-factor model is obviously CAPM in which the beta is proportional to the covariation of the asset with respect to the aggregate market portfolio. In the case r_0 is notated as r_m.

The beta of an asset is not directly observable and should be estimated. The traditional way of estimating betas relies on rolling linear regression, typically based on five years of monthly data, as estimated in the classical studies by Fama and MacBeth (1973) and Fama and French (1992). But recently, availability of high-frequency financial prices has encouraged to alternative ways for more accurately estimating betas. In particular, Andersen, Bollerslev, Diebold, and Wu (2005), Andersen, Bollerslev, Diebold, and Wu (2006), Bollerslev, Law, and Tauchen (2008) and Barndorff-Nielsen and Shephard (2004) among others, have all explored new procedures for measuring and forecasting period-by-period betas based on so-called realized variation measures. These measures constructed from calculation of higher frequency data within period (especially intraday) returns. Such studies generally confirm that the use of high-frequency data results in statistically far superior beta estimates relative to the traditional regression based procedures.

Another stream of recent literature is concerned with possibility of price discontinuities (jumps), e.g. (Andersen et al., 2007), (Barndorff-Nielsen & Shephard, 2006), (Huang & Tauchen, 2005), (Mancini, 2009), (Lee & Mykland, 2008) and (Aït-Sahalia & Jacod, 2009). In result of such researches, it appears that the market rewards severe price moves differently from smooth price variation. Consequently, we may expect different risk premium for two different types of price variation, while most existing pricing models neglect this probable differentiation.

Combining the above ideas and empirical observations obviously suggests decomposing the return within the linear factor model framework into the returns associated with continuous price moves (r_{m}^{c}) and discontinuous price moves (r_{m}^{d}). So, the one-factor model is described by Todorov and Bollerslev (2010) as:

$$r_i = \alpha_i + \beta_i^c r_{\mathrm{m}}^c + \beta_i^d r_{\mathrm{m}}^d + \epsilon_i \ . \quad i = 1. \dots . N \qquad (2)$$

Where by definition $r_{\mathrm{m}} = r_{\mathrm{m}}^c + r_{\mathrm{m}}^d$ and two separate betas represent the systematic risks attributable to each of the two return components. Using Eq. (2), we can attribute the overall systematic risk to either the continuous component r_{m}^c , or the discontinuous component r_{m}^d. Recognition of this, is important as the implication that $\beta_{\mathrm{m}}^c = \beta_{\mathrm{m}}^d = 1$ is critical in the identification of the β_i^c and β_i^d coefficients in (Todorov & Bollerslev, 2010).

In the case that $\beta_i^c = \beta_i^d$, the model reduces to the standard one-factor model. In other words, this kind of modeling remove the restriction of no difference assumption between continuous and discontinuous price moves and let the decomposed betas to be identified, if exist, without any restriction.

As another case, $\beta_i^d = 0$, may be assumed where jump risks for individual stocks are likely to be non-systematic and diversifiable. Observing $\beta_i^d > 0$ indirectly suggests non-zero jump sensitivities.

Patton and Verardo (2012) hypothesizes that as jumps are commonly associated with news arrival, a jump beta which exceeds continuous beta may imply that stocks update faster to unexpected. For investors, the knowledge that individual stocks respond differently to the continuous and jump components of systematic risk is likely to provide a valuable tool in managing portfolio diversification.

We can codify this research within 5 forthcoming hypotheses:

H1: Continuous beta (β^c) is significantly not zero.

If we show that continuous beta is not zero, it means that we should consider this kind of systematic risk in our decision of portfolio management and risk management.

H2: Discrete (jump) beta (β^d) is significantly not zero. Significance of β^d has a great importance for the literature of pricing models. It shows the pricing impact of jumpy component of systematic risk.

H3: Discrete (jump) beta (β^d) is more/less/equal important than continuous beta (β^c).

The unique characteristic of our multi-factor model is comparability of coefficients (βs). Except in the case of the equality of β^d and β^c, which means the factor model is converging to simple market model, superiority of each beta means the excess importance of that kind of systematic risk in risk (portfolio) management. Specifically if $\beta^d$is greater; it means that the asset would have larger reaction to news, events or irregularities.

Examination of H1, H2 and H3 is done in common context and provide us enough cognition about validity and applicability of jump-continuous market pricing model.

H4: premium of continuous risk component is significantly not zero.

H5: premium of discrete(jump) risk component is significantly not zero.

Using Fama and MacBeth (1973) approach for H4 and H5, we find the premia of two kinds of systematic risks along with indication of model efficiency and validity.

3. Methodology

3.1. Jumps detection

Methodology of (Todorov & Bollerslev, 2010) use the test statistic proposed by Barndorff-Nielsen and Shephard (2006) to detect jumps in the market portfolio. The test is based on realized volatility, realized bipower variation and realized quadpower variation at sampling frequency as below:

$$RV_{\mathrm{m}} = \sum_{j=1}^{[T/\Delta]} r_{\mathrm{m}.j}^2 \xrightarrow{p} [r_{\mathrm{m}}.r_{\mathrm{m}}]_T^2 \quad as \quad \Delta \to 0 \qquad (3)$$

$$BV_{\mathrm{m}} = \sum_{j=1}^{[T/\Delta]-1} |r_{\mathrm{m}.j}||r_{\mathrm{m}.j+1}| \xrightarrow{p} \mu_1^2 \int_0^T \sigma_s^2 ds \quad as \quad \Delta \to 0 \qquad (4)$$

$$DV_{\mathrm{m}} = \sum_{j=1}^{[T/\Delta]-3} |r_{\mathrm{m}.j}||r_{\mathrm{m}.j+1}||r_{\mathrm{m}.j+2}||r_{\mathrm{m}.j+3}| \qquad (5)$$

Using above calculations, $\hat{J}$ test statistic to detect jumps is introcuced by Barndorff-Nielsen and Shephard (2006):

$$\hat{J} = \frac{1}{\sqrt{\Delta}} . \frac{1}{\sqrt{\psi . \max(1/T . DV_{\mathrm{m}}/BV_{\mathrm{m}}^2)}} \left(\frac{\mu_1^{-2}. BV_{\mathrm{m}} - RV_{\mathrm{m}}}{RV_{\mathrm{m}}} \right) \xrightarrow{L} \mathcal{N}(0.1) \qquad (6)$$

Where:

$$\mu_1 = \sqrt{2/\pi}$$

$$\psi = \pi^2/4 + \pi - 5$$

Using this estimator, we can find jumps in systematic risk factor. Since, the validity of other forthcoming estimators is dependent on the existence of jumps, this is the basic test in our research methodology.

