Tasmanian School of Business and Economics
University of Tasmania

Discussion Paper Series N 2019-02

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ISBN 978-1-925646-73-3

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March 6, 2019

Abstract:

Using an extension of the standard CAPM beta we decompose the beta of Japanese banking stocks into diffusion and jump components using high frequency data from 2001 to 2012. We find that jump betas on average are larger than diffusion betas, indicating that Japanese banking stocks respond differently to information associated with continuous and discontinuous market movements. Larger banks are more sensitive to discontinuities than their counterparts; high leveraged banks are more exposed to unexpected market-wide news whereas profitable banks are equally sensitive to both continuous and jump market moves. By allowing for asymmetric preferences of investors for losses versus gains we show that diffusion and jump betas both carry large premia in both up and down markets, but that these premia differ substantially during periods of economic stress from those present during normal conditions.

Key words: Beta; Jumps; Japanese Banks, High-frequency data; stock returns.

JEL Classification: G12, G21, C58

This paper is part of Biplob Chowdhury's doctoral dissertation at Tasmanian School of Business and Economics, University of Tasmania, Australia.
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1. Introduction

The central issue in asset pricing theory is to identify premiums that investors require for bearing different types of systematic risks. The Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965) postulate that exposure to market risk is priced in asset returns. Over the next several decades, important works identified other types of risks as well that are important both in academia and practice (for a review, see Nagel (2013)). More recently, in the wake of the 2008 financial crisis, several works highlight the importance of understanding the role of rare events, or jump[1] events, in asset prices. events, in asset prices. In particular, Todorov and Bollerslev (2010) and Bollerslev and Todorov (2011) find that jumps in market returns and volatility play an important role in observed equity risk premium. In other words, investors' fear of jump events is priced in market returns. Bollerslev et al. (2015) build on these prior works and show that the predictability of equity risk premium is largely explained by investors' compensation for jump tail risk, which further establishes the role of jumps as a risk factor. However, the authors did not provide asset pricing test of systematic jump and diffusion risk factor in financial firms' security returns. Given this background, the main objective of this paper is provide a comprehensive empirical investigation of pricing time-varying jump and diffusive systematic risk in the cross-section of financial firms' stock returns.

Identifying the systematic risk factors among financial firms is important both in understanding the pricing generally and for public policy purposes. Financial firms make up a substantial fraction of the domestic equity market. Indeed, they have comprised almost 15% of the market value of all firms of equities listed on Tokyo Stock Exchange (TSE) in recent years, and their stock returns have been found to have a significant relationship with future economic growth. Moreover, extensive deregulation of financial and banking firms' asset and liability powers in the 1980s and 1990s increased the importance of regulatory control over the risk-taking behavior of these firms. Following years of discussion over how best to modify Basel I capital requirements, the recently adopted Basel III standards increasingly emphasize the use of market discipline as a major regulatory device. However, using market factors to evaluate and control risk-

[1] Jumps are infrequent but abnormal changes in stock prices, often driven by significant information shocks or liquidity shocks. In the continuous-time literature, a price movement of 3% (when the local volatility is less than 0.5%, thus of more than six standard deviations in volatility units) is typically modeled as a jump, that is, a discontinuous variation of the price process.

taking behavior of banks by either private market forces or public regulators requires an understanding of the risk factors that are priced in security markets for these firms. Moreover, the exclusion of financial firms can be questioned on both theoretical and empirical grounds. The theoretical structure originally developed by Modigliani and Miller (1958, 1963) demonstrates that leverage can change the risk profile (beta) of a firm but it does not invalidate the central principles of the CAPM. In this sense, it would be more desirable if the pricing model is generally applied rather than restricted to nonfinancial corporations.

In this paper, we examine the behavior of diffusive and jump systematic risk for the Japanese banking sector and how investors price these two systematic risks under different market conditions. We find that both jump and diffusion systematic risks are significantly priced in the cross-section of bank stock returns. We also demonstrate that investors exposed to jump and diffusion systematic risk on their investment in Japanese bank equities receive excess positive returns in upturn market, but that they suffer excess losses in downturn market.

The particular interest in studying the Japanese market is driven by its specific financial and governance system (relationship-based) and there are only few empirical studies of the Japanese market. The contribution of our study is to add to the existing literature based essentially on US market empirical and theoretical results are less studied countries, in particularly, the Japanese market. Also, the Japanese banking sector is strongly developed, but with a distinctly different character from that of most Western economies, including particularly strong direct linkages between the banks and companies in the real economy – strong enough for a particular form of 'wealth' contagion to emerge between the financial markets and real economy through the complex web of accounting interactions, as shown in Kiyotaki and Moore (2002). CAPM estimates for the banking sector are relatively rare, and recent estimates for Japan are rarer still; King (2009) provides empirical estimates for banking sectors across a range of countries, and demonstrates the differences in Japan, where relatively high beta have been maintained for over two decades, while a group of papers provide evidence for samples prior to the 21st century; Elyasiani and Mansur (2003), Gultekin et al. (1989), and Andersen et al. (2000) characterize volatility in the Japanese stock market based on a short sample of high frequency 5 min Nikkei 225 index return. To our knowledge there is no study of

CAPM for Japan which takes account of recent advances in high frequency financial econometrics although Andersen et al. (2006), Todorov and Bollerslev (2010), all evidence that using high frequency data improves estimation of beta over traditional regression based procedures using lower frequency data.

In the classical capital asset pricing model (CAPM), systematic risk, measured by beta, is determined by the asset's covariance with the market over the market variance. The CAPM assumes that security returns are generated by a continuous process. However, recent studies on the stochastic behaviour of the stock market generally agree that stock returns are generated by a mixed process with a diffusion component and a jump component. In this sense, the CAPM beta may only capture a part of a mixed process, and the standard CAPM beta is at best a 'summary proxy' for the systematic risk of a mixed-process, i.e. a weighted average of the diffusion component and the jump component. Therefore the beta of the CAPM is not an accurate risk measure when the price process has jumps. If so, it would be prudent to be able to split the standard beta into two component betas so as to capture the two risks separately: one component for continuous and small changes (diffusion beta) and the other for discrete and large changes (jump beta). These two types of risk are different in nature and require different treatments. They should be differently priced, hedged and managed. Consequently, being able to estimate them separately has implications for financial services, and hence the wider economy.

The paper uses developments in high frequency financial econometrics by Todorov and Bollerslev (2010) to estimate beta for the Japanese banking sector using high frequency intra-day data. The unique aspect of this approach is to decompose the systematic risk into a continuous and discontinuous component, following the asset pricing literature which suggests the evolution of prices follows a continuous process such as Brownian motion augmented with discrete jump events. The expected stock return is dependent on both sources of risk. The diffusive component of the return is determined by the covariance between the diffusion process driving the market return and the stock processes, a well-known continuous-time analogue of the discrete time β-representation. The jump component of the return is captured by the covariance between the jump-distributions of the market return and stock processes. We decompose standard CAPM beta into diffusion beta, attributable to general market volatility and jump beta associated with sudden disruption in the price process due to arrival of new information in the market. We aim to explain how individual stocks are influenced by systematic diffusive risk and jumps risk and we find that jump beta exceed the diffusion beta. The motivation for this separation comes from a learning argument akin to the one put forward in Patton and Verardo (2012) regarding short-term changes in beta in response to firm earning announcements. They hypothesize that beta may temporarily increase around earnings announcements as the market pays attention to the announcements in order to absorb any new information the announcements may contain and convey. Combining this argument with the known association of jumps with the arrival of unanticipated news[2], we expect that jump beta magnitudes to exceed diffusion beta magnitudes.

We estimate jump and diffusion beta for Japanese banking stocks for the period from January 2001 to December 2012. Our empirical findings rely on a 5–minute intraday sample frequency.[3] As expected, the jump betas exceed the diffusion betas for almost all banks in almost all time periods, consistent with the existing literature for firms in the US in Alexeev et al. (2017), Bollerslev et al. (2015), Todorov and Bollerslev (2010) and Indian banks in Sayeed et al. (2017) and the analysis of Neumann et al. (2016) that jumps play an important role in determining risk premia for the S&P500. We characterize the behavior of the price series for selected Japanese banks using the Barndorff-Nielsen and Shephard (2006), hereafter, BNS, jump detection test to establish evidence for the existence of jumps. We find 272 jump days out of 2866 trading days, corresponding to 115 jump months out of 144 months, where jumps are detected in the market. We find that on average the jump betas are usually 40% higher than the continuous betas. These estimates suggest that when news is sufficient to disrupt prices, that is to cause a jump, the speed with which news is disseminated into the market is likely to be even faster than previously estimated using the combined continuous and jump price process as in Patton and Verardo (2012). This is important for risk managers: if an asset behaves differently during a severe market downturn than it does at other times, this information offers the potential to significantly improve calculations such as Value at Risk (VaR). Moreover, if assets are combined in well-diversified portfolio, then an asset's systematic jump risk is

[2] Dungey and Hvozdyk (2012), Lahaye et al. (2011), and Andersen et al. (2007), among others.

[3] Estimates for diffusion, Jump and standard betas are computed on a month-by-month basis. High frequency data permits the use of 1-month non-overlapping windows to analyse the dynamics of our systematic risk estimates.

more relevant than the asset's total jump risk. This highlights the importance of decomposing systematic risk into its diffusion and jump components.

We relate the variation in betas to firm characteristics and find that financial leverage, capital adequacy, and firm size have significant impacts on each of the jump and continuous beta estimates. These relationships are informative for the debate about reducing systemic risk via options to constrain leverage or increase the capital base of the banking sector. We show that financial leverage has a positive effect on beta, indicating that a more heavily leveraged firm is more exposed to market movements, although we demonstrate that the impact of changes in leverage are economically very small. Greater capital adequacy also reduces both jump and continuous beta, but again requires relatively large changes to have a substantial economic effect. Thus, our results support the direction of the impact of policies to decrease leverage and increase the capital base on reducing systematic risk, but throw some doubt on the size of the changes needed to obtain an effective impact in reducing risk in the financial sector.

In addition to beta relationships, Bollerslev et al. (2015) have found the risk premiums associated with jump beta is statistically significant, while the diffusion beta does not appear to be priced in the cross-section. In another independent study on asset pricing Pettengill et al. (1995) showed that market premiums differ between up-markets and down-markets. These multiple insights lead one to expect not only an analogous dual beta behaviour over the entire sample periods but also risk-premium differences between up-markets and down-markets. Motivated by these empirical findings, we introduce and test a new 4-beta CAPM model by combining the diffusion and jump betas of Bollerslev et al. (2015) and the conditional betas of Pettengill et al. (1995) into a single model to detect any significant differences under differing market conditions. The main empirical contribution of this paper is to allow the state of the market to have an effect on the risk-return tradeoff. The motivation for this extension lies in the investor's asymmetric preferences between up-markets and down-markets. Investors care differently about downside losses as opposed to upside gain and demand additional compensation for holding stocks with high sensitivities to downside market movements. Our model includes upside market diffusion, upside market jump, downside market diffusion, and downside market jump components. Because of this decomposition, the model in this paper is sufficiently general to accommodate the research purpose of revealing how different factors are priced. Another feature of the model is that it explicitly allows individual stock prices to respond to the separated market components with different magnitudes. Accordingly, we can estimate the various exposures of a stock price to different risk factors and the associated risk premiums and specifically identify the most important systematic risk components that explain stock returns.

In the context of a portfolio of assets, we investigate whether down market risk is priced higher than up market risk. In particular, we carryout significance tests for the price difference between diffusion and jump risks in different market states. This has practical implications for pricing of diffusion and jump risks and can have a direct impact on investor's decision making. It may also shed some light on how investors react to various types of uncertainty. Bearing non-diversifiable jump risk is significantly rewarded, as is evident from the expensiveness of short maturity options written on the market index with strikes that are far from its current level; see Christoffersen et al. (2015) and Driessen and Maenhout (2013) for effects jump risk on options.

We find evidence of significant, and differing, relationships between each of the two measures of beta and stock returns. The estimated risk premia of the up and down markets are not significantly different from the corresponding negative risk premia. The estimated risk premia for both the diffusion and the jump risks for the two market states are found to be symmetric. However, the estimated risk premia between diffusion risk and jump risk for the up and down markets are not symmetric during the crisis and post-crisis periods. The results imply that investors in the Japanese market respond differently to diffusion risk and jump risk in the periods of up and down markets associated with different degrees of financial stress. Further, we find that large banks tend to have relatively high jump betas. Hence these banks deliver higher returns. We also find that the variation of jump beta is more dynamic than that of the standard and diffusion beta. Our finding that these relationships differ for the jump risk and diffusion risk components aligns with existing literature suggesting the need for a different risk premia for each component (Yan 2011; Pan 2002). Consistent with Bollerslev et al. (2015), we find evidence for a positive risk-return relationship, as jump beta is associated with higher returns on average than diffusion beta, consistent with evidence for bank equities in the US in Schuermann and Stiroh (2006) and Viale et al. (2009).

The results are robust to using both a portfolio approach and Fama–MacBeth regressions, different sample periods, as well as to the inclusion of a battery of control variables (including controls for size, BM ratio). Our jump market risk factor also wins the "horse-race" between the bank-specific risk factors previously proposed in the literature on asset pricing. Since a standard assumption asset pricing ("realized returns are a good proxy for expected returns") may not hold, we also estimate ex-ante measures of expected returns and find a consistent results. Our jump-diffusion two-beta asset pricing model provides an alternative to the CAPM. It prices both jump and diffusion risks. The empirical tests of this paper show that it is a better asset pricing model than the CAPM, particularly for the period when jumps are included in the price process. In a resulting modified CAPM expected returns are still linear in beta, but additional premia are required to compensate the investor for taking on jump risk.

The remainder of this paper is structured as follows. Section 2 discusses the methodological framework. We discuss our sample description in section 3. Section 4 presents the empirical results. Section 5 contains robustness check. Section 6 concludes the paper.

2. Modelling Framework

To investigate how diffusion and jump systematic risks in stocks are priced, we set up a model for stock price processes that explicitly incorporate diffusion and jump components. We then use Todorov and Bollerslev (2010)'s approaches to measure the exposures of a stock's returns to diffusion and jump risks.

2.1. Capital asset pricing model

Consider a one-factor capital asset pricing model (CAPM):

$$r_{i,t} = \alpha_i + \beta_{i,t} r_{m,t} + \varepsilon_{i,t}, \quad i = 1, \ldots\ldots N \tag{1}$$

where $r_{i,t}$ is the monthly stock return on stock *i*, and $r_{m,t}$ is the aggregate market returns at time *t*; α_i is the constant term for the asset *i*; and the idiosyncratic risk $\varepsilon_{i,t}$ is assumed to uncorrelated with $r_{m,t}$. The absence of arbitrage implies that:

$$E(r_{i,t}) = r_{f,t} + \beta_{i,t}\gamma_{m,t} \tag{1a}$$

where $r_{f,t}$ and $\gamma_{m,t}$ denote the risk-free rate and the premium for bearing market systematic risk. Eq. (1a) implies that in the cross-section of expected returns is solely driven by the variation in betas. The CAPM model basically depends on stock and market returns, which in turn, depends the underlying prices of individual stocks. It is now widely agreed in the literature that financial return volatilities and correlations are time-varying and returns follow the sum of a diffusion process and a jump process. [4]

For the above reasons, we define that the log-price (p_t) process of an asset at time *t* follows a continuous-time jump-diffusion process defined by the stochastic differential equation as follows:

$$dp_t = \mu_t dt + \sigma_t dW_t + k_t dq_t, \qquad \mathrm{t} \in [0, \mathrm{T}], \tag{3}$$

Where dp_t is the instantaneous change in logarithmic price for an asset at time *t*; μ_t is the instantaneous drift of the price process and σ_t is the diffusion process; with W_t a standard Brownian motion. The first two terms correspond to the diffusion part of the total variation process. The diffusion part which is responsible for the usual day-to-day price movement. The changes in stock prices may be due to variation in capitalization rates, a temporary imbalance between supply and demand, or the receipt of information

[4] See, for example, Merton (1976), among others.

which only marginally affects stock prices. The final term, $k_t dq_t$ refers to the jump component of p_t, where q_t is a counting process such that $dq_t = 1$ indicates a jump at time t, k_t is the size of jump at time t conditional on a jump occurring, which assumed to have mean μ_j and standard deviation σ_j. The jump part which is due to the receipt of any important information that causes a more than marginal change (i.e. abnormal change) in the price of stock. The arrival of this kind on information is random. The number of information is assumed to be distributed according to a poisson process.

If the return of stocks should be divided into jump part and diffusion part certainly the risk associated with returns of securities should be decomposed into two parts, too. The CAPM states that beta, a diffusion risk, is systematic and non-diversifiable. So is the jump risk when taking both diffusion process and jump process into account. The presence of jump variations in both individual assets and aggregate market affect co-variance estimations and consequently the estimations of realized beta and systematic risk. Thus it would be prudent to disentangle the jump component and the diffusion component in prices because they are basically two quite different sources of risk; see, e.g., Pan (2002) and Todorov (2009).

