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YOON JAEHYUN

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By

YOON JAEHYUN

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Abstract

This dissertation comprises of three essays in applied econometrics and machine learning. The essays present results of empirical analysis on the topics that cover firm productivity, monetary policy, and macroeconomic forecasting by machine learning models, focusing on the related data in Japan.

The first essay, titled "Impact of Foreign Ownership on Firm Productivity: Evidence from the Japanese Manufacturing Firms," presents the methodology to examine the impact of foreign ownership on firm productivity, using firm-level data of the Japanese manufacturing firms from 2000 to 2016. Firm productivity is estimated by Olley-Pakes semi-parametric estimation method to minimize the simultaneous problem in estimation of the firms' total factor productivity (TFP). The system GMM estimation is applied to address a possible endogeneity problem between foreign ownership and firm productivity. The evidence of this essay suggests the positive impact of foreign ownership on firm productivity in the case of manufacturing firms in Japan.

The second essay, titled "Physical investment of Japanese firms during QE and QQE periods: Did the transmission mechanism work?," analyzes the impact of Tobin'q, liquidity asset ratio, and debt ratio on the investment rate of firms and examines neoclassical and non-neoclassical transmission mechanism during QE and QQE periods. QE refers to Quantitative Easing cover the periods from 2001 and 2005. QQE refers to Quantitative-Qualitative Easing and covers the periods from 2013 to 2017. In order to address the endogeneity problem between the investment rate and the regressors, the system GMM estimation is applied. The result of this essay suggests that the neoclassical

transmission channel worked during the QE and QQE periods with the confirmation of the positive impact of Tobin'q on the firm investment. On the other hand, the non-neoclassical transmission channel did not work during QE and QQE periods as the impact of liquid asset ratio on the firm investment is confirmed to be not positive. It is also confirmed that the debt ratio turns out to have negative impacts on investment only for the QE period. During the QQE period and other periods, the coefficient turns out to have no significant impact on investment.

The third essay, titled "Forecasting of Real GDP Growth Using Machine Learning Models: Gradient Boosting and Random Forest Approach" presents machine learning models, including Gradient Boosting and Random Forest model, that produce forecasts on real GDP growth of Japan for the periods between 2001 and 2018. In the process of training the models, a customized cross-validation process is applied to improve the predictive power of the models. The forecasted data are compared with the benchmark forecasts made by International Monetary Fund (IMF) a (BOJ). The forecasts made by the machine learning machines are shown to be more accurate based on MAPE (mean absolute percentage error) and RMSE (root mean squared error).

This dissertation presents various analysis methods ranging from system GMM to machine learning models including Random Forest and Gradient Boosting models and the detailed analysis results to answer questions on empirical economic issues that cover firm productivity, monetary policy, and macroeconomic forecasting by machine learning models with focus on the Japanese data. It is expected that this dissertation would serve as stepping-stones for advancement of related applied econometric and machine learning research in the future.

Table of Contents

List of Figures

List of Tables

Chapter 1. Introduction

This dissertation comprises of three essays in applied econometrics and machine learning. The essays present results of empirical analysis on the topics that cover firm productivity, monetary policy, and macroeconomic forecasting by machine learning models, focusing on the related data in Japan.

After the introduction, Chapter 2 presents the first essay, titled "Impact of Foreign Ownership on Firm Productivity: Evidence from the Japanese Manufacturing Firms." This chapter examines the impact of foreign ownership on firm productivity in Japan, using firm-level data of the Japanese manufacturing firms from 2000 to 2016. Firm productivity is estimated by Olley-Pakes semi-parametric estimation method to minimize the simultaneous problem in estimation of the firms' total factor productivity (TFP). The system GMM estimation is applied to address a possible endogeneity problem between foreign ownership and firm productivity.

Chapter 3 presents the second essay, a co-work with Professor BAAK Saang Joon, titled "Physical investment of Japanese firms during QE and QQE periods: Did the transmission mechanism work?" This chapter analyzes the impact of Tobin'q, liquidity asset ratio, and debt ratio on the investment rate of firms and examines neoclassical and non-neoclassical transmission mechanism during QE and QQE periods.

Chapter 4 presents the third essay, titled "Forecasting of Real GDP Growth Using Machine Learning Models: Gradient Boosting and Random Forest Approach." This chapter introduces machine learning models, including Gradient Boosting and Random Forest model, that produce forecasts on real GDP growth of Japan for the periods between

2001 and 2018. In the process of training the models, a customized cross-validation process is applied to improve the predictive power of the models.

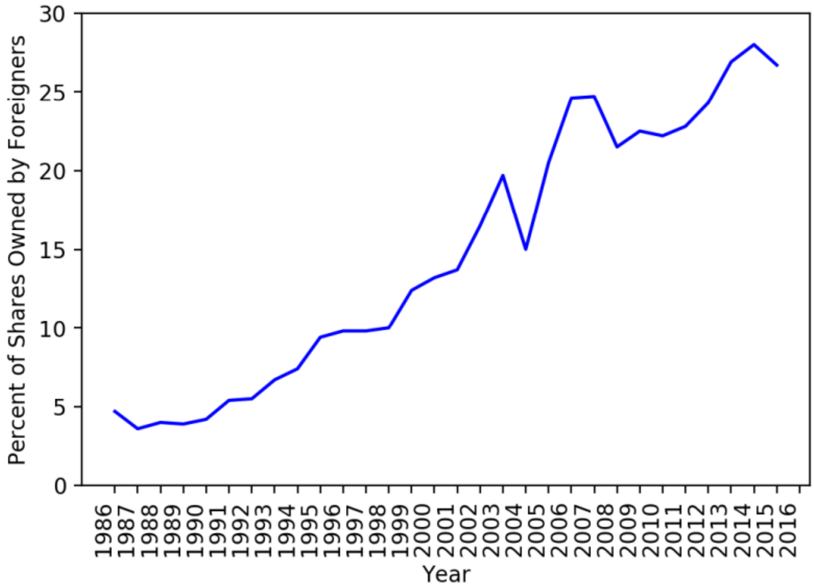
Lastly, Chapter 5 concludes this dissertation.

Chapter 2. Impact of Foreign Ownership on Firm Productivity: Evidence from the Japanese Manufacturing Firms

2.1 Introduction

Since late 1990s, Japan has experienced a drastic change in corporate ownership. This change is in line with the financial reform, the so-called "Big Bang" reform, initiated by the Japanese Prime Minister Hashimoto in 1996, which aimed to lower barrier of foreign investment in Japan and globalized its stock market. The reform includes the revised Foreign Exchange Law, which liberalized cross-border transactions in April 1998, and the Financial System Reform Law, the Banking Law, the Securities and Exchange Law, and the Insurance Business Law, enforced in December 1998. Along with the reform, the foreign ownership in listed firms in Japan has drastically increased. Accelerated by the reform in financial market, according to Tokyo Stock Exchange's 2016 Ownership Survey, as Figure 2.1 shows, the aggregate foreign ownership in Japan has risen from a mere 4.7% in 1986 to 26.5% in 2016. The increase in the foreign ownership led to decrease in insider ownership, which is held by traditional investors whose investment priority is not pure return on investment but a long-term relationship with the firms that they invested (Franks, Mayer, and Miyajima, 2014). It has been of high interest whether the lower insider ownership caused by higher foreign ownership leads to higher performance of the firm or not.

Figure 2.1. Aggregate foreign ownership of stock in Japan



Previous literature shows that the underlying interest of the foreign investors is different in many ways from those of the Japanese investors. Ahmadjian (2007) points out that due to legal obligations, U.S. and U.K. funds strictly follow how they can act with their investors' funds. On the other hand, the Japanese investors, especially institutional investors, often do not follow legal obligations strictly. While foreign funds primarily focus on the return over their investments, the Japanese investors are often involved in more complicated relationships of cross-holdings. This implies of a possibility that Japanese institutional investors may not be able to impose pressure on their invested firms compared to the foreign investors.

There are several views on how foreign ownership affects corporate performance. The first view is that foreign institutional investors take a monitoring role on their invested firms for a higher return on their investment. Aggarwal *et al.* (2010) finds evidence that foreign institutions take a role in shareholder activism, which lead to better corporate performance. There is also a view that foreign investors may contribute to corporate performance by bringing in valuable assets to the invested firms. Kimura and Kiyota (2007) shows that foreign investors bring in technology, managerial ability, connection to foreign markets into the invested firms to improve corporate performance. Backer and Sleuwaegen (2003) shows that in the case of the Belgian manufacturing firms, foreign ownership increases firm heterogeneity of the firms and contributes to aggregate productivity growth.

On the other hand, there is a view that foreign investors invest in foreign stocks as their diversification investment strategy and do not take an active role in monitoring their invested firms due to lack of information on the invested firms. (Miyajima and Ogawa, 2016). Javorcik (2004) finds that the effect on foreign investment on productivity enhancement of the firms in host country is not conclusive based on the Lithuanian case.

