A Test of the Adaptive Market Hypothesis using Non-Bayesian Time-Varying AR Model in Japan*

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Abstract

This paper examines the adaptive market hypothesis of Lo (2004, 2005) using the Ito and Noda's (2012) non-Bayesian time-varying AR model in Japan. As shown in Ito and Noda (2012), their degree of market efficiency gives us a more precise measurement of market efficiency than conventional moving window methods. The empirical results supports the AMH of Lo (2004, 2005) for data of the more qualified stock market in Japan.

1   Introduction

Economists have been changing their briefs on the efficient market hypothesis (EMH) for past forty years. In particular, Fama (1970), a leading economist in this field, changes his view. He uses some autocorrelation tests in his survey article; his findings suggest that stock markets are almost efficient. Two decades later, Fama (1991) addresses the same issue. He gives a slight different aspect reviewing vast literature concerning the market efficiency; Fama shows mounting evidence of predictability of stock returns. The story continues. Fama (1998) again reviews the empirical work on event studies concerning several long-term return anomalies. Malkiel (2003) and Schwert (2003) critically examine the validity of predictability reported in stock returns statistically. More recently, Yen and Lee (2008) suggest that support for the EMH has been changing in the periods.

Thus the EMH is almost supported in the 1960s, but it received attack from the school of behavioral finance in the 1990s.

Researchers in finance have experienced the timeless controversy over the EMH between proponents of the efficient market and advocates of behavioral finance (see Malkiel et al. (2005)). One can answer the reason why they do not attain any consensus on the EMH by considering a simple point on statistics. If a researcher concludes that the series of a financial commodity follows a random walk from his/her data, the conclusion is an evidence that supports the EMH. However, when he/she could not make such a conclusion from the data by testing the random walk hypothesis, the data do not provide with any evidence which supports and negates the EMH. Specifically, as Nyblom (1989) points out, a process with a single break point can also be a martingale process. Thus, even if the random walk hypothesis is rejected, we cannot deny the market efficiency because of other possibilities of martingales or returns.

In recent years, some economists attempt to reconcile the opposing sides. In fact, Lo (2004, 2005) proposes an alternative hypothesis, called the adaptive market hypothesis (AMH). He stresses an evolution of financial market when we talk about the market efficiency. In his new hypothesis, the reconciliation reaches between the proponents of the EMH and behavioral finance in a consistent manner; market efficiency is not an object to be statistically tested to reject but is a framework in which most researchers can discuss fruitfully. In the framework, one can explore the possibility that stock market evolves over time and market efficiency also varies with time (see, Ito and Sugiyama (2009), Kim et al. (2011) and Lim et al. (2013) conclude that the market efficiency varies with time in the U.S. stock market). Ito and Noda (2012) show that the U.S. stock market evolves over time, and the market efficiency in the U.S. stock market has a cyclical fluctuation with very long periodicity, from 30 to 40 years. Meanwhile, as far as we know, there is no literatures that directly examine whether the Japanese stock market evolves or not in the context of the Lo's (2004, 2005) AMH.

This paper examines the AMH of Lo (2004, 2005) in the Japanese stock markets: the Tokyo Stock Exchange first section and second section. In particular, we investigate whether the Japanese stock markets evolves over time its market efficiency changes over time, and the difference of trading volumes and the degree of market liberalization between the stock markets affects the degree of market efficiency. Then we consider the Ito and Noda's (2012) non-Bayesian time-varying autoregressive (TV-AR) model to measure the degree of market efficiency. As shown in Ito and Noda (2012), their degree of market efficiency gives us a more precise measurement of market efficiency than conventional moving window methods. We conclude that the Japanese stock market evolves over time and its market efficiency changes over time, and the empirical results supports that the AMH of Lo (2004, 2005) for data of the more qualified stock market in Japan.

This paper is organized as follows. Section 2 presents the hypotheses and Ito and Noda's (2012) non-Bayesian TV-AR estimation methods. Section 3 describes the data used. Section 4 shows the empirical result that the market efficiency in the Japanese stock market varies over time. Section 5 is for conclusion.

