Empirical Application of Markov Chain Monte Carlo Method on Realized Stochastic Volatility Model with Long Memory

Abstract

This paper aims to compare the performance of the Realized Stochastic Volatility (RSV) model and RSV model with superpositions of two AR(1) processes (RSV-AR2). The daily returns and the realized volatilities data of the German Stock Index (DAX), the Nikkei Stock Average (Nikkei), and the Standard&Poor's 500 Stock Index (S&P500) during the period from 2000 to 2016 are selected to analyze the estimation results with regard to different stock markets. Empirical study shows that the RSV-AR2 model can account for long memory property of realized volatilities. Samples of parameters and latent volatilities are drawn from the respective conditional posterior distributions by using the Markov Chain Monte Carlo (MCMC) method. This paper also computes the logarithm of the marginal likelihood to make comparison between models, where the auxiliary particle filter is taken to compute the logarithm of conditional likelihood. Moreover, two widely used financial risk measures — the 1-day-ahead value-at-risk (VaR) and expected shortfall (ES) forecasts — are also estimated to evaluate the predictive ability of the corresponding models.

Although many studies have shown that the long memory property of the realized volatilities should be taken into account, model adaption among different financial markets should also be taken into consideration. Estimation results of this paper suggest that the RSV-AR2 model is superior in describing the long memory property than the basic RSV model, which the latter is unable to capture this property, however, RSV model outperforms RSV-AR2 model by comparing the logarithm of marginal likelihoods during the sample period.

1. Introduction

The return volatility, which is defined as the variance or standard deviation of return, provides crucial information in financial risk management and in asset pricing. As a nonparametric estimator of the return volatility, the realized volatility proposed by Andersen and Bollerslev (1998) and Barndorff-Nielsen and Shephard (2001) is widely used in the estimation of the volatility. In the ideal market assumption, this measure can be considered as a consistent estimator of the latent volatility. However, the influence of the non-trading hour and market microstructure noise (MMN) in the real market will cause the realized volatility to be a biased estimator.

Specifically, on account that the variance of the limited opening hours is taken as the one-day volatility, the non-trading hour problem will lead to an underestimation of the true volatility. Besides, the MMN, which is caused by many reasons such as discrete trading, bid-ask spread and variation in trade sizes (O'Hara (1995) and Hasbrouck (2007)), will become more significant as the time interval approach to zero.

To cope with these issues, Hansen and Lunde (2005) proposed the scaled realized volatility to avoid the underestimation, while Barndorff-Nielsen et al. (2008) introduce the realized kernel to account for the microstructure noise.

On the other hand, the SV framework, which models the daily returns and logarithm of volatilities with a nonlinear specification, is established as a parametric approach to estimate the unobserved volatilities. The basic SV model, however, is still insufficient since the information loss of daily return may exert a negative influence on the precision of the estimates.

In order to extend such model to be more applicable, Takahashi et al. (2009) developed a realized stochastic volatility (RSV) model, in which the realized volatilities data are incorporated with the daily returns data simultaneously. With the introduction of the realized volatility, which is defined as the sum of squared intraday returns over a certain interval, additional information from high frequency returns data are provided to adjust the bias caused by information loss of daily returns to a certain extent. Besides, the asymmetric phenomenon, which interprets the negative dependence between return at date t and volatility at date $t+1$, can also be captured by considering the correlation coefficient of disturbance terms to be a nonzero number.

Furthermore, the long memory property of realized volatility has also been investigated in many empirical studies. On the basis of RSV model, Koopman and Scharth (2013) considers the logarithm of volatility processes as superpositions of independent ARMA processes to account for the long range dependence.

Following Takahashi et al. (2009) and Koopman and Scharth (2013), this paper performs empirical studies on RSV model and RSV model with superposition using daily returns and realized volatilities of three stock indices from year 2000 to year 2016. These models are also applied to draw the samples of 1-day-ahead logarithm of volatilities from their posterior predictive distributions, as well as to estimate the 1-day-ahead VaR and ES forecasts of daily returns. Furthermore, this paper also uses the corresponding backtesting procedures for VaR and ES and calculates the logarithm of the marginal likelihood to make comparison between models.

The remaining sections of this paper are organized as follows. Model specifications are introduced in section 2. Section 3 illustrates the approaches of generation and model comparison, based on which the estimation results are given in section 4. Section 5 concludes the paper.

2. Model Specifications

2.1 Volatility and Realized Measures

The return volatility of date t is represented as the integral of the instantaneous volatility $\sigma^2(s)$ over the interval $(t, t+1)$:

$$IV_t = \int_t^{t+1} \sigma^2(s) ds. \tag{1}$$

Since this integrated volatility cannot be observed or computed using an analytical method, some substitute approaches are applied to obtain the numerical solution.

The realized volatility (RV), which is the sum of squared intraday returns over day t, is widely used as a nonparametric estimator of the latent volatility.

$$RV_t = \sum_{i=0}^{n-1} r_{t,i}^2, \tag{2}$$

where $\{r_{t,i}\}_{i=0}^{n-1}$ represents the intraday returns data of day t. In the real market, however, this estimator is unlikely to be able to consistent with the latent volatility.

On the one hand, as the time interval close to zero, the bias of this estimator will increase due to the presence of the microstructure noise. The realized kernel (RK) proposed by Barndorff-Nielsen et al. (2008), which takes the following form, is able to allow for microstructure noise.

$$RK_t = \sum_{h=-H}^{H} k\left(\frac{h}{H+1}\right) \gamma_h, \tag{3}$$

where γ_h represents the autocovariance at lag h with high frequency data $\{r_j\}$:

$$\gamma_h = \sum_{j=|h|+1}^{n} r_j r_{j-|h|}, \tag{4}$$

and weight $k(\,)$ represents the Parzen kernel function which defined as:

$$k(x) = \begin{cases} 1 - 6x^2 + 6x^3, & 0 \le x \le 1/2 \\ 2(1-x)^3, & 1/2 \le x \le 1 \\ 0, & x > 1 \end{cases}. \tag{5}$$

On the other hand, to deal with the underestimation caused by the non-trading hour, Hansen and Lunde (2005) proposed a scaled realized volatility, which is the product of the realized volatility and the ratio of the variance of the daily return to the mean of the realized volatility.

$$SRV_t = cRV_t, \qquad c = \frac{\sum_{t=1}^{T}(R_t - \bar{R})^2}{\sum_{t=1}^{T} RV_t}. \tag{6}$$

2.2 RSV Model

The basic RSV model proposed by Takahashi et al. (2009) is specified as follows.

$$R_t = \exp(h_t/2)\varepsilon_t, \qquad t = 1, \cdots, T, \tag{7}$$

$$h_{t+1} = \mu + \phi(h_t - \mu) + \eta_t, \qquad |\phi| < 1, \qquad t = 1, \cdots, T-1, \tag{8}$$

$$x_t = \xi + h_t + u_t, \tag{9}$$

$$h_1 \sim N\left(\mu, \sigma_\eta^2/(1-\phi^2)\right),$$

$$\begin{pmatrix} \varepsilon_t \\ \eta_t \\ u_t \end{pmatrix} \sim N(\mathbf{0}, \mathbf{\Sigma}), \mathbf{\Sigma} = \begin{pmatrix} 1 & \rho\sigma_\eta & 0 \\ \rho\sigma_\eta & \sigma_\eta^2 & 0 \\ 0 & 0 & \sigma_u^2 \end{pmatrix}.$$

where R_t denotes the daily return and h_t denotes the logarithm of latent volatility at date t. Suppose that $(h_t - \mu)$ follows a stationary AR(1) process and the starting value h_1 follows a Gaussian distribution with the unconditional mean and variance of h_t. The disturbance terms ε_t and η_t are assumed to follow a bivariate normal distribution and ρ captures the dependence between R_t and h_{t+1}. x_t represents the logarithm of realized volatility at date t. In this asymmetric RSV model, the bias caused by microstructure noise and non-trading hours, which are considered to be two major factors that interfere with the accuracy of realized volatility, is modified by adding a constant term ξ in expression (9). A positive ξ displays an upward bias of realized volatility caused by the market microstructure noise, while a negative ξ shows a downward bias of realized volatility caused by the non-trading hours.

Let $\boldsymbol{\theta}$ be the parameter vector $\left(\mu, \phi, \xi, \rho, \sigma_\eta^2, \sigma_u^2\right)'$, $f(\boldsymbol{R},\boldsymbol{X} \,|\, \boldsymbol{\theta}, \boldsymbol{h})$ be the conditional joint probability density function where $\boldsymbol{R}=(R_1,R_2,\cdots,R_T)'$, $\boldsymbol{X}=(x_1,x_2,\cdots,x_T)'$, $\boldsymbol{h}=(h_1,h_2,\cdots,h_T)'$, respectively. Suppose that the disturbance terms ε_t and η_t follow a bivariate normal distribution, then the conditional posterior density for $\boldsymbol{\theta}$ and $\boldsymbol{h}$ is thus

$$\begin{aligned}
&\pi(\boldsymbol{\theta},\boldsymbol{h}|\boldsymbol{R},\boldsymbol{X}) \propto l(\boldsymbol{R},\boldsymbol{X},\boldsymbol{h}|\boldsymbol{\theta})\pi(\boldsymbol{\theta})\\
&\qquad\propto \exp\left\{-\frac{1}{2}\sum_{t=1}^{T}[h_t-R_t^2\exp(-h_t)]\right\}\times(\sigma_u^2)^{-\frac{T}{2}}\exp\left\{-\frac{(x_t-\xi-h_t)^2}{2\sigma_u^2}\right\}\\
&\qquad\times\sqrt{1-\phi^2}\left(\sigma_\eta^2\right)^{-\frac{T}{2}}(1-\rho^2)^{-\frac{T-1}{2}}\exp\left\{-\frac{1}{2\sigma_\eta^2}(1-\phi^2)(h_1-\mu)^2\right.\\
&\qquad\left.-\sum_{t=1}^{T-1}\frac{\left[h_{t+1}-(1-\phi)\mu-\phi h_t-\rho\sigma_\eta\exp(-h_t/2)R_t\right]^2}{2\sigma_\eta^2(1-\rho^2)}\right\}\pi(\boldsymbol{\theta}).
\end{aligned}$$

where $\propto$ is the symbol for proportionality and $\pi(\boldsymbol{\theta})=\pi(\mu)\pi(\phi)\pi(\xi)\pi(\rho)\pi\left(\sigma_\eta^2\right)\pi(\sigma_u^2)$.

2.3 RSV Model with Long Memory

To describe the long range dependence of the volatility process, Koopman and Scharth (2013) extended the RSV model by providing that the realized volatilities are superposed with a selected number of ARMA processes.

The previous studies have shown that the superpositions of two or three autoregressive processes are adequate to describe the long memory property of realized volatility. To balance the efficiency and comprehensiveness of the model, this paper uses an asymmetric RSV framework, which involves binary stationary AR(1) processes (which is referred to as a RSV-AR2 model in what follows) to evaluate the latent volatilities and parameters. Following Koopman and Scharth (2013), the RSV-AR2 model is defined as

$$R_t=\exp\left(\frac{h_{1t}+h_{2t}}{2}\right)\varepsilon_t,\qquad t=1,\cdots,T, \tag{10}$$

$$h_{1,t+1}=\mu+\phi_1(h_{1t}-\mu)+\eta_{1t},\qquad t=1,\cdots,T-1, \tag{11}$$

$$h_{2,t+1}=\phi_2 h_{2t}+\eta_{2t},\qquad t=1,\cdots,T-1, \tag{12}$$

$$x_t=\xi+h_{1t}+h_{2t}+u_t,\qquad t=1,\cdots,T, \tag{13}$$

$$h_{11}\sim N\left(\mu,\sigma_{\eta_1}^2/(1-\phi_1^2)\right),\qquad h_{21}\sim N\left(0,\sigma_{\eta_2}^2/(1-\phi_2^2)\right),$$

$$\begin{pmatrix}\varepsilon_t\\ \eta_{1t}\\ \eta_{2t}\\ u_t\end{pmatrix}\sim N(\boldsymbol{0},\boldsymbol{\Sigma}),\boldsymbol{\Sigma}=\begin{pmatrix}1 & \rho_1\sigma_{\eta_1} & \rho_2\sigma_{\eta_2} & 0\\ \rho_1\sigma_{\eta_1} & \sigma_{\eta_1}^2 & 0 & 0\\ \rho_2\sigma_{\eta_2} & 0 & \sigma_{\eta_2}^2 & 0\\ 0 & 0 & 0 & \sigma_u^2\end{pmatrix}.$$

where the logarithm of volatility is considered as superpositions of h_{1t} and h_{2t} to account for the long range dependence. ρ_1 and ρ_2 with constraint $\rho_1^2 + \rho_2^2 < 1$ capture the correlations of $(\varepsilon_t, \eta_{1t})$ and $(\varepsilon_t, \eta_{2t})$, respectively. The persistence coefficients are assumed to be $|\phi_1| < |\phi_2| < 1$ to ensure that (11) and (12) are stationary processes.