The purpose of this article is to examine the impact of foreign ownership on firm productivity, which is a major measure of corporate performance, in Japan. In fact, only few studies have been done on the impact of foreign ownership on productivity in Japan. For example, based on the manufacturing firms' data between 1994-1998, Fukao and Murakami (2005) shows that foreign direct investment brings more productivity in Japan. However, the study covers a relatively short period and does not consider a possible simultaneous problem between productivity and foreign ownership. Based on the firm level data of the Japanese manufacturing firms between 2000 and 2016, this article contributes to the literature by providing an empirical study using an Olley-Pakes semi-parametric estimation to minimize simultaneous problem in estimation of total factor productivity (TFP). In addition, the two-step system GMM estimation, which is a dynamic panel estimation, is used to address the potential endogeneity problem between foreign ownership and firm productivity.

2.2. Methodology and Data

2.2.1 Baseline Model

$$L\_TFP_{i,t} = \beta_0 + \beta_2 FO_{i,t} + \beta_3 L\_HHI_{i,t} + \beta_4 L\_TR_{i,t} + \beta_5 L\_TR2_{i,t} + \beta_6 EX_{i,t} + \varepsilon_{i,t} \quad (1)$$

The baseline model has the dependent variable, $L\_TFP_{i,t}$, which is log value of total factor productivity technology for firm i at time t, estimated by the method of Olley and Pakes (1996).[1] It has been argued that the use of OLS leads to a biased estimation of total factor productivity since OLS treats la l a les (Griliches and Mairesse 1995). In other words, simultaneous problem arises since the firms could choose their inputs, knowing their productivity (Marschak and Andrews 1944).

To deal with the simultaneous problem, this article uses the Olley-Pakes method for the estimation of TFP, using labor[2] and material cost as freely variables, capital as a state variable, and physical investments of firm as a proxy variable. The Olley-Pakes method uses a two-step procedure as follows. Consider the following Cobb-Douglas production technology for firm i at time t:

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1 The Olley-Pakes method has an option for firm exit. However, this option is not used in this study because the data set does not have specific information whether the firm exit because of liquidation or other reasons such as acquisition by another firm.

2 Labor is a firm's number of employees.

$$Y_{i,t} = \beta_0 + \beta_1 l_{i,t} + \beta_2 k_{i,t} + \omega_{i,t} + \varepsilon_{i,t} \tag{2}$$

$Y_{i,t}$ is the value of output. In this article, the value added is used as the proxy for output. $l_{i,t}$ is a 1 x J vector of log values of free variables, which the firm can change knowing their productivity. $k_{i,t}$ is a 1 x K vector of log values of state variables and $\varepsilon_{i,t}$ is a normally distributed idiosyncratic error term. The random component $\omega_{i,t}$ is the unobserved technical efficiency parameter and evolves according to a first-order Markov process as follows:

$$w_{i,t} = \mathrm{E}\left(\omega_{i,t} \middle| \omega_{i,t-1} \right) + u_{i,t} = g(\omega_{i,t-1}) + u_{i,t} \tag{3}$$

$u_{i,t}$ is a random shock component, which is assumed to be uncorrelated with the technical efficiency, the state variable in $k_{i,t}$, and the lagged free variables in $\omega_{i,t-1}$. The estimation assumes the following:

i) Investment demand, $i_{i,t} = f(k_{i,t}, \omega_{i,t})$, is a function of both the state variable and the technical efficiency parameter. The investment demand can be inverted as follows:

$$w_{i,t} = f^{-1}\left(i_{i,t}, k_{i,t}\right)$$

ii) $i_{i,t}$ is strictly monotone in $\omega_{i,t}$.

iii) $\omega_{i,t}$ is the only econometric scalar unobservable in $i_{i,t}$.

iv) The levels of $i_{i,t}$ and $k_{i,t}$ are determined at time t-1.

The above assumptions ensure the invertibility of $i_{i,t}$ in $\omega_{i,t}$ and lead to the partially identified model as follows:

$$Y_{i,t} = \beta_0 + \beta_1 l_{i,t} + \beta_2 k_{i,t} + \omega_{i,t} + \varepsilon_{i,t} = \beta_0 + \beta_1 l_{i,t} + \beta_2 k_{i,t} + f^{-1}(i_{i,t}, k_{i,t}) + \varepsilon_{i,t} \quad (4)$$

The model can be estimated by a non-parametric approach in the first stage estimation and eliminate the unobservable which causes the endogeneity problem. In the first stage, β_1 can be estimated, and this leads to the second stage in order to estimate β_2.

$$Y_{i,t} - \hat{\beta}_1 l_{i,t} = \beta_0 + \beta_2 k_{i,t} + g(\omega_{i,t-1}) + \varepsilon_{i,t} \quad (5)$$

$g(\omega_{i,t-1})$ is approximated by a n-th order polynomial and moment condition. In this article, the third order polynomial and moment condition are used. The log value of the residual from equation (5) is the dependent variable of Equation (1), $L\_TFP_{i,t}$. The Olley-Pakes estimation is conducted by "prodest" command of STATA introduced by Rovigatti and Mollisi (2018).

If the Olley-Pakes correction successfully corrects for biases, the coefficients on la l should increase compared to those from OLS estimations (Javorcik, 2004). Table 2.1 shows that the Olley-Pakes correction works well since, compared to OLS regression, the coefficients on la

.

In the equation (1), for the explanatory variables, $L\_TFP_{i,t-1}$ is the lagged value of the dependent variable. $FO_{i,t}$ is foreign ownership, which indicates the proportion of the shares owned by foreign investors. L_$HHI_{i,t}$ is log value of Herfindahl-Hirschman Index (HHI). HHI is a measure of market concentration, which is calculated by squaring the market share of each firm in the industry and summing the results.[3] HHI is a proxy for competition in market. A lower HHI indicates that the competition in the industry is higher. According to Syverson (2011), competition has a positive impact on firm productivity because competition increases market share of more efficient producers and forces those who are not efficient to exit. At the end, those who are productivity survives like the Darwinian theory of selection, and this results in higher firm productivity. In the case of Japan, Funakoshi and Motohashi (2009) finds that higher competition leads to higher TFP.

$\mathrm{L\_TR}_{\mathrm{i,t}}$ is a proxy for size of firm and is log value of total revenue deflated by Producer Price Index announced by Bank of Japan according to the firm's industry. $\mathrm{L\_TR}^2{}_{\mathrm{i,t}}$ is a squared value of $\mathrm{L\_TR}_{\mathrm{i,t}}$ and is used to test a nonlinear relationship between size of firm and productivity. Beck et al. (2005) finds that the size of a firm is closely related to the firm's performance. Based on the previous literature, this article also includes the size of the firm proxied by the total revenue in the estimation models.

$EX_{i,t}$ is the dummy variable that has the value of 1 if the firm exports or 0 if the firm does not export. According to Syverson (2011), in most cases, exporting firms are more productive than other firms that do not export. In addition, Aw *et al.* (2008) finds that based on the microdata of Taiwanese electronics firms, the firms that choose to export tend to be already more productive than other firms. Based on the previous literature, this article controls the impact of the export of a firm on productivity.

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3 The value of HHI may range from close to 0 to 10000.

Table 2.1. Comparison of coefficients from OLS and Olley-Pakes regressions

Sector	Olley-Pakes Regression			OLS Regression					
	L_L	L_K	Sum of coefficient	L_L	L_K	Sum of coefficient	Change in L_L coefficient	Change in L_K coefficient	Obs.
1	0.689***	0.122	0.811	0.586***	0.321***	0.907	+	-	1957
2	0.783***	0.538***	1.321	0.752***	0.226***	0.978	+	+	830
3	0.572**	-0.072	0.500	0.710***	-0.034	0.676	-	-	267
4	1.048***	0.206**	1.254	0.964***	0.145***	1.109	+	+	349
5	0.943***	0.200*	1.143	0.943***	0.060	1.003	-	+	234
6	0.904***	0.110***	1.014	0.916***	0.101***	1.017	-	+	2884
7	0.461	0.132	0.593	0.655***	0.235***	0.890	-	-	165
8	0.700***	0.431***	1.131	0.780***	0.247***	1.027	-	+	839
9	0.537***	0.445	0.982	0.441***	0.436***	0.877	+	+	765
10	0.302	0.893***	1.195	0.429***	0.412***	0.841	-	+	550
11	0.622***	0.569***	1.191	0.566***	0.320***	0.886	+	+	1058
12	0.788***	0.219***	1.007	0.846***	0.136***	0.982	-	+	3527
13	0.813***	0.042	0.855	0.925***	0.033*	0.958	-	+	3098
14	0.869***	0.425***	1.294	0.970***	0.041	1.011	-	+	1784
15	0.511***	0.537***	1.048	0.569***	0.218***	0.787	-	+	1443
Total	0.615***	0.253***	0.868	0.648***	0.244***	0.892	-	+	19750

Sector codes: 1= Food and beverages; 2=Textile mill products; 3=Lumber and wood products; 4=Pulp and paper; 5=Print; 6=Chemicals; 7=Petroleum and coal products; 8=Ceramics, stone and clay; 9=Iron and steel; 10=Non-ferrous metals; 11=Processed metals; 12=General-purpose, production, and business oriented machinery; 13-Electrical machinery; 14=Transport machinery; 15=Other products.
L_L and L_K are log values of number of total employees and real capital, respectively.
Standard errors are in parentheses. Significance levels are indicated by *** $p < .01$, ** $p < .05$, * $p < .1$.