2.2. Decomposing systematic risks: diffusion and jump components

Our framework motivating the different betas and the separate pricing of diffusion and jump market price risk and relies on the theory originally developed by Todorov and Bollerslev (2010) for decomposing market returns into two components: one associated with diffusion price movement and another associated with jumps. Hence in the presence of both components, Eq. (1) becomes:

$$E(r_{i,t}) = \alpha_i + \beta_{i,t}^c r_{m,t}^c + \beta_{i,t}^j r_{m,t}^j + \varepsilon_{i,t} \quad (4)$$

where $r_{i,t}$ is the stock return on stock *i*, α_i is a drift term, market risk $(r_{m,t})$ is modelled as a combination of a continuous $(r_{m,t}^c)$ and jump component $\left(r_{m,t}^j\right)$, and $\beta_{i,t}^c$ and $\beta_{i,t}^j$ denotes the responsiveness of each stock's movement to the diffusion and jump components of market risk and ε_i denotes the idiosyncratic term which may also made up a continuous and jump component. Standard factor models of risk implicitly assume that an asset's systematic risk is uncorrelated with jumps in the market (i.e. that the asset's beta does not change on days when the market experiences a jump).[5] Eq. (1) does not distinguish between the diffusion and jump components of total return, but does decompose total returns into systematic ($\beta_{i,t}r_{m,t}$) and nonsystematic ($\alpha_i + \varepsilon_{i,t}$) components. Any market jump is embedded in $r_{m,t}$, while any nonsystematic jump unique to firm *i* is included in the error tem. When the systematic risks exposure of a firm to both diffusion and jump price movements are identical, i.e. $\beta^c_{i,t}$ = $\beta^j_{i,t}$, then, the two-factor market of (4) model collapses to the usual one-factor market model, which relates the stock return $r_{i,t}$ to the total market return $r_{m,t} = r^c_{m,t} + r^j_{m,t}$. The restriction that $\beta^c_{i,t}$ = $\beta^j_{i,t}$ implies that the asset responds in the same way to market diffusion and jump price movements -or intuitively that the asset and the market co-move in the same manner during "normal" times and periods of "abrupt" market moves. If, on the other hand, $\beta^c_{i,t}$ and $\beta^j_{i,t}$ differ, empirical evidence for which is provided below, the cross-sectional variation in the diffusion and jump betas may be used to identify their separate pricing. The literature suggests that the two betas are not the same, i.e. the reactiveness of an asset return of the two components of systematic risk can be different, denoted by $\beta^c_{i,t}$ and $\beta^j_{i,t}$ respectively. Hence Eq. (1a) could be written as,

$$E(r_{i,t}) = \alpha_i + \beta^c_{i,t}\gamma^c_{m,t} + \beta^j_{i,t}\gamma^j_{m,t} \qquad (4a)$$

Where $\beta^c_{i,t}$ and $\beta^j_{i,t}$ represent the systematic risks associated with the market diffusion and jump movements, and $\gamma^c_{m,t}$ and $\gamma^j_{m,t}$ are the premiums for bearing these two systematic risks. This two-beta model hypostatized that the market rewards erratic price movements differently than the smooth variations, and thus the risk premium for the two different betas might be different.

2.3. Diffusion and jump betas estimation approach

Given that market returns contain two components, both of which display substantial volatility and which are not highly correlated -with each other, this raises the possibility that different types of stocks may have different betas with two components of the

[5] There is no need to test for a jump in the individual stock price, as the estimates of the diffusion and jump betas depend only on whether the factor was diffusion or experienced a jump. We focus explicitly on systematic jump risk, as measured by the exposure to non-diversifiable market-wide jumps and the jump beta since the seminal paper by Merton (1976) hypothesizes that jump risks for individual stocks are likely to be non-systematic.

market. The decomposition of the return for the market into separate diffusion and jump components that formally underlie $\beta_{i,t}^{c}$ and $\beta_{i,t}^{j}$ in equations (4a) are not directly observable. Instead, we assume that prices are observed at discrete time grids of length M over the active trading day$[0, T]$.[6]

We start by assuming that the intraday stock price processes for the aggregate market index, denoted by $dp_{m,t}$, and the ith stock, denoted by $dp_{i,t}$, follow general diffusion-time processes. To allow for the presence of jumps in the price process, we consider the following specification for stock i and aggregate market m. The log price process evolves as follows[7]:

For the market,

$$r_{m,t,s} \equiv dp_{m,t} = \alpha_{m,t}dt + \sigma_{m,t}dW_{m,t} + k_{m,t}dq_{m,t}, \quad (5)$$

and for the stock $i = 1, \dots, \mathrm{N}$,

$$r_{i,t,s} \equiv dp_{i,t} = \alpha_{i,t}dt + \beta_{i,t}^{c}\sigma_{m,t}dW_{m,t} + \sigma_{i,t}dW_{i,t} + \beta_{i,t}^{j}k_{m,t}dq_{m,t} + k_{i,t}dq_{i,t}, \quad (6)$$

where, $W_{m,t}$ and $W_{i,t}$ are standard Brownian motions for the market and asset i. $W_{m,t}$ and $W_{i,t}$ are orthogonal to each other, and $W_{i,t}$and $W_{j,t}$ for $i \neq \mathrm{j}$ can be correlated; $\alpha_{m,t}$ and $\alpha_{i,t}$denote the diffusive volatility of the aggregate market and stock i, respectively; and $q_{m,t}$ and $q_{i,t}$ refer to the pure jump Levy processes in the aggregate market and stock i, respectively. The individual jumps do not arrive together with market jumps, but $dq_{i,t}$and $dq_{j,t}$ for $i \neq \mathrm{j}$ can be correlated. $\beta_{i,t}^{c}$and $\beta_{i,t}^{j}$measure the responsiveness of an individual stock to the diffusion and jump component of market risk. In this framework,$[\beta_{i,t}^{c}, \beta_{i,t}^{j}]$ is assumed constant throughout each day but can change from day to day.

By explicitly allowing the individual loadings, or betas, associated with the market diffusive and jump risks to be time-varying, this decomposition of the continuous and discontinuous martingale parts of asset i 's return into separate components directly related to their market counterparts and orthogonal components (in a martingale sense)

[6] As empirical studies rely on discretely sampled returns; we denote discrete-time intraday returns on trading day t as
$r_{t,s} = p_{t,s} - p_{t,s-1}, \qquad s = 1, \dots, M; t = 1, \dots, T$
where $p_{t,s}$ refers to the s th intra-day log-price for day t; T is the total number of days in the sample and M refers to the number of intraday equally spaced return observations over the trading day t, which depends on the sampling frequency. As such, the daily return of the active part of the trading day is $r_t = \sum_{s=1}^{M} r_{t,s}$.
[7] The notation here is simplified relative to that in Todorov and Bollerslev (2010), see their article for more details.

is extremely general. For the diffusive part, this entails no assumptions and follows merely from the partition of a correlated bivariate Brownian motion into its orthogonal components. For the discontinuous part, the decomposition implicitly assumes that the relation between the systematic jumps in the asset and the market index, while time-varying, does not depend on the size of the jumps. See, Bollerslev et al. (2015) for more details.

In order to disentangle the $\beta_{i,t}^{c}$ and $\beta_{i,t}^{j}$, Todorov and Bollerslev (2010) propose a non-parametric beta estimation technique using multipower covariation/variation between the returns of individual stocks and the market portfolio for given diffusion and jump components respectively. They show that $\beta_{i,t}^{c}$ and $\beta_{i,t}^{j}$ can be theoretically identified.

Consider the estimation of diffusion betas. Suppose that neither the market or nor stock i, jumps, so that $q_{m,t} \equiv 0$ and $q_{i,t} \equiv 0$ almost surely. For simplicity, suppose also that the drift terms in Eq. in (5) and (6) are both equal to zero, so that,[8]

$$r_{i,t,s} = \beta_{i,t}^{c} r_{m,t,s} + \widetilde{r_{i,t,s}}\,, \quad \text{where } \widetilde{r_{i,t,s}} \equiv \int_0^t \sigma_s^2\, ds\,,$$

for any $s \in [0, t]$. In this situation, the ratio of the intra-day covariance between an asset and the market, and the market with itself will estimate diffusion beta using high-frequency intraday returns. The diffusion beta is given by

$$\beta_{i,t}^{c} = \frac{\sum_{s=1}^{M} r_{i,t,s}\, r_{m,t,s}}{\sum_{s=1}^{M} \left(r_{m,t,s}\right)^2}, \quad i = 1, \ldots\ldots N. \tag{7}$$

In general, the market may have a jump over the $[0, t]$ time-interval and the drift terms are not identically equal to zero. Meanwhile, it follows readily by standard argument that for $M \to \infty$, the impact of the drift terms are asymptotically negligible. However, to allow for the possible occurrence of jumps, the simple estimator defined above needs to be modified by removing the jump components. In particular, following Todorov and Bollerslev (2010), we consider their ratio statistics for the discretely sampled data series which consistently estimate the diffusion beta for $M \to \infty$, under very general conditions. These are:

[8] The drift term [i.e. α in Eq. (1)] has no effect on the asymptotic behavior of the beta estimates. In practice, for the frequencies used in this paper, the drift is negligible and very small to be of importance.

$$\hat{\beta}_{i,t}^{c} = \frac{\sum_{s=1}^{M} r_{i,t,s}\, r_{m,t,s}\, \mathbb{I}_{\{|r_{t,s}| \le \theta\}}}{\sum_{s=1}^{M} \left(r_{m,t,s}\right)^2 \mathbb{I}_{\{|r_{t,s}| \le \theta\}}} \tag{8}$$

Where, $\mathbb{I}_{\{|r_{t,j}| \le \theta\}}$ is the indicator function,

$$\mathbb{I} = \begin{cases} 1 & if \ \{|r_{t,s}| \le \theta\} \\ 0 & Otherwise \end{cases} \tag{9}$$

based on the truncation level, θ, for diffusion component. Intuitively, the estimation of the diffusion beta employs only the observations that does not contain any discontinuous term for individual stock and the market because this method guarantees that any jump component is not included in the estimation process.

Now, we turn to the estimation of jump beta. The actually observed high-frequency returns, of course, contain both diffusive and jump risk components. However, by raising the high-frequency returns to powers of orders greater than two the diffusion components become negligible, so that the systematic jump dominates asymptotically for $M \to \infty$.[9] As formally shown in Todorov and Bollerslev (2010), the following estimator is consistent for jump beta when there is at least one significant jump in the market portfolio for the given estimation window for $M \to \infty$.

$$\hat{\beta}_{i,t}^{j} = \operatorname{sign}\left\{\sum_{s=1}^{M} \operatorname{sign}\{r_{i,t,s}\, r_{m,t,s}\} \left|r_{i,t,s}\, r_{m,t,s}\right|^{\tau}\right\} \times \left(\frac{\left|\sum_{s=1}^{M} \operatorname{sign}\{r_{i,t,s}\, r_{m,t,s}\} \left|r_{i,t,j}\, r_{m,t,s}\right|^{\tau}\right|}{\sum_{s=1}^{M} \left(r_{m,t,s}\right)^{2\tau}}\right)^{\frac{1}{\tau}}, \tag{10}$$

Here, the power τ is restricted to be ≥ 2 so that the diffusion price movements do not matter asymptotically. The sign in Eq. (10) is taken to recover the signs of jump betas that are eliminated when taking absolute values. The estimation in Eq. (10) converges to $\hat{\beta}_{i,t}^{j}$ when there is at least one systematic jump (in the market portfolio) on $[0, T]$. Therefore, in order to calculate $\hat{\beta}_{i,t}^{j}$, we first need to test for the existence of jumps on the log-price series p_t of the market portfolio. The jump beta $\hat{\beta}_{i,t}^{j}$ in Eq. (10) has a similar interpretation to the market beta in the CAPM model. It allow us to assess sensitivity of an (or a portfolio of assets) to extreme market fluctuations. Lower jump beta would signify a resistance of an asset to mode as much as a market during extreme event (jump defensive assets),

[9] The basic idea of relying on higher orders powers of returns to isolate the jump component of the price has previously been used in many other situations, both parametrically and nonparametrically; see e.g., Barndorff-Nielsen and Shephard (2003).

whereas higher jump beta values represent high sensitivity of an asset exacerbating the effect of the market moves during the extreme event (jump cyclical assets).

Following Todorov and Bollerslev (2010) and Alexeev et al. (2017) we set the parameter values for θ, ϖ, and α estimate the $\hat{\beta}^{c}_{i,t}$ and $\hat{\beta}^{j}_{i,t}$ on both monthly and daily basis. For estimating the $\hat{\beta}^{c}_{i,t}$ and $\hat{\beta}^{j}_{i,t}$, the truncation threshold, $\theta = \alpha\Delta_n^{\varpi}$, uses $\varpi = 0.49$ and $\alpha \geq 0$, suggesting that the threshold values may vary across stocks and across different estimation window. The threshold for the diffusion price movement, $\theta = \alpha_i^c = 3\sqrt{BV_i^{[0,T]}}$ for $\hat{\beta}^{c}_{i,t}$ suggesting that the diffusion components discards only three standard deviation away from mean, and thus unlikely to be associated with diffusion price movements, where, $BV_i^{[0,T]}$ is the bi-power variation of the i-th stock at time $[0, T]$; the value of $\tau = 2$ for equation (10).

As shown in Eq. (9) and Eq. (10), these decomposed betas use only a portion of the observations that are mutually exclusive. We also consider the aggregated beta of theses decomposed betas to be the standard CAPM beta, which represent the overall sensitivity of an individual stock to the market. The estimator of the standard beta employs all available observations. Accordingly, we calculate the standard beta for an individual stock using the Eq. (7) in the spirit of Andersen et al. (2006)'s realized beta. It is important to note that Eq. (7) still defines the Standard Beta in a one-factor CAPM model. In the following, we refer to each of these three different beta estimates for stock i without the explicit time subscript as $\hat{\beta}^{c}_{i}$, $\hat{\beta}^{j}_{i}$ and $\hat{\beta}^{s}_{i}$ for short.

2.4. Jump detection methodology

We apply the nonparametric jump-detection test proposed by Barndorff-Nielsen and Shephard (2006) to detect jumps in the market portfolio.[10] BNS propose two general

[10] The BNS jump statistic is the main focus of study here for several reasons. First, we focus on studying the large and rare jumps since they are inherently more informative and are the major jump risks investors would face in financial markets. Second, among the competing jump measures, it is widely regarded as the most prominent. For example, Bollerslev et al. (2008), say, ". . . it is by far the most developed and widely applied of the different methods" (239). Third, Pukthuanthong and Roll (2015), find the BNS test has good size and power that compares favorably with other methods. Fourth, if the jump magnitudes are small, the separation of jumps from continuous co-movements and estimation of parameters becomes less precise (_ENREF_73)

measures based on realized power variations to test for jumps and to estimate the contribution of jumps to total variation- realized volatility (RV) and bi-power variation (BV). Realized, or historical, volatility of a sequence of prices p_t can be derived from the returns. The realized variance (RV) is defined as the sum of squared intraday-returns,

$$RV_t = \sum_{j=1}^{M} r_{t,s}^2 , \qquad t = 1, \dots, T \tag{11}$$

Where M is the sample length for jump detection (often daily). Note that equation (11) uses only returns from within each trading day (intraday returns), discarding any overnight returns (intraday-returns). As a result, any jumps resulted from overnight returns are excluded from realized variance. Using the theory of quadratic variation, the realized volatility will generally converge uniformly in probability to the quadratic variation as the sample frequency, M, of the underlying returns approaches infinity. That is realized volatility estimator includes the contributions of the continuous sample path variation in the form integrated volatility plus the jumps. We can re-write this as:

$$RV_t \xrightarrow{p} \underbrace{\int_0^t \sigma_s^2 \, ds}_{conttinuous} + \underbrace{\int_0^t k_s^2 \, ds}_{jump} \quad t = 1, \dots, T \tag{12}$$

Here $\int_0^t \sigma_s^2 \, ds$ is the integrated variance, and $\sum_{S=q_0}^{q_t} k_s^2$ is the quadratic variation of the jump part over the period from 0 to t (often a day). Jump tests are therefore designed to estimate jump component using high-frequency data.

Bipower variation (BV) is given by

$$BV_t = \mu_1^{-2} \sum_{j=2}^{M} |r_{t,s}||r_{t,s-1}| , \quad t = 1, \dots, T \tag{13}$$

where $\mu_1 = \sqrt{2/\pi}$. BV consistently estimates the integrated variance (i.e. jump free) when the sampling frequency goes to infinity. Intuitively, in the presence of any jump, one of the two consecutive returns is bound to be larger. The product of the smaller return and the larger returns, however, will be small and thus neutralize the effect of the jumps. Therefore,

$$BV_t \xrightarrow{p} \int_0^t \sigma_s^2 \, ds, \qquad for\ M \to \infty \tag{14}$$

Consequently the jump contribution to total variation is estimated from a combination of equations (13) and(14), for $M \to \infty$

$$RV_t - BV_t \to \sum_{S=q_0}^{q_t} k_s^2 , \quad t = 1, \dots ., T \tag{15}$$

Therefore, the difference between the RV_t and BV_t consistently estimates the jump contribution to the total variation. The J_t measure in theory restricted to be non-negative (asymptotically). However, in practice for finite value of M, BV_t may exceed RV_t so that J_t become negative. For detecting jump, we adopted the jump ratio test, proposed in Huang and Tauchen (2005) and Tauchen and Zhou (2011) where the test statistic:

$$RJ_t \equiv \frac{RV_t - BV_t}{RV_t}, \tag{16}$$

which converges to a standard normal distribution when scaled by its asymptotic variance in the absence of jumps. That is

$$ZJ_t = \frac{RJ_t}{\sqrt{\left[\left(\frac{\pi}{2}\right)^2 + \pi - 5\right]\frac{1}{M}\max\left(1, \frac{DV_t}{BV_t^2}\right)}} \xrightarrow{d} N(0,1) \tag{17}$$

where DV_t is the quad-power variation robust to jumps. The quad-power varaition is defined as

$$DV_t \equiv M\mu_1^{-4}\left(\frac{M}{M-3}\right)\sum_{j=4}^{M}|r_{t,s-3}||r_{t,s-2}||r_{t,s-1}||r_{t,s}|, \quad t = 1, \dots ., T \tag{18}$$

The ZJ_t statistic in equation (17) can be applied to test the null hypothesis that there is no jump in the return process on a trading day, t. Huang and Tauchen (2005) show that this test has very good size and power and is quite accurate for detecting jumps. Significant jumps are identified by the realizations of ZJ_t in excess of the 99.9% critical value $\emptyset_\alpha$.[11]

$$J_{t,\alpha} = I[ZJ_t > \emptyset_\alpha].[RV_t - BV_t] \tag{19a}$$

where I refers to the indicator function equal to one if a jump occurs and zero otherwise and the continuous sample path variation C_t is given as

[11] In the process of actual operation, we need to choose an appropriate α, and Tauchen and Zhou (2011) propose that when jump contributions are 10% and 80%, the significance level should be 0.99 and 0.999, respectively.

$$C_t = [RV_t - J_t] \quad (19b)$$

A simple procedure is relied upon to deduce the sign of significant jumps. We assume that there is at most one jump per day and, further assuming that the jump is predominant absolute return of days when there is a significant jump (see (Andersen et al. 2010; Tauchen and Zhou 2011)). [12] The sign for significant jump can be defined as

$$\sqrt{J_{sign,t}} = I(max|r(t, j = 1, \dots, m)|)\sqrt{J_t} \quad (20)$$

Where the sing indicator $I(.)$ is equal to 1 or -1 depending on the sign of the argument. The magnitude of the jump in Eq. (20) is in standard deviation form. Intuitively, the sign in Eq. (20) depends on the largest (in absolute sense) intraday return conditioned on the existence of significant jump, i.e., $I(t)$.