3. Generation Algorithm and Model Evaluation

3.1 Generation Algorithm

Given the respective prior distributions, the samples of the parameters and latent volatilities can be generated from the respective posterior distributions via the Bayesian based MCMC approach. Specifically, the RSV-AR2 model can be estimated by repeating the following generation steps of (1) – (5).

(1). Generate ϕ from $\pi\left(\phi \middle| \mu, \rho, \sigma_\eta^2, \boldsymbol{h}, \boldsymbol{R}\right)$.

(2). Generate $\left(\mu, \rho, \sigma_\eta^2\right)$ from $\pi\left(\mu, \rho, \sigma_\eta^2 \middle| \phi, \boldsymbol{h}, \boldsymbol{R}\right)$.

(3). Generate ξ from $\pi(\xi | \sigma_u^2, \boldsymbol{h}, \boldsymbol{X})$.

(4). Generate σ_u^2 from $\pi(\sigma_u^2 | \xi, \boldsymbol{h}, \boldsymbol{X})$.

(5). Generate $\boldsymbol{h}$ from $\pi(\boldsymbol{h} | \boldsymbol{\theta}, \boldsymbol{R}, \boldsymbol{X})$.

The generation methods of (ξ, σ_u^2) are straightforward in view of the natural conjugate of prior distributions. $\left(\phi, \mu, \rho, \sigma_\eta^2\right)$ are generated via the Metropolis-Hastings (MH) algorithm. In particular, considering that the existence of high autocorrelation in the latent volatilities may bring about inefficient MCMC samples, the block sampler, which is proposed by Omori and Watanabe (2008), is applied to improve the generation efficiency, and a linear Gaussian state space representation is established to explore the posterior mode of the volatilities in this paper.

Let $\boldsymbol{h}_1 = (h_{11}, h_{12}, \cdots, h_{1T})'$ and $\boldsymbol{h}_2 = (h_{21}, h_{22}, \cdots, h_{2T})'$. In the RSV-AR2 model, the values of $\boldsymbol{h}_2$ are considered as constants when $\mathbf{h}_1$ are generated and vice versa, therefore the generation procedures (1) – (5) can also be used to generate the parameters $\left(\mu, \phi_1, \rho_1, \sigma_{\eta_1}^2, \boldsymbol{h}_1\right)$ and only several steps are added to generate $\left(\rho_2, \sigma_{\eta_2}^2, \boldsymbol{h}_2\right)$. The generation algorithm for RSV-AR2 model is showed in appendix A in detail.

3.2 Logarithm of Marginal Likelihood

This subsection uses expression (14) to compute the logarithm of marginal likelihood

$\log m(\boldsymbol{R}, \boldsymbol{X})$, whose value is usually applied to evaluate the performance of the model, where a larger value corresponds to a superior performance of a particular model.

$$\log m(\boldsymbol{R}, \boldsymbol{X}) = \log l(\boldsymbol{R}, \boldsymbol{X}|\boldsymbol{\theta}) + \log \pi(\boldsymbol{\theta}) - \log \pi(\boldsymbol{\theta}|\boldsymbol{R}, \boldsymbol{X}). \qquad (14)$$

It is straightforward to calculate $\log \pi(\boldsymbol{\theta})$ by substituting the estimated parameters into the logarithm of prior density. Following Chib (1995) and Chib and Jeliazkov (2001), the logarithm of conditional posterior density $\log \pi(\boldsymbol{\theta}|\boldsymbol{R}, \boldsymbol{X})$ at $\boldsymbol{\theta}^*$ can be evaluated by applying the MCMC method where $\boldsymbol{\theta}^*$ is the estimation results of the posterior means.

The following will illustrate the algorithm of auxiliary particle filter (APF), which is applied to compute the logarithm of likelihood $\log l(\boldsymbol{R}, \boldsymbol{X}|\boldsymbol{\theta})$.

Let $\boldsymbol{R}_t = (R_1, \cdots, R_t)'$, $\boldsymbol{X}_t = (x_1, \cdots, x_t)'$, then the conditional probability density of the observations (R_t, x_t) takes the form of

$$l(R_t, x_t|h_t, \boldsymbol{\theta}) = \frac{1}{2\pi\sigma_u} \exp\left\{-\frac{1}{2}[h_t - R_t^2 \exp(-h_t)] - \frac{1}{2\sigma_u^2}(x_t - \xi - h_t)^2\right\},$$

and the conditional state density given the previous state and observations is

$$f(h_{t+1}|h_t, \boldsymbol{R}_t, \boldsymbol{X}_t, \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi(1-\rho^2)}\sigma_\eta} \exp\left\{-\frac{(h_{t+1} - \mu_{t+1})^2}{2(1-\rho^2)\sigma_\eta^2}\right\},$$

where $\mu_{t+1} = \mu + \phi(h_t - \mu) + \rho\sigma_\eta \exp(-h_t/2) R_t$. To apply the APF method, an index i is introduced and samples are drawn from the joint density $f(h_{t+1}, i|\boldsymbol{R}_t, \boldsymbol{X}_t, \boldsymbol{\theta})$, which is defined as

$$f(h_{t+1}, i|\boldsymbol{R}_t, \boldsymbol{X}_t, \boldsymbol{\theta}) \propto f(R_{t+1}, x_{t+1}|h_{t+1}) f(h_{t+1}|h_t, \boldsymbol{R}_t, \boldsymbol{X}_t, \boldsymbol{\theta}) \pi_t^{(i)}, \ \ i = 1, \cdots, I,$$

where $\pi_t^{(i)}$ denotes the normalized weight, which is also called the first stage weight. The index i is called an auxiliary variable as it is present simply to aid the task of the simulation (Pitt and Shephard (1999)). This joint density can be approximated by an importance function

$$g(h_{t+1}, i|\boldsymbol{R}_t, \boldsymbol{X}_t, \boldsymbol{\theta}) \propto f\left(h_{t+1}\middle|h_t^{(i)}, \boldsymbol{R}_t, \boldsymbol{X}_t, \boldsymbol{\theta}\right) g(i|\boldsymbol{R}_{t+1}, \boldsymbol{X}_{t+1}, \boldsymbol{\theta}).$$

In principle, samples from $g(h_{t+1}, i|\boldsymbol{R}_t, \boldsymbol{X}_t, \boldsymbol{\theta})$ can be obtained by simulating the index i with probability $\pi_t^{(i)}$, which is proportional to $g(i|\boldsymbol{R}_{t+1}, \boldsymbol{X}_{t+1}, \boldsymbol{\theta})$, and h_{t+1} from the transition density $f\left(h_{t+1}\middle|h_t^{(i)}, \boldsymbol{R}_t, \boldsymbol{X}_t, \boldsymbol{\theta}\right)$. Then resampling $\left(h_{t+1}^{(i)}, i\right)$ with the reweighted probability $\pi_{t+1}^{(i)}$, which is called the second stage weight. Finally, discard the index and therefore the resampled particles are from $f(h_{t+1}|\boldsymbol{R}_t, \boldsymbol{X}_t, \boldsymbol{\theta})$.

Algorithm for the APF is as follows:

Step 1. Initialization. For $t = 1$:

1-a. For $i = 1, \cdots, I$: Generate $h_1^{(i)} \sim N\left(\mu, \sigma_\eta^2/(1-\phi^2)\right)$ and compute

$$l\left(R_1, x_1 \middle| h_1^{(i)}, \boldsymbol{\theta}\right) = \frac{1}{2\pi\sigma_u} \exp\left\{-\frac{1}{2}\left[h_1^{(i)} - R_1^2 \exp\left(-h_1^{(i)}\right)\right] - \frac{1}{2\sigma_u^2}\left(x_1 - \xi - h_1^{(i)}\right)^2\right\},$$

$$w_1^{(i)} = l\left(R_1, x_1 \middle| h_1^{(i)}, \boldsymbol{\theta}\right),$$

$$\mu_2^{(i)} = \mu + \phi\left(h_1^{(i)} - \mu\right) + \rho\sigma_\eta \exp\left(-h_1^{(i)}/2\right) R_1,$$

$$l\left(R_2, x_2 \middle| \mu_2^{(i)}, \boldsymbol{\theta}\right) = \frac{1}{2\pi\sigma_u} \exp\left\{-\frac{1}{2}\left[\mu_2^{(i)} - R_2^2 \exp\left(-\mu_2^{(i)}\right)\right] - \frac{1}{2\sigma_u^2}\left(x_2 - \xi - \mu_2^{(i)}\right)^2\right\}.$$

1-b. Record

$$\bar{w}_1 = \frac{1}{I}\sum_{i=1}^{I} w_1^{(i)}.$$

1-c. For $i = 1, \cdots, I$: Normalize the importance weights to

$$\pi_2^{(i)} = \frac{w_1^{(i)}}{\sum_{j=1}^{I} w_1^{(j)}}.$$

1-d. For $i = 1, \cdots, I$: Introduce the index i as an auxiliary variable and compute

$$g(i|R_2, x_2, \boldsymbol{\theta}) = \frac{l\left(R_2, x_2 \middle| \mu_2^{(i)}, \boldsymbol{\theta}\right)\pi_2^{(i)}}{\sum_{j=1}^{I}\left(R_2, x_2 \middle| \mu_2^{(j)}, \boldsymbol{\theta}\right)\pi_2^{(j)}}.$$

Step 2. Iteration. For $t = 2, \cdots T$:

2-a. For $i = 1, \cdots, I$: Generate $\pi_t^{(k^{(i)})}$ from a discrete uniform distribution of which the elements are $\left(\pi_t^{(1)}, \cdots, \pi_t^{(I)}\right)$, and $k^{(i)}$ is the sequence number of the selected weight. Generate $h_t^{(i)} \sim N\left(\mu_t^{(k^{(i)})}, \sigma_\eta^2(1-\rho^2)\right)$. Then compute the following values

$$l\left(R_t, x_t \middle| h_t^{(i)}, \boldsymbol{\theta}\right)$$
$$= \frac{1}{2\pi\sigma_u} \exp\left\{-\frac{1}{2}\left[h_t^{(i)} - R_t^2 \exp\left(-h_t^{(i)}\right)\right] - \frac{1}{2\sigma_u^2}\left(x_t - \xi - h_t^{(i)}\right)^2\right\},$$

$$w_t^{(i)} = l\left(R_t, x_t \middle| h_t^{(i)}, \boldsymbol{\theta}\right) k^{(i)} / g\left(k^{(i)} \middle| R_t, x_t, \boldsymbol{\theta}\right),$$

$$\mu_{t+1}^{(i)} = \mu + \phi\left(h_t^{(i)} - \mu\right) + \rho\sigma_\eta \exp\left(-h_t^{(i)}/2\right) R_t,$$

$$l\left(R_{t+1}, x_{t+1} \middle| \mu_{t+1}^{(i)}, \boldsymbol{\theta}\right)$$
$$= \frac{1}{2\pi\sigma_u} \exp\left\{-\frac{1}{2}\left[\mu_{t+1}^{(i)} - R_{t+1}^2 \exp\left(-\mu_{t+1}^{(i)}\right)\right] - \frac{1}{2\sigma_u^2}\left(x_{t+1} - \xi - \mu_{t+1}^{(i)}\right)^2\right\}.$$

2-b. Record

$$\bar{w}_t = \frac{1}{I}\sum_{i=1}^{I} w_t^{(i)}.$$

2-c. For $i = 1, \cdots, I$: Normalize the importance weights to

$$\pi_{t+1}^{(i)} = \frac{w_t^{(i)}}{\sum_{j=1}^{I} w_t^{(j)}}.$$

2-d. For $i = 1, \cdots, I$: Compute

$$g(i|R_{t+1}, x_{t+1}, \boldsymbol{\theta}) = \frac{l\left(R_{t+1}, x_{t+1}\middle|\mu_{t+1}^{(i)}, \boldsymbol{\theta}\right)\pi_{t+1}^{(i)}}{\sum_{j=1}^{I}\left(R_{t+1}, x_{t+1}\middle|\mu_{t+1}^{(j)}, \boldsymbol{\theta}\right)\pi_{t+1}^{(j)}}.$$

Step 3. As $I \to \infty$, the consistent estimator of logarithm of likelihood $\log l(\boldsymbol{R}, \boldsymbol{X}|\boldsymbol{\theta})$ is then $\sum_{t=1}^{T}\log\bar{w}_t$.