2.2.2. Dynamic Panel Model

The simultaneity between productivity and foreign ownership is reported in previous literature (Alfaro *et al.* 2004; Nakano and Nguyen 2013). To account for the potential simultaneous problem between TFP and foreign ownership, this article uses a dynamic panel model in addition to the baseline model as follows:

$$L_{TFP\,i,t} = \beta_0 + \beta_1 L_{TFP\,i,t-1} + \beta_2 FO_{i,t} + \beta_3 L_{HHI\,i,t} + \beta_4 L\_TR_{i,t} + \beta_5 L\_TR2_{i,t} + \beta_6 EX_{i,t} + \varepsilon_{i,t} \quad (2)$$

Based on Equation (1), the model additionally controls the lagged dependent variable, $L\_TFP_{i,t-1}$. Nickell (1981) finds that the coefficient of the lagged dependent variable in a dynamic panel model may not be consistently estimated by OLS estimation due to the potential correlation between the error term and the lagged dependent variable. A firm's productivity may be influenced by the foreign ownership, industrial concentration, and size at time t-1. To control such endogeneity problem, this article uses the system GMM estimation developed by Blundell and Bond (1998). Yogo (2004) suggests that the generalized method of moments procedure (GMM) could allow more efficient estimation than other estimation methods like Two-Stage Least Squares (2SLS) estimation method when the model is overidentified and the sample size is large enough. The system GMM estimation is an augmented version outlined by Arellano and Bover (1995), which enhances the efficiency of the difference GMM proposed by Arella - Bond (1991) by using level equations in addition to the first difference equations in the model.

Following Arellano-Bond (1991) , the system GMM used in this article has two stages and uses the lagged endogenous and exogenous variables as instruments to form moment conditions. According to Arellano and Bond (1991) a

(1998), the two-stages would produce more asymptotically more efficient estimators, however, the two stage standard errors are often downward biased. Following (Roodman, 2009), in order to avoid the downward bias for more efficient estimation, in this study, the standard errors are estimated by the finite-sample correction method proposed by Windmeijer (2005)

To test the validity of the model, the Hansen (1982) J-test and the Arellano-Bond test for autocorrelation are employed in the system GMM estimation. The Hansen J-test tests the null hypothesis that the instruments are exogenous. The appropriate instruments should lead to acceptance of the null hypothesis. The Arellano-Bond test for autocorrelation tests the null hypothesis of no correlation and is applied to the differenced residuals. The Arellano-Bond test for AR(1) tests the null hypothesis that the differenced residuals in time t is related to both the disturbance in period t-1. Due to the presence of difference equations in the system GMM model, the residuals are correlated with one-time lag. The Arellano-Bond test for AR(2) tests the null hypothesis that the differenced residuals in time t is related to both the disturbance in period t-1 and the disturbance in period t-2. If the model specification is appropriate, the residuals should not be correlated across two-time lags. Otherwise further tests are required to test more lags (Bond and Meghir, 1994). The system GMM estimation in this article is executed by “xtabond2” command in STATA.

2.2.3. Data

This article uses an unbalanced panel data set of 1,458 publicly traded manufacturing firms listed in either the first or second section of the stock exchanges of Tokyo, Osaka, Nagoya, Sapporo, and Fukuoka, in Japan for the periods from 2000 to 2016. The financial statement data of those firms are obtained from *The Corporate Financial Databank* compiled by the Development Bank of Japan. The data set includes the data of the companies that did not survive until 2016, and the financial data from the listed companies are those audited by professional audit firms, following the Financial Instruments and Exchanges Act. From this point of view, this article uses the data with credibility and minimizes a potential problem caused by survival bias.

The data set includes 15 subcategories of manufacturing firms that comprise of food and beverages; textile mill products; lumber and wood products; pulp and paper; print; chemicals; petroleum and coal products; ceramics, stone and clay; iron and steel; non-ferrous metals; processed metals; general-purpose, production, and business-oriented machinery; electrical machinery; transport machinery; and other products.

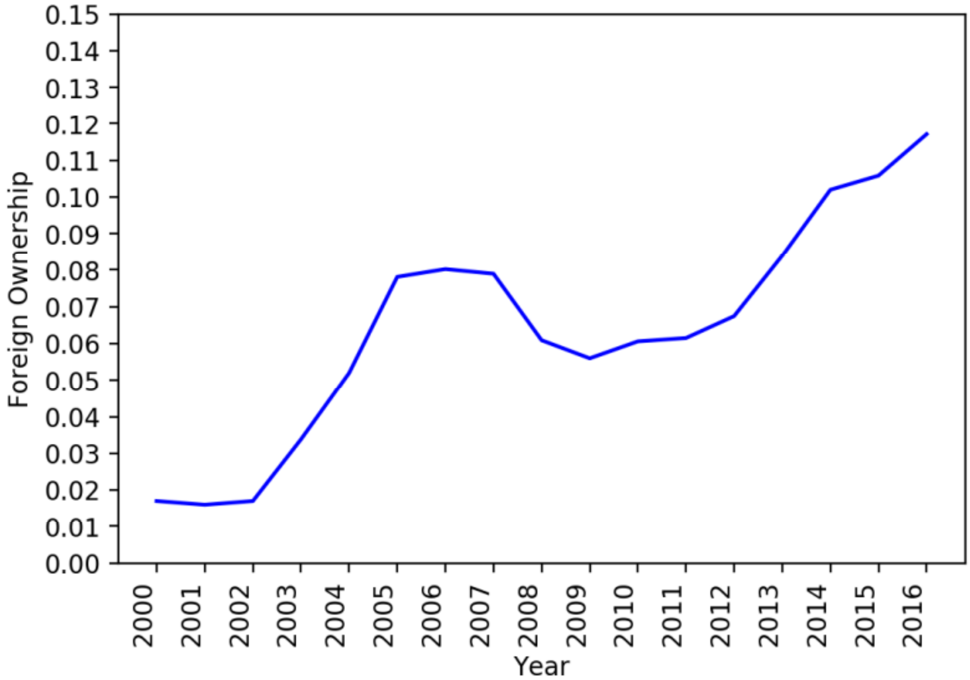
The descriptive statistics of the data used in this article is summarized in Table 2.2.

Table 2.2. Descriptive statistics

Variable	Mean	Median	SD	Min	Max	Obs.
L_TFP	2.566	2.573	0.061	1.694	2.933	19750
FO	0.103	0.056	0.118	0.000	0.900	19750
L_HHI	6.256	6.223	0.595	5.292	8.166	19750
L_TR	24.336	24.186	1.442	17.828	30.123	19750
L_TR^2	594.324	584.955	71.277	317.822	907.366	19750
L_FX	4.541	4.593	0.143	4.253	4.808	19750
EX	0.019	0.000	0.138	0.000	1.000	19750
L_K	23.807	23.687	1.758	13.377	29.515	19750
L_L	6.465	6.385	1.261	1.099	11.210	19750

Figure 2.2 presents the median value of foreign ownership for the firms analyzed in this study. Like the aggregate foreign ownership shown earlier in Figure 2.1, the foreign ownership has increased with the exception of the period of the global financial crisis between 2007 and 2009.

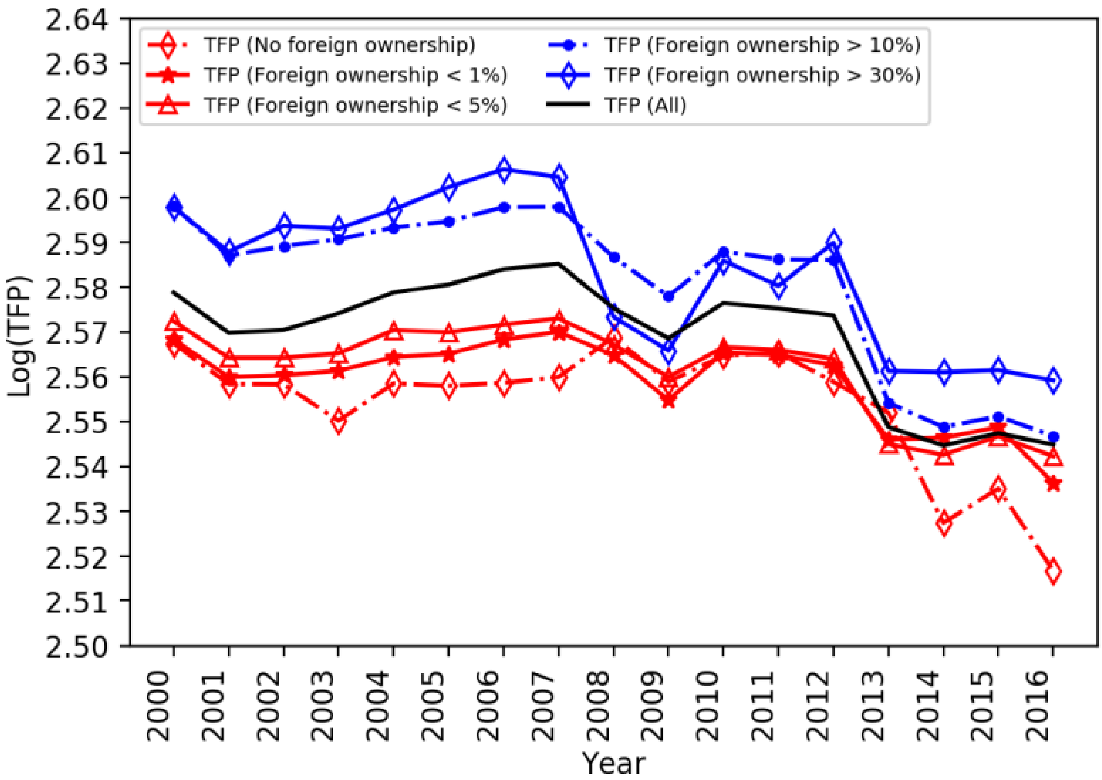
Figure 2.2. Foreign ownership of stock



* The lines represent the median values of foreign ownership of the firms analyzed in this study.