3.2. Jump Beta and Continuous Beta Estimation

In practice, we usually observe prices and returns every Δ time interval, from 0, Δ, 2Δ, …, to [T /Δ]·Δ. Keeping Δ fixed, we denote the Δ-period return on asset *i* by:

$$r_{i.j} = p_{i.j\Delta} - p_{i.(j-1)\Delta} \quad . \quad i = 0.1. \dots . [T/\Delta] \qquad (7)$$

Using vector notation, let the (N + 1) × 1 vector of the observed returns to be:

$$r_j = (r_{0.j}.r_{1.j}. \dots \; r_{N.j})'$$

i \ j			Assets
			0 1 2 . . . N
Time	1	Δ	
	.	2Δ	
	.	3Δ	
	.	.	
		.	
	T/Δ	T	

The consistent estimators for β_i^c and β_i^d given by Todorov and Bollerslev (2010) are constructed as follows. We set a truncation threshold:

$\theta = (a_0\Delta^{\omega}.a_1\Delta^{\omega}.\dots.a_N\Delta^{\omega})'$

Where:

$\omega \in \left(0.\frac{1}{2}\right)$

$a_i \geq 0$

$i = 0.\dots.N$

We allow for different truncation thresholds across different assets by controlling a_i. Providing an intuitive interpretation, for instance, when $a_i = 3$, price increment that is larger than three standard deviations is classified as jumps. The continuous price movement corresponds to those observations that satisfy $|r_j| \leq \theta$.

Asset i	**0**	**1**	**….**	**N**
truncation threshold	θ_0 $a_0\Delta^{\omega}$	θ_1 $a_1\Delta^{\omega}$	…. ….	θ_N $a_N\Delta^{\omega}$

The discrete-time estimator of the continuous beta, $\hat{\beta}_i^c$, is:

$$\hat{\beta}_i^c = \frac{\sum_{j=1}^{[T/\Delta]} r_{i.j} r_{m.j} \mathbb{1}_{(|r_j| \leq \theta)}}{\sum_{j=1}^{[T/\Delta]} r_{m.j}^2 \mathbb{1}_{(|r_j| \leq \theta)}} \quad . \quad for\ i = 1.\dots.N \qquad (8)$$

where $\mathbb{1}$ is the indicator function,

$$\mathbb{1}_{(|r_j| \leq \theta)} = \begin{cases} 1 & if \quad |r_j| \leq \theta \\ 0 & if \ \ otherwise \end{cases}$$

The discrete time estimator of $\hat{\beta}_i^d$ is

$$\hat{\beta}_i^d = sign\left\{\sum_{j=1}^{[T/\Delta]} sign\{r_{i.j} r_{m.j}\} |r_{i.j} r_{0.j}|^{\tau}\right\} \times \left\{\frac{\sum_{j=1}^{[T/\Delta]} sign\{r_{i.j} r_{m.j}\} |r_{i.j} r_{m.j}|^{\tau}}{\sum_{j=1}^{[T/\Delta]} r_{m.j}^{2\tau}}\right\}^{\frac{1}{\tau}} \qquad (9)$$

The power τ is restricted to τ ≥ 2 so that the continuous price movements do not matter asymptotically (see Todorov and Bollerslev (2010), for more details). The sign in (9) is taken to recover the signs of the jump betas that are eliminated when taking absolute values. The estimator in (9) converges to β_i^d when there is at least one systematic jump (in the market portfolio) on (0, T]. Therefore, in order to calculate $\hat{\beta}_i^d$, we first need to test for the existence of jumps on the log-price series p0 of the market portfolio.

Abovementioned estimators which are introduced by (Todorov & Bollerslev, 2010) based on mathematical and statistical assumptions, theorems and proofs, studied by simulation in (Alexeev et al., 2017).

3.3. Data processing

Based on the nature of the study and its dependency on high-frequency data, the records of all trades in the stock market were needed. Persistent and steady attendance of stock ticker symbol in the market and high tradability were so important for stocks to be qualified for such a research. Accordingly, the year 1392, in Persian calendar, (March 2013-March 2014) is selected. The year was outstanding in the aspect of number of trades in stock market. Number of trades in the year was 21,821,760. While total number of trades in 8 years (2008-2015) was 69,948,927. So, the year has 31% of total trades of the eight years. The other helpful property of the year was persistence of tradability of stocks in the year. According to TSE regulations, stocks ticker symbol must be closed (not tradable) in some corporate events. In the selected year, stocks have much less closed status comparing other years, which is important for studying time-varying and high frequency phenomena. Tradability of 497 stocks in the year is described in table 1 and table 2.

Table 1: number of tradable days

Tradable days	No. of stocks
241-243	2
236-240	30
231-235	25
226-230	27
221-225	42
216-220	31
211-215	25
206-210	25
200-205	24
Below 200	266
Total:	497

Table 2:number of trades per year

Trade per year	No. of stocks
Over 300,000	7
200,000-300,00	13
100,000-200,000	44
50,000-100,000	50
20,000-50,000	83
Below 20,000	300
Total:	497

Trades data records (21,821,760 records) were filtered in three below steps:

1) All trade records related to priorities and bonds are deleted. [1,336,321 records deleted]
2) Based on two criteria: number of trading days and mean trade per day, 100 stocks are selected from 497 stocks. Firstly, all stocks which have at least 200 trading days among 243 working days, were shortlisted. Among them, 100 stocks that were more traded, by the measure of mean trade per day, were chosen. [8,411,508 records deleted]
3) All trades out of the trading hours (9:00-12:30) were eliminated. [14,152 records deleted]

As a result of filtering, 12,059,779 trade records for 100 stocks remained. It means that the remained data, by 500 mean daily trades, are qualified for calculating intra-day return and time-varying beta. The underlying data are 5 min observations on prices during the sample period. The intra-day returns and prices data start from 9:00 a.m. and end at 12:30 p.m., observations with time stamps outside this window are removed. In the absence of trades within a 5-min interval, prices are filled with the previous observation. Thus we have 43 intra-day observations for 243 active trading days belonging to 52 calendar weeks and 12 calendar months.