3.3 VaR and ES

The one-day-ahead VaR forecast of date $t+1$ given the information up to date t $(\boldsymbol{I}_t)$ with probability α is defined as

$$Pr(R_{t+1} < VaR_{t+1}(\alpha)|\boldsymbol{I}_t) = \alpha. \quad (15)$$

In spite of its extensive utilization in the area of financial risk management, VaR is a yet imperfect measure for the reason that it simply discusses the quantile of the returns distribution and overlooks the information of the tail distribution. This problem is settled by developing another measure referred to as ES to account for the returns distribution that is beyond the quantile. The one-day-ahead ES forecast of R_{t+1} with probability α is given by

$$ES_{t+1}(\alpha) = E[R_{t+1} < VaR_{t+1}(\alpha), \boldsymbol{I}_t]. \quad (16)$$

By applying the previous T_0 observations to the RSV model recursively, the one-day-ahead VaR forecasts $\{VaR_{T_0+i}\}_{i=1}^{T_f}$ and one-day-ahead ES forecasts $\{ES_{T_0+i}\}_{i=1}^{T_f}$ are able to be calculated according to the following algorithm, where $T_f = T - T_0$ represents the number of VaR or ES forecasts.

Step 1. Set $i = 1$.

Step 2. Generate $\boldsymbol{\theta}^i = \left(\mu^i, \phi^i, \rho^i, \sigma_\eta^{i\,2}, \xi^i, \sigma_u^{i\,2}\right)'$ and $\boldsymbol{h}^i = \left(h_1^i, h_2^i, \cdots, h_{T_0}^i\right)'$ from the joint conditional posterior density $\pi\left(\boldsymbol{\theta}^i, \boldsymbol{h}^i \middle| \boldsymbol{R}, \boldsymbol{X}\right)$.

Step 3. Generate the sample of logarithm of one-day-ahead volatility from the posterior predictive distribution:

$$h_{T_0+1}^i \big| \cdot \sim N\left(\mu_{T_0+1}^i, \sigma_{T_0+1}^{i2}\right),$$

where the conditional mean and variance are given by

$$\mu_{T_0+1}^i = \mu^i + \phi^i\left(h_{T_0}^i - \mu^i\right) + \rho^i \sigma_\eta^i R_t \exp\left(-h_{T_0}^i/2\right), \quad \sigma_{T_0+1}^{i2} = \sigma_\eta^{i\,2}\left(1 - \rho^{i\,2}\right).$$

Step 4. Compute $VaR_{T_0+i}(\alpha) = \exp\left(h_{T_0+1}^i/2\right) z_i(\alpha)$, where $z_i(\alpha)$ is the α-quantile of the returns distribution.

Step 5. Randomly generate M samples of z_i from the returns distribution, where M is set to be a sufficiently large enough number, and compute the corresponding $\left\{R_{T_0+i}^m\right\}_{m=1}^M$ using $R_{T_0+i} = \exp\left(h_{T_0+1}^i/2\right) z_i$.

Step 6. Calculate $ES_{T_0+i}(\alpha) = E\left[R_{T_0+i}^m < VaR_{T_0+i}(\alpha), \boldsymbol{I}_{T_0+i-1}\right]$, which is the average of the violated R_{T_0+i}.

Step 7. Set $i = i + 1$, repeat from Step 2 if $i < T_f$ and end if $i = T_f$.

This algorithm is also available for RSV-AR2 model simply by substituting the parameter vector $\left(\mu, \phi, \rho, \sigma_\eta^2, \xi, \sigma_u^2\right)'$ to $\left(\mu, \phi_1, \phi_2, \rho_1, \rho_2, \sigma_{\eta_1}^2, \sigma_{\eta_2}^2, \xi, \sigma_u^2\right)'$.

The following backtesting methods are widely used to investigate the robustness of the predicted VaR and ES estimates.

Suppose that the number of the violated VaR forecasts among $\left\{VaR_{T_0+i}(\alpha)\right\}_{i=1}^{T_f}$ is T_v. Then the empirical failure rate (EFR) can be written as $EFR = T_v/T_f$. This paper calculates the following likelihood ratio (LR) statistic (Kupiec (1995)), which is asymptotically distributed as a $\chi^2(1)$ under the condition that the null hypothesis of $EFR = \alpha$ is true, to investigate the robustness of the predicted VaR estimates.

$$LR = 2\{\log[EFR^{T_v}(1-EFR)^{T_f-T_v}] - \log[\alpha^{T_v}(1-\alpha)^{T_f-T_v}]\}. \tag{17}$$

The measure $D(\alpha)$ proposed by Embrechts et al. (2005) is used to backtest the ES forecasts. Specifically, define $\delta_t(\alpha) = R_t - ES_t(\alpha)$ and denote $q(\alpha)$ as the empirical α-quantile of $\delta_t(\alpha)$. Let $\kappa_1(\alpha)$ and $\kappa_2(\alpha)$ be the sets of time points for which $\delta_t(\alpha) < 0$ occurs and $\delta_t(\alpha) < q(\alpha)$ occurs, respectively. Suppose that the respective number of $\kappa_1(\alpha)$ and $\kappa_2(\alpha)$ are counted to be T_1 and T_2, then the measure is written as

$$D(\alpha) = \frac{1}{2}(|D_1(\alpha)| + |D_2(\alpha)|), \tag{18}$$

where

$$D_1(\alpha) = \frac{1}{T_1}\sum_{t\in\kappa_1(\alpha)} \delta_t(\alpha), \quad D_2(\alpha) = \frac{1}{T_2}\sum_{t\in\kappa_2(\alpha)} \delta_t(\alpha). \tag{19}$$

This measure considers to average the absolute values of the standard backtesting measure $D_1(\alpha)$ and the penalty term $D_2(\alpha)$. A lower value of $D(\alpha)$ indicates better ES forecasts.

4.Empirical Studies

4.1 Data and Descriptive Statistics

To investigate the common features and typical characteristics with respect to different stock indices, this paper applies the daily returns and 5-minute realized volatilities of DAX, Nikkei, S&P500 to the RSV model and the RSV-AR2 model, respectively. The data are provided by Oxford-Man Institute’s Realized Library (Heber et al. (2009)), and the sample period is from January 3, 2000 to December 31, 2016. Table 1 summarizes the descriptive statistics of daily returns (in percentages) and the logarithm of realized volatilities (log*RV*) for the respective stock indices. The computational results are generated by using the MATLAB_R2015b software.

Table 1. Descriptive Statistics

	Mean	Stdev	Skew	Kurt	Min	Max	LB(10)
				DAX			
return	-0.0317	1.3257	-0.0908	7.7942	-9.4122	9.9934	0.38
logRV	0.0123	1.0167	0.3629	3.2018	-3.2246	4.0747	0.00
				Nikkei			
return	-0.0354	1.1831	-0.5466	13.5500	-10.5634	11.6581	0.43
logRV	-0.3240	0.8793	0.3302	3.5542	-2.9454	3.4747	0.00
				S&P500			
return	0.0090	1.1874	-0.1673	10.6668	-9.3511	10.2202	0.10
logRV	-0.5161	1.0835	0.4414	3.3805	-4.1221	4.3500	0.00

NOTE: Sample period is from January 3, 2000 to December 30, 2016 and sample sizes are 4301 (DAX), 4116 (Nikkei), 4247 (S&P500). LB(10) shows the *p* value of the Ljung-Box statistic up to 10 lags for the returns and realized measures where the heteroskedasticity is corrected following Diebold (1988).

For daily returns of an arbitrary stock index, the mean is not statistically significant from zero and the LB(10) statistic does not reject the null hypothesis of no autocorrelation at the 5% significance level, which indicates that the daily returns can be used directly without adjusting the mean and autocorrelation. In contrast, the small p-value of LB(10) statistic in logRV suggests that the latent volatilities are serially correlated. Therefore, it is reasonable to consider a RSV model with long memory.

4.2 Estimation Results

This paper applies the RSV model and the RSV-AR2 model to the three stock indices, respectively, where 5000 samples of the parameters and volatilities are generated via the methodology introduced in Section 3, after discarding 5000 samples as the burn-in period. The estimation results for respective stock indices are summarized in the following tables.

Table 2. Estimation results of RSV model

	Mean	Stdev	95% interval	CD	IF
			DAX (logml= -10900.10)		
μ	0.0746	0.0283	[0.0195,0.1302]	0.96	2.10
ϕ	0.9859	0.0003	[0.9852,0.9866]	0.55	12.02
ρ	-0.5198	0.0181	[-0.5562,-0.4854]	0.44	12.96
σ_η^2	0.0337	0.0008	[0.0322,0.0353]	0.72	5.65
ξ	-0.1266	0.0197	[-0.1655,-0.0878]	0.68	2.46
σ_u^2	0.3976	0.0133	[0.3710,0.4245]	0.41	4.30
			Nikkei (logml= -13054.01)		
μ	0.4580	0.0322	[0.3934,0.5193]	0.55	2.28
ϕ	0.9895	0.0005	[0.9884,0.9903]	0.29	4.46
ρ	-0.4427	0.0200	[-0.4808,-0.4042]	0.27	10.74
σ_η^2	0.0311	0.0010	[0.0292,0.0333]	0.33	5.65
ξ	-0.2555	0.0250	[-0.3050,-0.2060]	0.70	1.99
σ_u^2	0.4517	0.0169	[0.4181,0.4848]	0.32	3.47
			S&P500 (logml= -12992.87)		
μ	0.5039	0.0321	[0.4396,0.5664]	0.99	2.34
ϕ	0.9840	0.0009	[0.9821,0.9855]	0.70	7.29
ρ	-0.5352	0.0173	[-0.5684,-0.4995]	0.63	7.13
σ_η^2	0.0515	0.0025	[0.0472,0.0570]	0.62	9.57
ξ	-0.2906	0.0270	[-0.3423,-0.2374]	0.72	1.05
σ_u^2	0.4699	0.0194	[0.4312,0.5074]	0.77	1.85

Tables 2 - 3 describe the posterior means (Mean), the standard deviations of the posterior means (Stdev), the 95% Bayesian credible intervals (95% interval), the *p* values of the convergence diagnostic statistic (CD), and the inefficiency factors (IF) for respective stock indices and respective models. Specifically, the CD statistic tests whether the samples converge to the posterior distributions after the burn-in period, and the IF quantifies the relative efficiency loss under the corresponding generation methods. Besides, the results of logarithm of marginal likelihoods (logml) are also reported in the Tables for model comparison.

According to the estimation results, the null hypothesis that the recorded samples converge to the posterior distribution is not rejected at the 5% significance level for all parameters, and meantime the values of IF are relatively small (less than 15), which exhibit a robust and efficient generation method applied in this paper.

Table 3. Estimation results of RSV-AR2 model

	Mean	Stdev	95% interval	CD	IF
			DAX (logml= -12842.44)		
μ	0.0990	0.0218	[0.0555,0.1430]	0.86	1.50
ϕ_1	0.9576	0.0002	[0.9571,0.9580]	0.25	1.25
ϕ_2	0.9057	0.0015	[0.9030,0.9087]	0.60	1.54
ρ_1	-0.0120	0.0153	[-0.0422,0.0183]	0.33	1.05
ρ_2	-0.9206	0.0439	[-0.9685,-0.8361]	0.33	1.14
$\sigma_{\eta_1}^2$	0.0042	0.0001	[0.0040,0.0044]	0.80	1.49
$\sigma_{\eta_2}^2$	0.1258	0.0027	[0.1206,0.1311]	0.38	1.30
ξ	-0.0060	0.0219	[-0.0500,0.0375]	0.91	1.50
σ_u^2	0.1089	0.0024	[0.1044,0.1136]	0.34	1.01
			Nikkei (logml= -11110.58)		
μ	0.9047	0.0220	[0.8614,0.9469]	0.22	1.09
ϕ_1	0.9489	0.0001	[0.9487,0.9490]	0.91	1.01
ϕ_2	0.9812	0.0003	[0.9806,0.9818]	0.12	1.01
ρ_1	-0.8292	0.0050	[-0.8386,-0.8191]	0.59	1.09
ρ_2	-0.8924	0.0493	[-0.9887,-0.7940]	0.67	1.31
$\sigma_{\eta_1}^2$	0.0039	0.0001	[0.0037,0.0040]	0.33	1.10
$\sigma_{\eta_2}^2$	0.1032	0.0023	[0.0987,0.1077]	0.78	1.71
ξ	-0.2542	0.0220	[-0.2963,-0.2307]	0.47	1.10
σ_u^2	0.3464	0.0077	[0.3318,0.3622]	0.13	1.13
			S&P500 (logml= -11174.98)		
μ	0.4756	0.0217	[0.4337,0.5181]	0.38	1.46
ϕ_1	0.9653	0.0001	[0.9652,0.9654]	0.85	1.28
ϕ_2	0.9168	0.0013	[0.9142,0.9193]	0.87	1.59
ρ_1	-0.4190	0.0126	[-0.4439,-0.3947]	0.79	1.20
ρ_2	-0.8773	0.0372	[-0.9509,-0.8064]	0.28	1.20
$\sigma_{\eta_1}^2$	0.0009	0.0001	[0.0008,0.0009]	0.75	1.94
$\sigma_{\eta_2}^2$	0.1794	0.0039	[0.1719,0.1872]	0.13	1.29
ξ	-0.1957	0.0217	[-0.2381,-0.1537]	0.37	1.51
σ_u^2	0.1422	0.0031	[0.1363,0.1486]	0.23	1.24

The posterior means of parameter ϕ_1 for the RSV-AR2 model are estimated to be close to 1, similar with those of ϕ for the RSV model, which indicates the existence of high persistence of volatilities. The posterior means of ϕ_2, which are also close to 1, display high persistence of the second AR(1) process. These results suggest that the consideration of long memory property to the simple RSV model is reasonable.