Figure 2.3 presents the median values of log values of TFP of the firms analyzed in this study. The figure shows that the firms with higher foreign ownership tend to have higher productivity. For example, the firms with foreign ownership with more than 30 percent clearly has higher productivity than those with no foreign ownership. However, as mentioned earlier, since there is a possibility of reversal causality, it cannot be simply concluded that higher foreign ownership leads to higher firm productivity without a proper test. The test result on the impact of foreign ownership on firm productivity will be presented in the next section.

Figure 2.3. Firm total factor productivity (TFP)



* The lines represent the median values of TFP of the firm groups analyzed in this study.

2.3. Results

Table 2.3 summarizes the results of the baseline models including OLS, Fixed Effects, and Random Effects estimations. The result confirms the positive impact of foreign ownership on firm productivity. The estimation results also suggest significant evidence that market concentration, represented by L_$HHI_{i,t}$, has a negative impact on productivity and implies that less competition in industry leads to lower productivity. In the case of the size of firm, the estimation results do not suggest any significant evidence that productivity increases with size of firm. Export appears to have a positive impact on productivity only in the case of OLS.

Table 2.3. Baseline model estimation results

	OLS	Fixed Effects	Random Effects
Independent Variables	Dependent Variable: L_TFP		
FO	0.113*** (0.005)	0.043*** (0.011)	0.043*** (0.010)
L_HHI	-0.018*** (0.003)	-0.017*** (0.004)	-0.012*** (0.003)
L_TR	-0.002 (0.008)	0.026 (0.052)	0.026 (0.033)
L_TR2	0.000 (0.000)	-0.000 (0.001)	-0.000 (0.001)
EX	0.010*** (0.002)	-0.003 (0.005)	-0.002 (0.004)
Obs.	19750	19750	19750
R-squared	0.051	0.035	
Wald's Chi			1263.6

All regressions have industry sector fixed effects controlled. Standard errors are in parentheses. Significance levels are indicated by *** $p < .01$, ** $p < .05$, * $p < .1$

Table 2.4 summarizes the results of the dynamic panel models including OLS, Fixed Effects and System GMM estimations. In the case of System GMM estimation, regarding the validity of the instruments, the Arellano-Bond tests are conducted to examine serial correlation of the error structure. According to Arellano and Bond (1991), the estimators of the dynamic panel model require that there is a first-order serial correlation. The Arellano-Bond AR(1) test p-value is low, and it rejects the null hypothesis. The Arellano-Bond AR(2) test is used to test the absence of second order autocorrelation. The low AR(2) test p-value indicates the presence of MA(1) error term and shows a need for lagging the instrument set. If the Arellano Bond AR(2) is rejected, AR(3) test should be conducted. The AR(3) test shows the high p-value. This means that the null hypothesis cannot be rejected and suggests the absence of serial correlation in the error structure.

Table 2.4. Dynamic panel model estimation results

Variable	OLS	Fixed Effects	System GMM
Dependent Variable: L_TFP			
L_TFP(t-1)	0.821*** (0.005)	0.572*** (0.007)	0.997*** (0.252)
FO	0.022*** (0.003)	0.019*** (0.005)	0.626*** (0.210)
L_HHI	-0.011*** (0.002)	-0.013*** (0.002)	-0.017*** (0.005)
L_TR	0.009** (0.004)	0.052*** (0.011)	0.141*** (0.044)
L_TR2	-0.000** (0.000)	-0.001*** (0.000)	-0.003*** (0.001)
EX	0.003* (0.002)	-0.004 (0.003)	0.011* (0.006)
Obs.	18212	18212	18212
R-squared	0.722	0.462	
No. of Instruments			42
AR(1)			0.000
AR(2)			0.030
AR(3)			0.737
Hansen Test P-Value			0.241

All regressions have industry sector fixed effects controlled. Standard errors are in parentheses. Significance levels are indicated by *** $p < .01$, ** $p < .05$, * $p < .1$

In addition to the AR test, the Hansen J-test is conducted to test overidentification of instruments in the system GMM estimation. The null hypothesis is that the over-identifying restrictions are valid. According the statistic of the null hypothesis of the Hansen J-test cannot be rejected, and this confirms the validity of the instruments used in this article.

In the system GMM, the foreign ownership is treated as endogenous. The total number of instruments used is 42. Following Alfaro et al (2004), this article uses the real exchange rate[4] between the Japanese yen and U.S dollar as one of the instruments for foreign ownership in system GMM estimation.

The estimated coefficients of the lagged dependent variable are highly significant at 1 percent level and positively related with the current dependent variable. The result indicates that productivity shows high time persistence and justifies the system GMM estimation used in this article. The coefficients of the foreign ownership are also significant across all estimations. In the case of the system GMM, the result indicates that 1 percentage point increase in foreign ownership leads to about 0.06 percent increase in productivity. This implies that the foreign ownership has a positive impact on firm productivity even after considering a possible reversal causality between foreign ownership and firm productivity.

The estimation results suggest that there is significant evidence that size of firm increases productivity. In addition, all three models confirm that size of firm increases productivity at decreasing rate. In the case of export, the system GMM and OLS estimation suggests that export increases productivity whereas Fixed Effects estimation does not find any significant evidence on the impact of export on productivity.

In sum, based on the result of the system GMM estimation, the positive impact of foreign ownership on firm productivity of the manufacturing firms in Japan is confirmed.

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4 Real effective exchange rate provided by International Monetary Fund is used.

The size of firm and export are also shown to have a positive impact on firm productivity as previous literature with significant evidence.

2.4. Conclusion

The “Big Bang” reform started in 1996 liberalized the Japanese financial market, and the reform continued until early 2001. The reform resulted in substantial deregulation of the banking, securities, and insurance industries and improved information disclosure and the transparency of the financial market in Japan. This change led to the increased investment from foreign investors in the Japanese financial market.

Regarding the increase foreign investment, there has been high interest among researchers in finding out whether the increased foreign investment leads to a positive impact on the performance of the companies in Japan. Using the firm-level data of the Japanese manufacturing firms, this article examines the relationship between foreign ownership and firm productivity with system GMM estimation to address a possible endogeneity problem.

Based on the results from the baseline and dynamic panel model estimations, this article confirms the positive impact of foreign ownership on productivity in the case of the manufacturing firm in Japan from 2000 to 2016. The results also suggest that competition, firm size, and export have a positive impact on firm productivity.

The findings of this article imply that Japan’s “Big Bang” reform, which led to higher foreign ownership in the Japanese listed companies, has positive effect in improving performance of the firms. This further suggests that promotion of foreign investment could be a possible measure to increase firm productivity.

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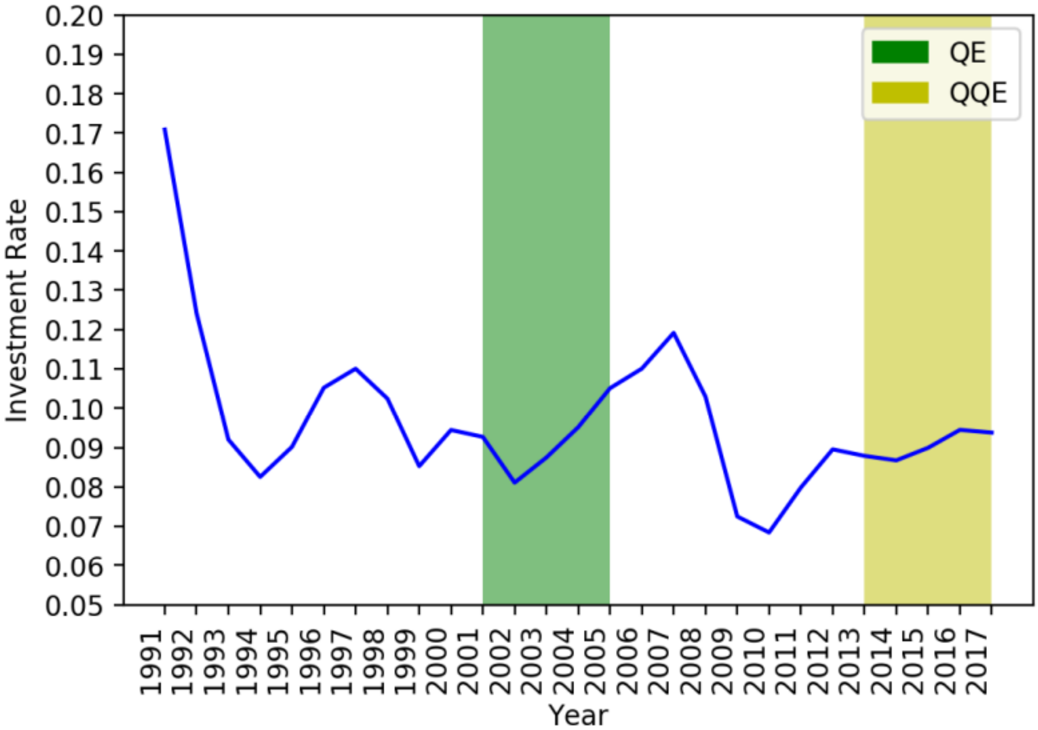
Chapter 3. Physical investment of Japanese firms during QE and QQE periods: Did the transmission mechanism work? : Evidence from the Japanese Manufacturing Firms