Once the realized jump size is filters out, we can estimate the jump mean μ_J , the variance σ_J and intensity λ_J as follows

$\mu_J =$ Mean of J_t

$\sigma_J =$ Standard deviation of J_t

$\lambda_J =$ Number of Realized jump Days /Number of Total Trading Days

Tauchen and Zhou (2011) show that, under empirically realistic settings, this estimation method of realized jump parameters is robust with respect to drift and diffusion function specifications. It makes easy to specify the jump arrival rate, avoiding elaborate estimation methods, and yields reliable results under various settings, for instance, when the sample size is either finite, increasing or shrinking.

3. Sample and Data

The sample consists of high frequency stock price data for 50 of the 63 commercial banks traded on the Tokyo Stock Exchange (TSE) for the period January 2001 through December 2012, a total of 3053 trading days (There were 13 banks where the data were not available). The sample period allows us to investigate the transmission of shock in

[12] The assumption of one jump per day fits to the compound Poisson jump process (Merton (1976)) also utilizes the Poisson jump process to describe rare and large return jumps which are presumably the responses to the arrivals of important news), and it should be pointed out that bipower variation also works for the infinite activity jumps despite the fact that we focus only on the case of rare and large jumps. Further, Bollerslev et al. (2015) consider that by their very nature, systematic jumps are relatively rare, and as such it is not feasible to identify different jump betas for different jump sizes, let alone identify the small jumps in the first place. This assumption also maps directly into the way in which we empirically estimate jump betas for each of the individual stocks based solely on the large- size jumps.

Japanese market in periods of calm and crisis (subprime and global financial crisis).The list of banks in the sample is provided in Table 1. Data are extracted from the Thompson Reuters Tick history (TRTH) database available via SIRCA. We use the Nikkei 225 index as a proxy for the market portfolio.[13]

The stock prices are sampled at a five minute frequency, as is standard in a large part of the high frequency literature. The choice of 5-minute sampling frequency reflects a trade-off between using all available data and avoiding the impact of market microstructure effects, such as infrequent or nonsynchronous trading; the issue of optimal sampling frequency choice is an ongoing research agenda, see for example Zhang (2011). Unlike the more commonly investigated US and European markets, daily trading on the TSE is interrupted by a lunch break, trading between 09:00 am - 11:00 am and 12:30 pm- 3:00 pm local time. We sample prices from 9:05 am-11:00 pm and 12.35 pm-3.00 pm, with overnight and over-lunch returns excluded from the data set.[14] Missing data at 5-minute intervals are filled with the previous price creating a zero return. Hansen and Lunde (2006) show that this previous tick method is a sensible way to sample prices in calendar time. These restrictions result in a final sample of 2866 active trading days (in 144 months), each consisting of 53 intraday day 5 min-returns for a total of 1, 61,809 observations.

Table 2 presents the market capitalization and turnover ratio on TSE over the sample. Market capitalization was rising steadily prior to the global financial crisis of 2008-2009 and the European debt crisis period, from April 2010 until the end of the sample market capitalization rose. By 2012 it was at a level similar to that at the beginning of the sample. The turnover ratio peaked in 2007, and has since declined.

4. Empirical results

In this section, we present the empirical results. In section 4.1, we start by examining large discontinuous changes, known as jumps, in Japanese bank stock prices. In section 4.2 and 4.3, we then examine empirically how individual stock prices respond to

[13]The Nikkei is a price-weighted index, consisting of 225 stocks in the first section of the TSE selected subject to certain industry-balance considerations. It represents the 50 % of the total market capitalization of the TSE.

[14] We are only concerned with the active trading period, and overnight information is beyond the scope of this study.

continuous, jump market moves in the context of single-factor model, and relate their variation to firm characteristics and economic conditions. Finally, in section 4.4, we examine how different systematic betas explain the stock returns.

4.1. Evidence on Asset-price Jumps

Empirical evidence suggests that asset prices display infrequent large movements that are too big to be Gaussian shocks. In Figure 1, we plot the time series of intraday returns on the Nikkei 225 index for the period 2001-2012. Occasional large spikes in the series suggest the presence of large moves (jumps). Consistent with this evidence, the kurtosis of market returns is 27, relative to 3 for normal distribution, as shown in the Table 1. Figure 2 shows the sample measures of daily-realized volatility, bi-power variation and jumps for the Japanese stock index. Market volatility was particularly high during the second half of 2008, associated with the disruptions to global markets around the period of the failure of Lehman Brothers, the rescue of AIG and other financial institutions. The plots reveal interesting volatility clustering and time variation of jump size along the sample period. The bottom panel of Figure 2 shows that, many of the largest realized volatilities are directly associated with jumps in the underlying price process.

Using the Barndorff-Neilsen and Shepard test we find a total number of 272 jump days in the Nikkei index in the sample period. The proportion of jump days of the total is 9.4%, consistent with the proportions reported for other developed markets, including for the S&P500, 8.54% jump days in Todorov and Bollerslev (2010) from 2001 to 2005 and 3.5% jump days in. Alexeev et al. (2017) for 2003 and 2011. Of the 144 months in our sample, 115 contain at least one jump day. The results suggest that the frequencies of jump occurrence in Japanese equity market are slightly higher than the US market.

Table 3 reports the summary statistics for daily volatilities and jumps for the Nikkei 225 stock index. The mean realized volatility is ($\sqrt{RV}$) is 0.27%, while average bi-power variation ($\sqrt{BV}$) is 0.24%. The average absolute jump size ($\sqrt{J}$) is 0.09%. The unconditional distribution of both volatility measures and jumps (J_t), are highly skewed and leptokurtic, with the relative jump measure, J_t, clearly indicating a more positive skewness and a higher degree of leptokurtosis than the daily realized volatilities, and suggesting that they occur on a small number of occasions with large impact on the Japanese index return.

From Table 3, we observe that, for the equity index, approximately 85% (BV_t/RV_t) is due to continuous components of returns and the jump contribute 14% ((J_t/RV_t) of realized variation. Andersen et al. (2007) find a similar jump contribution to RV for the S&P 500 index.

Table 4 provides an annual picture of the identified jump days for the period January 2001- December 2012.[15] The number of jumps ranges from 10 to 39 in the Japanese market. The prevalence of jumps decreases during the period of most global financial stress in 2007 and 2008, consistent with Chatrath et al. (2014) who show that jump frequency does not increase in periods of stress. Overall, the results show that the numbers of jumps does not vary a great deal across the sample period – in most years the majority of months contain jumps. A plausible explanation for our findings is that investors may under-react to news about shocks as they already revising their expectations of the aggregate economy using the information from the economy. Patton and Verardo (2012) propose a simple learning model in which investors use information on firm announcements to revise their expectations about other firms and the entire economy. Another possible explanation is that during the crisis period the threshold of jump identification increases with the overall market volatility. Therefore, some large price discontinuities, generally classified as jumps during the calm period, may be classified as continuous movements during the crisis period.

Concerning the jump measures, we further split the resulting time series jump into positive and negative parts that will be denoted as positive jumps and negative jumps, respectively. This separation is important from a practical perspective. Practically, investors are mostly concerned about negative jumps. The ability to disentangle the negative jumps provides us with an important tool for risk management. From Panel A of Table 4, we observe that Japanese's capital market comprises a slightly higher number of positive than negative jumps but the disparity is not statistically significant. The asymmetry is in contrast with Lahaye et al. (2011), who find equity market tend to show more negative jumps. Perhaps our findings suggest that bank stocks in Japan are more like to move together with the market under rising conditions than falling conditions. The jump intensities, which represent the number of jumps per unit of time[16], characterize

[15] See footnote 1.
[16] In our case these values are the number jumps per year

the jump activity. For both the positive and negative jumps, the jump intensity is not substantially different. We extend the analysis of the jump characteristics of this market through examining the distribution of the jump variation in Panel B of Table 4. Panel B of Table 4 displays the summary statistics for mean jump size as well as exhibits statistical characteristics of positive and negative jumps. The conditional mean on jump size, is 0. 003% over the entire sample period, which indicates that the average value of the negative jump sizes is greater than that of the positive jump sizes. The positive and negative parts have approximately the same magnitude (means are close in absolute values), as well as similar standard deviations over the entire sample period. We also observe that the average jump size is much higher for post-crisis period compared to the crisis period. Interestingly, during the post- crisis period the mean jump size is negative, indicating that the average value of positive jump sizes is smaller than that of negative jump size. This findings suggest that the importance of jumps has increased after the crisis period. Further, comparing positive and negative jumps, we find an asymmetry between the positive and negative parts of the jump. For instance, the mean (in absolute value terms) and volatility of the positive jump sizes in the three sub-sample period are approximately similar, while the mean and volatility of the negative jump sizes display large variability in the three sub-sample period. During the crisis period, the intensity and the jump size of negative jumps are at least twice as high as those obtained for the post-crisis period; and are significantly larger compared to pre-crisis period, a result as we would expect that the largest magnitude should be observed for the negative jumps. In contrast, crisis negative jumps are less frequent but of larger size compared to the post-crisis period. See, panel A of Table 4.

Motivated from these identified jump days (with their corresponding jump months) we now estimate monthly continuous systematic risk (diffusion beta) and jump systematic risk (jump beta) for the sample period. Particularly, we estimate the diffusion and discontinuous betas of 50 listed Japanese banks on a daily and month basis using the Todorov and Bollerslev approach. We then investigate the relationship between different betas and other firm characteristics.

4.2. Decomposing Systematic Risk into Diffusion and Jump Components

The subsection presents the results of beta estimation that follows the approach defined in Eq. (8) and Eq. (10). We undertake our analysis on the estimates of diffusion and jump betas at monthly, and not daily, frequencies as both Todorov and Bollerslev (2010) and Alexeev et al. (2017) show that daily betas do not provide analytically tractable results. [17] Estimates of diffusion and jump betas are computed on a month-by-month basis. High frequency 5 minute data permits the use of 1-month non overlapping windows to analyses the dynamics of our systematic risk estimates. Table 5 reports the average monthly diffusion and jump beta estimates for each of the 50 banks in the sample along with their respective 95% confidence intervals. The jump betas exceed the diffusion beta for every institution. Using the corresponding 95% confidence intervals in Table 5, we find no evidence of overlapping interval between the jump betas, $\hat{\beta}_i^j$ and diffusion betas, $\hat{\beta}_i^c$ for any stock. The highest betas are observed for Sumito Mitusui Financial Group, with a diffusion beta, $\hat{\beta}_i^c$ of 0.88, and jump beta $\hat{\beta}_i^j$ of 1.50. The lowest diffusion beta, $\hat{\beta}_i^c$ is 0.01 for the Nanto Bank, $\hat{\beta}_i^j$ is 0.46 for the Yachiyo bank. The diffusion betas, are below unity for all Japanese banks during the sample period except for the Sumito Mitusui Financial Group, which has a beta very close to the market beta. This implies that stock returns of Japanese banks associated with continuous market movement respond less to aggregate market. [18]

The resulting values jump betas, $\hat{\beta}_i^j$ are higher than the diffusion betas, $\hat{\beta}_i^c$, consistent with the small existing literature for firms in the US in Alexeev et al. (2017), Bollerslev et al. (2015), Todorov and Bollerslev (2010). The results for the Japanese banks are also similar to those for the Indian banks recorded in Sayeed et al. (2017) in that the average diffusion beta is generally smaller than one, which implies that in response to the diffusive market movements, the returns of banking stocks move less than the market return for the wider variety of stocks contained in the CNX500 index, but the diffusion

[17] We also estimated the daily betas and the daily betas estimates are obviously somewhat noisy and difficult to interpret. Meanwhile, the estimated monthly betas appear much more stable, while still showing interesting and clearly discernable pattern over time. Therefore, we concentrate on monthly betas.

[18] The issue still remains as to why the average diffusion beta values are on the whole much lower than was expected in finance theory. One of the possible reasons is that these stocks might not have sufficient trading volume to respond sufficiently to changes in the market. If high proportions of these stocks are held by parties such as government, institutions or other companies who are not trading actively, the returns of these companies may not be as sensitive to shocks in the market, and therefore have a lower beta value. Alternatively, the lower beta values may be the result of the market becoming more volatile over time. Over the past decades, there have been increasing numbers of IT and telecommunications listing on the Japanese stock market. These companies' stocks are considered as highly volatile stocks. As such, the banking industry may have become relatively less volatile due to the presence of these highly volatile stocks. Since the beta values measures the relative volatility in stock returns between individual companies and the market, the beta values for these stocks may indeed have fallen.

beta for Japanese banks indicates considerably more defensive capacity than evident in the Indian banks. This result supports the notion that the returns on individual stocks are most strongly correlated with market returns on days when the market experiences a jump (as jumps are associated with news arrival). Across individual stocks, 40% of the banks have jump betas higher than the market beta.

Figure 3 plots the cross-sectional average of the betas estimated for the standard single factor CAPM model, and the diffusion, and jump betas. It is immediately apparent from Figure 3 that in every case where jumps are present, the Japanese banks have a jump beta which exceeds the diffusion beta estimated for that month, on average by 0.75. The sample contains two periods of readily identifiable stress - the first in the third quarter of 2008 associated with the bankruptcy of Lehman Brothers, and the second in the first half of 2010 associated with the Greek debt crisis - and in both of these periods the gap between the diffusion and jump betas reduces. That is, there is more attention paid to volatility risk (the diffusion component of the systematic risk) in the market than jump risk caused by news. This can be partly explained by the high market volatility during the crisis periods. During times of high market stress, the overall market environment becomes relatively more important than unexpected news shocks to the system. The reaction to frequent unexpected news during stressed market times may be a feature of the overall market conditions. The results for the Japanese banks are similar to those for the US financial sector stocks recorded in Gajurel (2015) in that there is a consistently positive gap between the jump and diffusion betas for these stocks, but the diffusion beta for Japanese banks indicates considerably more defensive capacity than evident in the US financial sector. Overall, the plot demonstrates that the diffusion beta is generally lower than the standard CAPM estimate, but that the jump beta can sometimes be considerable higher.

Jump betas which are higher than continuous betas provide information about the speed of information absorption in the market. Patton and Verardo (2012) posit that information arrival in individual stocks may result in a temporarily statistically significantly higher beta during the time of news arrival as this information is disbursed to the rest of the market. Although they use an event study to demonstrate this in US stocks over time around company earnings events, it is well known that financial asset prices jump in response to news; see for example Dungey et al. (2009), Lahaye et al. (2011). The beta decomposition provided by the Todorov and Bollerslev (2010) method is another means of separating the way in which markets react to information. In the case of the Japanese banks, the information associated with the normal process of continuous updating (the diffusion beta) is absorbed at a slower rate than the market, perhaps reflecting the role of the banks in driving credit for other sectors. However, unexpected news, which promotes a price jump, is absorbed faster as evidenced by the increased jump beta. However, compared with estimates of Patton and Verardo (2012) for US S&P500 stocks the banks are not providing a strong mechanism to disseminate information to the rest of the economy; the jump beta estimates rarely exceed 2 as they do in the US analysis (which is not restricted to financial firms). The difference in the estimated diffusion and jump betas estimated leads us to consider the importance of segregating these results for portfolio diversification.

4.2. Firm Characteristics

Firm characteristics usually have strong impact on firm's sensitivity to systematic risk. For example, we would expect that larger firms are less vulnerable to market risks, and hence have lower beta. To explore the roles of firm characteristics in understanding the estimates of diffusion and jump betas, we conduct regression analysis in using form's size, profitability, leverage, and capital ratio.

Influential variables from the existing literature include leverage, which has a positive relationship with beta, for example Mandelker and Rhee (1984), with Buiter and Rahbeir (2012) specifically signaling the potential systemic risk of high leverage in the banking sector. Hong and Sarkar (2007) also find that beta is an increasing function of leverage.

The effect of size on bank systematic risk is debated. While Demsetz and Strahan (1997) find that large banks tend to diversify their business more efficiently and are less prone to bankruptcy, Saunders et al. (1990) and Haq and Heaney (2012) find that bank systematic risk increases with bank size as large banks could be more sensitive to general market movements than small banks.