The asymmetric phenomenon are suggested by the negative estimates of posterior means of the correlation coefficients ρ in the RSV model and ρ_1 and ρ_2 in the RSV-AR2 model. The results of ρ_2, which describe the negative correlation between R_t and $h_{2,t+1}$, exhibit stronger correlation than those of ρ_1. Thus, with regard to each of the three stock indices, the correlation between R_t and $h_{2,t+1}$ is the main factor that brings about the asymmetric phenomenon during the sample period in such model.

The estimation results of $\sigma_{\eta_2}^2$ are much larger than $\sigma_{\eta_1}^2$ for the investigated indices, which demonstrates a larger variance of h_{2t} than h_{1t}. These results imply that as the superposed AR processes grow in number, the variances of which will also increase accordingly. Hence, it is necessary to select the AR processes with appropriate number in order to refrain from redundant modelling.

The biases of realized volatilities are corrected through the constant term ξ. The negative estimates of ξ indicate that the existence of microstructure noise results in an underestimation of the volatilities. Also, the relatively large estimates of variance σ_u^2 indicate a high level of noise in the realized volatilities.

It is also noteworthy that by comparing the logarithm of marginal likelihoods, the RSV-AR2 model outperforms the RSV model for the DAX and S&P500, while the conclusion is opposite for the Nikkei during the investigated time period.

In view of the above-mentioned analysis, the RSV-AR2 model is superior over the RSV model in capturing the long term property of realized volatilities, which the latter is unable to describe this property. On the other hand, the results of marginal likelihood indicate that considering a model with more complicated specification may not always improve the performance of the estimation results.

This paper also generates the 1-day-ahead volatility for $t = 3001, \cdots, T$, by applying the previous 3000 observations to the RSV model and RSV-AR2 model recursively, where T is the sample size of the observations. Thus the forecast numbers for DAX, Nikkei and S&P500 are 1301, 1116, 1247, respectively. The 1-day-ahead VaR forecasts $\{VaR_t\}_{t=3001}^{T}$ and 1-day-ahead ES forecasts $\{ES_t\}_{t=3001}^{T}$ are also computed on the basis of these volatility estimates.

Table 4 shows the results of empirical failure rate (EFR), p-values of the Kupiec LR test (LR) for the VaR forecasts and the results of evaluation criteria $D(\alpha)$ for the ES forecasts at $\alpha =$

$1\%, 5\%, 10\%$.

According to the results, the EFR is not significantly different from the probability α for both models of all stock indices when $\alpha = 10\%$ at the 5% significance level. This implies that the two models are robust to predict the 10% VaR forecasts. In virtual of other cases, on the other hand, the null hypothesis that $EFR = \alpha$ is rejected even at the 1% significance level. In addition, most of the EFRs are slightly larger than their corresponding α. The VaR violations may due to the reason that the models are applied to a relatively long time period from year 2000 to year 2016, in which the contaminated time periods of the financial crisis in years 2008 and 2012 are included. Also, in most of the cases, the lower $D(\alpha)$ indicate a superior predictive ability of the RSV-AR2 model during the investigated time period.

Table 4. Results for VaR and ES

		RSV			*RSV-AR2*	
α	1%	5%	10%	1%	5%	10%
			DAX			
EFR	0.02	0.07	0.11	0.02	0.07	0.12
LR	0.00	0.01	0.48	0.00	0.00	0.06
$D(\alpha)$	0.37	0.28	0.28	0.30	0.26	0.25
			Nikkei			
EFR	0.03	0.07	0.11	0.03	0.07	0.11
LR	0.00	0.00	0.11	0.00	0.00	0.16
$D(\alpha)$	0.67	0.49	0.42	0.70	0.47	0.40
			S&P500			
EFR	0.04	0.07	0.11	0.02	0.06	0.10
LR	0.00	0.14	0.13	0.01	0.18	0.72
$D(\alpha)$	0.29	0.30	0.26	0.29	0.26	0.20

Comparisons of the latent volatilities generated from the RSV model and the RSV-AR2 model with the realized volatilities are depicted in Figure 1 and Figure 2, where full lines denote the generated volatilities and dotted lines denote the realized volatilities.

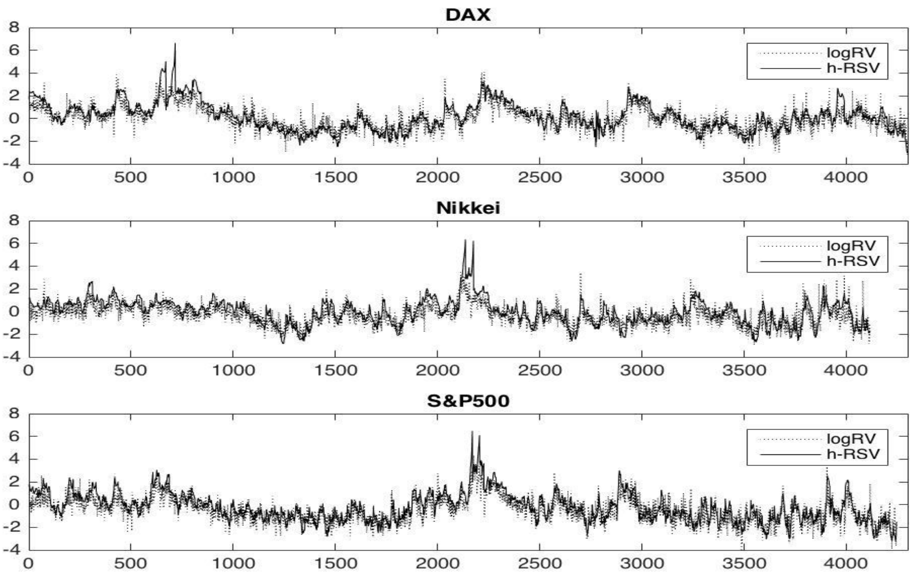

Figure 1. Realized volatilities and volatilities generated from RSV model

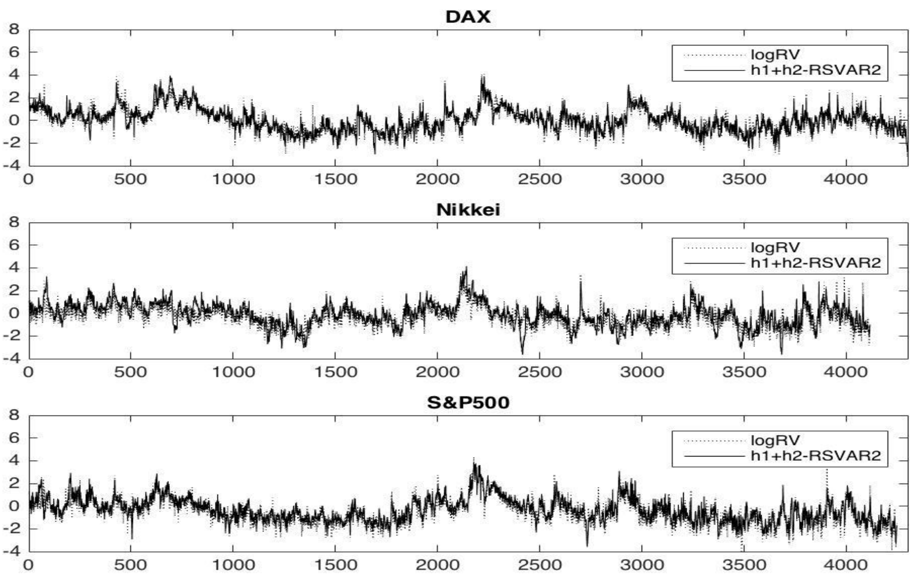

Figure 2. Realized volatilities and volatilities generated from RSV-AR2 model

5. Conclusion

This paper applies the daily returns and realized volatilities to the RSV model and RSV-AR2 model to estimate the latent volatilities for DAX, Nikkei and S&P500, where the samples of parameters and volatilities are obtained via the MCMC approach. The logarithm of marginal likelihoods and the VaR and ES forecasts are computed to make comparisons between the models. Empirical study shows that the RSV-AR2 framework can account for the long memory property of realized volatilities and can get better ES forecasts by specifying the volatility process as superpositions of two independent AR(1) processes, but it does not always show smaller logarithm of marginal likelihood than the RSV model. Thus, which model fit the data better should be considered on a case by case basis.

Appendix A. Generation Algorithm

This section introduces the generation techniques for the RSV-AR2 model, which can also be extended to a RSV model with superpostions of multiple AR(1) processes. In particular, volatilities with single AR(1) process is taken as the basic RSV framework and thus this algorithm is also available for such a model.

Let $\boldsymbol{\theta}_{AR}$ denote the parameter vector $\left(\mu, \phi_1, \phi_2, \rho_1, \rho_2, \sigma_{\eta_1}^2, \sigma_{\eta_2}^2, \xi, \sigma_u^2\right)'$. Equations (10) – (13) can be rewritten to the following form with substitution of $\alpha_{1t} \equiv h_{1t} - \mu$, $\alpha_{2t} \equiv h_{2t}$, $\sigma_e \equiv \exp(\mu/2)$, $e_t \equiv \sigma_e \varepsilon_t$, $c \equiv \xi + \mu$,

$$R_t = \exp\left(\frac{\alpha_{1t} + \alpha_{2t}}{2}\right) e_t, \qquad t = 1, \cdots, T. \tag{A1}$$

$$\alpha_{1,t+1} = \phi_1 \alpha_{1t} + \eta_{1t}, \qquad t = 1, \cdots, T-1. \tag{A2}$$

$$\alpha_{2,t+1} = \phi_2 \alpha_{2t} + \eta_{2t}, \qquad t = 1, \cdots, T-1. \tag{A3}$$

$$x_t = c + \alpha_{1t} + \alpha_{2t} + u_t, \qquad t = 1, \cdots, T. \tag{A4}$$

It has been investigated that this specification is less complicated to work with by generating the latent α_{1t} and α_{2t} rather than generating the latent h_{1t} and h_{2t} with respect to $\rho_i \neq 0$ $(i = 1,2)$.

A.1 Generation of $\boldsymbol{\theta}_{AR}$

The prior distributions of parameters are assumed as follows.

$$\mu \sim N(\mu_0, \sigma_0^2), \qquad (\phi_1+1)/2 \sim Beta\left(a_{\phi_1}, b_{\phi_1}\right), \quad (\phi_2+1)/2 \sim Beta\left(a_{\phi_2}, b_{\phi_2}\right),$$
$$\sigma_{\eta_1}^2 \sim IG\left(\alpha_{\eta_1}, \beta_{\eta_1}\right), \qquad (\rho_1+1)/2 \sim Beta\left(a_{\rho_1}, b_{\rho_1}\right), \qquad \sigma_{\eta_2}^2 \sim IG\left(\alpha_{\eta_2}, \beta_{\eta_2}\right),$$
$$(\rho_2+1)/2 \sim Beta\left(a_{\rho_2}, b_{\rho_2}\right), \qquad \xi \sim N\left(\mu_{\xi_0}, \sigma_{\xi_0}^2\right), \qquad \sigma_u^2 \sim IG\left(\alpha_{u_0}, \beta_{u_0}\right),$$

where $Beta(a,b)$, $IG(\alpha,\beta)$ and $W(S,\nu)$ denote the beta distribution with parameters (a,b), the inversed gamma distribution with shape parameter α and scale parameter β, the Wishart distribution with parameters (S,ν), respectively.