3.1. Introduction

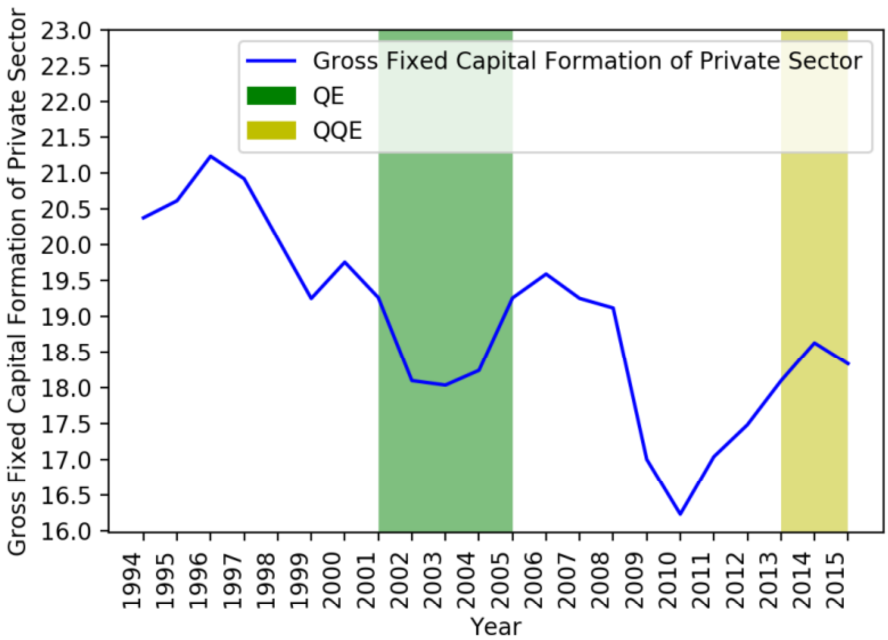
Sluggish fixed investment of Japanese firms has been widely raised in the literature as one of main causes of the so-called lost decades of Japan. (Horioka, 2006; Hori et al., 2006 among others). After the burst of the Japanese bubble, as is well known and reasonably expected, the amount of fixed investment of the Japanese manufacturing sector sharply decreased in early 1990s. Although the sharp decrease was ceased in the mid-1990s, it did not increase back as Figure 3.1 illustrates. According to BOJ (2013 and 2017), the non-financial sector turned into net savers in late 1990s, and then it never returned to its previous position as net borrowers despite the zero interest policy and the quantitative easing policy of the Bank of Japan. As a result, as Figure 3.2 shows, the share of private investment in the Japanese GDP almost continually declined for the last 25 years. As lack of investment demand was recognized as one of the main causes of the long recession of Japan, a substantial amount of literature tried to determine the causes of investment stagnation in Japan.

Figure 3.1. Median values of investment rate of Japanese manufacturing firms



The definition of the investment rate is written in section 3.3.2.

Figure 3.2. Gross fixed capital formation of private sector in Japan (% of GDP)



Data Source: World Development Indicator of World Bank

Among them, Hori et al. (2006) analyzed, using a model similar to those adopted by Hoshi and Kashyap (1990), Hoshi et al. (1991), Hayashi and Inoue (1991), and Hayashi (2000), the financial data of listed Japanese firms for the period from 1991 to 2000. Their major explanatory variables of the fixed investment of Japanese firms are Tobin's q and cash flow.[5]

Tobin's q is the market value of a firm divided by the replacement cost of capital of the firm. A high q is expected to encourage a firm to increase investment because its market value is high relative to the cost of fixed capital it buys. Hori et al. (2006) found a significantly positive coefficient for Tobin's q. Because Tobin's q was decreasing during the period which Hori et al. (2006) explored, they concluded that "a scarcity of productive investment opportunities" was the primary cause of stagnant fixed investment of Japanese firms.

Since its introduction in Tobin (1969), Tobin's q has been regarded as a neoclassical transmission channel because higher stock prices induced by an expansionary monetary policy will raise q, leading more investment.[6] Therefore, the findings of Hori et al. (2006) show that the neoclassical transmission mechanism was working through Tobin's q in the 1990s in Japan, although transmission mechanism was not discussed by the authors.

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[5] Hong et al. (2007) applied a similar model to an analysis of the investment of Korean conglomerates, and they also reported a significantly positive coefficient for Tobin's q.

[6] See Boivin et al. (2010) for more detailed discussion on Tobin's q as a neoclassical transmission channel of monetary policies.

In addition, Hori et al. (2006) also reported that investment was more sensitive to cash flow among the firms who hold less liquid assets, implying firms hold liquid assets to relax future liquidity constraints. The finding shows that the balance sheet effect, a non-neoclassical transmission channel, also worked in the 1990s in Japan although they did not explicitly mention the balance sheet effect in their paper.

As Bernanke and Gertler (1995) and Boivin et al. (2010) explain, cash flow or liquid asset should not affect investment decision of firms if there is no asymmetric information problem between borrowers and lenders. However, if lenders (especially banks) have asymmetric information problems, they discriminate borrowers based on the net worth of their firms. In that case, firms with a smaller amount of liquid asset may suffer liquid constraint and be restricted in their investments because liquid asset is regarded as a proxy for net worth by lenders.

Ogawa (2006) a . (2006) also included Tobin's q and cash flow in their estimation equation of fixed investment, but focused more on other variables such as debt ratio and financial environment. Ogawa (2006) explored the effects of mainly debt ratio and lending attitude of financial institutions on fixed investment of Japanese listed and unlisted firms using the data from 1993 to 1998. He reported lending attitude has a much bigger impact than debt ratio, and then concluded that sluggish investment of Japanese non-manufacturing firms and small firms in the manufacturing sector in the 1990s could be well explained by unsoundness of Japanese financial institutions. Fukuda et al. (2006), focused on small and medium sized Japanese firms by using the financial statement data of only unlisted firms. Although they analyzed a different time span (1997-

2003) and different firm groups from Ogawa (2006), they found similar results. That is, the debt ratio of a firm and also financial turmoil of the firm's main bank had a negative impact on investment of the firm. Of interest is that Ogawa (2006) and Fukuda et al. (2006) also reported significantly positive coefficients for Tobin's q and cash flow.

Masuda (2015) adopted a very similar estimation equation of investment to those in the papers discussed above. However, the main focus of the paper is the balance sheet effect, a non-neoclassical transmission channel rather than causes of sluggish investment. In addition, the work of Masuda (2015) is the only research, to our best knowledge, that investigate the effects of the first Quantitative Monetary Easing (QE hereafter) of Bank of Japan on fixed investment using firm level financial data.

The central bank of Japan launched the famous zero interest policy in 1999 to encourage economic activities including fixed investment of Japanese firms. However, because the effectiveness of the aggressive expansionary monetary policy was questioned soon, Bank of Japan experimented the QE policy for the first time in the modern history. The first Japanese QE was implemented from March 2001 to March 2006. Then, the second QE, also known as QQE (Quantitative-Qualitative Easing, hereafter QQE), has been implementing since April 2013.

The papers that examined the effects of the two QEs analyzed macro data in general and reported positive effects of the non-conventional policies. The survey paper of Ugai (2006) reports that the first QE had the effect to lower down the Japanese yield curve and improved the credit environment for Japanese firms. Honda et al. (2007) argue that the first QE stimulated the aggregate demand through a stock price channel. BOJ (2015) and Kan et al. (2016) report that QQE had a positive effect on the aggregate demand by reducing real interest rates.