2 Hypotheses and Estimation Methods

In this section, we first introduce the two hypotheses regarding the market efficiency: the EMH and the AMH. And we show the empirical methods to compute the time-varying degree of market efficiency as shown in Ito and Noda (2012). Their idea is essentially based on the theory of impulse responses, analyzing how a shock propagates over time. Furthermore, considering the Japanese stock market with time-varying structure, we obtain the time-varying degree by estimating a non-Bayesian TV-AR model.

2.1 The EMH and The AMH

The EMH has an implication that market price reflects any exogenous shock at once in financial markets. Mathematically, one often represents it in the following way:

$$E[x_t \,|\, \mathcal{I}_{t-1}] = 0, \tag{1}$$

where x_t denotes the return of a security at t and $\mathcal{I}_{t-1}$ is the (increasing) information set at $t-1$, some σ-field to which $x_{t-1}, x_{t-2}, \cdots$ is adapted. Note that the EMH holds when the (log) price of the security follows a random walk process. In other words, one can say that the security price is "determined by accident."

Thus, when one consider the situation where the hypothesis does not always hold, it is natural to consider that the (excess) stock return follows a moving average process with infinite terms, MA(∞):

$$x_t = u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \cdots, \tag{2}$$

where $\{u_t\}$ is a i.i.d. process. Since $\mathcal{I}_{t-1}$ is a σ-field to which x_{t-1} is adapted and $\{\mathcal{I}_{t-1}\}$ a system of increasing information sets, the following equation holds:

$$E[x_t \,|\, \mathcal{I}_{t-1}] = \beta_1 u_{t-1} + \beta_2 u_{t-2} + \cdots.$$

Then, the EMH holds if and only if $0 = \beta_1 = \beta_2 = \cdots$.

While Lo (2004, 2005) propose an alternative hypothesis, the AMH, which is based on an evolutionary approach to economic interactions. He calculates the time-varying first order autocorrelations with moving window. And he shows that there exist efficient periods and inefficient ones in the stock market. However, the time-varying structure of the stock market efficiency remains to be elucidated. We consider the AMH that the degree of market efficiency fluctuates over time and reflects evolving market conditions: bubbles, market crashes, legal reforms, deregulations, and technological innovations. Therefore, we not only measure the time-varying degree of market efficiency, but also investigate whether the stock market evolves through time

2.2 Non-Bayesian Time-Varying AR Model

The above discussion show the significance of estimation of AR models for financial data. This subsection introduces Ito and Noda's (2012) non-Bayesian TV-AR estimation method for analyzing financial data of which data generating process is of time-varying.

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In financial economics, AR models,

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_q x_{t-q} + u_t,$$

have been frequently used for analyzing time series of stock returns of a financial asset, where $\{u_t\}$ satisfies $E[u_t] = 0$, $E[u_t^2] = 0$ and $E[u_t u_{t-m}] = 0$ for all m. Whereas α_ℓ's are assumed to be constant in ordinary time series analysis, we suppose the coefficients of the AR model to vary with time. We apply it to the real financial market because we have experienced many financial crises such as the recent Lehman fall, which suggests the existence of structural changes in stock markets.

$$x_t = \alpha_{0,t} + \alpha_{1,t} x_{t-1} + \cdots + \alpha_{q,t} x_{t-q} + u_t,$$

where $\{u_t\}$ satisfies $E[u_t] = 0$, $E[u_t^2] = 0$ and $E[u_t u_{t-m}] = 0$ for all m. We call this model a non-Bayesian TV-AR; we often abbreviate it TV-AR in the following part of this paper. We should suppose a parameter dynamics as restrictions of parameters when we estimate a non-Bayesian TV-AR model using data. The assumption that each AR coefficients vary as a martingale is a general one when we consider parameter dynamics:

$$\boldsymbol{\alpha}_{t-1} = E[\boldsymbol{\alpha}_{t-1} \mid \mathcal{I}_{t-1}],$$

where $\boldsymbol{\alpha}_t = (\alpha_0 \ \alpha_1 \ \cdots \ \alpha_q)$ and $\{\mathcal{I}_t\}$ is an increasing sequence of σ-fields to which $\boldsymbol{\alpha}_t$ is adapted. Defining $\Delta_t = \boldsymbol{\alpha}_t - \boldsymbol{\alpha}_{t-1}$, we assume

$$E[\Delta_t{}^t \Delta_t \mid \mathcal{I}_{t-1}] = \delta^2 G_{t-1},$$

for some known matrix $\{G_{t-1}\}$.