By maintaining a capital buffer to absorb losses that may arise from unexpected shocks higher capital ratios are expected to decrease bank beta; representing higher bank solvency and lower perceived risk,(Keeley and Furlong 1990). Prior empirical studies also provide evidence of an inverse relationship between profitability and systematic risk. Other work, Borde et al. (1994), finds a positive relationship between return on assets and beta during the period, 1988-1991, for US insurance companies, indicating that finance industries with higher profitability are exposed to greater systematic risk because they are more profitable when taking more credit risks in business.

Based on the above discussion, we anticipate the following relationships between beta and these five explanatory variables; that beta increases with leverage, increases with bank size and with profitability, but decreases with higher capital ratios. We now proceed to investigate these relationships for both jump and continuous systematic risk using the following regression framework.

$$\beta_{i,t} = \alpha_0 + \sum_{i=1}^{m} \gamma X_{i,t} + \sum_{t=1}^{2002-2012} \theta_i (time\ dummies)_t + \mu_{i,t} \quad (21)$$

where $\beta_{i,t}$ = either diffusion beta ($\hat{\beta}_{i,t}^{c}$) or jump beta ($\hat{\beta}_{i,t}^{j}$) for bank i, at period t; $X_{i,t}$ represents the firm characteristics variables -- firm size, profitability, debt leverage, and capital ratio -- and $\mu_{i,t}$ is the model residual. We also include time dummies to control for macro-level shocks and unobserved time heterogeneity. The monthly firm characteristics data come from Thompsons DataStream. Following previous studies, we measure firm size by the market value of equity. Profitability is computed as earnings before interest, taxes, depreciation, and amortization over Total assets. Leverage is the ratio of total debt to total assets. The capital ratio is measured as book value of equity divided by total assets. The descriptive statistics for bank characteristics variables are presented in Table 5.

Panel B of Table 5 reports the correlation matrix amongst all variables including the standard one factor, jump and diffusion beta estimates. The three betas are positively and highly correlated with each other (with values ranging from 0.67 to 0.80) as evident in Figure 3.[19] In terms of firm characteristics variables, diffusion beta, and jump beta are positively correlated to size, leverage and profitability. Multicollinearity amongst the firm characteristics variables is limited to 0.38, between leverage and firm size.[20]

Table 7 reports the results from the regression analysis. The first three columns of results consider the role firm characteristics in the behavior of the diffusion beta and the final

[19] To ease our analysis, we exclude month for which we do not find a significant jump in the market.

[20] As a rule of thumb, multicollinearity is likely to exist when the independent variables are highly correlated, i.e., r = 0.80 and above (Gujarati and Porter 2009) .

three columns for the jump beta. The first two columns explore subsets of the explanatory variables, with leverage included (excluded) in column 1(2) and the capital ratio excluded (included). It is clear from a comparison of columns 1-3 that in the continuous case when both leverage and capital ratio are included neither have a significant effect, but when they are included individually they do so. This is not the case for the jump betas.

The preferred results of column (3) in each case reveal that diffusion beta is positively affected by both firm size and profitability, as anticipated. The effects of leverage (positive) and bank capital (negative) are insignificant but the signs are also consistent with those expected. Jump beta is also affected by firm size and profitability, but with an additionally a significant positive effect from leverage, while the capital ratio is insignificant.

The results support that larger Japanese banks are more sensitive to market movements than smaller institutions, regardless of whether they occur through a jump or not. However, the effect of size is larger for the jump beta than diffusion beta, implying that large banks react more to information transmitted by abrupt changes even more than they do to continuous changes. The result is consistent with previous studies particularly for US bank holding companies and European banks (Saunders et al. 1990; Haq and Heaney 2012).

Profitable banks are more sensitive to both continuous and jump systematic risk than their less profitable counterparts, supporting the hypothesized positive risk-return relationship. A decrease of one percentage point in the profitability ration is estimated to lead to decrease of 0.002 in the diffusion beta, assessed at the mean value of profitability, this is equivalent to a decrease in the profitability ratios for Japanese banks from 12% to 11% resulting in a decrease in diffusion beta of 0.002. It immediately apparent that a large change in profitability would be required to alter beta to economically meaningful extent. However, in this case the impact of continuous movements is slightly more impactful than jump movement; that is the effect for profitable banks is not importantly different if the information arrival through price arrives abruptly or continuously. A possible reason is that profitable banks often employ aggressive business strategies and consequently exhibit higher risk. Borde et al. (1994) reach the same conclusion for US insurance companies.

While leverage is not statistically significant in determining diffusion beta, it has a positive effect on jump beta. The results reveal that financial firms with higher leverage (debt capital) are more responsive to jumps in the market. As higher leverage ratios make financial firms riskier, these highly leveraged firms are more sensitive to market jumps. Information arrival through abrupt price movements may cause banks to adjust their business behavior, whereas planning should have eliminated this channel in relation to the known continuous price process.

To gain some sense of the economic relevance of these results we calculate that an increase in bank size by 1 percentage point (assessed at the mean) is associated with a 0.32 percentage point increase in continuous beta and 0.42 percentage point increase in jump beta. An increase in profitability and leverage by 1 percentage point would increase bank continuous systematic risk by a mere 0.001 point and 0.008 point respectively, while the jump beta effects are for increases by 0.001 point and 0.034 point respectively. Bank size is clearly the largest economic effect in our firm characteristic set.

The recent global financial crisis (GFC) is an exogenous shock to a firm's investment choices and thus it provides an opportunity to understand the relative importance of these determinates of bank systematic risk and jump risk and how these factor evolved with the changes in world economy during the crisis period. Yamori et al. (2013) suggest that Japanese experience with their economic collapse in the 1990s enhanced the ability of the financial system to respond; through programs implemented including deferrals for interest rate and principal payments and the extension of further loans. The government also introduced support measures which partly explain the willingness of banks to extend credit, applying guarantee measures which absorbed their risk of loss, and loosening capital adequacy requirements. Whilst the drop in business conditions reported from Tankan was severe, the contraction of credit conditions was much less so; see Yamori et al. (2013).

Although no major failures took place in the Japanese financial industry during the GFC period Miyakoshi et al. (2014) find evidence of the transmission of risk from the manufacturing industry to the financial industry, observing that the Japanese exporting industry, including the Toyota, Honda, and Nissan motor vehicle companies, suffered extraordinary deficits in the two fiscal years following the crisis. To characterize the betas and to aid our discussion, we split the sample period into crisis (July 2007 to May 2009) and the non-crisis period.[21]

The following model is used to explore the impact of the financial crisis on the relationship between different betas and its determinants:

$$\beta_{i,t} = \alpha_0 + \sum_{i=1}^{m} \gamma X_{i,t} + \sum_{i=1}^{m} \gamma_1 \quad X_{i,t} + \sum_{i=1}^{m} \gamma_{2,t} D_t \, X_{i,t} + \sum \theta_t \, (time\ dummies) + \mu_{i,t} \qquad (22)$$

where we introduce a GFC dummy D_t= 1 for the crisis period July 2007- May 2009..

Table 8 reports the results of the impact of the GFC on the relationship between the betas and firm characteristics. Focusing on column (3) for each of the beta regressions in Table 8 shows that the effects of firm size, profitability and leverage reported in Table 7 are retained – continuous beta is positively related to firm size and profitability, and jump beta is positively related to firm size, profitability and leverage.

In relation to how the GFC affects the association between different betas and bank characteristics variables, we observe some interesting results from multiplicative interaction terms. The estimated coefficients on Profitability*GFC is positive and statistically significant. This suggests that the impact of profitability on continuous beta increased during the GFC period.

There are two important further results. For diffusion beta, there is a significant addition to the impact of profitability on beta during the crisis period. In the crisis period the impact of profitability is increased by almost 60 percent, more profitable firms reflected more of the market movements (or perhaps in the context of the environment, the market was strongly associated with the loss of profitability of the banking sector). The jump beta, however, does not show any change in its relationship with profitability between the non-crisis and crisis periods. Rather, it has a dramatic increase (almost doubling) of the impact of leverage. During the crisis period being more leveraged resulted in a greater beta in response to abrupt price movements. There is also a statistically significant shift in the intercept term for the jump beta, supporting a more negative intercept during the crisis than non-crisis periods.

[21] We use the crisis period identified in Dungey and Gajurel (2014).

The jump beta, however, does not show any change in its relationship with profitability between the non-crisis and crisis periods. Rather, it has a dramatic increase (almost doubling) of the impact of leverage. During the crisis period, being more leveraged resulted in a greater beta in response to abrupt price movements. There is also a statistically significant shift in the intercept term for the jump beta, supporting a more negative intercept during the crisis than non-crisis periods. Banks with larger debt obligations (relative to equity) are more sensitive to market fluctuations during financial distress. It is not surprising that banks with low debt are seen as attractive during volatile times and become safe havens for investors.

Overall, the results show that the four firm characteristic variables significantly influence not only continuous systematic risk but also jump risk of banks.

4.3. The Risk-Return Relationship

Theoretically, Merton (1976) assumes stock jump risk is diversifiable, while papers such as Santa-Clara and Yan (2010) assume market jump risk is priced. We consider whether jump risks are priced cross-sectionally. The conventional CAPM implies that securities have the same expected returns if they have the same betas. The expected risk-return relationship of the jump-diffusion model is different. The jump-diffusion model has two different types of betas instead of one. One measures the systematic risk when no jump occurs, and the other measures the systematic risk when a jump occurs. Different securities have different diffusion and jump beta risks. Hence, securities will have different expected returns even if they have the same diffusion betas.

The conventional CAPM implies two-fund separation which claims that all investors hold the same portfolios, a market portfolio and a riskless asset. This is no longer true in the jump-diffusion model because investors may have different preferences to diffusion and jump betas. It would be difficult, if not impossible, to find a portfolio that is optimally invested and which has the same premium for both the diffusion and jump risks of its component securities.

The importance of these risks is now a fundamental premise of the option pricing literature and those studies have argued that the risk premia associated with jump risks are different from the premia associated with diffusion risks (see, e.g., Pan (2002); Todorov (2009) and references therein). This motivates our test of whether the two types of betas carry separate risk premia. It is especially important to determine the contribution of jumps to periods of market stress because jump risk, either in returns or in volatility, cannot typically be hedged away, and investors may demand a large premia to carry these risk; for instance, Pan (2002). We focus on the contemporaneous relationships between realized factor loadings and realized stock returns, as in Cremers et al. (2015); Ang et al. (2006), who themselves follow a long tradition in asset pricing in considering the contemporaneous relation between realized factor loadings and realized stock returns (e.g., Fama and MacBeth (1973); Fama and French (1993); Lewellen and Nagel (2006); among others). A contemporaneous relation between factor loadings and risk premiums is the foundation of a cross-sectional risk-return relation.

The test assets we use in our pricing regressions are individual stocks rather than portfolios. Ang et al. (2010) show that constructing portfolios ignores important information (especially, as stocks within particular portfolios having different betas) and leads to larger standard errors in cross-sectional data. In our empirical analysis, we choose panel regression with both period and cross section fixed effects over the conventional Fama and MacBeth (1973) cross-sectional regressions. Although Fama and Macbeth (FM) regression is a standard methodology to validate an asset pricing model, Petersen (2009) and Pasquariello (1999) indicate that FM two step procedures do not properly explain estimation errors and lack independence between cross-sectional errors. Therefore, we focus on individual stocks rather than portfolios, estimating panel regressions using all stocks in our sample as follows:

$$\bar{r}_{i,t} = \alpha_0 + \gamma_c \widehat{\beta_{i,t}^c} + \gamma_j \widehat{\beta_{i,t}^J} + \emptyset SIZE_{i,t} + \theta BM_{i,t} + \varepsilon_{i,t} \tag{23}$$

where $\bar{r}_{i,t}$ is the realized excess return on stock i the t-th month. We use the average monthly return as a proxy for realized excess returns, as there are no risk-free rates in Japan comparable to U.S. Treasury bill rates. [22] $\beta_{i,t}^s$, $\beta_{i,t}^c$, $\beta_{i,t}^j$ are the standard beta, the continuous beta, and the jump beta of firm i at month t, from our estimates in section 4.2. For comparison, we also estimate similar regressions by replacing the two betas by the standard CAPM beta $\beta_{i,t}^s$. Based on these panel regressions, with fixed effects in both the

[22] Alexeev et al. (2017) also use the average monthly return as a proxy for realized excess returns in order to extract the risk premia.

cross-section (firms) and period (time) dimensions, we then estimate the risk premiums associated with the different betas and explanatory variables.

Table 9 presents the unconditional regression results for the stock returns and each of the three betas ignoring the possible conditional beta/return relationship. The first three models show results for univariate regressions of returns on each beta. In model (4) of Table 9, we examine the effect of including both the continuous and jump beta estimates without considering the influence of size and BM effects. Model (5) in Table 9 examine the effect of including both the diffusion and jump beta estimates after controlling for size and BM effects.

The parameter loadings on the standard beta, the diffusion beta, and the jump beta in models (1) to (3) of Table 9 are all positive and significant, consistent with CAPM theory. Model (4) in Table 9 shows that the diffusion beta becomes insignificant when controlling for jump beta. However, the effect of jump beta remains significant even after controlling the effect of diffusion beta. From Table 9, it can be observed that, even in combination with variable size and BM, the significant relationship between average returns and jump beta persists in all bivariate regressions. This implies that stocks with high sensitivities to jump risk can expect higher returns, that is, jump risks carry a positive market price for risk.

4.3.1. Diffusion and Jump Risk in Up and Down Markets

The unconditional results are consistent with existing asset pricing tests in a broad setting. However, since excess returns may behave differently in up and down markets, we now consider these different phases in the market risk-return model.

Bollerslev et al. (2015) find that the risk premium associated with jump beta is statistically significant, while the diffusion beta does not appear to be priced in the cross-section. The decompositions of Todorov and Bollerslev (2010) and Bollerslev et al. (2015) do not make a distinction between upside market and downside market risk. The arguments based on asymmetric preferences by investors are, however, equally applicable in a context where we disentangle diffusion risk and jump risk. In particular, given the pricing results of Bollerslev et al. (2015), it is unclear whether down market risk is priced higher than up market risk. In particular, we to test for the price diffusion risk and jump risk between different market states. We examine this for three reasons.

First, there is a problem when researchers test the CAPM empirically using ex-post realized returns rather than the ex-ante expected returns upon which the CAPM is based. All investors recognize on average (expected) market returns must be greater than the risk-free rates. However, there must be some cases where the risk-free return exceeds the market return, otherwise no rational investor would ever invest in risk-free assets. In this case, we observe a reverse relationship between market beta and returns. In addition, besides this conceptual argument, in an ex-post context, the CAPM claims that high beta portfolios have higher expected returns than low beta portfolios given their higher risk due to the higher probability of greater losses, implying there must be some non-zero probability that the realized return of the low beta security will be greater than that of the high beta security, otherwise no rational investor would hold a low beta portfolio. The CAPM thus requires that the realized market return will with non-zero probability be less than the risk-free rate, and the realized return for high beta portfolios will with non-zero probability be lower than low beta portfolios. Pettengill et al. (1995) infer that periods when the realized returns for high beta portfolios are less than low beta portfolios occur when the realized market return is less than the risk-free rate, implying a positive relationship between beta and returns when the excess market return is positive (up market), and a negative relationship when the excess market return is negative (down market). It is thus necessary to distinguish between up and down markets in the relation between beta and realized returns in order to take into account such a "realization bias". If not, ignoring this conditional relation (to test for an unconditional positive relation between beta and realized returns) might be biased against finding a systematic relation, due to aggregation of positive and negative excess market return period. Second, information on the states of any asset market is relevant for investors. Investors who may follow a market timing strategy can obtain a long position under a bull (up) market and a neutral or short position under a bear (down) market. Investors that do not engage in market timing strategies may incorporate the different behavior of asset returns in their risk management (Perez-Quiros and Timmermann 2000). Third, up and down markets can affect asset pricing, as they are an important source of time variation in risk premia; see, for example, Ang et al. (2006).

To examine the relationship between beta and realized returns conditional on the sign of excess market return, testing is modified by including a dummy variable in the panel regression Eq. (23), thus allowing of positive and negative excess market returns to be separated following the methodology of Pettengill et al. (1995) as follows:

$$\bar{r}_{i,t} = \alpha_0 + \gamma_{c\,up}\,\delta.\widehat{\beta_{i,t}^{c}} + \gamma_{c\,down}\,(1-\delta).\widehat{\beta_{i,t}^{c}} + \gamma_{jup}\delta.\widehat{\beta_{i,t}^{J}} + \gamma_{jdown}(1-\delta).\widehat{\beta_{i,t}^{J}}$$
$$+ \sum_{n=1}^{m} \left[\emptyset_{up}\,\delta.X_{i,t} + \emptyset_{down}\,(1-\delta).X_{i,t}\right] + \varepsilon_{i,t} \qquad (24)$$

where δ =1 if $r_{mt} > 0$ (an up market) and δ =0 if $r_{mt} < 0$ (a down market). In this study, we include diffusion beta, jump beta, standard beta as well two firm-specific explanatory variables: firm size (SIZE) and book-to-market ration (BM). Incorporating a dummy variable into the regression allows for the existence of a negative realized market risk premium. We expect $\alpha_{i,t} = 0$ and $\gamma_{c\,up}$ ($\gamma_{c\,down}$) to be positive (negative) and statistically significant, implying the significance of beta as a risk measure. Monthly estimates $\gamma_{c\,up}$ are averaged from ($\overline{\gamma_{c\,up}}$) from which the following hypotheses are tested: $H_o : \overline{\gamma_{c\,up}} = 0$ against the alternative $H_o : \overline{\gamma_{c\,up}} > 0$, and $H_o : \overline{\gamma_{c\,down}} = 0$ against the alternative H_o : $\overline{\gamma_{c\,down}} < 0$

Table 10 presents our baseline results. Model (1) in Table 10 shows a significant positive (negative) relationship between standard beta and return during up and (down) markets, consistent with Pettengill et al. (1995); Pettengill et al. (2002); Hodoshima et al. (2000); Hur et al. (2014). When we decompose the CAPM beta into a diffusion and jump betas in up and down markets as in models (2) to (4) we see that both the betas attract a significant premium at the 1% level respectively. The results also show that the jump beta carries the larger premia of the two in both up and down markets. The null hypothesis of no beta–return relations ($H_o : \gamma_{c\,up} = 0$ and $H_o : \gamma_{c\,down} = 0$) is clearly rejected. Using the results in Table 2.10 for our preferred model (5), a 2-standrad-deviation difference in jump beta during the whole sample period, for the 5-min sampling frequency will lead to a difference in expected return of 2*0.6404* 0.5%*12 = 7.68% and 2*0.6404* 0.6%*12 = 9.22% per year, respectively for the up and down markets, which are large and economically meaningful difference in expected return. These are very close to estimates in Bollerslev et al. (2015) in the US market. This supports the argument that when the market is doing well higher risk banks, as measured by the two betas, would have greater returns than less risky banks. On the other hand, higher risk banks would do worse than less risky banks when the market is overall is doing poorly. We find that diffusion and jump beta remain significant in even after controlling for size and BM effects in up and down markets. The improvements in the adjusted-R^2 statistics as compared to the 2-beta model support the modeling of the up and down market conditional relationships.