Different from the papers mentioned above, Masuda (2015) analyzed the effect of the first QE using firm level micro data by adopting the framework of Hori et al. (2006), Ogawa (2006) and Fukuda et al. (2006). Masuda (2015) extended the coverage of the data to 1970 to 2006, and specifically explored whether the QE policy of Bank of Japan reduced the balance sheet effect. If the central bank provides more liquidity to the economy, then the external finance premium that should be paid by those firms who have less liquid asset will be reduced. Therefore, the effect of liquid asset is expected to decline during the first QE period. Masuda (2015) reported that liquidity constraint was reduced especially for large corporations during the first QE period in Japan, implying that the QE policy influenced the real economic activity.

However, because the work of Masuda (2015) does not cover the period after the first QE policy, it is not certain whether the change in the balance sheet effect was truly caused by the policy or it is only a result of some unrevealed environmental changes since early 2000s. For example, a lower level of debt ratio in 2000s might alleviate wariness of lenders and, as a result, might reduce the external finance premium. If the impact of liquid asset on investment was truly reduced for the period from 2001 to 2005 due to the QE policy, however, its impact is expected to increase back during the non-QE and non-QQE period from 2006 to 2012.

Against this background, the present paper aims to further investigate whether the neoclassical and/or the non-neoclassical transmission channel worked during the QE periods by analyzing financial statement data of Japanese listed companies covering not only the first QE period but also the periods between the QE and QQE periods (2006-2012) and QQE period (2013-2017). Considering a misspecification problem, the regression model adopted in the paper includes various control variables which are also expected to affect investment decision of Japanese firms. However, a more decisive improvement of the present paper can be found by the estimation methodology. Different from the papers mentioned above, the present paper employs the system GMM as its estimation tool because some explanatory variables are suspected to have endogeneity problem. To our best knowledge, this paper is the first trial to examine the neoclassical and non-neoclassical transmission channels in the investment decision of Japanese firms during the period covering both the first and QQE periods using the methodology of the system GMM.

3.2. Methodology

3.2.1. Unbalanced Dynamic Panel Model

The following dynamic panel model is estimated to determine the factors which affect investment decisions of Japanese listed firms using unbalanced panel data of their financial statements.

$$IR_{i,t} = \left(\frac{I_{i,t}}{K_{i,t-1}}\right) = \beta_0 + \beta_1 IR_{i,t-1} + \beta_2 Q_{i,t} + \beta_3 Q_{i,t} D_{i,t}^{QE} + \beta_4 Q_{i,t} D_{i,t}^{QQE}$$

$$+\beta_5 LAR_{i,t} + \beta_6 LAR_{i,t} D_{i,t}^{QE} + \beta_7 LAR_{i,t} D_{i,t}^{QQE}$$

$$+\beta_8 DR_{i,t} + \beta_9 DR_{i,t} D_{i,t}^{QE} + \beta_{10} DR_{i,t} D_{i,t}^{QQE}$$

$$+\mu_i + \delta_t + \varepsilon_{i,t} \qquad (1)$$

where subscripts *i* and *t* denote a firm *i* and a year *t*, respectively. The fixed effects are captured by the firm dummy, μ_i, and δ_t. is the time dummy. The idiosyncratic disturbance is denoted by $\varepsilon_{i,t}$.

The dependent variable, $IR_{i,t}$, is investment rate which is the ratio of investment made in time t over fixed capital at the end of time t-1.[7] Considering that investment is fairly time persistent, the one-lagged value of investment, $IR_{i,t-1}$, is included as an explanatory variable. As Nickell (1981) proves, the one-lagged dependent variable causes endogeneity problem because it is correlated with μ_i. Therefore, the present paper estimates Equation (1) using the system GMM of Blundell and Bond (1998) which is widely used for dynamic panel models with such endogeneity problem.

Among other explanatory variables, $Q_{i,t}$ is Tobin's q, $DR_{i,t}$ debt ratio, and $LAR_{i,t}$ liquid asset ratio at time t. This study considers $Q_{i,t}$, $DR_{i,t}$, and $LAR_{i,t}$ to be endogenous

[7] More detailed definitions of the variables in Equation (1) will be provided in the following section.

variables. The endogeneity problem possibly caused by them will be discussed in the section 3.2.4 in which the estimation methodology and results are presented.[8]

In Japan, a fiscal year of a firm typically ends at the end of March. Therefore, the annual financial statement of a typical Japanese firm published in year *t* reports its business performance from April of *t-1* to March of *t*. In this present paper, the data contained in such a report are treated as the data of year *t-1*. In the case that the fiscal year ends at other than March, we determine the corresponding year by the following principle: If the fiscal year ends before or in May, the data contained in year *t* reports are treated as the data of year *t-1*, and as the data of year *t* otherwise. In other words, for example, the financial statements reported in May 2001 is regarded as containing the data of 2000, while those reported in June 2001 is regarded as containing the data of 2001.

3.2.2 Definitions of the Variables

This section presents specific definitions of the variables in Equation (1) and explains how they are computed by the data from financial statements.

[8] Researchers such as Masuda (2015) often employ time t-1 explanatory variables to remove the endogeneity problem which may be caused by employing time t explanatory variables. However, as previously discussed, time t-1 explanatory variables may also cause endogeneity problem. This also justifies the use of the system GMM along with the presence of one-lagged dependent variable as an explanatory variable.

Investment rate ($\frac{I_{i,t}}{K_{i,t-1}}$)

Table 3.1. Six categories of tangible fixed assets

J	Category	Depreciation rate (δ^j)
1	Buildings	0.0470
2	Structures	0.0564
3	Machinery/Equipment	0.0949
4	Ships	0.1470
5	Autos/Trucks	0.1470
6	Tools/Fixtures	0.0884

The investment rate is defined to be the real value of investment ($I_{i,t}$) divided by the real value of tangible fixed capital of the previous year ($K_{i,t-1}$). The real value of tangible fixed capital ($K_{i,t}$) is calculated by the permanent inventory valuation method in the following way. First, tangible fixed assets ($NK_{i,t}$) in a financial statement are split into six categories that are listed in Table 3.1 along with the depreciation rate of each category (δ^j).

$$NK_{i,t} = \sum_{j=1}^{6} NK_{i,t}^{j}$$

Second, the nominal investment ($NI_{i,t}^{j}$) in each category is calculated by the following equation:

$$NI_{i,t}^{j} = NK_{i,t}^{j} - NK_{i,t-1}^{j}$$

Third, the nominal value of investment ($NI_{i,t}^{j}$) is deflated by a corresponding whole sale price index to obtain the real investment in each category ($I_{i,t}^{j}$). The whole sale price index for each category (P_t^j) is obtained from the Corporate Goods Price Index provided by the Bank of Japan.

$$I_{i,t}^{j} = \frac{NI_{i,t}^{j}}{P_t^j}$$

Fourth, it is assumed that the real value of a tangible asset is equal to its nominal (book) value at the initial year (t_0). Since the database used in this research reports consistent data from 1977, the initial year is set to be 1977 for the firms which were listed in the Japanese stock market from 1977 or before. In the case of the firms which were listed after 1977, the first year listed is used as the initial year.

$$K_{i,t_0}^{j} = NK_{i,t_0}^{j}$$

Fifth, the time series of real fixed capital in each category is obtained using the perpetual inventory equation below.

$$K_{i,t}^{j} = (1 - \delta^j)K_{i,t-1}^{j} + I_{i,t}^{j}$$

Then, finally the real fixed capital ($K_{i,t}$) and the real investment ($I_{i,t}$) are the summations of the real amounts of the six categories.

$$I_{i,t} = \sum_{j=1}^{6} I_{i,t}^{j}$$

$$K_{i,t} = \sum_{j=1}^{6} K_{i,t}^{j}$$

In the meantime, the replacement cost of the real fixed capital ($PK_{i,t}$) is computed as follows:

$$PK_{i,t} = \sum_{j=1}^{6} P_{i,t}^{j} K_{i,t}^{j}$$

Average Tobin's q ($Q_{i,t}$)

$$Q_{i,t} = \frac{(market\ value\ of\ outstanding\ stocks + interest\ bearing\ debts) at\ time\ t}{A_{i,t-1} - NK_{i,t-1} + PK_{i,t-1}}$$

where $A_{i,t}$ is the book value of total assets. The market value of outstanding stocks is computed by multiplying average stock price to the number of outstanding stocks.[9]

9 The average Tobin's q adopted in the paper was originally proposed by Lindenberg and Ross (1981) and was modified by Smirlock et al. (1984). This form of Tobin's q is widely used in the literature including Lang and Stulz (1994) and Hori et al. (2006).

QE dummy ($\boldsymbol{D_{i,t}^{QE}}$)

$D_{i,t}^{QE}$ is one for the years 2001-2005 and zero otherwise.

QQE dummy ($\boldsymbol{D_{i,t}^{QQE}}$)

$D_{i,t}^{\boldsymbol{QQE}}$ is one for the years 2013-2017 and zero otherwise.

Liquid asset ratio ($\boldsymbol{LAR_{i,t}}$)

$$LAR_{i,t} = \frac{(cash\ and\ cash\ equivalent + bills\ receivable + accounts\ receivable + securities)\ at\ time\ t}{A_{i,t-1} - NK_{i,t-1} + PK_{i,t-1}}$$

Debt ratio ($\boldsymbol{DR_{i,t}}$)

$$DR_{i,t} = \frac{interest{-}bearing\ debt\ at\ time\ t}{A_{i,t-1} - NK_{i,t-1} + PK_{i,t-1}}$$

3.2.3 Data

This research analyzes the data of manufacturing Japanese corporates that are listed in either the first or second section of the stock exchanges of Tokyo, Osaka, Nagoya, Sapporo, and Fukuoka. The financial statement data of those firms are obtained from *The Corporate Financial Databank* compiled by the Development Bank of Japan.