(1) Generation of ϕ_1 and ϕ_2

Let $\boldsymbol{\alpha}_1 = (\alpha_{11}, \cdots, \alpha_{1T})'$ and $\boldsymbol{\alpha}_2 = (\alpha_{21}, \cdots, \alpha_{2T})'$. The respective conditional posterior density of ϕ_i $(i = 1,2)$ can be expressed as

$$\pi\left(\phi_i \middle| \rho_i, \sigma_{\eta_i}^2, \boldsymbol{\alpha}_i, \boldsymbol{R}\right)$$
$$\propto (1+\phi_i)^{a_{\phi_i}-1}(1-\phi_i)^{b_{\phi_i}-1}\sqrt{1-\phi_i^2}\exp\left\{-\frac{\left(\phi_i-\mu_{\phi_i}\right)^2}{2\sigma_{\phi_i}^2}\right\}, \qquad \text{(A5)}$$

where

$$\mu_{\phi_i} = \frac{\sum_{t=1}^{T-1}\left\{\alpha_{i,t+1} - \rho_i\sigma_{\eta_i}\sigma_e^{-1}\exp[-(\alpha_{1t}+\alpha_{2t})/2]R_t\right\}\alpha_{it}}{\rho_i^2\alpha_{i1}^2 + \sum_{t=2}^{T-1}\alpha_{it}^2}, \qquad \sigma_{\phi_i}^2 = \frac{\sigma_{\eta_i}^2\left(1-\rho_i^2\right)}{\rho_i^2\alpha_{i1}^2 + \sum_{t=2}^{T-1}\alpha_{it}^2}.$$

Candidate ϕ_1^* is generated from $TN_{(-1,1)}\left(\mu_{\phi_1}, \sigma_{\phi_1}^2\right)$ while ϕ_2^* is generated from $TN_{(-1,|\phi_1|)}\left(\mu_{\phi_1}, \sigma_{\phi_1}^2\right)$ in consideration of the restriction that $|\phi_2| < |\phi_1| < 1$. $TN_{(a,b)}(\mu, \sigma^2)$ represents a truncated normal distribution within the interval (a,b). Given the current value ϕ_i, accept ϕ_i^* with probability

$$min\left\{\frac{(1+\phi_i^*)^{a_{\phi_i}-1}(1-\phi_i^*)^{b_{\phi_i}-1}\sqrt{1-\phi_i^{*2}}}{(1+\phi_i)^{a_{\phi_i}-1}(1-\phi_i)^{b_{\phi_i}-1}\sqrt{1-\phi_i^2}}, 1\right\}.$$

(2) Generation of $\boldsymbol{\Gamma}$

The logarithm of conditional posterior density about $\boldsymbol{\Gamma}$ is

$$\log\pi(\boldsymbol{\Gamma}|\phi_1, \phi_2, \boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, \boldsymbol{R})$$
$$= const - \log\sigma_{\eta_1} - \log\sigma_{\eta_2} - \frac{\alpha_{11}^2(1-\phi_1^2)}{2\sigma_{\eta_1}^2} - \log\sigma_e - \frac{\alpha_{21}^2(1-\phi_2^2)}{2\sigma_{\eta_2}^2}$$
$$- \frac{R_T^2}{2\sigma_e^2\exp(\alpha_{1T}+\alpha_{2T})} - \frac{\nu_1+3}{2}\log|\boldsymbol{\Gamma}| - \frac{1}{2}tr(\boldsymbol{\Gamma}_1^{-1}\boldsymbol{\Gamma}^{-1}). \qquad \text{(A6)}$$

where

$$\nu_1 = \nu_0 + T - 1, \qquad \boldsymbol{\Gamma}_1^{-1} = \boldsymbol{\Gamma}_0^{-1} + \sum_{t=1}^{T-1} \boldsymbol{\tau}_t \boldsymbol{\tau}_t',$$

$$\boldsymbol{\tau}_t = \begin{pmatrix} R_t \exp[-(\alpha_{1t} + \alpha_{2t})/2] & 0 \\ \alpha_{1,t+1} - \phi_1 \alpha_{1t} & 0 \\ 0 & 1 \\ 0 & \alpha_{2,t+1} - \phi_2 \alpha_{2t} \end{pmatrix}.$$

Generate the candidate matrix $\boldsymbol{\Gamma}^{*-1} \sim W(\boldsymbol{\Gamma}_1, \nu_1)$, and accept it with probability

$$min\left\{ \frac{\sigma_{\eta_1}\sigma_{\eta_2}\sigma_e \exp\left[-\frac{(1-\phi_1^2)\alpha_{11}^2}{2{\sigma_{\eta_1}^*}^2} - \frac{(1-\phi_2^2)\alpha_{21}^2}{2{\sigma_{\eta_2}^*}^2} - \frac{R_T^2}{2{\sigma_e^*}^2 \exp(\alpha_{1T} + \alpha_{2T})} \right]}{\sigma_{\eta_1}^*\sigma_{\eta_2}^*\sigma_e^* \exp\left[-\frac{(1-\phi_1^2)\alpha_{11}^2}{2\sigma_{\eta_1}^2} - \frac{(1-\phi_2^2)\alpha_{21}^2}{2\sigma_{\eta_2}^2} - \frac{R_T^2}{2\sigma_e^2 \exp(\alpha_{1T} + \alpha_{2T})} \right]}, 1 \right\}.$$

If $\boldsymbol{\Gamma}^{*-1}$ is accepted, new draws ${\sigma_e^*}^2, \rho_1^*,\ {\sigma_{\eta_1}^*}^2,\ \rho_2^*,\ {\sigma_{\eta_2}^*}^2$ are obtained by computing $\boldsymbol{\Gamma}^*$ and therefore $\mu^* = \log{\sigma_e^*}^2$; else, remain the previous $\sigma_e^2,\ \rho_1,\ \sigma_{\eta_1}^2,\ \rho_2,\ \sigma_{\eta_2}^2\ \ \mu$.

(3) Generation of ξ and σ_u^2

Generate $\xi | \sigma_u^2, \boldsymbol{h}, \boldsymbol{X} \sim N\left(\mu_{\xi_1}, \sigma_{\xi_1}^2\right)$ and $\sigma_u^2 | \xi, \boldsymbol{h}, \boldsymbol{X} \sim IG\left(\alpha_{u_1}, \beta_{u_1}\right)$ where

$$\mu_{\xi_1} = \frac{\sigma_{\xi_0}^2 \sum_{t=1}^T (x_t - h_{1t} - h_{2t}) + \sigma_u^2 \mu_{\xi_0}}{T\sigma_{\xi_0}^2 + \sigma_u^2}, \qquad \sigma_{\xi_1}^2 = \frac{\sigma_{\xi_0}^2 \sigma_u^2}{T\sigma_{\xi_0}^2 + \sigma_u^2},$$

$$\alpha_{u_1} = \alpha_{u_0} + \frac{T}{2}, \qquad \beta_{u_1} = \beta_{u_0} + \frac{1}{2}\sum_{t=1}^T (x_t - \xi - h_{1t} - h_{2t})^2.$$

(4) Generation of $\boldsymbol{h}_1$ and $\boldsymbol{h}_2$

This paper considers $\boldsymbol{h}_2$ as constants while $\boldsymbol{h}_1$ are generated and vice versa. The block sampler (Omori and Watanabe (2008)), which provides an efficient generation technique, is applied to obtain the samples of latent volatilities. The generation algorithm is given as follows.

Step1. Divide $\boldsymbol{\eta}_i$ into $K+1$ blocks by selecting K knots randomly following Shephard and Pitt (1997). For the $k-th$ block $(k = 1, \cdots, K+1)$, define the vectors of disturbance terms and latent variables as $\boldsymbol{\eta}_i^{(k)} = \left(\eta_{i,s}, \cdots, \eta_{i,s+m-1}\right)'$ and $\boldsymbol{\alpha}_i^{(k)} = \left(\alpha_{i,s+1}, \cdots, \alpha_{i,s+m}\right)'$.

Step2. Iterate the smoothing algorithm (Omori and Watanabe (2008)) several times to explore the posterior modes $\hat{\boldsymbol{\eta}}_i^{(k)}$ and $\hat{\boldsymbol{\alpha}}_i^{(k)}$ for respective blocks.

Step3. Define the logarithm of proposal density function $\log g\left(\boldsymbol{\eta}_i^{(k)} \middle| \cdot\right)$ approximate to

$\log f\left(\boldsymbol{\eta}_i^{(k)}\middle|\cdot\right)$ with a second-order Taylor expansion around the modes $\widehat{\boldsymbol{\eta}}_i^{(k)}$.

Step4. Generate a candidate $\boldsymbol{\eta}_i^{*(k)}$ from $g\left(\boldsymbol{\eta}_i^{(k)}\middle|\cdot\right)$ using a simulation smoother, given the current value $\boldsymbol{\eta}_i^{(k)}$ and accept it with probability

$$min\left\{\frac{f\left(\boldsymbol{\eta}_i^{*(k)}\middle|\cdot\right)g\left(\boldsymbol{\eta}_i^{(k)}\middle|\cdot\right)}{f\left(\boldsymbol{\eta}_i^{(k)}\middle|\cdot\right)g\left(\boldsymbol{\eta}_i^{*(k)}\middle|\cdot\right)},1\right\}.$$

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Fintech Trend in Korea

1 Fintech

2 Fintech trend in Korea

3 Implication

1. Fintech

FinTech is a combination of finance and technology, which means introducing ICT into finance and providing financial services in a faster and more convenient way.

1. Fintech

Korean traditional financial institutions that felt threatened are actively using ICT technologies,

competing against FinTech companies,

and actively cooperating with FinTech companies

to participate in FinTech innovation.

2. Fintech Trend in Korea

One of the most popular FinTech services is mobile payment in Korea.

Mobile Pay was introduced and activated in second half of 2015 as a means of entering card information into Smartphones and paying with Smartphones.

In particular, Naver and Kakao are fiercely competing to secure subscribers by providing services using their platforms.

2. Fintech Trend in Korea

Naver Pay, which was released by Naver in June 2015,

is a type of FinTech provided by Naver

and is easily paid through payment method that registered bank account, check card, or credit card in advance.

2. Fintech Trend in Korea

Naver has been expanding its users

since its inception by combining its various services

including Naver Webtoons and Naver Music. With one Naver ID,

it can easily be paid at 110,000 online stores.

NAVER = Web Portal

2. Fintech Trend in Korea

Kakao also introduced Kakao Pay in all of its services,

including Kakao Driver,

and recently released a bill service for Kakao Pay.

2. Fintech Trend in Korea

We can pay and manage local taxes,

Such as car taxes and resident taxes, as well as utility bills such as city gas and electricity bills.

We can manage our bills in one place.

Its advantage is that it can also make payments through Kakao Pay.

2. Fintech Trend in Korea

A variety of wearable devices such as smart watches are also appearing, threatening plastic cards.

Unlike Smartphones, wearable devices that are worn on the body are easier to use for mobile payments.

Due to this reason, most wearable devices that are recently released have mobile payment function.

2. Fintech Trend in Korea

The reason platform ICT companies are active in the mobile payment market

is based on the purpose of collecting data.

Analysis of customer information and financial transaction patterns collected through mobile devices into big data

can be advantageous in providing on demand financial service that matches customer characteristics.

2. Fintech Trend in Korea

In the banking industry,

the change has started since the opening of the K-bank and Kakao bank in 2017.

2. Fintech Trend in Korea

The two banks are targeting customers who have been heading to existing commercial banks

by offering easy account opening, money transfer, high interest rates

and low lending rates, low fees and convenient services.

2. Fintech Trend in Korea

Internet-specialized banks, K-bank and Kakao bank which were created

thanks to the rapid deployment of smartphones and the aggregation, processing,

and transmission of large amounts of data,

provide existing banking services such as payment through the Internet and call centers only.

2. Fintech Trend in Korea

Young people in their 20s and 30s are familiar with the use of mobile devices such as smartphones,

and those in their 40s and 50s who have been using institutional financial services

have become major users of Internet-specialized banks.

2. Fintech Trend in Korea

Now, with the combination of FinTech and ICT, smartphones

have become service contacts instead of windows.

2. Fintech Trend in Korea

The introduction of Internet banks has changed the business strategy of banks centered on the offline market,

which have been easy to make profits from the gap in interest margins,

while maintaining lending rates as high as possible.

2. Fintech Trend in Korea

For example, commercial banks have changed their mobile banking platform

to a simple and intuitive screen instead of smart phone banking apps

that have listed various but somewhat complex menus since the launch of Kakao Bank.

It is also decreasing number of uses of public certificates and security cards.

2. Fintech Trend in Korea

The overseas remittance market is also undergoing a major change.

The competition began when Kakao Bank lowered its overseas remittance

fee to at least 5 U.S. dollars, a tenth of the rate of existing banks.

2. Fintech Trend in Korea

In addition, the competition between banks and FinTech industries

to protect the overseas remittance market

is expected to intensify as FinTech startups have recently jumped into the foreign currency industry.

3. Insur-tech

Insur-tech is a combination of insurance and information technology,

which means insurance products and services that maximize the convenience of consumers through convergence between the two.

3. Insur-tech

Crowd-based Insurance services are
a form of peer-to-peer (P2P) contract that is used
by people with the same insurance needs that are not provided by the existing insurance market.

3. Insur-tech

Insurance Curation Service recommends insurance products tailored to your lifestyle to customers

who can not compare thousands of different guarantees

and

special products individually.