The 5 min sampling frequency is chosen as relatively conventional in the high frequency literature, especially for univariate estimation, see for example (Andersen et al., 2007), (Lahaye, Laurent, & Neely, 2011), (Dungey et al., 2009), (Patton & Verardo, 2012) and (Alexeev et al., 2017). We call each 5 min period, a 'return horizon'. Estimates of β^c and β^d are computed on a month-by-month and week-by-week basis which we call them 'beta estimation windows'.

High frequency data permits the use of 1-month or 1-week non-overlapping windows to analyze the dynamics of our systematic risk estimates. We construct an equally weighted portfolio of all investible stocks in each estimation window as the benchmark market portfolio which has been common throughout the literature of market model testing since (Jensen, Black, & Scholes, 1972) and used by recent researches of time-varying beta like (Alexeev et al., 2017). We use equally weighted portfolios rather than value weighted ones to avoid situations where the weight on one stock is disproportionally large relative to other portfolio constituents.

3.4. Parameter values

We started the analysis by setting most of the parameter values to be the same as in Todorov and Bollerslev (2010). Similar value setting is done by other researches which applied Todorov and Bollerslev (2010) approach like: (Alexeev et al., 2017), (Patton & Verardo, 2012), (Dungey & Yao, 2013) and (Sayed et al., 2015).

$$\omega = 0.49$$
$$a_i = 3\sqrt{BV_i} \quad . \ i = 0.1. \dots . \ N$$
$$\tau = 2$$

So, we calculate BV_i , a_i and θ_i respectively for each asset and for market index. Using θ_i as a truncation threshold for asset i , the return horizons which contain jumps are detected. Table 3 demonstrates calculated values and number of jump horizons for couple of assets. Recall that when calculating $\hat{\beta}_i^c$ by Eq. (8), only those observations that satisfy $|r_j| \leq \theta$ are used.

Table 3: Value setting and truncation thresholds for assets

Stock	BV_i	a_i	θ_i	$\lvert r_j\rvert \geq \theta$
Maskan Investment	0.165849	1.221737	0.014161	635
Pars Minoo	0.172658	1.246564	0.014449	589
Novin Bank	0.131976	1.089856	0.012633	552
Dana Insurance	0.14735	1.151586	0.013348	520
Bahman	0.163497	1.213045	0.014061	506
Iran Carbon	0.171897	1.243814	0.014417	479
Saipa	0.172143	1.244705	0.014428	472
Iran Khodro	0.154091	1.177634	0.01365	465
Saderat Bank	0.091548	0.907706	0.010521	404
Zoob Ahan	0.133533	1.096265	0.012707	356

4. Results

According to the methodology, we use the non-parametric test in Barndorff-Nielsen and Shephard (2006) and Huang and Tauchen (2005) based on the difference in the logarithmic daily realized variance and bipower variation measures to find jumps in market portfolio. Since, our used market portfolio is less susceptible to market microstructure "noise" than many of the hundred stocks in the sample; we rely on a finer 5 min sampling frequency in the implementation of the tests.

Using a significance level of 1%, we detect jumps in our equally weighted market portfolio on 136 out of 243 trading days using the statistic $\hat{\mathcal{J}}$ given in Eq. (6); that is 55.9% trading days. While similar ratio in the research of Alexeev et al. (2017) is 7.1% and Patton and Verardo (2012) find significant jumps on 4.04% of the days. Andersen et al. (2007) used the same ratio test statistic too and report 7.6% at 1% significant level. All these researches used S&P500 data. Since, we use the same estimators and the same parameter values as they applied; it indicates that discrete and jumpy movements in TSE are considerably more than S&P500.

The result showed the greater importance of studying jump movement and consequently jump beta and jump premiums in TSE context. Moreover, since the efficiency and performance of (Todorov & Bollerslev, 2010)'s estimators substantially depends on the existence of enough jumps in market portfolio, high percent of jumpy days is a good news for validity of our estimation in this research.

4.1. Betas calculation and characteristics

We used 5-min return horizons for estimating Betas in weekly and monthly estimation windows. It means that in the month-by-month approach, 1200 estimation equations are calculated; and in the week-by-week approach, 5200 estimation equations executed which take huge time and effort of programming and data organizing. The estimations resulted in 12 couples of betas of each stock monthly and 52 couples of betas of each stock weekly.

Figure 1 shows $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ for 5 representative stocks during the sample time span. The right hand figure is weekly presentation of betas and the left hand one is monthly demonstration. Blue line shows $\hat{\beta}_i^c$ and red dots show $\hat{\beta}_i^d$. A simple glance on diagrams, suggests no common trends in $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$. Moreover, no correlation between $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ is inferred visually. It means that separation and decomposing beta into two components of continuous and discrete is important. Furthermore, visual inconstancy and having no trend during time span convey unknown cause and effect relationships and provide an opportunity for studying them.

The other visual inference from representative diagrams is superiority of $\hat{\beta}_i^d$ than $\hat{\beta}_i^c$, most of the time. This phenomenon would be tested accurately in the following section. If it is correct, risk and portfolio managers should pay special attention to discrete component of systematic risk.

4.2. Betas significance and comparison

As described in section 2, the first hypothesis of the research is about existence and significance of Continuous beta (β^c). To examine the hypothesis we study if $\bar{\beta}_i^c$ is zero or not. If it is zero, it means that this kind of systematic risk has no influence on asset pricing and should be omitted from pricing modellings. Table 4 is constructed to study this hypothesis. Average of β^c for each 100 stocks along with confidence interval of 5% significance level are mentioned in the table. It means that the β_i^c value is in confidence interval by 95% of probability.