Observing the relationship between size and returns, size is virtually not priced at all during up market and is priced negatively during down markets. The observe results argues against the distress risk explanation between the beta and size relationship. A number of authors have suggested that the size premium represents payment for some sort of distress risk. Campbell and Vuolteenaho (2004) suggest that the payment to small firms represents payment for a greater sensitivity to cash flow risk. Other authors (see for example, Vassalou and Xing (2004)) have suggested that the size premium may exist because small firms have greater default risk than large firms. Likewise, Chan and Chen (1991) argue that many small-firm securities are "fallen angels" that have declined in market value because of adverse market conditions and face the possibility of further distress. To the extent that small-firm securities do attract a premium for some form of distress or default risk, a relationship between the size effect and market conditions is clearly suggested. If small-firm securities attract a premium for distress risk, this premium ought to be realized when investors are generally optimistic. In market states where investors are pessimistic, firms with higher distress risk should experience low returns as investors re-value these securities downward to compensate for high default risk. Thus, in down markets small-firm securities should perform poorly relative to large-firm securities, but in up-markets investors in small-firm securities is rewarded for holding distress or default risk.

The hypothesis that a size effect resulting from payment to risk should be paid in up markets is consistent with arguments made by Lakonishok et al. (1994). They argue that value stocks ought to underperform glamor stocks in adverse market conditions if the value premium results from compensation for risk. This follows because in adverse market conditions high-risk value stocks ought to be unattractive to risk-averse investors. Further support for the hypothesis that a distress risk premium should be paid to size in up markets rather than in down markets is provided by Perez - Quiros and Timmermann (2000). They argue that small firms rapidly lose asset value in recessions; therefore small firms should experience greater losses than large firms in bear market periods associated with economic recessions. Thus the size premium, if paid for distress risk, ought to be paid in up markets.

As reported in Table 10, statistics revealed size is virtually not priced at all during up markets and is priced negatively, with a monthly premium of 0.35%, during down markets. There is no relationship between size and returns in up markets after considering the role of beta. Contrary to the distress risk explanation of the size effect, the relationship between size and returns comes entirely from down markets. The observed results appear to contradict the generally hypothesized pricing relations. Our results are inconsistent with Campbell and Vuolteenaho (2004), and Vassalou and Xing (2004), arguments that the payment to small firms represents payment for a greater sensitivity to cash flow risk and greater default risk or these firms are more likely to get adversely affected in bad market states. Therefore our findings indicate that 'relative distress' argument used in Fama and French (1996) to justify risk adjustment using factor loadings on SMB portfolios can be questioned.

It is plausible however that if small firms do face higher financial distress cost, they may optimally structure themselves (e.g. through financial leverage or other operating decisions) to insulate themselves against bad states of the world. Under those circumstances the stock returns may behave as we find here even though other aspects of financial performance may be more affected by bad times. This explanation is consistent with George and Hwang (2010) argument for distress risk and leverage puzzle in stock returns. Another explanation is that, the unique risk characteristics of firms in Japanese market may imply the existence of a significant negative size effect in down markets. To the extent that size reflects diversification of activities, liquidity, timeliness and quality of corporate information disclosure, and the level of transactions costs involved, larger firms tend to have lower non-market risk. However, a special feature of the Japanese market is that, unlike the US market, most large firms are in the finance and real estate property sectors, which are exposed heavily to systematic risk factors on an international scale, such as interest rate risk, inflation risk, and political uncertainties, whereas most small firms are engaged in trading or manufacturing business which is less vulnerable to market risk. So, large firms possess large betas and small firms possess small betas. This gives rise to a positive correlation between size and beta (See, Table 6). In sum, it may be generalized that large firms in Japanese market have large total risk (large market risk plus small non-market risk) and small firms have small total risk (small market risk plus large non-market risk). This helps explain the positive (negative) size effect during up (down) markets. Thus, in the Japanese market, it may be argued that size also proxies for risk but with a pricing effect reverse to that generally suggested by theory and evidence.

With respect to BM, a statistically significant negative relationship is found during the down markets, consistent with Pettengill et al. (2002). The results suggest that in good times when the market returns are up the market is less worried about bankruptcy. However, in bad times when the market returns are down, the market is more concerned about bankruptcy, distressed companies with high BM ratios will suffer low returns (security prices decrease) as the distressed risk is priced back into the security. Such an explanation implies a negative BM pricing effect during down markets.

Overall, the consistent message from the regressions in Table 10 is that reward for bearing jump risk and diffusion risk is always positive, remarkably stable and statistically significant. Our findings provide strong evidence that high-risk stocks market outperform low-risk stocks markets when the realized world market is positive and similarly the high-risk stock markets incur higher losses when the realized world market return is negative.

5. Robustness and Extensions

5.1. Sub-sample and Sorting analyses

This section describes several extensions of the analysis in section 4.3.1. To check the robustness of our empirical findings, following Wu and Lee (2015), we first extend the Eq. (2) to a model with regime dependent constant term: $\alpha_{i,t} = \alpha_{1,t}$ for up market and $\alpha_{i,t} = \alpha_{2,t}$ for down market. The empirical results are reported in Table 11.

The estimates of $\alpha_{1,t}$ and $\alpha_{2,t}$ are now significantly positive and significantly negative, respectively, which captures the positive mean excess return in the up market and the negative mean excess return in down market. The coefficients for diffusion beta and jump beta are qualitatively similar to those with a time-invariant constant term reported in Table 10.

As Lanne and Saikkonen (2006) point out the presence of a constant term renders conditional mean estimation very inaccurate when the constant term estimates appears to be significant, we therefore employ the restriction $\alpha_{i,t} = 0$ to address this estimation problem. As shown in Table 11, the estimated coefficients are qualitatively similar those reported in Table 10.

The existing literature indicates that risk factors such as conditional volatility (Lundblad 2007) or implied volatility (Connolly et al. 2005) are elevated during recessions. Investors also tend to avoid risky assets and behave differently under extreme market conditions. Thus we investigate whether extreme market movements, such as financial crisis, could alter the parametric estimates of the risk-return relationship. We re-estimate our jump-diffusion model under pre-crisis, crisis, and post-crisis periods and show how the risk-return relationship varies under different economic conditions. Each of the three sub periods describes a different episode of the stock market. We again concentrate on up and down markets.

Table 12 presents these pre-crisis, crisis and post-crisis results. In the pre-crisis period, exposure to diffusion and jump risks are rewarded with returns during up markets and are penalized with losses during down markets. In transitioning from the pre-crisis to the crisis period, we find that both the premium and discount for diffusion beta increase whereas both the premium and discount for the jump beta decrease in the crisis period. By contrast, both the premium and discount for the diffusion and jump beta show opposite results in transitioning from the crisis to the post-crisis period. In the pre-crisis (or stable) period both the betas are priced significantly, with the jump premium larger than the diffusion premium. Large surprises are priced higher than small surprises. In the crisis (or unstable) period both the betas are still significantly priced but the diffusion premium is now larger than the jump premium. Small surprises are priced higher than large surprises. In the post-crisis (or recovery) period only the jump risk is priced significantly. Any large good news is wanting and much appreciated and any further large bad news is penalized heavily.

Given the above relationships found between betas and returns, we test for symmetry between betas and returns during up and down markets over the full sample and the three periods to compare the relative magnitudes of the different premiums for both the diffusion and jump betas. A two population t-test is used to test the symmetrical relationship between the mean of estimated up market risk premium and the estimated down market risk premium from the Equation (24). The results reported in Panel A of

Table 13 clearly do not reject the null hypothesis of symmetry over the total testing period, and the three sub periods with the exception of the pre-crisis period (only at the 10% significance level). We can safely say that the absolute values of the premiums for both the diffusion and jump risks are generally symmetrical for up and down markets.

In addition, since the premiums associated with discontinuous, or jump, risks often appear to be quite different from the premiums associated with diffusion risks, we test whether the premiums associated with diffusion and jump risks are of equal magnitude by testing the equality of pairs of the regression coefficients ($\gamma_{c\ up}$ and $\gamma_{j\ up}$; $\gamma_{c\ down}$ and $\gamma_{j\ down}$) as shown in Panel B of Table 13. Comparing the relative magnitudes of the different premiums, we see that the symmetrical relationship only exists in the up markets of the total sample and the pre-crisis sub-sample periods. However, the estimated risk premiums for diffusion risk and jump risk reject symmetry for the down markets of all periods and the up markets of the crisis and post-crisis periods. We also notice (in conjunction with Table 12) that for the crisis period the diffusion component for up markets are the dominant pricing ingredients whereas for the post-crisis period the jump component is the dominant factor. During the crisis period, we do not expect positive jumps and consequently the market does not have a premium for positive jumps. In post-crisis, the market compensates by having a higher premium for positive jumps (i.e. expecting a fast recovery), and at the same time having a higher discount for the negative jumps as still remember the recent past crisis. For the pre-crisis period, we do not observe a clear difference between the estimated risk premiums for diffusion and jump risks during up markets and down markets.

For our robustness checks, we use size sorted portfolio analysis to see whether our baseline results remain valid; see Table 14. Our results indicate that when compared with low-beta ones, high-beta portfolios earn higher returns in up markets and incur losses in down markets. For comparability with previous studies, we also use Fama–MacBeth regressions to estimate model (3). We present the regression results in Table 15. Over all our base line results remain robust, although some coefficients lose significance. The results are consistent with Bollerslev et al. (2015) who observed a positive relation between a stock's return and its jump beta for all stocks that are constituents in the S&P 500 index over 1993-2010 (that is, the jump beta may have a different price of risk than the diffusion beta), and with Schuermann and Stiroh (2006) and Viale et al. (2009) who provide evidence on the risk factors priced in bank equities. Schuermann and Stiroh (2006) examine the weekly returns for the U.S. banks form 1997-2005 and show that the market risk factor dominates in explaining bank returns, followed by the Fama-French factors. Viale et al. (2009) identify common risk factors in US banks stocks from 1986-2003 applying CAPM, Fama-French factors , and ICAPM and find that market factor are significant explanators of the cross section of bank stock returns.

5.2. Control for bank-specific risk factors

The linear factor models used so far intend to capture risks faced by firms in general. While one could argue that these asset pricing models should also work for banks, they were not constructed to capture bank-specific risks. One potential concern is that we are not adequately controlling for such risks, implying that we might be merely capturing that high-risk banks are outperform than low-risk banks. To address this, we evaluate the role of specific fundamentals variables in explaining the cross-section of expected bank stock returns. Subsequently, we employ variables that have been shown to be important in determining the fundamental riskiness of banks of reflect changes in business practices that may affect bank risks.

We now rerun our regressions while adding four bank-specific risk factors to the jump-diffusion linear factor model. The bank-specific risk factors that we add to the our models include: tier 1 risk-based capital ratio, market-valued capital ratio, profitability, and leverage (Bouwman et al. 2017; Chen 2011). Table 16 reports the results. The first three model of results consider the role bank fundamentals variables in explaining the cross-section of expected bank stock returns and the final three columns for the jump beta. The second and third model explore subsets of the explanatory variables, with tier 1 ratio included (excluded) in model 2(3) and the capital ratio excluded (included). Model (4) of Table 16, we examine the effect of including both the diffusion and jump beta estimates and all control variables. From Table 16, it can be observed that, even in combination with variable tier 1 risk-based capital ratio, total risk-based capital ratio, profitability, and leverage, size and BM, the significant relationship between average returns and diffusion betas (and jump betas) persists in all bivariate regressions. This finding implies that during up markets high beta bank exhibit higher returns than low beta bank supporting while during down markets high beta bank earn a lower return than low beta bank.

5.3. Diffusion risk, Jump risk and ex-ante expected returns

Yet virtually all of the empirical literature use realized returns as a proxy for expected returns because market data on market expectations of future returns are not available.[23] Consistent with this literature, the results we discuss so far focus on cotemporaneous relations between diffusion and jump betas and bank stock returns. During his AFA Presidential Address, however, Elton (1999) argued that realized returns are a poor measure of expected returns and that more effort should be put into estimating expected returns. We therefore now verify our results using expected returns in Eq. (25). Table 17 shows that when we use ex-ante measures of expected (instead of realized) returns, diffusion beta and jump beta is priced in both up and down markets: high risk banks do earn higher returns than low-risk banks during up market and vice versa for down market. These results confirm our main results.

5.4. Time series of jump betas

Economic risks change with business cycles, and investors' attentiveness to risks varies with time. Accordingly, although betas do not change dramatically over a short period of time, they can be time-varying over a long horizon. If jump betas reflect such risks well, they would change over time in accordance with the risks. Therefore, in this section, we investigate how jump betas vary in a descriptive way. We illustrate the time series of jump betas along with diffusion and jump betas to examine whether the change in jump betas over time differs from that of the other betas. Figure 3 shows that the time series of portfolio betas, based on monthly quintile sorts for each of the three different betas and all of the individual stocks in the sample. The figure suggests that the variation in the standard beta and diffusion beta sorted portfolios in Panel A and B are clearly fairly close, as would be expected. However, the plots for the jump beta quintle portfolios in Panel C, are distinctly different and more dispersed than the standard and diffusion betas quintile portfolios. Jump beta is significantly different from diffusion and standard beta. Our estimates shows that there is interesting variation across assets and across time in the jump components of the market beta. Therefore, jump betas incorporate information

[23] The underlying assumption is that information surprises tend to cancel out over longer time horizons and realized returns are therefore an unbiased estimate of expected returns.

about the overall economic conditions well and this property can be related to the significant premium with jump betas.

5.5. Relationship between jump betas and liquidity

As the previous sections show, jump betas appear to deliver important fundamental pricing information. However, there may be a concern that the information embedded in jump betas is associated with liquidity because liquidity constraints are negatively related to business conditions and positively related to risks. In addition, as Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) document that market wide liquidity is an important factor for pricing stocks. To confirm that the results in this paper are not driven by liquidity effects, we investigate the correlations between the monthly jump betas and the proxies for liquidity. Considering the literature, we use the logarithm of monthly number of shares traded (trading volume), and the monthly realized variance as liquidity proxies. Table 18 reports the correlations between jump betas and each liquidity proxy. Overall, the correlations between jump betas and liquidity proxies are less than 10%. In addition, the correlations are less than 28% during crisis and post-crisis, respectively.

Although a simple correlation would not provide a decisive result, we believe that such low correlations are sufficient to support the conclusion that jump betas contain fundamental information that is different from that of liquidity. Considering these findings, we argue that jump betas are significantly related to economic fundamentals and that the dynamic variations in the cross-section of jump betas are sufficiently wide to clearly distinguish the characteristics of individual stocks.

The results support the initial hypothesis of this paper that jump beta is larger than that of diffusion beta, in line with the approach of Patton and Verardo (2012) emphasizing that the role of learning in disseminating information to the market is supported by higher beta around information rich events (such as jumps). Further, our panel results show that the jump betas convey more information than the diffusion beta in the explanation of average returns, supporting the importance of separating jump and diffusion beta in assessing risk premia.

6. Conclusions

Empirical asset pricing literature have been widely documented that stock returns exhibit both stochastic volatility and jumps. Significant jumps have been found in stock prices and equity market indexes, suggesting that jump risk is part of systematic risks. Since jump risk is priced, adding jump risk into the traditional finance models has significant empirical and theoretical meanings. This paper aims to provide an empirical framework to tie jumps into a fundamental economic model of valuation—the jump-diffusion two-beta asset pricing model.

In this paper, we seek to understand how an individual bank's equity prices respond to continuous and discrete market moves and how these corresponding distinct systematic risks or betas, are priced. Particularly, we investigate the systematic diffusive and jump risks exposures of Japanese banks for the 2000-2012 period. We use an extension of CAPM to relate a bank stock's return to two types of systematic risk exposures as measured by two types of beta: the diffusion beta and the jump beta. The diffusion beta is associated with the stock's sensitivity to a market continuous movement while, jump beta is associated with the stock's sensitivity to a market discontinuous movement.