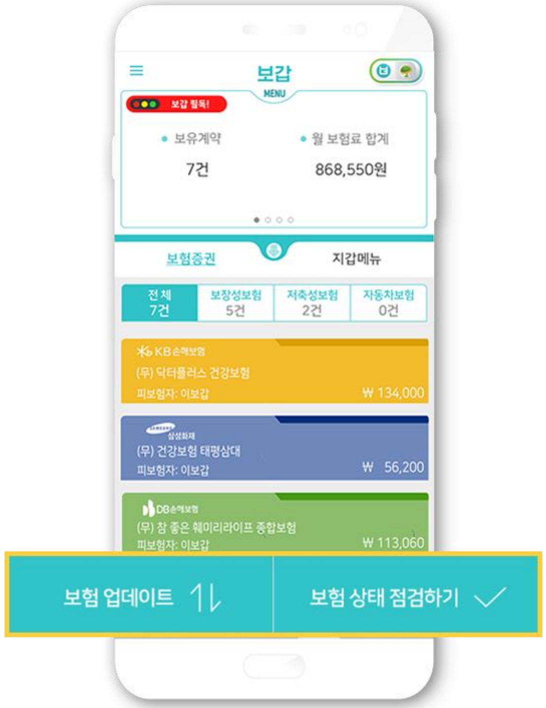
3. Insur-tech

Insurance management services are designed to help consumers manage the details of subscription insurance products at a glance

and manage them

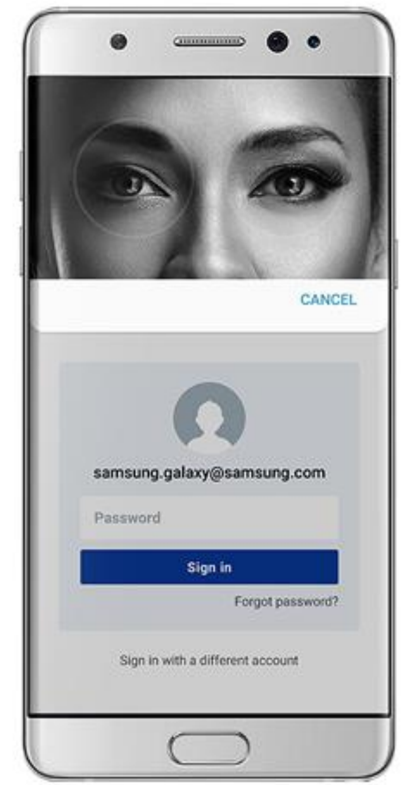
directly

through applications.



3. Insur-tech

Insurance service such
as fingerprint, iris and others has emerged
through a certificate of living body.



3. Insur-tech

After insurance subscribers install applications on their smartphones,

they will be able to apply for insurance products or claim insurance premiums

if they recognize fingerprints and iris.

This was a cumbersome entry process that allowed customers who were reluctant to buy insurance to come in.

3. Insur-tech

There are active reviews on introducing Watson Explorer that has AI function at the center of major insurance companies.

The main business of Watson Explorer is to determine whether (or how much) to pay insurance claims when they receive them.

It is a loss assessment work service.

Watson Explorer

4. Implication

Unlike the rapidly changing global trend, complex financial regulations,

concerns about security, and difficulties

in utilizing financial big data

are holding back the FinTech market.

4. Implication

The publicity of financial institutions has been emphasized

as the financial industry is the foundation of the economic system

along with the real economy and directly related to the smooth investment and financing activities of businesses.

4. Implication

As a result, there have been strong public regulations against the financial industry in Korea.

This domestic financial environment served as a limiting factor to the activation of startup companies seeking to advance into fin-tech services

such as crowdfunding, P2P lending, overseas remittance, and Bitcoin.

4. Implication

In response, the Korean government is also actively seeking to create the Fin-Tech ecosystem.

As the government plans to actively improve regulations on fin-tech,

including the introduction of sandbox system, chances are high that the Fin-Tech market will be activated.

4. Implication

Regulatory sandboxes

are an institution that exempts regulatory application for a period of time to allow demonstration of new technologies and services.

It is predicted that slow development of new industries due to complicated regulations

such as shared economy and FinTech will become more active

4. Implication

Although its departure was delayed,

the Korean FinTech industry has a foundation for rapid growth

based on advanced ICT infrastructure and various application services.

4. Implication

Although it seems to be behind the global trend,

Internet banks have emerged, and a variety of fin-tech companies,

such as block chains, RoboAdvisor, and overseas remittance,

have come into life with new services.

4. Implication

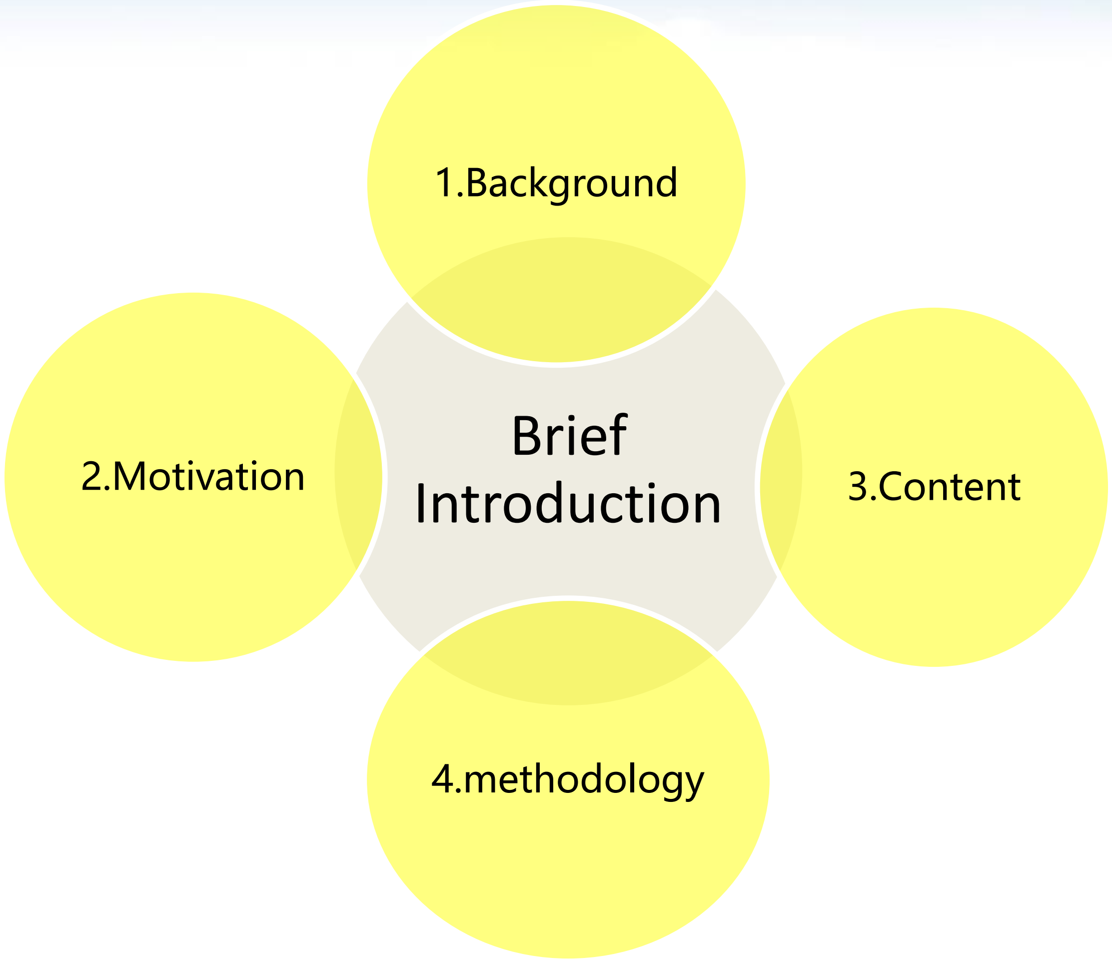
FinTech is expected to change the nations financial paradigm

as it grows with the entry of various startups.

Corporate Social Responsibility(CSR) Reporting Standard in China: Overview and Prospect

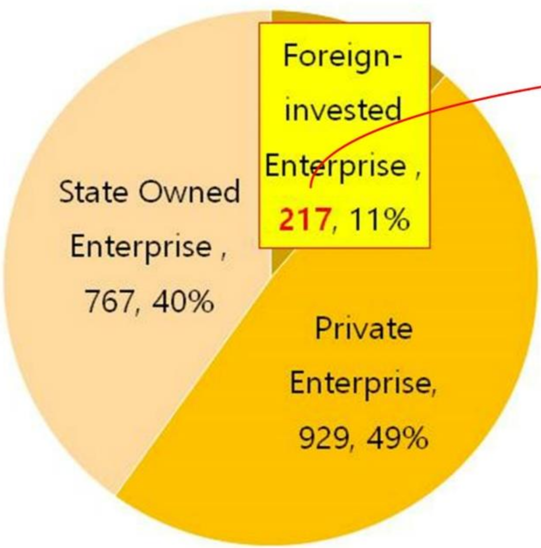
Hanyi, Zhang（Qingdao University of Technology）
Bin Heng, Yin（Ocean University of China）

Introduction

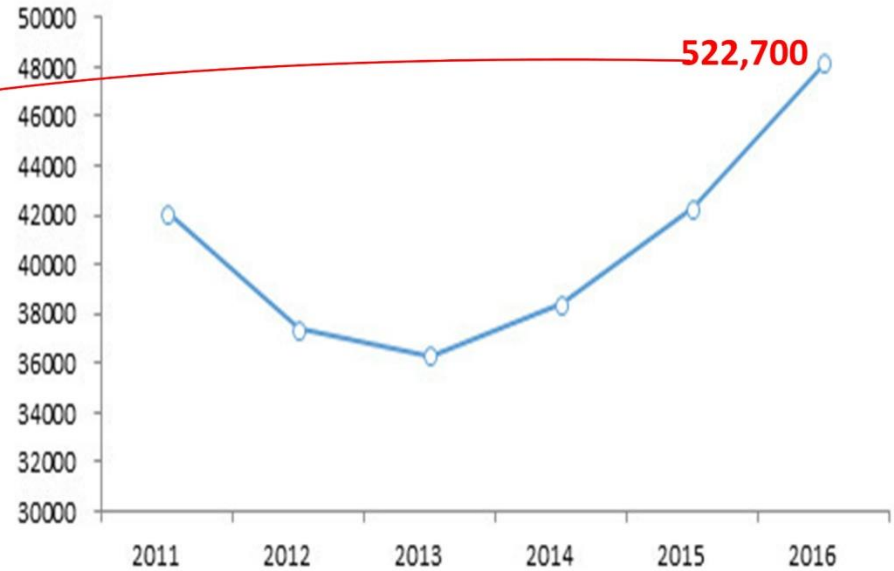


◆ Background 1

Number of Reports Issued by Enterprises of Different Properties in 2017

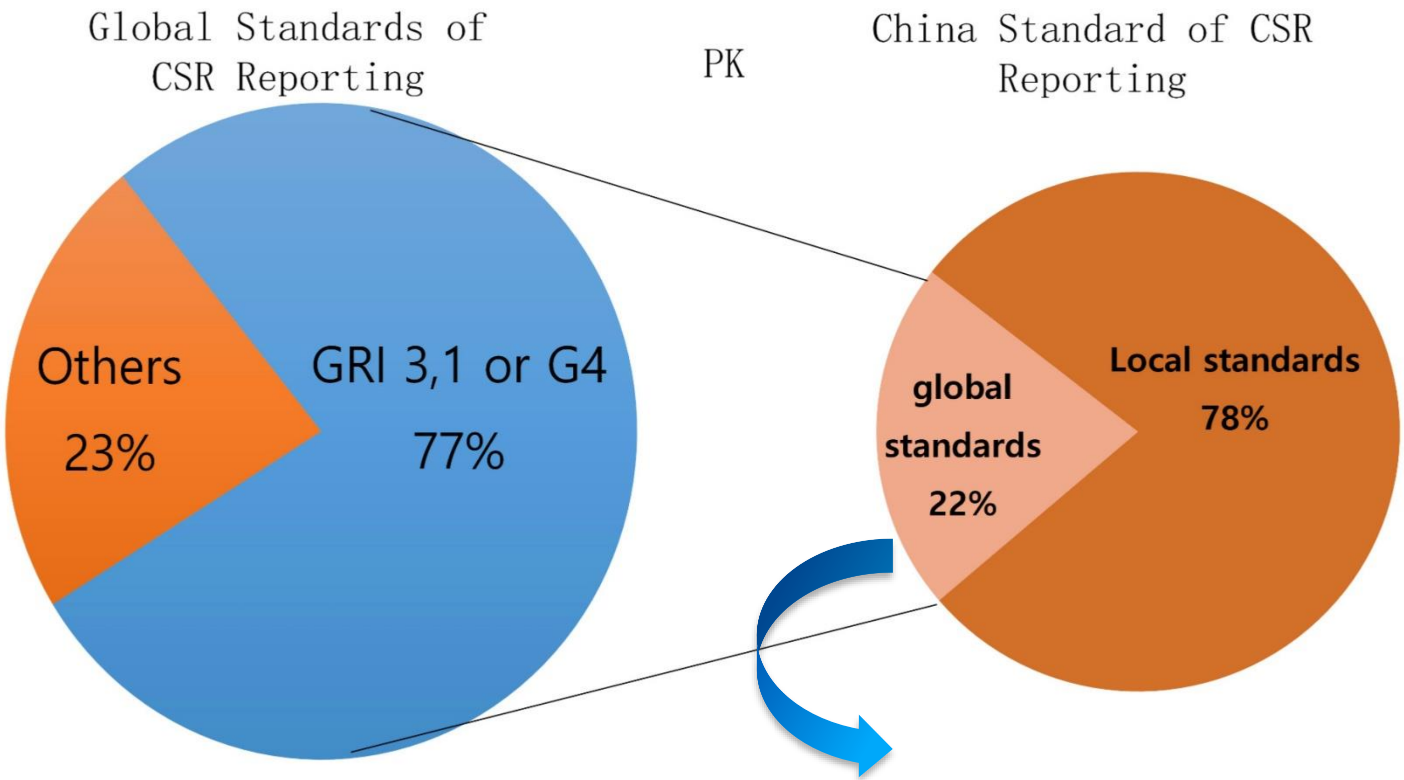


Numbers of foreign companies by the end of 2016



Data source: 《Golden Bee CSR Report Index 2017 》
the State Administration for Industry & Commerce of the People's Republic of China

◆ Background 2



- Is it necessary?
- Which one to choose?