As marked in the table by †, only 6 stocks' confidence interval contain zero. It means that in 96 stocks (96% of observations), null hypothesis of $\beta^c = 0$ is rejected at significance level of 5%. So, this kind of systematic risk is not omissible from pricing modellings and inevitable in risk management considerations.

Examination method of hypothesis 2 is similar to the previous hypothesis. As shown in table 5, in 11 sample stocks, the confidence interval includes zero. In other words, in 89 stocks (89% of observations) null hypothesis of $\beta^d = 0$ is rejected at significance level of 5%. So, the result is "jump beta exists". It means that incorporating information of jumps and jump betas into portfolio management can help to obtain better outcomes for tracking performance and hedging. Since there is close relation between jumps and news, it implies how the market absorb information.

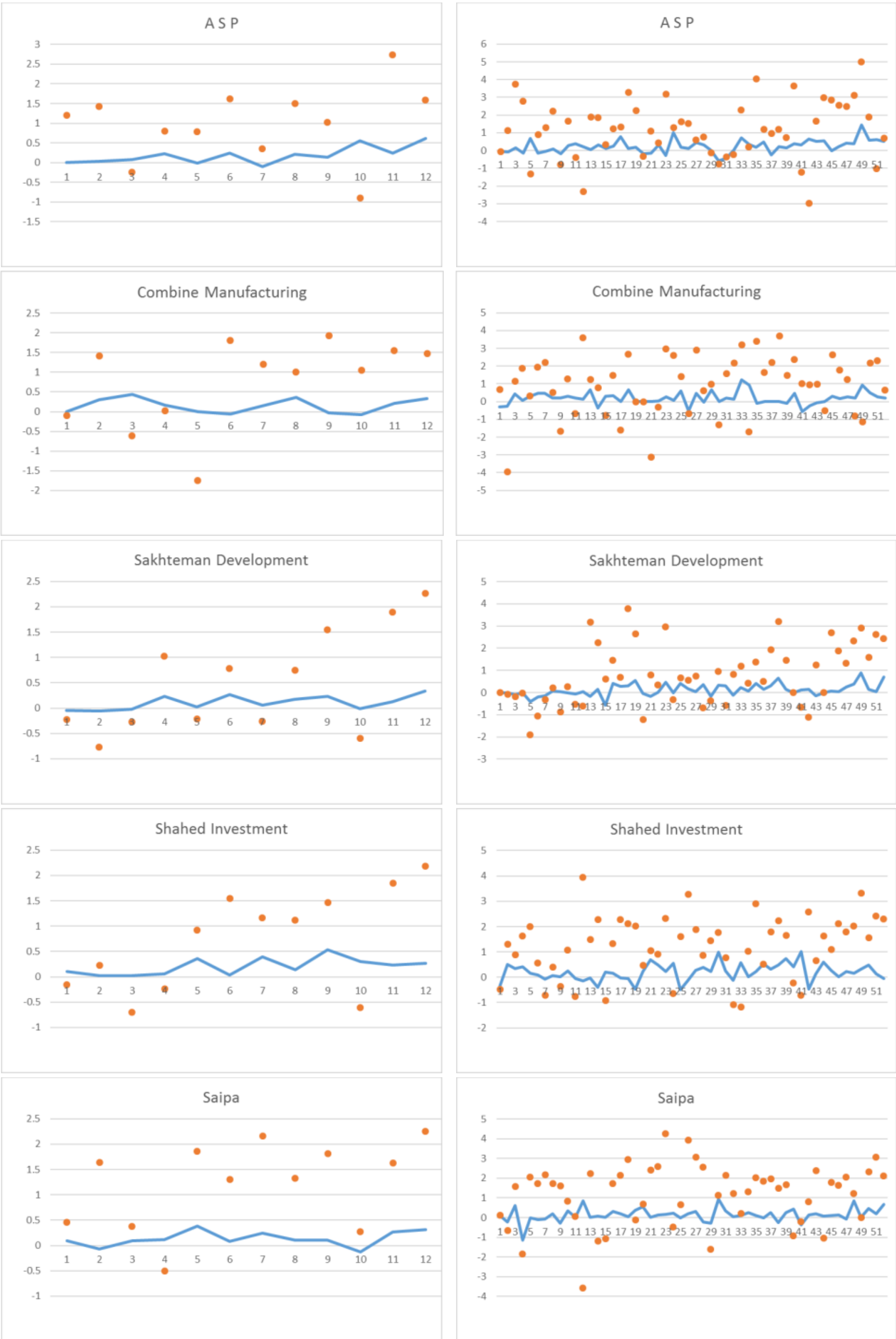

figure 1: Diagrams-showing $\widehat{\beta}_i^c$ and $\widehat{\beta}_i^d$ of five representative stocks

Table 4: Continuous beta average and confidence interval of 100 stocks.