The estimated jump betas are consistently larger than the diffusion betas in our empirical results, and firm fundamentals play important roles in determining firm's cost of capital in the 2-beta model. We find that large banks are more sensitive to jumps than the small banks and highly leverage banks are more exposed to market jumps. Profitable banks are sensitive to both continuous and jump market moves. We then empirically investigate whether the diffusive and jump risks are separately priced under both conditional and unconditional market states. Our empirical findings suggest that jump risks are priced separately from the corresponding diffusive risks. Assuming that investors tend to behave differently under up and down market conditions, we also test whether the risk premiums for diffusion and jump risk are asymmetric under different market conditions. We introduce and test a new 4-beta CAPM model by combining the diffusion and jump betas of Todorov and Bollerslev (2010) and the conditional betas of Pettengill et al. (1995), into a single model to detect any asymmetries under differing market conditions. We demonstrate that investors exposed to diffusion and jump systematic risks on their investment in Japanese bank equities receive excess positive returns in upturn market, but that they suffer excess losses in downturn market. We also provide evidence that under extreme market movements, such as during the recent financial crisis, the absolute value of the beta premiums can differ substantially in significance and magnitude.

Our main contribution is that we confirm evidence that both diffusion and jump systematic risks are separately priced by Japanese investor and they are not related to one another. Our results also suggest that portfolios designed to hedge large discontinuous market movements might have to be constructed differently from portfolios intended to hedge the more common continuous day-to-day market movements. Thus, disentangling and pricing the two types of systematic risks separately is clearly important for the investment and risk management decisions of portfolio investors and companies.

References

Acharya, V. V., and L. H. Pedersen. 2005. Asset pricing with liquidity risk. *Journal of Financial Economics* 77 (2):375-410.

Alexeev, V., M. Dungey, and W. Yao. 2017. Time-varying continuous and jump betas: The role of firm characteristics and periods of stress. *Journal of Empirical Finance* 40:1-19.

Andersen, T. G., T. Bollerslev, and J. Cai. 2000. Intraday and interday volatility in the Japanese stock market. *Journal of International Financial Markets, Institutions and Money* 10 (2):107-130.

Andersen, T. G., T. Bollerslev, and F. X. Diebold. 2007. Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The Review of Economics and Statistics* 89 (4):701-720.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and G. Wu. 2006. Realized beta: Persistence and predictability. *Advances in econometrics* 20:1-39.

Andersen, T. G., T. Bollerslev, P. Frederiksen, and M. Ørregaard Nielsen. 2010. Continuous-time models, realized volatilities, and testable distributional implications for daily stock returns. *Journal of Applied Econometrics* 25 (2):233-261.

Ang, A., J. Chen, and Y. Xing. 2006. Downside risk. *Review of Financial Studies* 19 (4):1191-1239.

Ang, A., J. Liu, and K. Schwarz. 2010. Using stocks or portfolios in tests of factor models. USA: Columbia University and University of Pennsylvania.

Barndorff-Nielsen, O. E., and N. Shephard. 2003. Realized power variation and stochastic volatility models. *Bernoulli* 9 (2):243-265.

———. 2006. Econometrics of testing for jumps in financial economics using bipower variation. *Journal of financial Econometrics* 4 (1):1-30.

Bollerslev, T., T. H. Law, and G. Tauchen. 2008. Risk, jumps, and diversification. *Journal of Econometrics* 144 (1):234-256.

Bollerslev, T., S. Z. Li, and V. Todorov. 2015. Roughing up Beta: Continuous vs. Discontinuous Betas, and the Cross-Section of Expected Stock Returns. *Journal of Financial Economics* Forthcoming

Bollerslev, T., and V. Todorov. 2011. Tails, fears, and risk premia. *The Journal of finance* 66 (6):2165-2211.

Borde, S. F., K. Chambliss, and J. Madura. 1994. Explaining variation in risk across insurance companies. *Journal of Financial Services Research* 8 (3):177-191.

Bouwman, C. H., H. Kim, and S.-O. S. Shin. 2017. Bank Capital and Bank Stock Performance. In *Mays Business School*.

Buiter, W., and E. Rahbeir. 2012. Debt, Financial Crisis and Economic Growth. Paper read at Conference on Monetary Policy and the Challenge of Economic Growth at the South Africa Reserve Bank, Pretoria, South Africa, November.

Campbell, J. Y., and T. Vuolteenaho. 2004. Bad Beta, Good Beta. *American Economic Review* 94 (5):1249-1275.

Chan, K., and N. F. Chen. 1991. Structural and return characteristics of small and large firms. *The Journal of finance* 46 (4):1467-1484.

Chatrath, A., H. Miao, S. Ramchander, and S. Villupuram. 2014. Currency jumps, cojumps and the role of macro news. *Journal of International Money and Finance* 40 (0):42-62.

Chen, S. 2011. Capital ratios and the cross-section of bank stock returns: Evidence from Japan. *Journal of Asian Economics* 22 (2):99-114.

Christoffersen, P., B. Feunou, and Y. Jeon. 2015. Option valuation with observable volatility and jump dynamics. *Journal of Banking & Finance* 61:S101-S120.

Connolly, R., C. Stivers, and L. Sun. 2005. Stock Market Uncertainty and the Stock-Bond Return Relation. *Journal of Financial and Quantitative Analysis* 40 (01):161-194.

Cremers, M., M. Halling, and D. Weinbaum. 2015. Aggregate Jump and Volatility Risk in the Cross-Section of Stock Returns. *The Journal of finance* 70 (2):577-614.

Demsetz, R. S., and P. E. Strahan. 1997. Diversification, size, and risk at bank holding companies. *Journal of Money, Credit, and Banking*:300-313.

Driessen, J., and P. Maenhout. 2013. The world price of jump and volatility risk. *Journal of Banking & Finance* 37 (2):518-536.

Dungey, M., and D. Gajurel. 2014. Equity market contagion during the global financial crisis: Evidence from the world's eight largest economies. *Economic Systems* 38 (2):161-177.

Dungey, M., and L. Hvozdyk. 2012. Cojumping: Evidence from the US Treasury bond and futures markets. *Journal of Banking & Finance* 36 (5):1563-1575.

Dungey, M., M. McKenzie, and L. V. Smith. 2009. Empirical evidence on jumps in the term structure of the US Treasury Market. *Journal of Empirical Finance* 16 (3):430-445.

Elyasiani, E., and I. Mansur. 2003. International spillover of risk and return among major banking institutions: A bivariate GARCH model. *Journal of Accounting, Auditing & Finance* 18 (2):303-330.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33 (1):3-56.

———. 1996. Multifactor explanations of asset pricing anomalies. *The Journal of Finance* 51 (1):55-84.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*:607-636.

Gajurel, D. P. 2015. Essays on financial contagion and financial crises. Doctoral Dissertation, Tasmanian School of Business and Economics, Univeristy of Tasmania, Australia.

George, T. J., and C.-Y. Hwang. 2010. A resolution of the distress risk and leverage puzzles in the cross section of stock returns. *Journal of Financial Economics* 96 (1):56-79.

Gujarati, D. N., and D. C. Porter. 2009. *Basic Econometrics*. Boston, MA: McGraw-Hill.

Gultekin, M. N., N. B. Gultekin, and A. Penati. 1989. Capital controls and international capital market segmentation: The evidence from the Japanese and American stock markets. *The Journal of finance* 44 (4):849-869.

Hansen, P. R., and A. Lunde. 2006. Realized variance and market microstructure noise. *Journal of Business & Economic Statistics* 24 (2):127-161.

Haq, M., and R. Heaney. 2012. Factors determining European bank risk. *Journal of International Financial Markets, Institutions and Money* 22 (4):696-718.

Hodoshima, J., X. Garza–Gómez, and M. Kunimura. 2000. Cross-sectional regression analysis of return and beta in Japan. *Journal of Economics and Business* 52 (6):515-533.

Hong, G., and S. Sarkar. 2007. Equity Systematic Risk (Beta) and Its Determinants*. *Contemporary Accounting Research* 24 (2):423-466.

Huang, X., and G. Tauchen. 2005. The relative contribution of jumps to total price variance. *Journal of financial Econometrics* 3 (4):456-499.

Hur, J., G. Pettengill, and V. Singh. 2014. Market states and the risk-based explanation of the size premium. *Journal of Empirical Finance* 28:139-150.
Keeley, M. C., and F. T. Furlong. 1990. A reexamination of mean-variance analysis of bank capital regulation. *Journal of Banking & Finance* 14 (1):69-84.
King, M. R. 2009. The cost of equity for global banks: a CAPM perspective from 1990 to 2009. *BIS Quarterly Review, September*.
Lahaye, J., S. Laurent, and C. J. Neely. 2011. Jumps, cojumps and macro announcements. *Journal of Applied Econometrics* 26 (6):893-921.
Lakonishok, J., A. Shleifer, and R. W. Vishny. 1994. Contrarian investment, extrapolation, and risk. *The Journal of finance* 49 (5):1541-1578.
Lanne, M., and P. Saikkonen. 2006. Why is it so difficult to uncover the risk–return tradeoff in stock returns? *Economics Letters* 92 (1):118-125.
Lewellen, J., and S. Nagel. 2006. The conditional CAPM does not explain asset-pricing anomalies. *Journal of Financial Economics* 82 (2):289-314.
Lintner, J. 1965. Security Prices, Risk, and Maximal Gains from Diversification. *The Journal of Finance* 20 (4):587-615.
Lundblad, C. 2007. The risk return tradeoff in the long run: 1836–2003. *Journal of Financial Economics* 85 (1):123-150.
Mandelker, G. N., and S. G. Rhee. 1984. The impact of the degrees of operating and financial leverage on systematic risk of common stock. *Journal of Financial and Quantitative Analysis* 19 (01):45-57.
Merton, R. C. 1976. Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics* 3 (1):125-144.
Miyakoshi, T., T. Takahashi, J. Shimada, and Y. Tsukuda. 2014. The dynamic contagion of the global financial crisis into Japanese markets. *Japan and the World economy* 31:47-53.
Modigliani, F., and M. H. Miller. 1958. The cost of capital, corporation finance and the theory of investment. *The American Economic Review*:261-297.
———. 1963. Corporate income taxes and the cost of capital: a correction. *The American Economic Review* 53 (3):433-443.
Neumann, M., M. Prokopczuk, and C. W. Simen. 2016. Jump and Variance Risk Premia in the S&P 500. *Journal of Banking & Finance*.
Pan, J. 2002. The jump-risk premia implicit in options: Evidence from an integrated time-series study. *Journal of Financial Economics* 63 (1):3-50.
Pasquariello, P. 1999. The Fama-MacBeth Approach Revisited. *New York University–Stern School of Business Working Paper*.
Pastor, L., and R. F. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111:642-685.
Patton, A. J., and M. Verardo. 2012. Does beta move with news? Firm-specific information flows and learning about profitability. *Review of Financial Studies* 25 (9):2789-2839.
Perez-Quiros, G., and A. Timmermann. 2000. Firm size and cyclical variations in stock returns. *The Journal of finance* 55 (3):1229-1262.
Petersen, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22 (1):435-480.
Pettengill, G., S. Sundaram, and I. Mathur. 1995. The conditional relation between beta and returns. *Journal of Financial and Quantitative Analysis* 30 (01):101-116.
———. 2002. Payment For Risk: Constant Beta Vs. Dual-Beta Models. *The Financial Review* 37 (2):123-135.

Pukthuanthong, K., and R. Roll. 2015. Internationally correlated jumps. *Review of Asset Pricing Studies* 5 (1):92-111.

Santa-Clara, P., and S. Yan. 2010. Crashes, volatility, and the equity premium: Lessons from S&P 500 options. *The Review of Economics and Statistics* 92 (2):435-451.

Saunders, A., E. Strock, and N. G. Travlos. 1990. Ownership structure, deregulation, and bank risk taking. *The Journal of Finance* 45 (2):643-654.

Sayeed, M., M. Dungey, and W. Yao. 2017. High frequency characterization of Indian banking stocks. *Journal of Emerging Markets Finance* Forthcoming.

Schuermann, T., and K. J. Stiroh. 2006. Visible and hidden risk factors for banks: Staff Report, Federal Reserve Bank of New York.

Sharpe, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk*. *The Journal of finance* 19 (3):425-442.

Tauchen, G., and H. Zhou. 2011. Realized jumps on financial markets and predicting credit spreads. *Journal of Econometrics* 160 (1):102-118.

Todorov, V. 2009. Variance risk-premium dynamics: The role of jumps. *Review of Financial Studies*:hhp035.

Todorov, V., and T. Bollerslev. 2010. Jumps and betas: A new framework for disentangling and estimating systematic risks. *Journal of Econometrics* 157 (2):220-235.

Vassalou, M., and Y. Xing. 2004. Default risk in equity returns. *The Journal of finance* 59 (2):831-868.

Viale, A. M., J. W. Kolari, and D. R. Fraser. 2009. Common risk factors in bank stocks. *Journal of Banking & Finance* 33 (3):464-472.

Wu, S.-J., and W.-M. Lee. 2015. Intertemporal risk–return relationships in bull and bear markets. *International Review of Economics & Finance* 38:308-325.

Yamori, N., K. Kondo, K. Tomimura, Y. Shindo, and K. Takaku. 2013. Japanese banking regulations and SME finance under the global financial crisis. *Japanese Journal of Monetary and Financial Economics* 1 (1):59-90.

Yan, S. 2011. Jump risk, stock returns, and slope of implied volatility smile. *Journal of Financial Economics* 99 (1):216-233.

Zhang, L. 2011. Estimating covariation: Epps effect, microstructure noise. *Journal of Econometrics* 160 (1):33-47.

Table 1: List of Sample Banks

No	Banks	No	Banks	No	Banks
1	Aichi Bank	21	Hiroshima Bank	41	Shinsei Bank
2	Akita Bank	22	Hokkoku Bank	42	Shizuoka Bank
3	Aomori Bank	23	Hokuetsu Bank	43	Sumito Mitsui Financial Gp
4	Aozora Bank	24	Hokuhoku Financial Gp.	44	Suruga Bank
5	Awa Bank	25	Hyakugo Bank	45	Tochigi Bank
6	Bank Of Iwate	26	Hyakujushi Bank	46	Toho Bank
7	Bank Of Kyoto	27	Iyo Bank	47	Tokoyo Tomin Bank
8	Bank Of Nagoya	28	Joyo Bank	48	Yachiyo Bank
9	Bank Of Okinawa	29	Juroku Bank	49	Yamagata Bank
10	Bank Of The Ryukyus	30	Kagoshima Bank	50	Yamaguchi Finl.G.
11	Bank Of Yokohama	31	Keiyo Bank		
12	Chiba Bank	32	Miyazaki Bank		
13	Chugoku Bank	33	Musashino Bank		
14	Daishi Bank	34	Nanto Bank		
15	Fukui Bank	35	Nishi-Nippon City Bank		
16	Fukuoka Financial Group	36	North Pacific Bank		
17	Gunma Bank	37	Ogaki Kyoritsu Bank		
18	Hachijuni Bank	38	Oita Bank		
19	Higashi Nippon Bank	39	San-In Godo Bank		
20	Higo Bank	40	Seventy-seven Bank		

Table 2: Market capitalization and turnover of analyzed stock market

Stock Exchange (Country)		
Tokoyo(Japan)	**Stock market capitalization**	**Turnover ratio**
2001	60.67	72.37
2002	54.10	73.06
2003	62.05	85.13
2004	74.55	98.84
2005	91.25	119.79
2006	105.95	135.45
2007	104.49	142.74
2008	86.09	140.84
2009	67.10	127.10
2010	74.60	114.50
2011	68.58	108.90
2012	61.80	99.80

Table 3: Summary Statistics for Daily Volatilities and Jumps (figure scaled by 100 with the exception of skewness and kurtosis)

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
RV_t	0.0013	0.0004	0.0952	0.0000	0.0044	11.900	186.429
$\sqrt{RV_t}$	0.2693	0.2119	3.0857	0.0049	0.2472	3.942	29.964
BV_t	0.0012	0.0003	0.0998	0.0000	0.0043	13.111	231.500
$\sqrt{BV_t}$	0.2435	0.1847	3.1595	0.0034	0.2452	3.994	31.201
J_t	0.0002	0.0000	0.0173	0.0000	0.0006	15.706	362.712
$\sqrt{J_t}$	0.0905	0.0674	1.3151	0.0000	0.1032	3.029	22.806

Table 4: Descriptive statistics of High-frequency jumps
Panel A: Yearly statistics of significant jumps.

Yearly estimates for Nikkei 225 market index. Number of jumps denote the number of days with jumps. Prop denotes the proportion of days with jumps. The statistic based on Brandroff-Nielson and Shephard framework is used to identify days with jump. Thereafter. The test Anderson et al., (2007) is applied to determine the sign of jumps.

Year	Jump freq.	Jump prop	Positive jump freq.	Positive jump prop	Negative jump freq.	Negative jump prop
2001	14	5%	6	4%	8	6%
2002	26	10%	8	6%	18	14%
2003	14	5%	6	4%	8	6%
2004	39	14%	13	9%	26	20%
2005	33	12%	21	15%	12	9%
2006	20	7%	16	11%	4	3%
2007	10	4%	5	4%	5	4%
2008	17	6%	9	6%	8	6%
2009	25	9%	16	11%	9	7%
2010	30	11%	17	12%	13	10%
2011	23	8%	16	11%	7	5%
2012	21	8%	8	6%	13	10%
Total no of Jump	272		141		131	

Panel B: Summary statistics of jump size

The Table displays the summary statistics for mean jump size as well as exhibits statistical characteristics of positive and negative jumps.