This martingale formulation, introduced by Nyblom (1989) and Hansen (1990, 1992), has substantial flexibility and covers a wide range of parameter dynamics. It allows, for instances, a stochastic process with a single structural break as Nyblom (1989) points out and a random walk as specified in many articles. Nyblom (1989) and Hansen (1990, 1992) provide us with some statistics to test constancy of the parameter of linear models as well as of non-linear models with the null hypothesis of constancy and the alternative one of the martingale of parameters. In this paper, we use Hansen's (1992) statistic (For the detail of test statistics, see Hansen (1992)). In this paper, among several alternatives of Hansen's test, i.e. martingale formulation, we choose the assumption that all AR coefficients except for the one corresponding to constant follow independent random walk processes since the mean of stock returns is constant in the long-run. Specifically,

$$\alpha_{\ell,t} = \alpha_{\ell,t-1} + v_{\ell,t}, \ (\ell = 1, 2, \cdots, q)$$

where $\{v_{\ell,t}\}$ satisfies $E[v_{\ell,t}] = 0$, $E[v_{\ell,t}^2] = 0$ and $E[v_{\ell,t} v_{\ell,t-m}] = 0$ for all m and ℓ.

2.3 Time-Varying Impulse Responses and Time-Varying Long-Run Multipliers

In this subsection, we show the method the time-varying impulse responses and the time-varying long-run multipliers as shown in Ito and Noda (2012). We calculate them from

the non-Bayesian TV-AR coefficients in each period, estimated by using the method in the previous subsections; we calculate confidence intervals for each coefficients based on the covariance matrix estimated at the same time. While Ito and Noda's (2012) idea is simple, the reader should take two notices: (1) the non-Bayesian TV-AR model which we estimate is just an approximation of the real data generating process, which is supposed to be some very complex nonstationary process and (2) we consider the estimated AR(q) model index by each period t, which is stationary, as a local approximation of the underlying complex process.

First, we estimate some AR(q)'s, which are time invariant, for $q = 1, 2, \cdots$ to find the appropriate order using the Schwartz Bayesian information criterion (SBIC). After the order is determined, we estimate the TV-AR(q) by the above method. From the TV-AR(q) model, we derive the TV-MA(∞) model:

$$x_t = u_t + \beta_{1,t} u_{t-1} + \beta_{2,t} u_{t-2} + \cdots .$$

Suppose that we already estimated each of the TV-AR coefficients vector $^t(\hat{\alpha}_{1,t}\ \hat{\alpha}_{2,t}\ \cdots \hat{\alpha}_{q,t})$ as well as the time invariant constant term $\hat{\alpha}_0$. We derive the time-varying interim multipliers for impulse response analysis for each period and the time-varying long-run multipliers for T vectors $^t(\hat{\alpha}_0\ \hat{\alpha}_{1,t}\ \hat{\alpha}_{2,t}\ \cdots \hat{\alpha}_{q,t})$.

$$\hat{\beta}_{0,t} = 1, \ \hat{\beta}_{k,t} = \sum_{j=1}^{k} \hat{\beta}_{k-j,t} \hat{\alpha}_{j,t},$$

$$\hat{\phi}_{\infty,t} = \frac{1}{1 - \hat{\alpha}_{1,t} - \hat{\alpha}_{2,t} \cdots - \hat{\alpha}_{q,t}}.$$

3 Data

This paper uses the monthly returns for the Tokyo Stock Price Index (TOPIX) and the Tokto Stock Exchange Second Section Stock Price Index (TSE2) from October 1961 to June 2012, obtained from *The monthly statistics report of Tokyo Stock Exchange*.[1] In practice, we take log first difference of time series of the stock price index. Figure 1 presents time series plots of the returns for the TOPIX and TSE2.

(Figure 1 around here)

For the estimations, each variables that appears in the moment conditions should be stationary. To check whether the variables satisfy the stationarity condition, we use the ADF-GLS test of Elliott et al. (1996). Table 1 provides some descriptive statistics and the results of the ADF-GLS test. The ADF-GLS test rejects the null hypothesis that the variables contains a unit root at conventional significance levels.[2]

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[1]Tokyo Stock Exchange defines that the TSE2 is a free-float adjusted market capitalization-weighted index that is calculated based on all the domestic common stocks listed on the Tokto Stock Exchange Second Section.