stock	$\bar{\beta}_i^c$	*stock*	$\bar{\beta}_i^c$
A S P	0.1855 [0.0620 , 0.3089]	Melli Lead&Zinc	0.2015 [0.1324 , 0.2705]
Iran Telecom	0.1808 [0.1074 , 0.2542]	Loole Manufac.	0.1445 [0.0794 , 0.2097]
Alborz Insurance	0.1494 [0.0662 , 0.2327]	Melli Copper	0.2926 [0.2105 , 0.3748]
Iran Transfo	0.1560 [0.0603 , 0.2517]	Mobarakeh Steel	0.2708 [0.1961 , 0.3455]
Ghandi Manufac.	0.0587 [-0.0094 , 0.1268] †	Iran Alloy	0.1930 [0.1098 , 0.2761]
Milad Steel	0.0075 [-0.0104 , 0.0253] †	Gharmahal Food	0.2796 [0.1640 , 0.3952]
Iranian Petrochem.	0.0037 [-0.0365 , 0.0438] †	Bama	0.1949 [0.1437 , 0.2462]
Alborz Distribution	0.1883 [0.1204 , 0.2562]	Chadormaloo	0.1891 [0.1001 , 0.2782]
Sahand Rubber	0.2583 [0.0873 , 0.4293]	Kermanshah Petro.	0.2605 [0.1627 , 0.3583]
Combine Manufac.	0.1529 [0.0506 , 0.2553]	Iran Zinc Mines	0.1947 [0.1048 , 0.2846]
Tooka Reil	0.1553 [0.0937 , 0.2168]	Ardakan Ceramic	0.5918 [0.4107 , 0.7730]
Sakhteman Develop.	0.1086 [0.0303 , 0.1870]	Glass&Gas	0.2658 [0.1988 , 0.3328]
Tehran Maskan	0.2230 [0.1298 , 0.3162]	Golgohar	0.2156 [0.1442 , 0.2869]
Shahed Investment	0.2048 [0.1107 , 0.2989]	Sabanoor	0.4735 [0.3427 , 0.6044]
North-east Maskan	0.2661 [0.1016 , 0.4307]	Hamedan Glass	0.2164 [0.0994 , 0.3335]
North-west Maskan	0.2360 [0.1105 , 0.3615]	Dadeh Pardazi	0.0921 [0.0033 , 0.1809]
Maskan Investment	0.1021 [0.0241 , 0.1801]	Khavar Mianeh Min.	0.1730 [0.0934 , 0.2526]
North Excavation	0.1300 [0.0516 , 0.2084]	Hamrah Avval	0.1992 [0.1382 , 0.2602]
Hekmat Bank	0.0216 [-0.0039 , 0.0470] †	Alborz Investment	0.1235 [0.0150 , 0.2320]
Khavar Diesel	0.1413 [0.0362 , 0.2464]	Omid Investment	0.1204 [0.0827 , 0.1580]
Bahman	0.1826 [0.0932 , 0.2721]	Ansar Bank	0.1363 [0.0404 , 0.2321]
Pars Khodro	0.0868 [0.0285 , 0.1451]	Melli Inv.	0.2060 [0.1559 , 0.2562]
Zamyad	0.1390 [0.0720 , 0.2060]	Behshahr	0.1731 [0.0800 , 0.2663]
Saipa	0.1332 [0.0485 , 0.2179]	Saderat Bank	0.1987 [0.1011 , 0.2964]
Saipa Diesel	0.0801 [0.0187 , 0.1415]	Mellat Bank	0.1493 [0.0752 , 0.2234]
Iran Khodro Gostar	0.1994 [0.0993 , 0.2995]	BooAli Inv.	0.1774 [0.0841 , 0.2707]
Iran Khodro	0.0693 [-0.0028 , 0.1413] †	Bime Investment	0.1026 [0.0122 , 0.1930]
Dana Insurance	0.0561 [-0.0064 , 0.1185] †	Parsian Bank	0.2337 [0.1569 , 0.3105]
Day Bank	0.2131 [0.0826 , 0.3436]	Pasargad Bank	0.1826 [0.0956 , 0.2697]
Zoob Ahan	0.2560 [0.1582 , 0.3538]	Petrochemical Inv.	0.2944 [0.2296 , 0.3592]
Parsian E-Com	0.1468 [0.1025 , 0.1912]	Post Bank	0.1399 [0.0850 , 0.1948]
Iran Kish	0.1566 [0.1021 , 0.2112]	Tejarat Bank	0.1218 [0.0531 , 0.1904]
Sepahan Cement	0.1903 [0.1251 , 0.2556]	Melli Tose'e	0.2597 [0.1595 , 0.3600]
Tehran Cement	0.2064 [0.1262 , 0.2866]	Pars Tooshe	0.1599 [0.0889 , 0.2310]
East Cement	0.1757 [0.0647 , 0.2867]	Kharazmi	0.2410 [0.1322 , 0.3498]
West Cement	0.2150 [0.1222 , 0.3078]	Rena	0.1129 [0.0195 , 0.2062]
Fars Cement	0.2613 [0.1879 , 0.3347]	Saipa Inv.	0.2202 [0.1243 , 0.3161]
Semega Inv.	0.1453 [0.0626 , 0.2280]	Sakhteman Inv.	0.2107 [0.1292 , 0.2922]
Pasargad Oil	0.4085 [0.2305 , 0.5866]	Sapah Inv.	0.2960 [0.1752 , 0.4167]
Pardis Petrochem.	0.2302 [0.1566 , 0.3038]	Sina Bank	0.1721 [0.0603 , 0.2838]
Pars Soot	0.1168 [0.0304 , 0.2031]	Behshahr Ind.	0.0950 [0.0095 , 0.1805]
Iran Carbon	0.2796 [0.2068 , 0.3524]	I&M Inv.	0.2089 [0.1247 , 0.2930]
Shiraz Petrochem.	0.2439 [0.1608 , 0.3269]	Ghadir Inv.	0.2287 [0.1353 , 0.3220]
Iran Petrochem.	0.2960 [0.2042 , 0.3879]	Saipa Rayan	0.1711 [0.0935 , 0.2487]
Pars Minoo	0.2567 [0.1830 , 0.3304]	I&M Leasing	0.1645 [0.0750 , 0.2540]
Azarab	0.3206 [0.2357 , 0.4055]	Ghadir Leasing	0.1696 [0.0750 , 0.2643]
Fars Petrochem.	0.1856 [0.1193 , 0.2518]	Mines&Metals Inv.	0.2229 [0.1615 , 0.2843]

stock	$\bar{\beta}_i^c$	stock	$\bar{\beta}_i^c$
Kalsimin	0.3086 [0.2316 , 0.3855]	Mellat Inv.	0.2388 [0.1430 , 0.3346]
Bahonar Copper	0.1204 [0.0209 , 0.2200]	Naft Inv.	0.1238 [0.0452 , 0.2023]
Khoozestan Steel	0.1867 [0.1192 , 0.2543]	Novin Bank	0.1516 [0.0829 , 0.2203]

Table 6 is used to study hypothesis 3. The comparison of β^c and β^d is done by t-statistics which show us if two values are equal or not. Symbols *, ** and *** showed significance levels of 10%, 5% and 1%, respectively. As shown in table 6, there are 14 stocks which do not distinguish β^d from β^c with abovementioned significances. 57 stocks showed difference with significance level of 1%; 20 stocks, 5% and 9 stocks, 10%. So, difference of β^c and β^d is strongly confirmed.