3.2.4 Endogeneity Problem and the System GMM

The dynamic panel model, Equation (1), is estimated by the system GMM of Arellano and Bover (1995) and Blundell and Bond (1998).

As Nickell (1981) shows, the coefficient of the lagged dependent variable in a dynamic panel model such as Equation (1) (that is $IR_{i,t-1}$ here) is not consistently estimated by conventional OLS estimators even after controlling fixed effects or random effects due to the endogeneity problem that the lagged dependent variable is correlated to the error terms. In addition, Tobin's q, the debt ratio and the liquid asset ratio at time t also have the possibility of endogeneity problem in some respects. If those explanatory variables have endogeneity problem, their coefficient estimates obtained by a fixed or random effect model will be inconsistent.

To obtain consistent estimates in such a situation, Arellano and Bond (1991) proposed to use the difference GMM model that utilizes the orthogonality condition that the lagged dependent variable is not correlated to first-differenced error terms. Arellano and Bover (1995) and Blundell and Bond (1998) improved the efficiency of the difference GMM model by developing the system GMM model which adds level equations to first difference equations in the model.

The two step GMM estimation method is used to estimate the coefficients in the model and the standard errors are estimated by the method of Windmeijer (2005) to correct for the downward bias of finite samples.[10] In addition, to test for the validity of the model, the Hansen (1982) J-test and the Arellano-Bond AR(2) and AR(3) (AB test, hereafter) tests are also implemented in the following section. The null hypothesis of the Hansen J-test is that the instruments are exogenous. Therefore, if we employ appropriate instruments the null hypothesis should be accepted. The null hypothesis of the AB AR(2) test is that the differenced residuals do not show AR(2) behaviour. If the AB AR(2) is rejected, AB AR(3) test should be conducted. If the AR(3) test shows a high p-value, this means that the null hypothesis cannot be rejected and suggests the absence of serial correlation in the error structure.

3.3. Results

As previously discussed, $IR_{i,t-1}$, $Q_{i,t}$, $LAR_{i,t}$, and $DR_{i,t}$ are regarded as endogenous (or not strictly exogenous) variables. Therefore, their lagged values are used as instruments, and these instruments should be at least two-time lagged from the endogenous explanatory variables due to the AR(1) behavior of the differenced residuals. The lag lengths of these instruments are determined in the way to increase the p-values of the Hansen J test and/or the AB AR(2) and AB AR(3) test. In addition, all strictly exogenous variables are also included in the set of instruments.

[10] The xtbond2 command of Roodman (2009) was used to estimate the system GMM model using STATA.

Table 3.2. Regression results for all firms

Explanatory variables	(1) System GMM	(2) FE	(3) OLS
$IR_{i,t-1}$	0.298***	0.129***	0.277***
	(0.094)	(0.011)	(0.010)
$Q_{i,t}$	0.074***	0.046***	0.028***
	(0.019)	(0.003)	(0.002)
$Q_{i,t}D_{i,t}^{QE}$	-0.044	0.017	0.016
	(0.126)	(0.011)	(0.010)
$Q_{i,t}D_{i,t}^{QQE}$	-0.063**	-0.019**	-0.012
	(0.032)	(0.009)	(0.008)
$LAR_{i,t}$	0.396***	0.101***	0.068***
	(0.107)	(0.011)	(0.006)
$LAR_{i,t}D_{i,t}^{QE}$	-0.891*	0.000	-0.029
	(0.465)	(0.020)	(0.019)
$LAR_{i,t}D_{i,t}^{QQE}$	-0.502**	0.008	-0.013
	(0.220)	(0.026)	(0.022)
$DR_{i,t}$	0.024	0.025**	-0.002
	(0.078)	(0.010)	(0.005)
$DR_{i,t}D_{i,t}^{QE}$	-0.469***	-0.054***	-0.042**
	(0.174)	(0.018)	(0.017)
$DR_{i,t}D_{i,t}^{QQE}$	-0.097	-0.011	-0.009
	(0.140)	(0.027)	(0.022)
N. of observation	19779	19779	19779
N. of firms	1464	1464	1464
R-squared		0.107	0.160
Arellano-Bond AR(1) test	0.000		
Arellano-Bond AR(2) test	0.034		
Arellano-Bond AR(3) test	0.487		
Hansen test statistic	0.363		
Number of instruments	60		

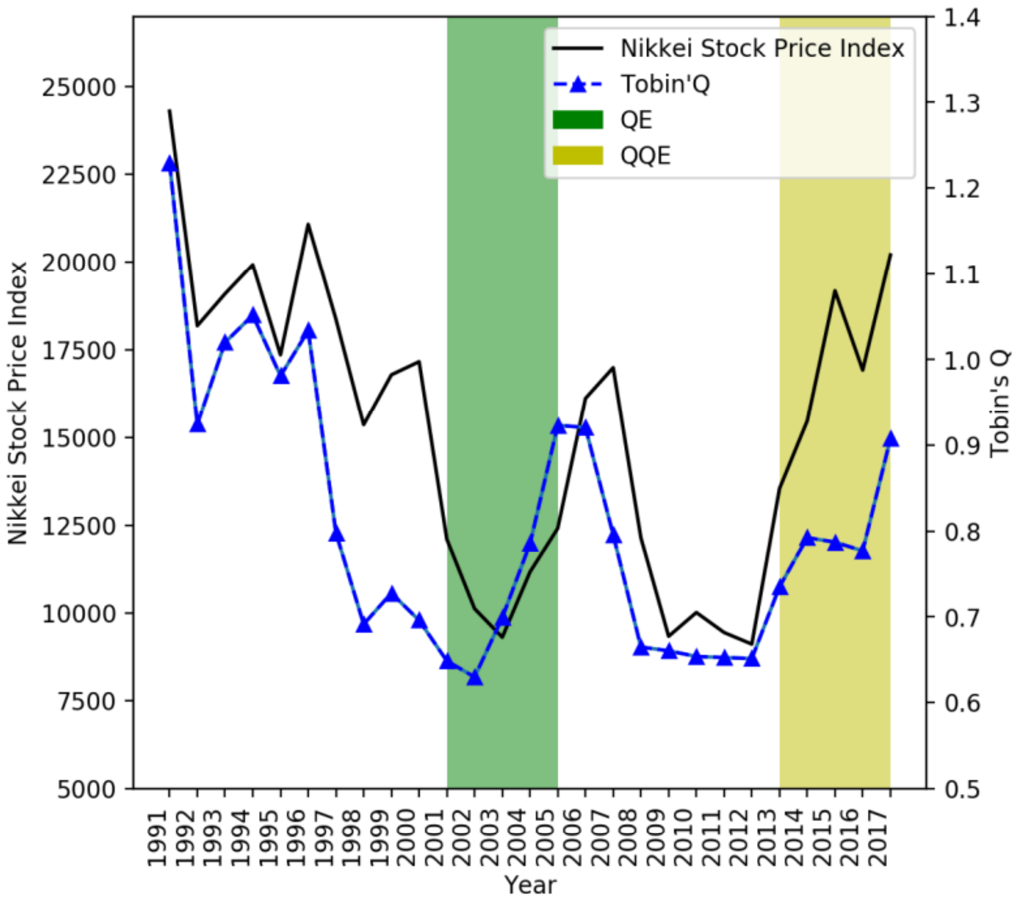
The numbers in parentheses are p-values.

* p<0.10, ** p<0.05, *** p<0.01

The first column in Table 3.2 shows the estimation results of equation (1) based on system GMM estimation. There are 1464 firms during the period analyzed. Column 2 in Tables 2 report the estimation results based on fixed effect estimation. Column 3 presents the result based on OLS estimation. Figures 3.4 and 3.5 illustrate the median values of the variables in Equation (1).

The coefficient of Tobin's q is significantly positive in all columns. In addition, it does not significantly change during the QE period but reduced during the QQE period according to the result by system GMM estimation. Even though the coefficient is reduced, the coefficient stays to be positive all periods. The result implies that the neoclassical transmission mechanism worked in Japan, and it appears that the neoclassical transmission mechanism worked as the coefficient of Tobin's q is positive. Figure 3.3 illustrates the median values of Tobin's q for the period covered in the research. It is clearly observed that Tobin's q rises during both QE and QQE periods, and it is mainly due to an increase in overall stock prices. Figure 3.3 shows that the stock price index and Tobin's q show very similar dynamics.