[2]We confirm that there are no size distortions that Elliott et al. (1996) and Ng and Perron (2001) pointed out in making the ADF-GLS test for small samples (see a column $\hat{\phi}$ of the table 1 for details). Therefore, we use the Modified Bayesian Information Criterion (MBIC), not the Modified Akaike Information Criteria (MAIC) to select an optimal lag order for the ADF-GLS tests.

(Table 1 around here)

4   Empirical Results

First, we present a preliminary AR(q) estimations with whole sample. Second, we examine whether the AR estimates change over time or not using the parameter constancy test of Hansen (1990, 1992). Third, we estimate the non-Bayesian TV-AR models, and calculate the time-varying impulse responses and the time-varying long-run multipliers as shown in Ito and Noda (2012).

4.1   Preliminary Estimations and Parameter Constancy Tests

We assume a model with constant and use the SBIC of Schwarz (1978) as an optimal lag order selection criteria in an AR(q) estimation. In our estimations, we choose a first and third-order autoregressive (AR(1) and AR(3)) model for the TOPIX and TSE2, respectively. Table 2 shows preliminary results for the above models using the whole sample.[3]

(Table 2 around here)

The AR estimates are statistically significant at conventional levels except for the constant terms and third-order autoregressive term in the equation of the TSE2. In particular, the first-order autoregressive estimates are about 0.32 (TOPIX) and 0.44 (TSE2), is relatively high. Because they indicates that a shock at any month affects the return of two month later at least 10% (TOPIX) and 20% (TSE2).

Now, we investigate whether there exhibits a parameter constancy in the above AR models using Hansen's (1990, 1992) tests under random parameters hypothesis. Table 2 also presents the result of the parameter constancy test; we reject the null of constant all parameters against the parameter variation as random walk at the 1% statistical significant level. Therefore, we estimate the time-varying parameters of the above AR models to investigate whether gradual changes occur in the Japanese stock market.

4.2   Non-Bayesian TV-AR Estimations

We adopt a non-Bayesian time-varying estimation method similar to Ito and Noda (2012) for estimating our TV-AR models. Their method demonstrates a particular advantage over a simple moving window method. Kim et al. (2011) and Lim et al. (2013), for example, measure the time-varying autocorrelation using a simple moving window method, but a window width in their paper is not optimal and has no empirical background.[4] Meanwhile, we can calculate the optimal window width for smoothing the estimates by using the time-varying estimation method as shown in Ito and Sugiyama (2009) and Ito and Noda (2012).

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[3]We use the heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimator of Newey and West (1987, 1994).

[4]They admit that they select their window width as an example.

Figure 2 provides the time-varying estimates of the selected models.[5]

(Figure 2 around here)

We confirm that the all parameters of autoregressive terms change over time in our TV-AR models. In particular, the first-order autoregressive terms fluctuate wildly through time as same as shown in Ito and Sugiyama (2009) and Ito and Noda (2012).

4.3 Time-Varying Impulse Responses and Time-Varying Long-Run Multipliers

In this subsection, we estimate the time-varying impulse responses and time-varying long-run multipliers which based on above non-Bayesian TV-AR(1) and TV-AR(3) model.[6]

Figure 3 provides that the three-dimensional representation of the time-varying impulse responses in our models.

(Figure 3 around here)

We find that the time path of the effects of an exogenous shocks vary widely with time. Then, we calculate the time-varying long-run multipliers to analyze the total effects of shocks. Figure 4 shows that the total effects of shocks, the degree of market efficiency, changes over time.[7]

(Figure 4 around here)

The degree of market efficiency declines (rises) in the period of bubbles (panics: market crashes, and economic crises) as is obvious from the table 3. In periods of bubble with full of unreliable information, some investors could gain huge windfalls, which suggests that the market is inefficient; in periods of panic, an average investor hardly beats the stock market overall, which suggests that the market is efficient.