Comparing $\bar{\beta}_i^c$ and $\bar{\beta}_i^d$ for 100 stocks shows us that except one stock, $\bar{\beta}_i^d$ is greater than $\bar{\beta}_i^c$. Moreover, the estimated monthly $\hat{\beta}^c$ and $\hat{\beta}^d$ for individual stocks show that the estimated jump beta is higher than the continuous beta, almost 87% of the time. The ratio is 80% for weekly estimates of $\hat{\beta}^c$ and $\hat{\beta}^d$. This indicates that, most of the times, stocks are more sensitive to the sudden arrival of new information to the market than the generic market volatility. The result is similar to the result of (Alexeev et al., 2017), (Patton & Verardo, 2012), (Todorov & Bollerslev, 2010) and (Sayed et al., 2015) which reported β^d is being higher than β^c. But, there is an interesting dominance in our results. We find that, on average, the jump betas are 180% higher than continuous betas. The percentages reported by all abovementioned researches are below 100%. This is another witness to reinforce the particular importance of jump betas in Iran stock market as an emerging market.

So, we find that the beta on jump movements substantially exceeds that on the continuous component, and that the majority of the information content for returns lies with the jump beta. This supports the hypothesis that the continuous and jump betas in the augmented CAPM specification of equation (2) differ, and that a single factor CAPM model may miss information which is important for effective portfolio diversification and pricing.

Table 5: Discrete beta average and confidence interval of 100 stocks.

stock	$\bar{\beta}_i^d$	stock	$\bar{\beta}_i^d$
A S P	0.9901 [0.4542 , 1.5260]	Melli Lead&Zinc	0.9163 [0.5295 , 1.3030]
Iran Telecom	1.0068 [0.7465 , 1.2670]	Loole Manufac.	1.4946 [0.8934 , 2.0959]
Alborz Insurance	1.8592 [0.3987 , 3.3197]	Melli Copper	0.6854 [0.0650 , 1.3058]
Iran Transfo	1.3699 [0.8669 , 1.8728]	Mobarakeh Steel	0.9306 [0.5893 , 1.2719]
Ghandi Manufac.	1.4435 [0.5681 , 2.3189]	Iran Alloy	0.8029 [0.2630 , 1.3429]
Milad Steel	0.9015 [0.1226 , 1.6805]	Gharmahal Food	0.9911 [0.3885 , 1.5937]
Iranian Petrochem.	0.9107 [0.4030 , 1.4184]	Bama	1.2648 [1.0303 , 1.4994]
Alborz Distribution	1.4147 [0.9696 , 1.8598]	Chadormaloo	0.8374 [0.4518 , 1.2230]
Sahand Rubber	1.8601 [1.0449 , 2.6753]	Kermanshah Petro.	1.0581 [0.6998 , 1.4164]
Combine Manufac.	0.7482 [0.1134 , 1.3830]	Iran Zinc Mines	0.7853 [0.4269 , 1.1436]
Tooka Reil	1.3681 [0.7614 , 1.9747]	Ardakan Ceramic	1.7169 [1.2271 , 2.2067]
Sakhteman Develop.	0.4936 [-0.0886 , 1.0757] †	Glass&Gas	1.4180 [0.9446 , 1.8914]
Tehran Maskan	1.5767 [0.6328 , 2.5206]	Golgohar	0.9180 [0.6586 , 1.1775]
Shahed Investment	0.7311 [0.1709 , 1.2913]	Sabanoor	2.6308 [0.4653 , 4.7964]
North-east Maskan	1.0144 [0.5975 , 1.4314]	Hamedan Glass	1.5715 [0.9453 , 2.1976]
North-west Maskan	0.9516 [0.3634 , 1.5398]	Dadeh Pardazi	0.3256 [-0.6318 , 1.2830] †
Maskan Investment	0.6250 [0.0605 , 1.1896]	Khavar Mianeh Min.	0.8401 [0.3659 , 1.3143]
North Excavation	0.7094 [0.0491 , 1.3696]	Hamrah Avval	0.6959 [0.4946 , 0.8973]
Hekmat Bank	0.2982 [-0.3267 , 0.9232] †	Alborz Investment	0.9584 [0.5961 , 1.3207]
Khavar Diesel	1.1386 [0.4934 , 1.7838]	Omid Investment	0.8362 [0.3735 , 1.2989]