◆ Background 3

- Chinese government has strongly involved in CSR initiative and has been interested in making its own CSR standards complying with global standards as well as emphasizing the Chinese Characteristics.

- Chinese Academy of Social Science (CASS) published the current advisement CASS-CSR 4.0 at the end of last year which is a representative CSR Reporting Guideline in China but the relevant researches are almost non-existent.

Purpose of this Study

1
- To introduce how can access Chinese CSR development.

2
- To explain why should pay more attention on Chinese local CSR standard.

3
- To distinguish the major differences between CASS-CSR4.0 and GRI G4.

Final purpose: In order to contribute to the literature in this area.

Framework of this Study

Method of this study

Ⅰ. Introduction

Ⅱ.Overviewing the policies, laws and regulations on CSR performance in China

- Literature researches

Ⅲ. Reviewing the current CSR reporting requirements and guidelines in China

- Literature researches， Comparison

Ⅳ. Introduction of CASS-CSR 4.0

- Literature researches， Interview the director of CASS CSR Center

Ⅴ. Conclusion and prospect

Findings of this study

1.While complying with GRI-G4, CASS-CSR 4.0 takes “China characteristics” into consideration adding corruption to corporate social responsibility.

2.Refer to the ESG of Hong Kong Stock Exchange, add some specific quantitiable indicators such as carbon intensity and carbon sinks into environmental responsibility。

3.Meanwhile, companies are required to publish negative information and encourage third-party verification to improve the credibility of the report and the efficiency of government supervision.

4.CASS-CSR 4.0 continues to provide a handbook as a general framework and handbook for each of the 46 industries. Compared with the previous versions, the current guideline provide a handbook for each different issue.

5.Finally, it is also the innovation of the current version. “value management” has been included in order to maximize the value of the report.

Prospect and Suggestion

- In the future, the realization of corporate social responsibility in China will be performed in 3ways:
  - General social responsibilities will continue to be adjusted by ethics;
  - Moral bottom line responsibilities will rise to mandatory requirements of the law;
  - the other CSRs which cannot be directly constrained by law can be bound by informal legislative body such as CASS in terms of guidelines or standards.
- Localization of responsibilities should become an important strategy for foreign companies in the next world of CSR.
- Foreign companies are advised to pay attention on the existing policies and guidelines concentrating with poverty alleviation, pension, environmental protection, innovation and entrepreneurship, medical health and so on.
- Taking the third-party verification procedures in consideration is helpful to creat a good public opinion atmosphere for foreign companies.

Thank you for your attention

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Corporate Social Responsibility as a driver for Consumer's Loyalty

Maria Ulpah[1]

The objective of this paper is to find out whether consumer's perception of Corporate Social Responsibility (CSR) policy of bank will affect the consumer's loyalty. We tried to see the direct effect of CSR to consumer's loyalty and the indirect effect to loyalty by using two mediating variables, namely satisfaction and trust, We split the CSR aspect into two main aspects, namely Business CSR and Philanthropic CSR. To test the hypotheses, we carried survey for bank customer who has bank account for more than 3 years. The result found that business CSR had a direct effect and indirect effect to consumer's loyalty. However, the philanthropic CSR did not have affect the consumer's trust.

Keywords: Corporate social responsibility, Customer Satisfaction, Loyalty, banking.

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1. Introduction

Over the past years, corporate social responsibility (CSR) has become the important issues in business and academics. CSR concept was first formally defined by Bowen (1953) as “the obligations of businessmen to pursue those policies, to make decisions, or to follow those lines of action which are desirable in terms of the objectives and values of our society”. Since then, other scholars have started to refine the definition of CSR to making it more precise. Sethi (1975) was the first to classify CSR into three categories, namely social obligation, social responsibility and social responsiveness. While Carol (1979,1991) categorize CSR into four areas, namely economic, legal, ethical and philanthropic.

Many studies have been conducted in order to test and verify the importance of CSR and many findings were mostly supportive of the positive benefits of CSR implementation. Empirical research has shown that CSR has strategic value to enhance a competitive advantage for an organization, which would contribute to better financial performance. The importance of CSR on various industries has also become popular on recent year, including in banking industry. Banks is considered as the most important institutions in any economy in the world. Banks have attempted to get trustworthiness from the stakeholders by implementing socially responsible principles through the CSR project. The objective of social responsibility and ethical principles in banking is to achieve an adequate economic performance by considering social and environmental dimension.

Due to business specifications of commercial banks such as operations with customers’ deposits, banks have been exposed to permanent public spotlight. In this context, customer satisfaction is a crucial factor of bank’s performance and its fundamental asset called trustworthiness. Customer satisfaction can be derived from various aspects such as quality of services provided, product prices or banking fees and branch availability. Furthermore, high level of customer satisfaction usually results in increased customer loyalty to the bank satisfaction are essential for evaluating the social pillar of CSR in banks.

This paper is focused on CSR and its effects on satisfaction and loyalty of bank customers and in Indonesia. The study focus on to to find out if there are positive relationships between business practice CSR reputation and satisfaction, trust and a loyalty, and also the relationship between philanthropic CSR reputation and trust; and lastly how the CSR can contribute positively to building loyalty and hence profitability,

The structure of the paper will be as follows. The first part provides a brief theoretical background focused on CSR and satisfaction in banks including a conceptual model which is followed by data description, conceptual framework and method used. Then, it will be followed by results and discussion and finally, the last part will provide a conclusion.

2. Theoretical Background

It is clear that corporate social responsibility is important for any business, , if done properly, could result in a good reputation, such as reducing idiosyncratic risk, improving stakeholders' perceptions of corporate reputation, nd positive financial performance (Goyal and Santa-Clara, 2003; Luo and Bhattacharya, 2009). Nowdays, CSR has become a more mature topic and an important strategic management tool, which companies and scholars are keen to find out how to use it to fulfill both firm objectives, social and financial objectives. While there has been quite a number of research studies and discussions about the influence of CSR on customers' satisfaction, brand trust, and even loyalty, there has been little discussion on the moderating impact of these factors on loyalty. Moreover, most analyses that tried to link CSR to trust, satisfaction and loyalty did not distinguish between the different aspects of CSR.

This study has a different approach by splitting CSR into two aspect, namely business practice CSR (hereafter we called as Business CSR) and Philanthropic CSR. The main difference between Business CSR and Philanthropic CSR is basically based the targeted stakeholder. Business CSR is based on the customer perception of the firm's engagement in CSR activities within a firm's core business operations targeted at it customers (Carroll, 1991; Homburg et al., 2013). While, Philanthropic CSR is based on the Customer perception of the firm's engagement in CSR activities targeted at philanthropic interaction with the community and non-profit organizations and its voluntary actions aiming to contribute in improving the overall quality of life of people in the society (Carroll, 1991; Homburg et al., 2013).

2.1 CSR in banking industry

For a bank-based nation, banks are considered as one of the drivers of economy. The financial industry in Indonesia is experiencing a very rapid development and growth. One of the indicator is shown by the increasing numberof players in the industry. On of the consequences of this development is also the increasing level of competition the speed of banking deregulation. This leads the banks should look for many way profitable to differentiate themselves against competitors.

The tight level of competition demands all banks to be more capable delivering high value services that can foster satisfaction and trust for customers to create high loyalty from customers (Barcelos et al., 2015). Customer loyalty depends on many factors, such as CSR activities, (Kazemi & Omidi, 2015); satisfaction customer satisfaction (Barcelos et al., 2015; Chung et al., 2015; Kazemi & Omidi, 2015) and customer trust (Nha et al., 2013, Barcelos et al., 2015; Kazemi & Omidi, 2015).

Globalization has awakened the growing awareness of business responsibilities on community. CSR is widely assessed as a bond of responsibility that is feasible to run for ensure sustainable benefits for companies and all stakeholders . CSR is considered important for a business to build trust and confidence in the stakeholders interests.

Many previous research has find out that activities of the company have a positive effect on customer satisfaction and satisfaction are also influential to increase customer loyalty. In addition, the convenience of customers in partnering with banks can provide satisfaction to customers.. Satisfaction has been recognized as an important part of the strategy company. Thus, it is expected that positive CSR is related to satisfaction customers (Chung et al., 2015). The trust felt by the customer is the foundation upon which the decision is based to transact or continue business relationships with financial institutions (companies). Trust emerges as a manifestation of confidence from customers towards financial institutions. Trust is as a mediating variable between the customer's perception of social identity companies with customer loyalty to the company (Nha et al., 2015). Customer trust and satisfaction must establish customer loyalty. Loyalty customers (customers) are considered as important goals for growth and sustainability company life. Customer loyalty is an important foundation to develop competitive advantage. Previous research has shown that CSR has an impact important to customer attitudes, customer satisfaction and loyalty (Chung, et al., 2015).

However, positive contribution of CSR to financial performance did not appear in all empirical studies. Some research confirmed that corporate philanthropy did not contribute to better financial performances or profitability (Seifert et all, 2003). Another research study on South African firms also showed that CSR did not create significant differences in companies' financial performances (Chetty, , 2015). A few research studies found a negative financial contribution from CSR, due to high costs incurred in CSR, which resulted in reduced profits and shareholder wealth, echoing Friedman's view (Fernandez and Souto, 2009; Porter and Kramer, 2002).

2.2 Customer satisfaction, trust loyalty in banking industry

Satisfaction reflects a customers's judgment about bank's actual performance and their their expectations. If the bank's performance exceeds expectations, then the customer is very happy (Kotler & Keller, 2016). Satisfaction is not attached to the product or service itself, but satisfaction also included in the customer's perception of the attributes of the product or service provided. With Thus, different consumers will reveal varying levels of satisfaction for experience over the same service. Satisfaction has been recognized as an important part of the firm's strategy and become the main driver of the company's profitability for long run horizon (Chung et al., 2015).

Another aspect that may be a factor, which influences the bank's customer loyalty, is trust. Trust is considered as an important factor in developing long-term relationships between organizations (Nha et al., 2013). Trust reflects the credibility of the company in the eyes of consumers that has affect on long-term orientation and relationship between consumers and banks. In a marketing context, trust is usually linked with consumers' expectations of the firm's capacity to assume liability and fulfill the promises. This hope is based on competence, honesty, and virtue company. Competence is a skill that reflects the company's capacity to conduct transactions and to meet consumer expectations. Honesty is associated with fulfillment of promises made by the company, and virtue is the willingness of the company to consider the interests of consumers when planning and making decisions for engagement with consumers (Nha et al., 2013; Kazemi & Omidi, 2015). The role of trust allows a company to develop and maintaining customer loyalty. (Barcelos et al., 2015).

Bank’s customer loyalty is an important goal for survival and growth of a bank.. Knowing and understanding the culture of loyalty is considered a key element in giving long-term profitability for the company (Chung et al., 2015). Loyalty comes when customers resist the temptation to move to another bank. Loyalty can be seen from two perspectives, namely attitude and behavior loyalty. Loyalty attitude expressed the customer's desire to build relationships with the company. Loyalty as an attitude indicated by a commitment or an emotional bond to the brand or the company. While behavioral loyalty is customer support an. While behavioral loyalty is customer support given to the company. The loyalty approach as behavior involves consistency customer in re-purchase or re-use the services. (Kazemi & Omidi, 2015).