(Table 3 around here)

We can confirm that there are significant three differences between the TOPIX and TSE2 about the degree of market efficiency. First, the degree of market efficiency of the TSE2 is lower than the TOPIX ones in most periods. Second, the degree of market efficiency of the TSE2 fluctuates more widely than the TOPIX ones. Third, the degree of market efficiency of the TOPIX is less volatile since the burst of the bubble economy, but TSE2 ones is not.

We consider that the following fact might explain those differences occurring in the Japanese stock market. There are differences in criteria for listing between the TOPIX

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[5]When we compute the expected returns based on time-varying models with time invariant intercept, they exhibit much smaller than the original timeseries of the stock price. It supports our assumption about the intercept.

[6]We confirm that the models hold local stationarity by checking whether all the absolute values of eigenvalues of each local AR(1) and AR(3) are less than one.

[7]We report the approximative confidence intervals for each period by using the delta method in figure 4. And the bootstrap p-test rejects the null hypothesis that any AR coefficients vectors are zero at 1% significant levels.

and TSE2: (1) number of shareholders, (2) tradable shares, and (3) market capitalization of shares listed. Those facts indicate that trading volumes and the degree of market liberalization are quite different between the TOPIX and TSE2 since Japanese financial big bang (see also table 3). Figure 4 also shows that the degree of market efficiency of the TOPIX not only varies with time, but also evolves over time since the burst of the bubble economy. In particular, the degree of market efficiency of the TOPIX soon reflects the shock of "Bankruptcy of Lehman Brothers", but the TSE2 ones does not. Our empirical results suggest that the AMH of Lo (2004, 2005) for data of the more qualified stock market in Japan.

5   Concluding Remarks

This paper examines the adaptive market hypothesis of Lo (2004, 2005) in the Japanese stock markets (TOPIX and TSE2). In particular, we measure the Ito and Noda's (2012) degree of market efficiency which is based on the time-varying long-run multipliers. As shown in Ito and Noda (2012), their degree of market efficiency gives us a more precise measurement of market efficiency than conventional moving window methods. The empirical results shows that (1) the degree of market efficiency changes over time in the TOPIX and TSE2, (2) the degree of market efficiency of the TSE2 is lower than the TOPIX ones in most periods, and (3) the degree of market efficiency of the TOPIX evolves over time since the burst of the bubble economy, but the TSE2 ones does not. Therefore, we conclude that the empirical results supports the AMH of Lo (2004, 2005) for data of the more qualified stock market in Japan.

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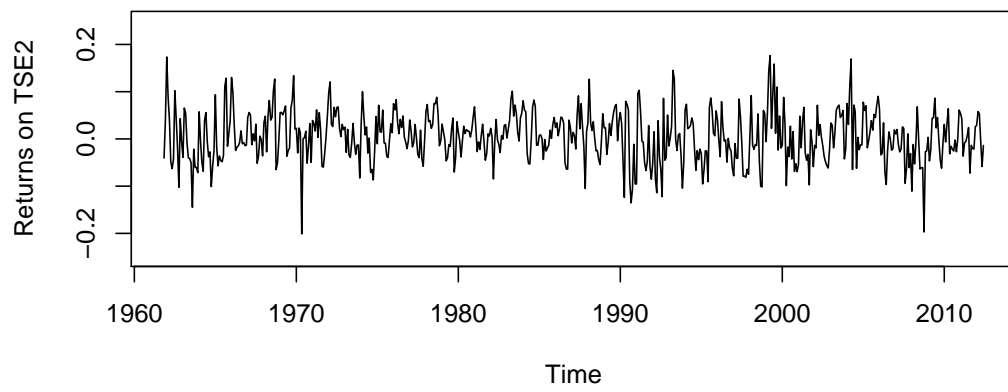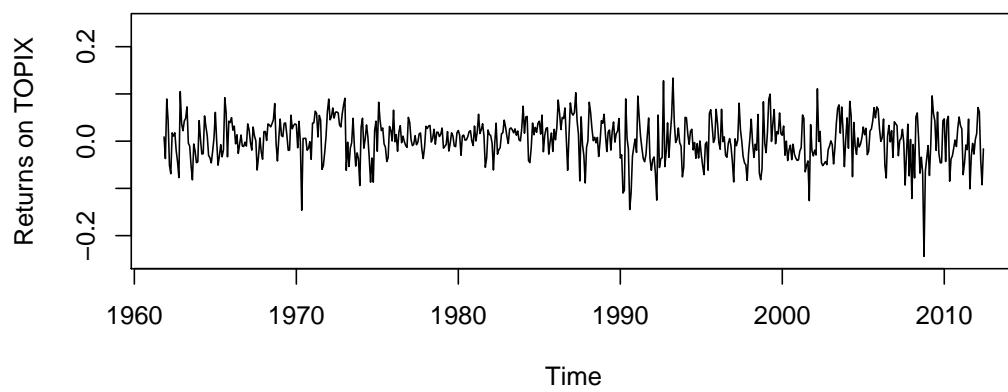Figure 1: The Returns on the TOPIX and TSE2