stock	$\bar{\beta}_i^d$	stock	$\bar{\beta}_i^d$
Bahman	1.2079 [0.8247 , 1.5910]	Ansar Bank	0.5469 [-0.0409 , 1.1346] †
Pars Khodro	1.6273 [0.5622 , 2.6924]	Melli Inv.	0.7721 [-0.1318 , 1.6760] †
Zamyad	1.2067 [0.6124 , 1.8010]	Behshahr	1.1182 [0.6045 , 1.6318]
Saipa	1.2162 [0.7265 , 1.7060]	Saderat Bank	0.4226 [-0.2676 , 1.1128] †
Saipa Diesel	1.2376 [0.5644 , 1.9108]	Mellat Bank	0.9956 [0.4948 , 1.4964]
Iran Khodro Gostar	1.2758 [0.7802 , 1.7715]	BooAli Inv.	0.8607 [0.2220 , 1.4993]
Iran Khodro	1.7258 [0.8870 , 2.5647]	Bime Investment	0.7879 [0.2943 , 1.2815]
Dana Insurance	1.3298 [0.3456 , 2.3139]	Parsian Bank	0.7254 [0.2816 , 1.1693]
Day Bank	1.0102 [0.5922 , 1.4282]	Pasargad Bank	0.6637 [0.0791 , 1.2484]
Zoob Ahan	1.2483 [0.7368 , 1.7599]	Petrochemical Inv.	1.4170 [1.0809 , 1.7530]
Parsian E-Com	1.0171 [0.7439 , 1.2904]	Post Bank	1.1289 [0.8542 , 1.4037]
Iran Kish	0.8471 [0.3141 , 1.3800]	Tejarat Bank	0.9742 [0.5910 , 1.3574]
Sepahan Cement	1.1977 [0.7903 , 1.6052]	Melli Tose'e	1.6653 [0.7360 , 2.5946]
Tehran Cement	1.2559 [0.8001 , 1.7116]	Pars Tooshe	1.1071 [0.6656 , 1.5487]
East Cement	0.9116 [0.3086 , 1.5145]	Kharazmi	0.1429 [-1.1949 , 1.4807] †
West Cement	1.3866 [0.8021 , 1.9710]	Rena	1.0460 [0.4488 , 1.6433]
Fars Cement	1.0285 [0.6053 , 1.4516]	Saipa Inv.	2.0475 [-0.0330 , 4.1279] †
Semega Inv.	2.3901 [0.5789 , 4.2012]	Sakhteman Inv.	1.3508 [0.7391 , 1.9624]
Pasargad Oil	1.2770 [0.8548 , 1.6993]	Sapah Inv.	0.9927 [0.5446 , 1.4408]
Pardis Petrochem.	1.7912 [0.0416 , 3.5408]	Sina Bank	1.0275 [0.7066 , 1.3485]
Pars Soot	1.0536 [0.3685 , 1.7388]	Behshahr Ind.	0.7757 [-0.0097 , 1.5612] †
Iran Carbon	1.4696 [1.0304 , 1.9088]	I&M Inv.	0.9231 [0.4547 , 1.3915]
Shiraz Petrochem.	0.9264 [0.4004 , 1.4523]	Ghadir Inv.	1.1820 [0.9633 , 1.4007]
Iran Petrochem.	0.6219 [0.2488 , 0.9950]	Saipa Rayan	1.1615 [0.6163 , 1.7066]
Pars Minoo	1.0234 [0.5063 , 1.5405]	I&M Leasing	1.2151 [0.6210 , 1.8092]
Azarab	1.5543 [1.1258 , 1.9829]	Ghadir Leasing	0.9866 [0.5953 , 1.3779]
Fars Petrochem.	0.9075 [0.6013 , 1.2136]	Mines&Metals Inv.	0.9081 [0.4291 , 1.3871]
Kalsimin	1.3904 [0.2296 , 2.5511]	Mellat Inv.	1.1957 [0.7504 , 1.6410]
Bahonar Copper	1.0151 [0.5280 , 1.5023]	Naft Inv.	1.1784 [0.5590 , 1.7979]
Khoozestan Steel	2.1840 [-0.5590 , 4.9270] †	Novin Bank	0.6678 [-0.4009 , 1.7364] †

Table 6: T-test statistics for comparing β_i^c and β_i^d of 100 stocks.

Stock	t-statistic	stock	t-statistic
A S P	2.8547**	Melli Lead&Zinc	4.0810***
Iran Telecom	7.3819***	Loole Manufacturing	4.6474***
Alborz Insurance	2.2544**	Melli Copper	1.2847
Iran Transfo	4.9236***	Mobarakeh Steel	3.8440***
Ghandi Manufacturing	3.1196***	Iran Alloy	2.3719**
Milad Steel	2.2597**	Gharmahal Food	2.6253**
Iranian Petrochemical	3.5376***	Bama	8.0220***
Alborz Distribution	5.3114***	Chadormaloo	3.2972***
Sahand Rubber	3.5814***	Kermanshah Petrochemical	4.6471***
Combine Manufacturing	1.8053*	Iran Zinc Mines	3.3172***
Tooka Reil	3.8177***	Ardakan Ceramic	4.6379***
Sakhteman Development	1.4626	Glass&Gas	4.8902***
Tehran Maskan	2.9258**	Golgohar	5.3749***
Shahed Investment	1.9531*	Sabanoor	1.9278*
North-east Maskan	4.2689***	Hamedan Glass	4.0176***

Stock	***t-statistic***	***stock***	***t-statistic***
North-west Maskan	2.4502**	Dadeh Pardazi	0.4808
Maskan Investment	1.8952*	Khavar Mianeh Mines	3.0052**
North Excavation	1.8058*	Hamrah Avval	5.8106***
Hekmat Bank	0.8811	Alborz Investment	5.5027***
Khavar Diesel	3.3374***	Omid Investment	3.0767**
Bahman	6.4013***	Ansar Bank	1.5471
Pars Khodro	2.8202**	Melli Investment	1.2072
Zamyad	3.4702***	Behshahr	3.6897***
Saipa	4.7036***	Saderat Bank	0.7102
Saipa Diesel	3.5656***	Mellat Bank	3.4932***
Iran Khodro Gostaresh	4.1600***	BooAli Investment	2.1480*
Iran Khodro	3.7976***	Bime Investment	2.8208**
Dana Insurance	2.5965**	Parsian Bank	2.1941*
Day Bank	4.2326***	Pasargad Bank	1.7065
Zoob Ahan	4.1191***	Petrochemical Investment	6.9411***
Parsian E-Commerce	6.6932***	Post Bank	6.9737***
Iran Kish	2.6459**	Tejarat Bank	4.5342***
Sepahan Cement	4.7973***	Melli Tose'e	2.9696**
Tehran Cement	4.7450***	Pars Tooshe	4.4819***
East Cement	2.4883**	Kharazmi	0.1481
West Cement	3.7460***	Rena	3.3473***
Fars Cement	3.6733***	Saipa Investment	1.7085
Semega Investment	2.4441**	Sakhteman Investment	3.8924***
Pasargad Oil	5.9283***	Sapah Investment	3.3056***
Pardis Petrochemical	1.7335	Sina Bank	6.5794***
Pars Soot	2.6762**	Behshahr Industeries	1.6553
Iran Carbon	4.7594***	I&M Investment	3.1127***
Shiraz Petrochemical	2.8327**	Ghadir Investment	8.5659***
Iran Petrochemical	1.8244*	Saipa Rayan	3.9222***
Pars Minoo	2.7589**	I&M Leasing	3.4434***
Azarab	6.0230***	Ghadir Leasing	3.9548***
Fars Petrochemical	5.7121***	Mines&Metals Inv.	2.9141**
Kalsimin	1.8166*	Mellat Inv.	4.3462***
Bahonar Copper	3.5317***	Naft Inv.	3.6939***
Khoozestan Steel	1.4319	Novin Bank	0.9378