	Total sample period		
	Mean	Med	Std. Dev.
Jump size	-0.0029	-0.0011	0.0411
Postive jump size	0.0188	0.0084	0.0329
Negative jump size	-0.0261	-0.0182	0.0362
	Pre-crisis period		
Jump size	-0.0033	-0.0012	0.0423
Postive jump size	0.0227	0.0142	0.0301
Negative jump size	-0.0271	-0.0157	0.0376
	Crisis period		

Jump size	-0.0078	-0.0017	0.0560
Postive jump size	0.0243	0.0193	0.0311
Negative jump size	-0.0453	-0.0460	0.0560
	Post-crisis period		
Jump size	-0.0002	-0.0001	0.0343
Postive jump size	0.0125	0.0042	0.0364
Negative jump size	-0.0178	-0.0182	0.0215

Table 5: Average monthly beta

		95% confidence interval			95% confidence interval	
Banks	**Beta C**	**CI_low**	**CI_up**	**Beta J**	**CI_low**	**CI_up**
Aichi bank	0.10	0.018	0.180	0.78	0.765	0.804
Akita bank	0.14	0.046	0.207	0.77	0.753	0.795
Aomori bank	0.09	0.000	0.146	0.64	0.620	0.651
Aozora bank	0.38	0.266	0.496	1.14	1.088	1.191
Awa bank	0.16	0.080	0.235	0.82	0.801	0.843
Bank of Iwate	0.15	0.063	0.224	0.77	0.748	0.796
Bank of Kyoto	0.40	0.318	0.486	0.92	0.902	0.946
Bank of Nagoya	0.21	0.123	0.296	0.93	0.903	0.955
Bank of Okinawa	0.10	0.014	0.174	0.70	0.676	0.715
Bank of the Ryukyus	0.24	0.149	0.318	0.76	0.734	0.779
Bank of Yokohama	0.63	0.538	0.720	1.09	1.067	1.123
Chiba bank	0.65	0.554	0.735	1.16	1.141	1.185
Chugoku bank	0.29	0.211	0.372	0.85	0.827	0.869
Daishi bank	0.21	0.118	0.288	0.92	0.904	0.940
Fukui bank	0.10	0.011	0.165	0.73	0.713	0.747
Fukuoka financial group	0.68	0.587	0.782	1.47	1.433	1.508
Gunma bank	0.44	0.348	0.529	1.07	1.051	1.099
Hachijuni bank	0.39	0.297	0.472	1.08	1.058	1.102
Higashi Nippon bank	0.15	0.041	0.224	0.74	0.720	0.763
Higo bank	0.18	0.099	0.262	0.81	0.793	0.828
Hiroshima bank	0.33	0.241	0.411	0.95	0.931	0.974
Hokkoku bank	0.17	0.088	0.250	0.83	0.818	0.848
Hokuetsu bank	0.10	-0.014	0.157	0.70	0.673	0.726
Hokuhoku finl.gp.	0.41	0.298	0.515	1.21	1.180	1.250
Hyakugo bank	0.23	0.135	0.302	0.89	0.871	0.915
Hyakujushi bank	0.22	0.133	0.302	1.02	0.999	1.047
Iyo bank	0.32	0.237	0.404	0.93	0.905	0.947
Joyo bank	0.40	0.306	0.487	1.12	1.098	1.142
Juroku bank	0.25	0.160	0.334	0.94	0.914	0.958
Kagoshima bank	0.20	0.114	0.278	0.81	0.794	0.827
Keiyo bank	0.25	0.149	0.316	0.84	0.824	0.865
Miyazaki bank	0.09	0.002	0.162	0.62	0.609	0.640
Musashino bank	0.34	0.247	0.416	0.99	0.971	1.015
Nanto bank	0.01	-0.046	0.053	0.50	0.499	0.505

Nishi-Nippon city bank	0.34	0.242	0.442	1.16	1.121	1.198
North Pacific bank	0.08	0.289	0.496	1.13	0.361	1.183
Ogaki Kyoritsu bank	0.20	0.116	0.281	0.91	0.878	0.935
Oita bank	0.11	0.030	0.194	0.77	0.749	0.783
San-in Godo bank	0.24	0.159	0.325	0.90	0.875	0.924
Seventy-seven bank	0.41	0.316	0.498	1.06	1.036	1.092
Shinsei bank	0.50	0.383	0.620	1.35	1.310	1.393
Shizuoka bank	0.62	0.536	0.702	1.06	1.033	1.081
Sumito Mitsui finl.gp	0.88	0.768	0.977	1.50	1.463	1.543
Suruga bank	0.44	0.351	0.533	1.04	1.019	1.068
Tochigi bank	0.13	0.039	0.198	0.69	0.668	0.706
Toho bank	0.15	0.058	0.224	0.73	0.703	0.754
Tokoyo Tomin bank	0.36	0.260	0.451	1.09	1.065	1.119
Yachiyo bank	0.14	0.045	0.230	0.46	0.431	0.489
Yamagata bank	0.09	0.016	0.162	0.71	0.697	0.720
Yamaguchi finl. gp	0.45	0.361	0.538	1.21	1.187	1.242

Table 6: Descriptive statistics and Correlation Matrix

Panel A: Descriptive statistics of the firm characteristics

Variable	Obs	Mean	Std. Dev.	Median	25th percentile	75th percentile
Firm size	6510	8.20	0.34	8.16	7.95	8.42
Profitability (%)	6450	12.08	16.30	14.17	10.47	17.99
Leverage (%)	6585	94.24	1.41	94.35	93.58	95.13
Capital ratio (%)	6585	5.96	3.10	5.47	4.58	6.30

Panel B: Correlation Matrix of all the Variables

Variables	Std. beta	Diff beta	Jump beta	Firms size	Profitability	Leverage	Capital ratio
Std. beta	1						
Diffu beta	0.80	1					
Jump beta	0.67	0.38	1				
Firms size	0.56	0.56	0.26	1			
Profitability	0.08	0.04	0.08	-0.04	1		
Leverage	0.20	0.23	0.10	0.38	-0.24	1	
Capital ratio	0.01	0.02	0.01	-0.02	0.06	0.02	1

Table 7: Betas and Firm Characteristics

This table presents the regression results between the different betas and firm characteristics. The sample consists of 6522 observations from 47 banks in Japan, available from the Thompson DataStream database from 2001-2012. *Firm Size*= natural log of market capitalization. *Profitability*= Earnings before interest, taxes, depreciation and amortization /Total assets. *Leverage Ratio*= Total debt over total assets. *Capital Ratio*= book value of equity divided by total assets. All firm characteristics data are obtained from the DataStream database. *Time dummies* are a dummy variable that accounts for the year fixed effects (FE). **Standard errors** are displayed in parentheses below the **coefficients.** Time dummies are included but not shown. The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively. The baseline econometric model is:

$$\boldsymbol{\beta_{i,t} = \gamma_1 Firm\ size_{i,t} + \gamma_2 Profitability_{i,t} + \gamma_3 Leverage_{i,t} + \gamma_4 capital\ ratio_{i,t} + time\ dummies_{i,t} + \varepsilon_{i,t}}$$

	$\widehat{\boldsymbol{\beta}}^{c}$			$\widehat{\boldsymbol{\beta}}^{j}$		
Variables	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Firm Size	0.321***	0.312***	0.318***	0.421***	0.363***	0.421***
	(0.023)	(0.022)	(0.024)	(0.044)	(0.040)	(0.045)
Profitability	0.001***	0.001***	0.001***	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.008*		0.004	0.033***		0.034***
	(0.004)		(0.006)	(0.010)		(0.011)
Capital ratio		-0.006**	-0.004		-0.006	-0.001
		(0.003)	(0.003)		(0.004)	(0.005)
Constant	-3.311***	-2.439***	-2.876***	-6.156***	-2.480***	-6.219***
	(0.540)	(0.175)	(0.655)	(1.135)	(0.330)	(1.296)
N	6450	6450	6450	5194	5194	5194
Chi-squared	4053.5	4056.7	4056.5	1089.7	1077.4	1087.2
R-squared	**0.49**	**0.48**	**0.49**	**0.21**	**0.20**	**0.21**

Table 8: Betas and Firm Characteristics (The impact of GFC period)

This table represents the impact of the financial crisis on the relation between different betas and its determinants. D_t= GFC dummy which equals 1 for crisis period if the year is July 2007- May 2009 and otherwise zero to account for non-crisis period; $D_t \times X_{i.t}$= interaction term between GFC dummy (D_t) and each bank-specific variable $X_{i.t}$ (i.e. firm size, profitability, debt leverage, and capital ratio). *Time dummies are* a dummy variable that accounts for the year fixed effects (FE). **Standard errors** are displayed in parentheses below the **coefficients.** Time dummies are included but not shown. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$\widehat{\boldsymbol{\beta}}^{c}$			$\widehat{\boldsymbol{\beta}}^{j}$		
Variables	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Firm Size	0.320***	0.313***	0.313***	0.426***	0.374***	0.443***
	(0.023)	(0.022)	(0.024)	(0.043)	(0.039)	(0.041)
Profitability	0.001***	0.001***	0.001***	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Leverage	0.007		0.003	0.029***		0.028***
	(0.005)		(0.006)	(0.010)		(0.011)
Capital ratio		-0.005*	-0.004		-0.006	-0.003
		(0.003)	(0.003)		(0.004)	(0.004)
Profitability*GFC dummy	0.001**	0.001**	0.001**	-0.0001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Leverage*GFC dummy	-0.005		-0.007	0.029		0.044**

	(0.005)		(0.006)	(0.019)		(0.021)
Capitalratio*GFC dummy		-0.001	-0.002		0.005	0.014
		(0.002)	(0.002)		(0.008)	(0.009)
GFC dummy	0.575	0.085***	0.740	-2.748	0.022	-4.159**
	(0.511)	(0.018)	(0.572)	(1.808)	(0.064)	(2.021)
Constant	-3.211***	-2.450***	-2.701***	-5.825***	-2.573***	-5.872***
	(0.544)	(0.175)	(0.663)	(1.131)	(0.316)	(1.198)
N	6450	6450	6450	5194	5194	5194
Chi-squared	4155.3	4157.9	4153.4	1100.0	1092.5	1128.6
R-squared	**0.49**	**0.49**	**0.49**	**0.21**	**0.20**	**0.21**

Table 9: Unconditional Risk-Return trade-off for Individual Banks

The table reports estimates from unconditional panel regressions of monthly stock returns without splitting markets into up and downs for individual stocks on just their stock market betas (Beta), Size (in natural logarithm) and BM (in natural logarithm) over the whole sample period. The sample consists of 47 banks in Japan that are constituents of Nikki 225 index over the period of 2001-2012. Clustered **Standard errors** are displayed in parentheses below the **coefficients**. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Model				
Risk Premia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Standard Beta	0.007*				
	(0.004)				
Diffusion Beta		0.007*		0.006	0.005
		(0.004)		(0.004)	(0.004)
Jump Beta			0.003*	0.003*	0.003*
			(0.001)	(0.002)	(0.002)
Size					0.708
					(1.08)
BM					0.028***
					(0.007)
Constant	-0.009***	-0.008***	-0.009***	-0.009***	-0.088
	(0.002)	(0.002)	(0.002)	(0.002)	(0.131)
R-squared	**0.04**	**0.04**	**0.04**	**0.04**	**0.04**

Table 10: Risk-Return trade-off for Individual Banks during up and down markets

The table reports estimates from pooled regressions of monthly stock returns in up and down markets for individual stocks on just their stock market betas (Beta) over the whole sample period. The sample consists of 47 banks in Japan that are constituents of the Nikki 225 index over the period of 2001-2012. Clustered **Standard errors** are displayed in parentheses below the **coefficients**. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Model				
Risk Premia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Up Market				
Standard Beta	0.077***				
	(0.004)				
Diffusion Beta		0.089***		0.028***	0.015***
		(0.005)		(0.004)	(0.004)
Jump Beta			0.040***	0.033***	0.006***
			(0.003)	(0.003)	(0.002)
Size					0.328
					(0.207)
BM					-0.002
					(0.005)
	Down Market				
Standard Beta	-0.086***				
	(0.004)				
Diffusion Beta		-0.102***		-0.024***	-0.016***
		(0.005)		(0.006)	(0.006)
Jump Beta			-0.045***	-0.039***	-0.006**
			(0.004)	(0.004)	(0.003)
Size					-0.350*
					(0.200)
BM					-0.017***
					(0.002)
Constant	0.001	0.002	0.001	0.001	0.004
	(0.001)	(0.001)	(0.003)	(0.003)	(0.025)
R-squared	**0.45**	**0.29**	**0.43**	**0.44**	**0.57**

Table 11: Risk-Return trade-off for Individual Banks during up and down markets with a regime dependent constant term

The table reports premia estimates and their standard errors as in Table 2, but for different constant terms. Clustered **Standard errors** are displayed in parentheses below the **coefficients**. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Monthly Return	
Risk Premia	**Constant≠ 0**	**Constant=0**
	Up Market	
Diffusion Beta	0.013***	0.029***
	(0.004)	(0.005)
Jump Beta	0.005**	0.034***
	(0.002)	(0.002)
Constant	0.045***	-
	(0.002)	
	Down Market	
Diffusion Beta	-0.006	-0.024***
	(0.005)	(0.006)
Jump Beta	-0.008***	-0.038***
	(0.002)	(0.003)
Constant	-0.046***	-
	(0.003)	
R-Squared	**0.56**	**0.44**

Table 12: Risk-Return trade-off for Individual Banks during up and down markets: Sub Sample Analysis

The table reports premia estimates and their standard errors as in Table 2, but for different subsamples. Clustered **Standard errors** are displayed in parentheses below the **coefficients**. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Sample Periods		
Risk Premia	**Pre-crisis Period**	**Crisis Period**	**Post-Crisis Period**
	Up Market		
Diffusion Beta	0.035***	0.057***	0.006
	(0.007)	(0.008)	(0.005)
Jump Beta	0.040***	0.016***	0.046***
	(0.004)	(0.005)	(0.005)
	Down Market		
Diffusion Beta	-0.023***	-0.046***	-0.008
	(0.007)	(0.013)	(0.010)
Jump Beta	-0.038***	-0.022**	-0.041***
	(0.004)	(0.009)	(0.006)
Constant	0.001	-0.004	-0.009*
	(0.002)	(0.006)	(0.005)
R-Squared	**0.41**	**0.45**	**0.52**

Table 13: Test of Symmetry Hypothesis

The table report the t-statistic for testing the symmetry hypothesis between the risk premia $\gamma_{c\ up}$ *and* $\gamma_{j\ down}$ in up and down markets. Results are for the full testing period as well as sub sample periods. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A				
	Full Sample period t-statistic	Pre-crisis	Crisis	Post-crisis
$\gamma_{c\ up} + \gamma_{c\ down} = 0$	0.37	1.13	0.51	0.04
$\gamma_{j\ up} + \gamma_{j\ down} = 0$	0.61	0.08	0.24	0.20
Panel B				
	Full Sample period t-statistic	Pre-crisis	Crisis	Post-crisis
$\gamma_{c\ up} + \gamma_{j\ up} = 0$	0.50	0.22	15.64***	23.46***
$\gamma_{c\ down} + \gamma_{j\ down} = 0$	2.74*	1.75	1.37	5.17**

Table 14: Risk-Return trade-off for size-sorted stock portfolios during up and down markets

This table reports the estimates of the risk prices from pooled OLS regression using size sorted portfolios, which are rebalanced each year. **Standard errors** are displayed in parentheses below the **coefficients.** The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Size Sorted Portfolios (Quintiles)				
Premia	Small	2	3	4	Large
	Up Market				
Diffusion Beta	0.031***	0.022**	0.0320***	0.065***	0.054***
	(0.007)	(0.010)	(0.012)	(0.017)	(0.017)
Jump Beta	0.019***	0.039***	0.026***	0.034***	0.046***
	(0.006)	(0.007)	(0.005)	(0.007)	(0.008)
	Down Market				
Diffusion Beta	-0.049***	-0.021**	-0.033**	-0.065***	-0.050**
	(0.008)	(0.010)	(0.015)	(0.016)	(0.024)
Jump Beta	-0.028***	-0.035***	-0.045***	-0.032***	-0.042***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.013)
Constant	0.012**	-0.003	0.011***	0.003	0.007
	(0.005)	(0.005)	(0.004)	(0.004)	(0.007)

Table 15: Fama-Macbeth cross-sectional regressions

This table investigates the cross-sectional pricing of jump and continues risk in up and down markets. The sample period is from January 2001 to December 2012. We run Fama–MacBeth regressions of 12-month excess returns on contemporaneous realized betas. Observations are at the monthly frequency and we adjust standard errors accordingly using 2 Newey–West lags. Standard errors are displayed in parentheses below the coefficients. The asterisks *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Model				
Risk Premia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Up Market				
Standard Beta	0.025				
	(0.058)				
Diffusion Beta		0.004		0.002	0.025
		(0.086)		(0.020)	(0.026)
Jump Beta			0.037***	0.031***	-0.005
			(0.005)	(0.006)	(0.021)
Size					-0.006
					(0.219)
BM					-0.001
					(0.006)
	Down Market				
Standard Beta	-0.093***				
	(0.008)				
Diffusion Beta		-0.091***		-0.019	-0.067*
		(0.024)		(0.012)	(0.037)
Jump Beta			0.046***	-0.045***	-0.011
			(0.005)	(0.007)	(0.016)
Size					-0.377*
					(0.225)
BM					-0.017
					(0.017)
Constant	0.002	0.002	0.001	0.001	0.035
	(0.004)	(0.004)	(0.004)	(0.004)	(0.029)
R-squared	**0.40**	**0.29**	**0.39**	**0.45**	**0.55**

Table 16: Risk-Return trade-off for Individual Banks during up and down markets controlling explicitly for various bank-specific risk factors

This table uses to examine the relation between bank betas and bank stock returns in up and down markets for individual stocks over the whole sample period while controlling explicitly for various bank-specific risk factors. The sample consists of 47 banks in Japan that are constitutes of Nikki 225 index over the period of 2001-2012. *Firm Size*= natural log of market capitalization. *Profitability*= Earnings before interest, taxes, depreciation and amortization /Total assets. *Leverage Ratio*= Total debt over total assets. The regulatory capital ratios include: *Tier 1 Risk-Based Capital Ratio*= tier 1 capital over total risk-weighted assets, and *Market-valued Capital Ratio*= market value of equity divided by total assets. Clustered **Standard errors** are displayed in parentheses below the **coefficients.** The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively.