Table 1: Descriptive Statistics and Unit Root Tests

	Mean	SD	Min	Max	ADF-GLS	Lag	$\hat{\phi}$	$\mathcal{N}$
TOPIX	0.0033	0.0439	−0.2439	0.1336	−17.8589	0	0.3103	608
TSE2	0.0050	0.0531	−0.2012	0.1765	−14.0311	0	0.5094	608

Notes:

(1) "ADF-GLS" denotes the ADF-GLS test statistics, "Lag" denotes the lag order selected by the MBIC, and "$\hat{\phi}$" denotes the coefficients vector in the GLS detrended series (see equation (6) in Ng and Perron (2001)).

(2) In computing the ADF-GLS test, a model with a time trend and a constant is assumed. The critical value at the 1% significance level for the ADF-GLS test is "−3.42".

(3) "$\mathcal{N}$" denotes the number of observations.

(4) R version 2.15.1 was used to compute the statistics.

Table 2: Preliminary Estimations and Parameter Constancy Tests

	$Constant$	R_{t-1}	R_{t-2}	R_{t-3}	R^2	L_C
$R_{TOPIX,t}$	0.0022	0.3173	–	–	0.0977	35.2108
	[0.0017]	[0.0398]	–	–		
$R_{TSE2,t}$	0.0027	0.4416	−0.0953	0.0481	0.1698	54.3983
	[0.0020]	[0.0435]	[0.0435]	[0.0428]		

Notes:

(1) "R_{t-1}", "R_{t-2}", "R_{t-3}", "$\bar{R}^2$", and "L_C" denote the AR(1) estimate, the AR(2) estimate, the AR(3) estimate, the adjusted R^2, and the Hansen's (1992) joint L statistic with variance, respectively.

(2) Newey and West's robust standard errors are in brackets.

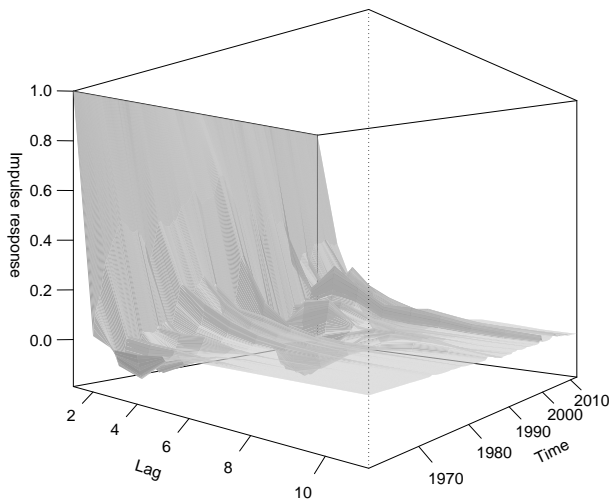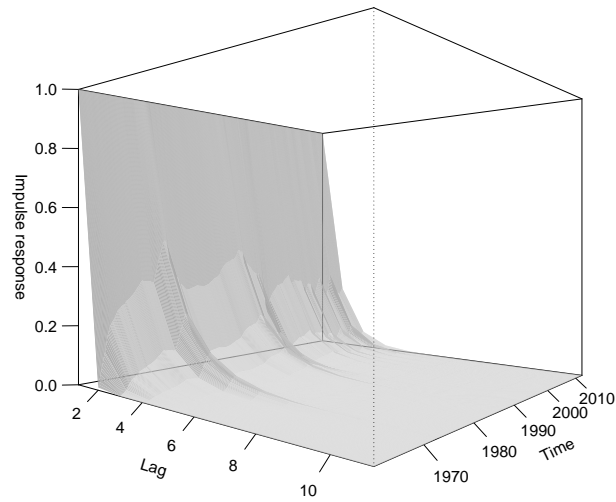(3) R version 2.15.1 was used to compute the estimates.