4.3. Jump and Continuous Risk premia

We will further explore the relationship between the two systematic risk components and the expected stock returns using the Fama and MacBeth (1973) cross-sectional regressions. According to Eq. (2), overall systematic risk can be decomposed into two distinct components – continuous risk and jump risk, where the factor loadings, $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ measure the sensitivities of individual stocks towards the two risk factors. Having these two distinct beta estimates for all 100 constituent stocks during the time span allows us to estimate risk premia on each of the systematic risk components. But, the approach implemented in Todorov and Bollerslev (2010) does not allow for a direct breakdown of market returns themselves into continuous and discontinuous components.

However, viewing these two components as separate risk factors to firms that are exposed to market fluctuations suggests that the two-stage (Fama & MacBeth, 1973) regression can be used to estimate premia rewards to each of these factors. As these two factors drive stock returns, this approach can be used to price how much return one would expect to receive for a particular level of systematic factor exposure.

As a first stage we take the estimates of $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ from the model in (2) for each asset, i = 1, …, N, and each time period (each month in our case). These reveal the extent to which each asset return is influenced by the continuous and discontinuous movements in the market, as discussed in the previous section. In order to extract the premia we undertake a second stage consisting of a set of S regressions; we estimate risk premia using betas computed monthly, resulting in S=12 distinct estimates. We run cross-sectional regressions for each month s = 1, …, S in form of eq. (10).

$$\bar{r}_{i.s} = \alpha_s + \gamma_s^c \hat{\beta}_{i.s-1}^c + \gamma_s^d \hat{\beta}_{i.s-1}^d + \epsilon_{i.s} \qquad (10)$$

where:

$\bar{r}_{i.s}$= average monthly return on stock *i* in the *s-th* month.

$\hat{\beta}_{i.s-1}^c$= continuous systematic risk factor from the previous month.

$\hat{\beta}_{i.s-1}^d$= discrete systematic risk factor from the previous month.

Table 7: The result of cross-sectional regressions of Fama-Macbeth approach

	$\bar{\gamma}^c$	$\bar{\gamma}^d$	r^2	F
1	-0.1455***	0.0506***	0.1109	6.0497***
2	-0.1383*	0.0367***	0.0986	5.3064***
3	0.0830	-0.0592***	0.1516	8.6657***
4	-0.3119**	-0.0383***	0.1406	7.9326***
5	-0.0530	0.0666***	0.2002	12.1414***
6	-0.0189	0.0803***	0.3728	28.8303***
7	0.2134**	-0.0209	0.0598	3.0836**
8	0.0299	0.0820***	0.1478	8.4122***
9	-0.1554*	0.0596***	0.2646	17.4487***
10	0.0957	-0.0432***	0.3574	26.9692***
11	0.1273	-0.0147	0.0234	1.1637
12	0.1369*	-0.0022	0.0320	1.6030

The method is used for examination of the hypotheses 4 and 5. The result of execution of the method is shown in table 7. According to the hypotheses 4 and 5, we explore the existence of continuous risk premium and discrete risk premium and consequently model performance. In table 7, the symbols *, ** and *** showed significance levels of 10%, 5% and 1%, respectively. As shown in the last column of table 7, F-statistic which shows the general significance of regression model (not being all coefficients zero) is statistically significant for 10 out of 12 estimations.

Concentrating on hypothesis 4 , $\bar{\gamma}^c$ is statistically not zero in 6 out of 12 estimated cross-sectional regressions. Therefore, risk premium of continuous movements of market factor exists and is not negligible. Similarly, we explore the status of $\bar{\gamma}^d$ which is significantly not zero in 9 out of 12 estimated regressions, all with 1% significance level. As can be inferred from table 7, jump risk premium ($\bar{\gamma}^d$) is obviously stronger than continuous risk premium ($\bar{\gamma}^d$), so reinforces the importance of β^d.

5. Discussion and Conclusions

We used the recent literature of high-frequency financial econometrics along with that of jump beta in systematic risk and pricing models; and explore the situation of jumps and jump beta in Iran's stock market (known as Tehran Stock Exchange) as an important emerging market. Using the recent techniques to separate jumps from the continuous component of the price process, we distinguished between the continuous and the jump systematic risk components in the market portfolio and captured the time variation in those estimated betas.

We estimated CAPM continuous beta and jump beta for 100 elected most tradable stocks from TSE over the sample period of March 2013 to March 2014 (year 1392 in Persian calendar), using 5-min return horizons. We find that, on average, the jump betas are 180% higher than continuous betas. This estimate suggests that when news is sufficient to disrupt prices, that causes a jump, the speed with which news is disseminated into the market is likely to be faster than previously estimated using traditional CAPM.

Moreover, we demonstrated that the number of jumpy days for market portfolio as well as risk premium of discrete component of market factor is considerable. All results reinforce the importance of jump component of systematic risk. Since, decomposing systematic risk to discrete and continuous components is a new approach which has yet been experienced by few researches around the world and has no history in Iran stock market, some other studies around this subject are necessary. Studying structural properties and restrictions in TSE which result in great number of jumpy trading days may be a subject for research.

Finding optimal return horizon, detecting optimal beta estimation window and using greater sample data in aspect of number of assets and time span are necessary to have finer and more accurate results. The relationship between stock continuous beta and jump beta with stock's industry and its other fundamental properties like financial and operational leverage may be another area of research. Moreover, based on high-frequency data and time-varying nature of beta, studying the effects of corporate events and macroeconomic events on continuous and discrete betas is another research opportunity.

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