	Model			
Risk Premia	**(1)**	**(2)**	**(3)**	**(4)**
	Up Market			
Diffusion Beta				0.014**
				(0.006)
Jump Beta	0.005**	0.008***	0.005**	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Size			-0.498	-0.063
			(0.544)	(0.657)
BM			0.012*	0.014**
			(0.007)	(0.006)
Tier 1 Risk-Based Capital Ratio	-0.002*		-0.001	-0.001
	(0.001)		(0.001)	(0.001)
Market-valued Capital Ratio		0.043	-0.059	-0.081*
		(0.036)	(0.047)	(0.044)
Profitability	-0.046***	-0.031***	-0.050***	-0.050***
	(0.013)	(0.007)	(0.012)	(0.012)
Leverage	-0.089	0.004	0.071	0.022
	(0.054)	(0.040)	(0.099)	(0.106)
	Down Market			
Diffusion Beta				-0.010*
				(0.006)
Jump Beta	-0.004	-0.009***	-0.003	-0.002
	(0.003)	(0.002)	(0.004)	(0.004)
Size			0.819	0.517
			(0.553)	(0.526)
BM			-0.029***	-0.030***
			(0.006)	(0.006)
Tier 1 Risk-Based Capital Ratio	0.001		0.001	0.001
	(0.001)		(0.001)	(0.001)
Market-valued Capital Ratio		0.109**	0.161***	0.178***
		(0.048)	(0.045)	(0.044)
Profitability	0.016	0.002	0.027***	0.027***
	(0.010)	(0.009)	(0.009)	(0.010)
Leverage	-0.228***	-0.089**	-0.236**	-0.185*
	(0.054)	(0.039)	(0.105)	(0.106)
Cons	0.153***	0.043	0.059	0.049

	(0.052)	(0.037)	(0.070)	(0.072)
R-squared	**0.58**	**0.56**	**0.59**	**0.59**

Table 17: Ex-ante Risk-Return trade-off for Individual Banks during up and down markets

This table uses ex-ante measures of expected returns (instead of realized returns) to examine the relation between bank betas and bank stock returns in up and down markets for individual stocks over the whole sample period. The sample consists of 47 banks in Japan that are constitutes of Nikki 225 index over the period of 2001-2012. Clustered **Standard errors** are displayed in parentheses below the **coefficients**. The asterisks *, **, and *** indicate the significance at the 10%, 5%, and 1% level, respectively.

	Model	
Risk Premia	**(1)**	**(2)**
	Up Market	
Diffusion Beta	0.009**	0.005
	(0.004)	(0.006)
Jump Beta	0.005***	0.008***
	(0.002)	(0.002)
Size		0.124
		(0.293)
BM		-0.015**
		(0.007)
	Down Market	
Diffusion Beta	-0.006	-0.013***
	(0.005)	(0.005)
Jump Beta	-0.006**	-0.002
	(0.003)	(0.003)
Size		0.267
		(0.293)
BM		-0.0167***
		(0.005)
Cons	-0.002	-0.023
	(0.002)	(0.036)
R-squared	**0.02**	**0.03**

Table 18: Relationship between jump betas and liquidity

This table reports correlations between jump betas and liquidity. We investigate whether information embedded in jump betas is different from that in a liquidity proxy. As proxies for liquidity, we use the monthly trading volume, and monthly realized variances. The column denoted by "Full sample period" provides the correlations during the beta estimation period (January 2001 to December 2012), the column "Pre-crisis" shows those during the pre-crisis period, the column "Crisis" shows those during the pre-crisis period, and the column "Post-crisis" reports those during the expansion period.

Liquidity	Full Sample period	Pre-crisis	Crisis	Post-crisis
Volume	0.023	0.024	0.112	0.284
Variance	0.070	0.134	-0.070	-0.004

Figure 1: Intraday returns for the Nikkei 225 index at 5 minute frequency for 2001 through 2012.

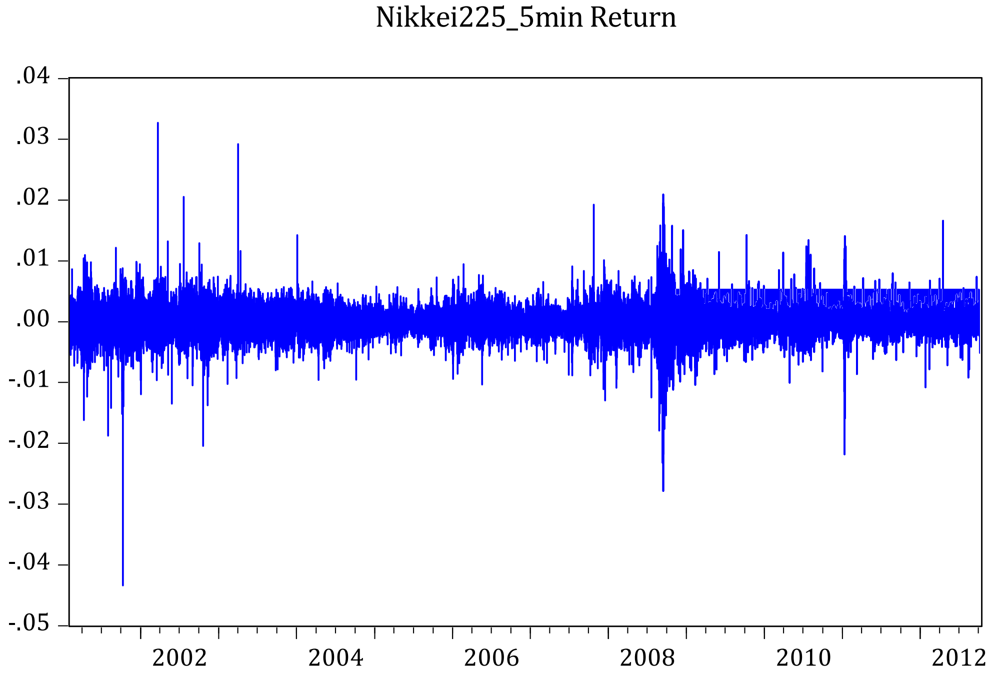


Figure 2: Realized Volatilities, Bipower Variations and Jumps

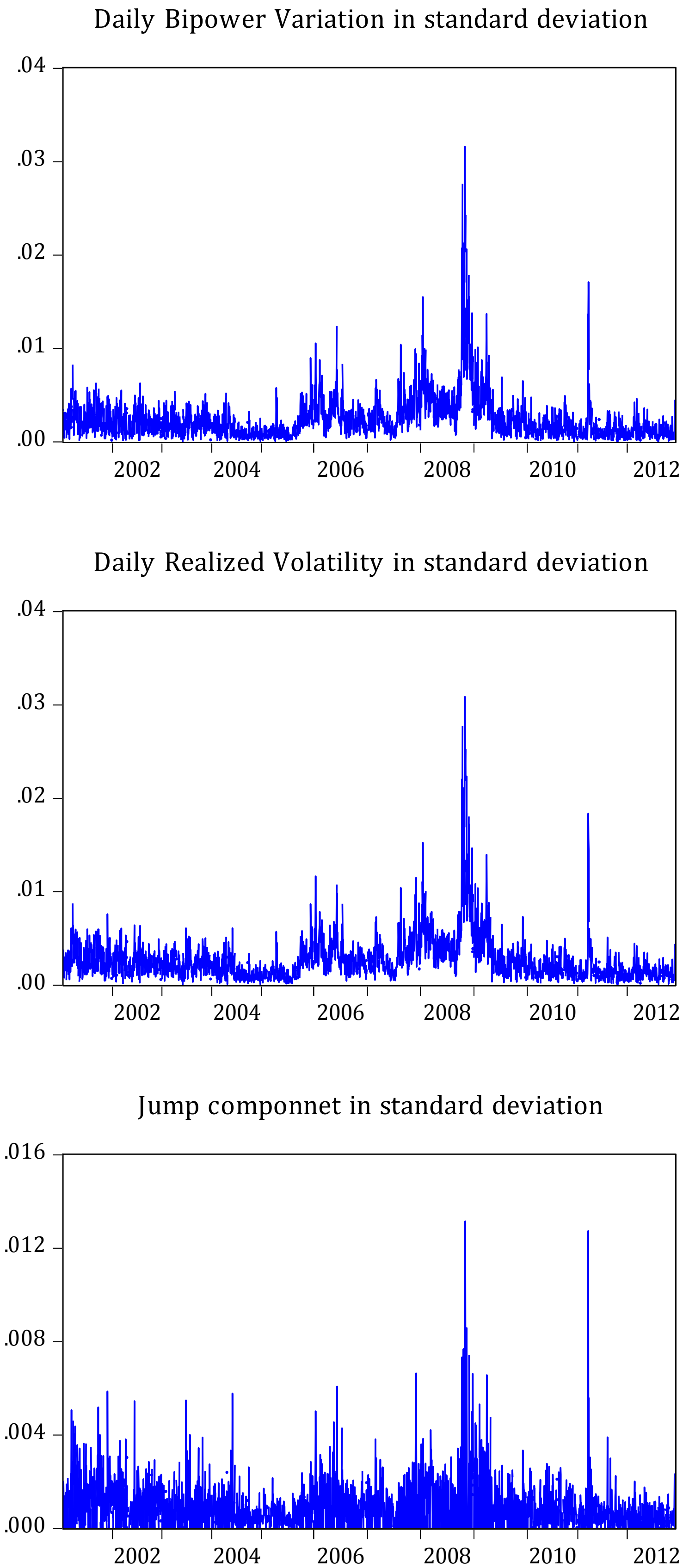


Figure 3: Cross-section monthly mean Betas for Continuous and Jump months

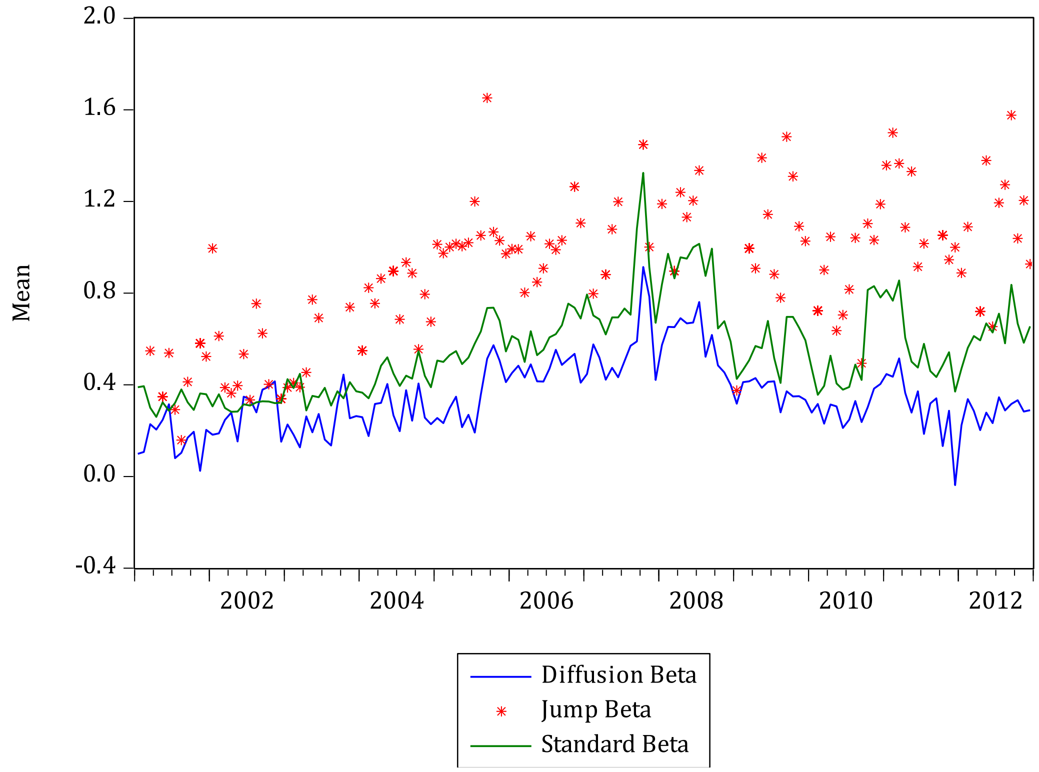
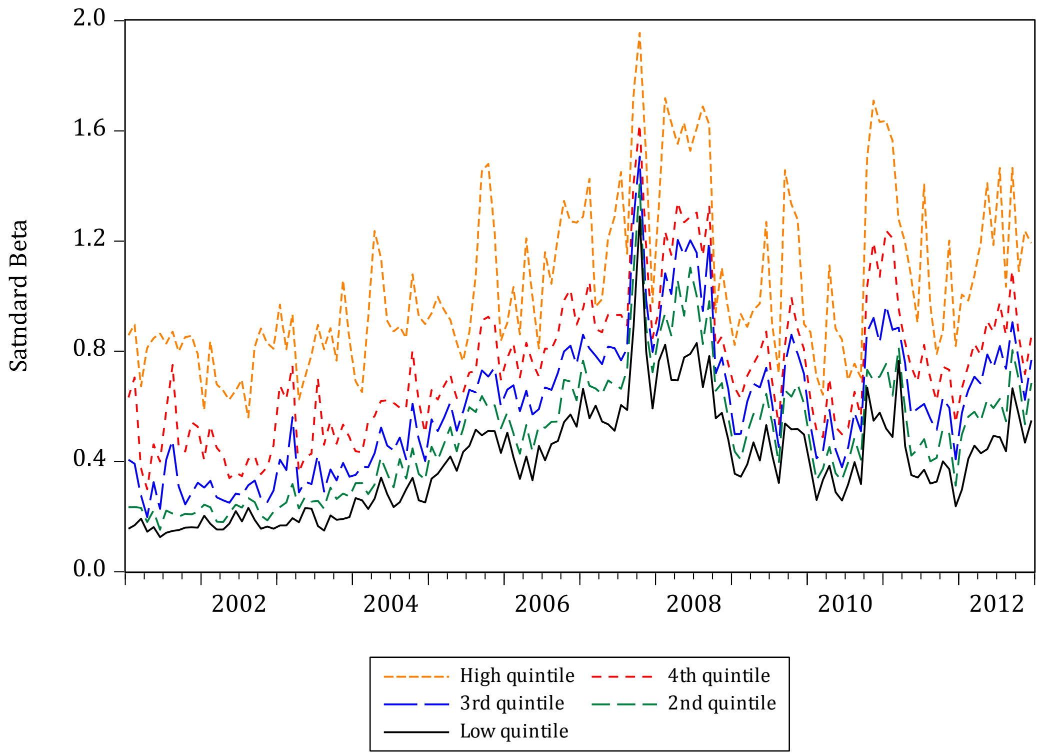


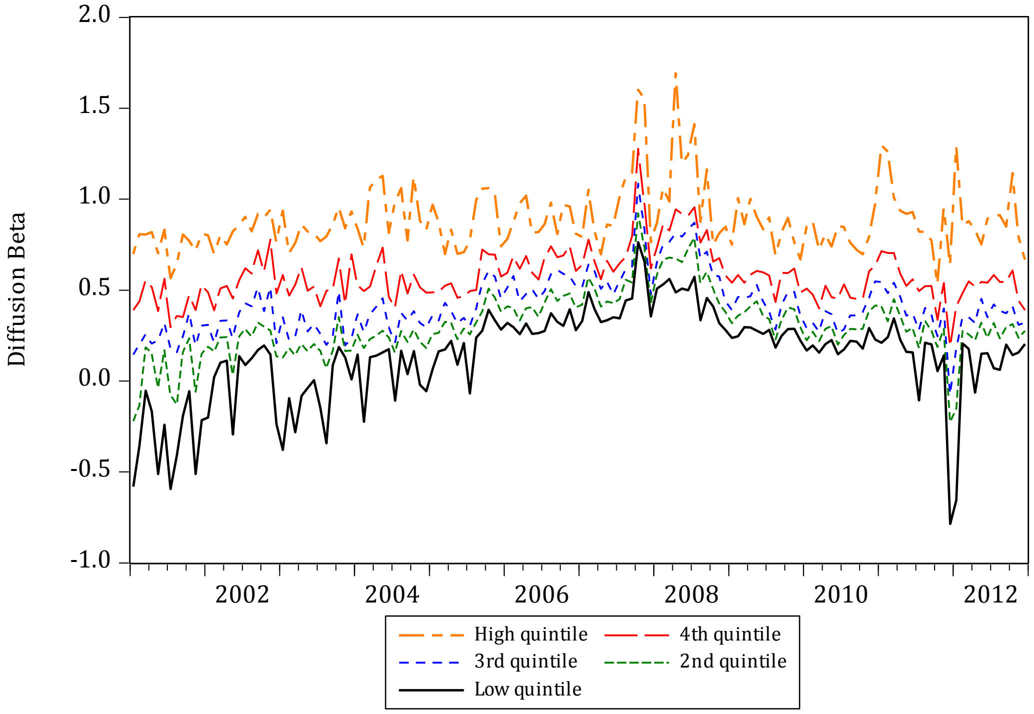
Figure 4: Time series plots of betas

The figure displays the time series of betas for equally weighted beta-sorted quintiles portfolios. Panel A shows the result for the standard beta sorted portfolios, Panel B the diffusion beta sorted portfolios and Panel C the jump beta sorted portfolios.

Panel (A): Standard beta



Panel (B): Diffusion beta



Panel (C): Jump beta