Figure 2: Non-Bayesian TV-AR Estimations
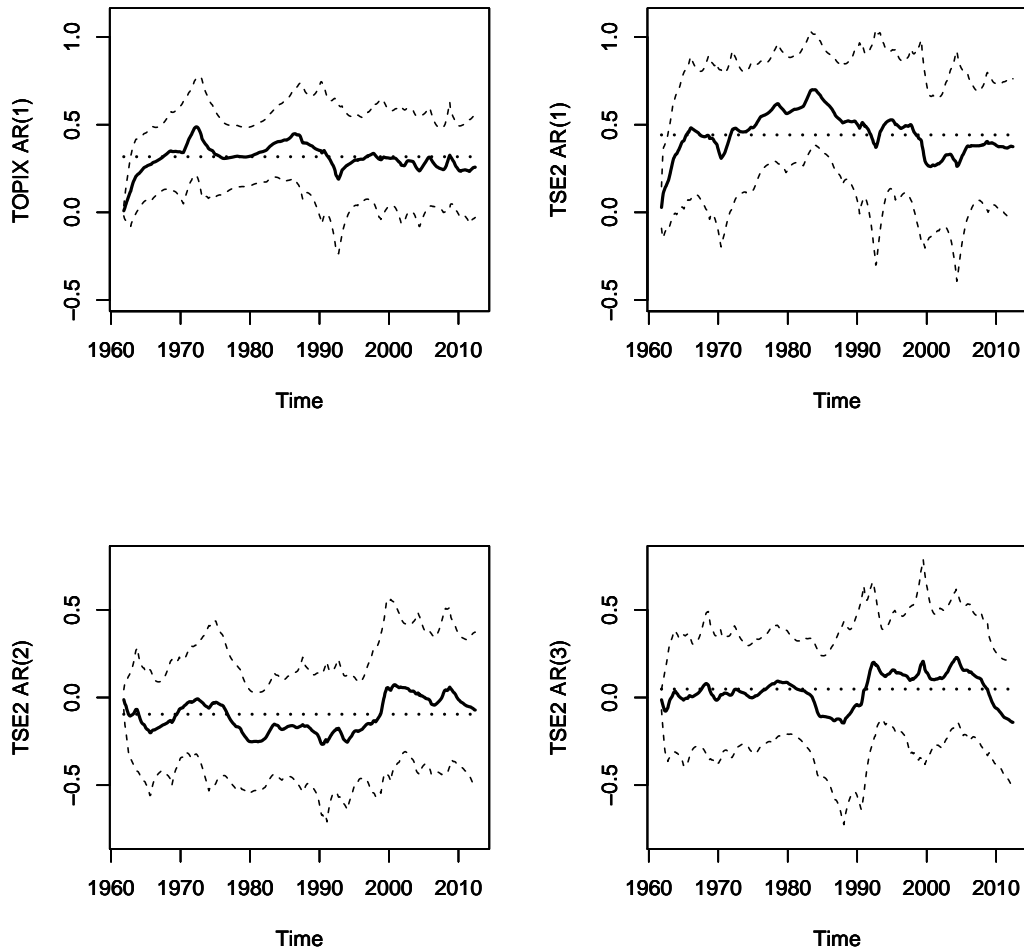
Notes:

(1) The dashed lines represent represent upper and lower bounds of the TV-AR estimates at the 95% confidence intervals for each period.

(2) The Newey and West's HAC estimator is used for calculating the confidence intervals.