2.3 Conceptual framework and hypothesis development

CSR programs of a Bank can be increase the loyalty of the customer. The more satisfied consumers of the program CSR conducted by a bank then loyalty is also stronger (Chung et al., 2015; Barcelos et al. 2015; Kazemi & Omidi .2015). Since we splitting the CSR aspect into Business CSR and Philanthropic CSR, Then , The hypothesis proposed is:

H1: Business CSR directly affects the customer's loyalty

H2: Customer’s satisfaction mediates the relationship between Business CSR and customer loyalty

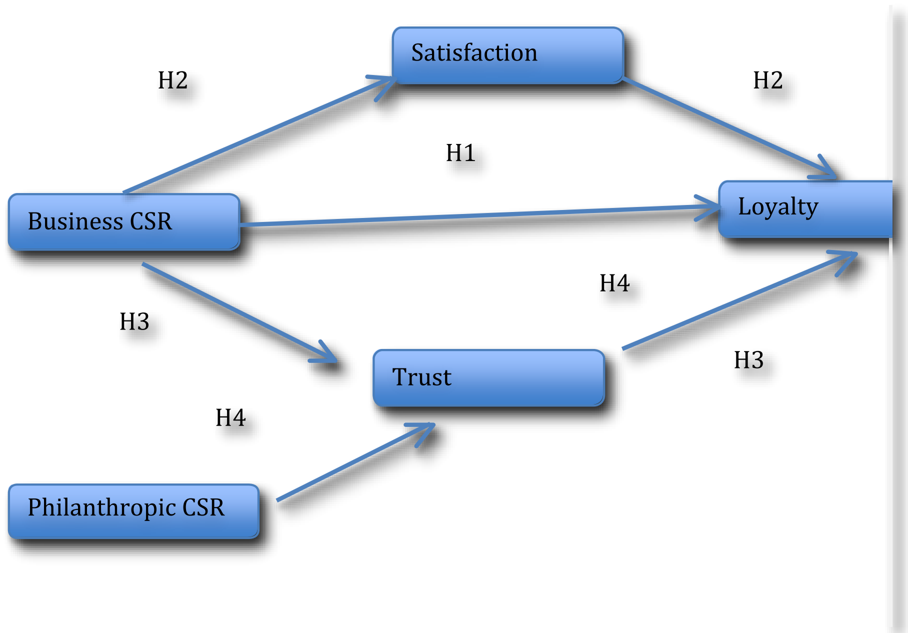
H3: Customer’s trust mediates the relationship between Business CSR and customer loyalty.

While regarding the Philanthropic CSR , the hypothesis proposed is as follows :

H4: Customer’s trust mediates the relationship between Philanthropic CSR and customer loyalty.

The research model proposed on the basis of the proposed hypothesis can be seen on Figure 1.

Figure 1. Research Model



3. Data and Methods

Research respondents is a bank's customer who has joined or has bank account for 3 year and amounted to 170 bank's customers. Simple random sampling is used and questionnares were distributed through online survey. Research instrument in the form of questionnaires The questionnaire contains 43 indicator statements and each statement in the questionnaires used 5 Likert scale ranging from strongly disagree until strongly agreed. 27 statement consists of 6 statements about Business CSR, 6 statements about Philanthropic CSR, 6 statements on satisfaction, 4 s statements of trust and 5 statement about loyalty Pre-test done for test the reliability and validity of research instruments. Based on the results of the validity test shows that all statements on CSR, satisfaction, trust and loyalty has a correlation coefficient value with the total score of all statement larger than 0.30, so that all of these indicators are qualified validity of the data and can be declared valid. The result of the reliability test that four research instruments are CSR, satisfaction, trust and loyalty has a Cronbach's Alpha coefficient greater than 0.60 so the whole the statement qualifies the instrument's reliability and can be stated.

Table 1.Descriptive statistics –Observed Variables

Variables	Obs	Mean	Std. Dev.
BusinessCSR1	170	3.84	0.81
BusinessCSR2	170	3.75	0.89
BusinessCSR3	170	3.61	0.87
BusinessCSR4	170	3.40	0.73
BusinessCSR5	170	3.68	0.83
BusinessCSR6	170	3.68	0.83
PhilanthropicCSR1	170	3.37	0.80
PhilanthropicCSR2	170	3.22	0.80
PhilanthropicCSR3	170	3.51	0.71
PhilanthropicCSR4	170	3.29	0.69
PhilanthropicCSR5	170	3.08	0.69
PhilanthropicCSR6	170	3.28	0.78
Satisfaction1	170	3.81	0.67
Satisfaction2	170	3.79	0.78
Satisfaction3	167	3.62	0.77
Satisfaction4	170	3.88	0.68
Satisfaction5	170	4.04	0.63
Satisfaction6	170	3.83	0.71
trust1	170	3.96	0.66
trust2	170	3.61	0.76
trust3	170	3.78	0.65
trust4	170	3.66	0.72
loyalty1	170	3.79	0.73
loyalty2	170	3.65	0.70
loyalty3	170	3.61	0.76
loyalty4	170	3.50	0.78
loyalty5	170	3.30	0.88

Table 2. Respondents Profile

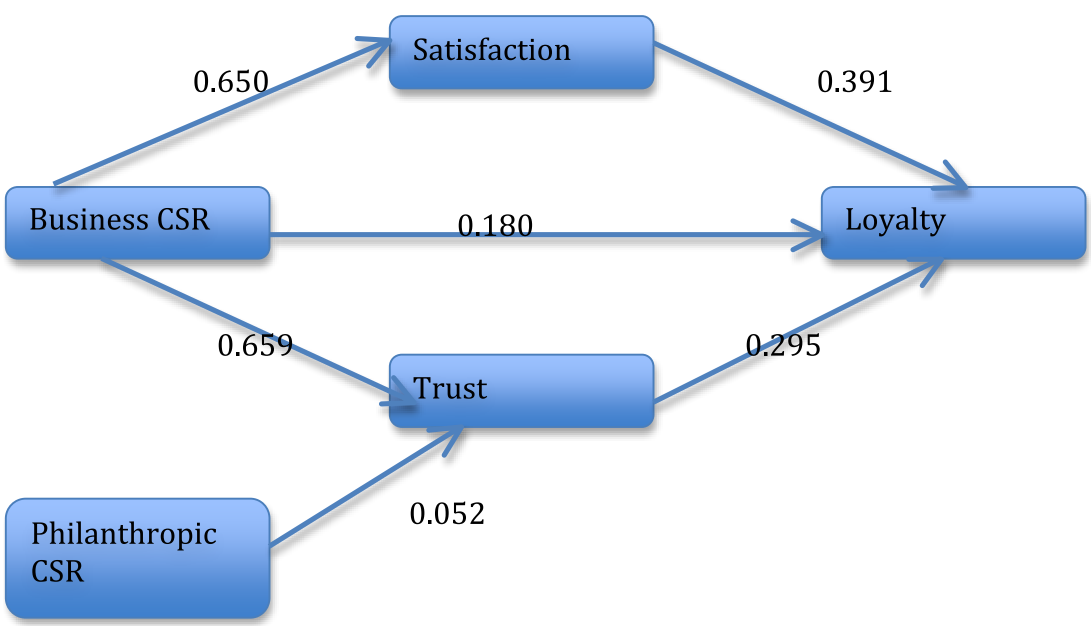
Item	Variables	Percentage
Gender	Male	27.65
	Female	72.35
Age	20-30	42.35
	31-40	45.88
	41-50	10.59
	More than 51	2
Occupation	Student	8.24
	Private Sector Employee	5.88
	Civil Servant Employee	38.82
	Professional (Doctors, Lawyers, etc)	24.71
	House wife	15.29
	Others	7.06
Income (IDR)	Less than 1.000.000	3.12
	1.000.000-2.000.000	5.62
	2.000.001-5.000.000	19.38
	5.000.001-10.000.000	32.5
	10.000.001-20.000.000	15
	20.000.001-30.000.000	11.25
	More than 30.000.001	13.12
Education	High school	4.71
	Undergraduate	8.82
	Master Degree	50.59
	Doctoral Degree	29.41
	Others	6.47
Marital Status	Married	55
	Separated/Divorced	2.5
	Single	42.5
No of Bank account	1 bank account	15.88
	2 bank account	34.12
	3 bank account	27.06
	more than 3 bank account	22.94

From 170 respondents, 27.65% were male and 72.35% were female. The sample was slightly skewed to young adults with 42.35% aged 20-30, followed by the group of respondents aged 31-40 (45.88%), aged 41-50 (10.59%) and those aged more than 51 (2%). Amongst all respondents, 88.82% had a relatively high level of education at undergraduate degree level or above. Amongst the 170 respondents, 32.15% of respondents earned a monthly income from IDR5.000.000-IDR10.000.0000. The majority of respondents were either never married/single (42.5%) or currently married (55%). Regarding the number of bank account owned by respondent, almost 84.12% respondent owned more than 1 bank account either in the same bank or different bank.

The questionnaire survey was constructed according to conceptual model, thus it incorporated questions on CSR, satisfaction, trust and loyalty of the bank. For both customers and employees the scale of questions was measured as follows: 1 = very dissatisfied, 2 = dissatisfied, 4 = satisfied and 5 = very satisfied.

4. Results and Discussion

Figure 2. SEM Model



The structural model was evaluated by examining the structural paths, t-statistics, and variance explained (the R-squared value). In the model, business CSR and philanthropic CSR were exogenous construct variables as their causes were unknown and hence not represented in the model, and they were specified as causes for other variables (as can be seen from figure 1). To establish the goodness fit of model, fit indexes were conducted by observing the Chi-square, RMSEA, NFP, TLI and CFI and the results indicate that the model fit well with the data obtained. All goodness-of-fit statistics were within an acceptable fit level.

Table 3. Summary of Hypothesis Testing

Hypothesis	Exogeneous Variable	Mediating Variables	Endogeneous Variable	Standardized Coefficient	Probability	Decision
H1	Business CSR		Loyalty	0.181	0.000	Hypothesis is supported
H2	Business CSR	Satisfaction	Loyalty	0.254	0.000	Hypothesis is supported
H3	Business CSR	Trust	Loyalty	0.194	0.000	Hypothesis is supported
H4	Philanthropic CSR		Trust	0.052	0.544	Hypothesis is not supported

Based on the result, that Business CSR has a positive effect on customer loyalty (γ = .0.181, p<.01), in support of H1.

By using satisfaction construct variable as mediating variable, this study uncover a significant effect of Business CSR on satisfaction (γ = .0.650, p<0.01), which has a significant influence on customer loyalty (γ = .391, p<0.01). The product of these effects is significant (γ = .250, p<0.01), indicating a mediating role of trust as predicted in H2. Thus it can be concluded that Business CSR gives direct influence to the consumer's loyalty, and also indirect influence through the consumer's trust and satisfaction. Since the majority of respondents has level of education above undergraduate degree level, they seems to have S1 understanding and awareness of CSR and the business sustainability. In addition, all respondent has also has become bank's customer for at least 3 years indicating that they have been loyal enough to the bank.

In the Meantime, by using trust construct as mediating variable, We uncover a significant effect of Business CSR on trust (γ = .0.659, p<0.01), which has a significant influence on customer loyalty (γ = .295, p<0.01). The product of these effects is significant (γ

= .19, p<0.01), indicating a mediating role of trust as predicted in H3. In contract with Business CSR, Philanthropic CSR has no significant effect on trust, hence it did not support H4. The result is quite consistent with the the research of Kazemi and Omidi (2015) and Chung et al. (2015). The customer also perceive that the variable of satisfaction and trust can strengthen the influence of Business CSR activity on the loyalty of bank’s customer. This is consistent with the previous study which states that the satisfaction variable can positively be strengthening the influence of CSR on customer loyalty (Chung et al., 2015).

In this study, business practice CSR was found to have a positive relationship with satisfaction and trust, which is consistent with many different empirical research studies (Azmat and Ha, 2013). The relationship was the strongest (0.659) in terms of all the relationship on the construct model. However, it is inconsistent with the result from the relationship between philanthropic CSR and trust was that is found insignificant and very weak (0.052).

The literature has advised that when banks engage in ethical business practices targeted at primary stakeholders like customers, they will gain business practice CSR reputation, which serves as an indication of a company’s trustworthiness (Homburg et al., 2013). The positive relationship between trust and loyalty was compared to the relationship between perceived service quality and trust. This concurred with previous studies, which have seen varying results on antecedents of trust, while the contribution of trust to attitudinal loyalty was seen to be strong (Homburg et al., 2013).

An insignificant relationship between philanthropy and trust was supported by other research, and could be related to consumers’ scepticism of philanthropy by corporations (Wu and Chen, 2015).

5. Conclusion

This study tried to investigate the direct effect of CSR and indirect effect through mediating variables, namely satisfaction and trust, to consumer's loyalty. The research divided the CSR aspect into two different aspect, Business CSR and Philanthropic CSR. The findings concluded that business CSR can make a significant contribution to customer loyalty through direct and through the mediating factors of satisfaction and trust. Together with the confirmation of a relationship between perceived service quality, trust and attitudinal loyalty, the research has confirmed the positive contribution of business CSR towards profitability, which is developed by establishing attitudinal loyalty through building better satisfaction and trust. On the other hand, philanthropic CSR reputation was found not a significant driver to customer's loyalty.The implication of this research for bank management is to consistently implementing the CSR initiatives to improve customer satisfaction and formulate effective communication strategy and CSR strategy in general in order to enhance the customer satisfaction, trust and loyalty.

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