(3) The dotted lines also represent the AR estimates with whole sample, respectively.
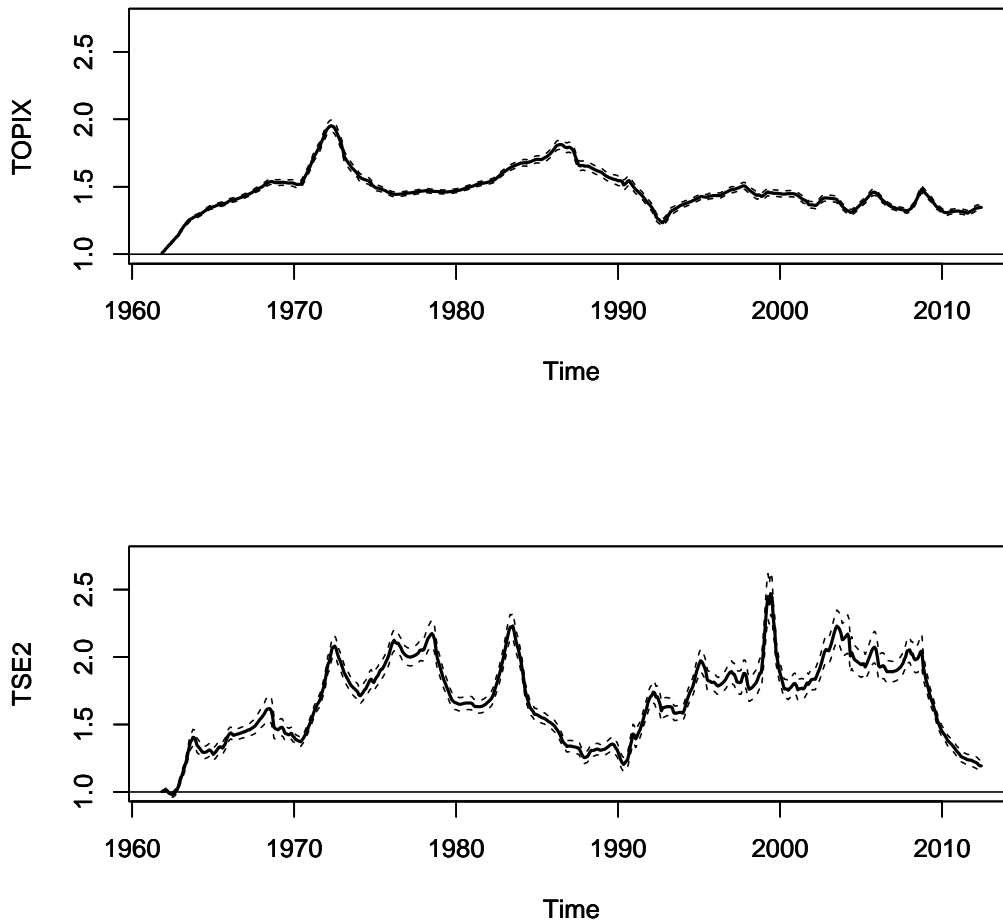
(4) R version 2.15.1 was used to compute the estimates.

Figure 3: Time-Varying Impulse Responses

<u>Notes</u>:

(1) The top figure represents the time-varying impulse responses for the TOPIX.

(2) The bottom figure also represents the time-varying impulse responses for the TSE2.

(3) R version 2.15.1 was used to compute the estimates.

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Figure 4: Time-Varying Long-Run Multipliers

Notes:

(1) The top panel of the figure shows the time-varying long-run multipliers for the TOPIX.

(2) The bottom panel of the figure shows the time-varying long-run multipliers for the TSE2.

(3) The dashed lines represent upper and lower bounds of the time-varying long-run multipliers at the 95% confidence intervals for each period by using the delta method.

(4) R version 2.15.1 was used to compute the estimates.

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Table 3: Dates of Major Histrical Events for the Japanese Stock Market

Events	Start Dates	End Dates
Market Crashes		
Black Monday	1987:10	-
Bankruptcy of Lehman Brothers	2008:10	-
Economic Crises		
1973 Oil Crisis	1973:10	-
1979 Oil Crisis	1979:01	-
Asia Financial Crisis	1997:07	-
Bubbles		
Asset Price	1986:12	1991:02
Dot-com	1995:08	2000:03
Legal Reforms and Deregulations		
Financial Big Bang	1998:04	2002:03

Notes:

(1) The end dates for market crashes, and economic crises are unspecified because of no consensus.

(2) The dates for bubbles basically follow *the index of business condition* by the Cabinet Office, Goverment of Japan (http://www.esri.cao.go.jp/en/stat/di/di-e.html).