Figure 3.3. Stock price and Tobin's q

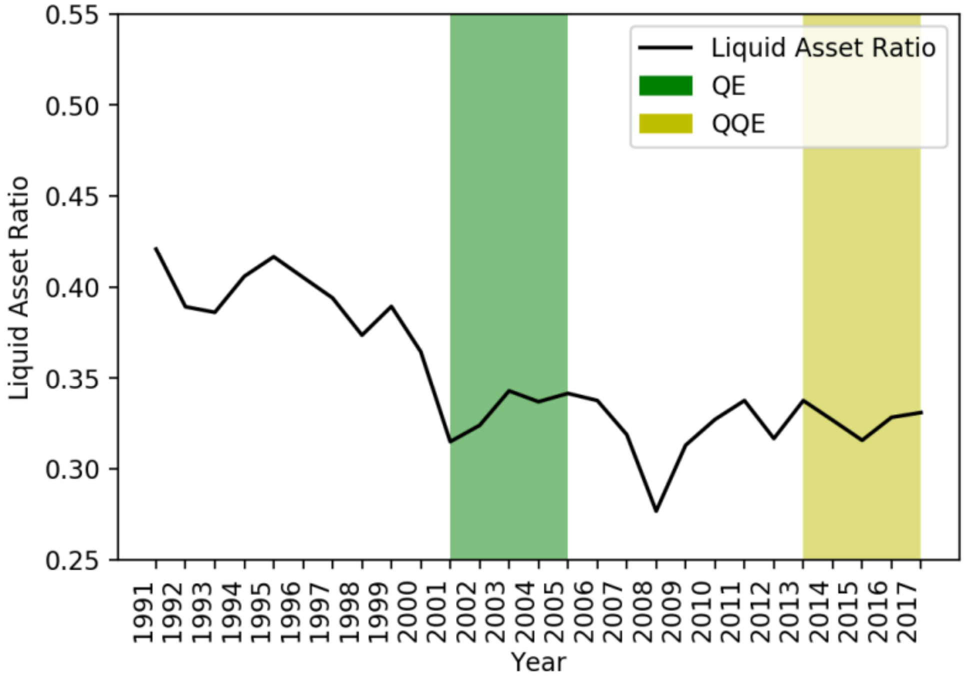


The Stock price index in the graph is the annual average of the Nikkei index of the first section of the Tokyo Stock Exchange obtained from the Nikkei Value Search.

Tobin's q is the median values of Tobin's q whose definition is written in section 2.

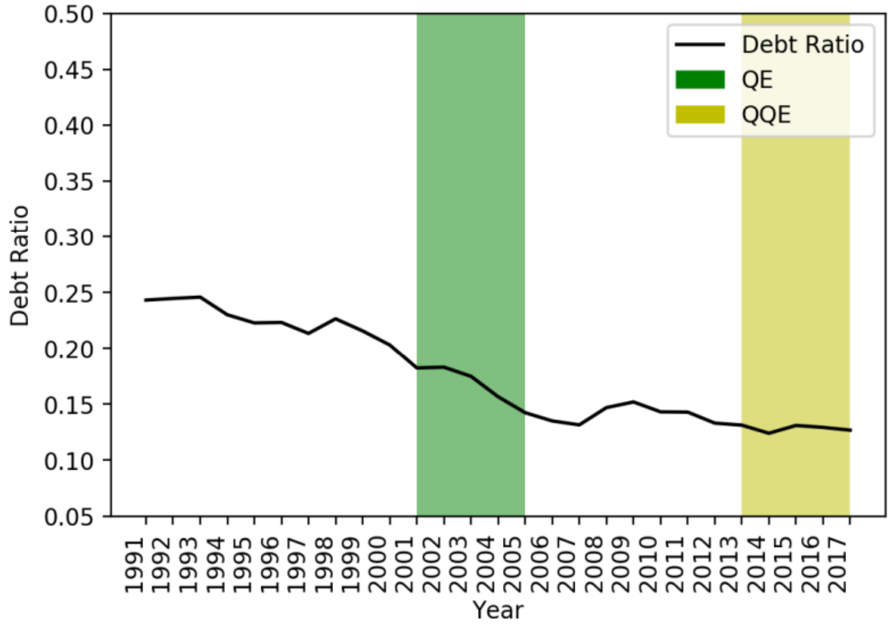
The coefficient of liquid asset is significantly positive for all firms and for large firms. The significantly positive coefficient value of the liquid asset is consistent with the findings of Hori et al. (2006) and Masuda (2015). According to the result by system GMM, the coefficient is reduced during QE and QQE periods. In fact, the impact of liquid asset turned to be negative during both QE and QQE periods. This implies that the liquidity restriction was reduced during QE and QQE periods.

Figure 3.4. Liquid asset ratio



The debt ratio has no statistically significant impact on the investment rate according to the system GMM estimation. However, the impact became negative during QE period. This implies the presence of debt-overhang in Japan during QE period. This further shows that high debt ratio was a hurdle for investment of firms in Japan during QE period. In fact, Figure 3.5 shows that the debt ratio has declined during QE period, but not so much during QQE period. This shows that the firms reduced their debt more actively during QE period compared to QQE period.

Figure 3.5. Debt ratio



The debt ratio has a non-negative impact on investment of large firms during non-QQE period and a negative impact during QE period. In the case of the positive impact during the non-QE period, this finding contradicts the wide-spread belief in the literature that investment stagnation of Japanese corporates during the 1990s resulted from their deleveraging efforts. (See Eggertsson and Krugman, 2012; Koo, 2008). If it is true, the impact of debt ratio on investment should be negative not only for during the QE period but also for the entire time period covered in the paper (1991-2017). This puzzle demands further investigation of the issue including the consideration of measurement errors and mis-specification problem of our estimation equation.

3.4. Conclusion

This paper investigates whether the first (QE) and the second quantitative easing policy

(QQE) in Japan influenced physical investment decisions of Japanese publicly listed firms through neoclassical and non-neoclassical transmission channels using their financial statement data from 1991 to 2017.

Empirical test results show that the coefficient of Tobin's q is significantly positive. Because Tobin's q rose during the QE and QQE periods, the positive coefficient of Tobin's q indicates that the QE policy had positive impacts on investment of Japanese listed firms. That is, the neo-classical transmission channel worked during the QE and QQE periods.

The coefficient of liquid asset ratio is estimated to be positive during the periods excluding QE and QQE periods indicating that the balance sheet effect channel did not work during QE and QQE periods. The coefficient reduces significantly during both the QE and QQE periods. This implies that liquidity constraint changed significantly for manufacturing firms during the QE and QQE periods.

Finally, the debt ratio turns out to have negative impacts on investment only for the QE period. During the QQE period and other periods, the coefficient turns out to have no significant impact on investment.

Appendix

Table 3.A.1. Regression results for all firms with variations

Explanatory variables	(1) System GMM	(2) System GMM	(3) System GMM	(4) FE	(5) FE	(6) FE	(7) OLS	(8) OLS	(9) OLS
$IR_{i,t-1}$	0.567***	0.365***	0.487***	0.131***	0.129***	0.130***	0.286***	0.277***	0.284***
	(0.102)	(0.093)	(0.099)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
$Q_{i,t}$	0.038**	0.060***	0.041**	0.052***	0.047***	0.052***	0.031***	0.028***	0.030***
	(0.018)	(0.017)	(0.019)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
$Q_{i,t}D_{i,t}^{QE}$	-0.120	0.022	-0.308**	0.014	0.015	0.016	0.010	0.015	0.012
	(0.134)	(0.122)	(0.130)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
$Q_{i,t}D_{i,t}^{QQE}$	-0.048*	-0.055*	-0.043	-0.022**	-0.019**	-0.022**	-0.015*	-0.011	-0.016*
	(0.028)	(0.030)	(0.032)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
$LAR_{i,t}$		0.299***			0.100***			0.069***	
		(0.059)			(0.011)			(0.006)	
$LAR_{i,t}D_{i,t}^{QE}$		-0.397			0.010			-0.023	
		(0.370)			(0.020)			(0.019)	
$LAR_{i,t}D_{i,t}^{QQE}$		-0.327**			0.010			-0.012	
		(0.146)			(0.025)			(0.020)	
$DR_{i,t}$			-0.207***			0.022**			-0.017***
			(0.050)			(0.010)			(0.005)
$DR_{i,t}D_{i,t}^{QE}$			-0.152			-0.050***			-0.031*
			(0.152)			(0.018)			(0.016)
$DR_{i,t}D_{i,t}^{QQE}$			0.207**			0.002			-0.008
			(0.097)			(0.027)			(0.021)
N. of observation	19779	19779	19779	19779	19779	19779	19779	19779	19779
N. of firms	1464	1464	1464	1464	1464	1464	1464	1464	1464
R-squared				0.098	0.106	0.099	0.151	0.160	0.152
Arellano-Bond AR(1) test	0.000	0.000	0.000						
Arellano-Bond AR(2) test	0.000	0.007	0.001						
Arellano-Bond AR(3) test	0.346	0.952	0.474						
Hansen test statistic	0.000	0.020	0.023						
Number of instruments	60	60	60						

The numbers in parentheses are p-values.

* p<0.10, ** p<0.05, *** p<0.01

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Chapter 4. Forecasting of Real GDP Growth Using Machine Learning Models: Gradient Boosting and Random Forest Approach

4.1. Introduction

The ability to forecast macroeconomic variables is highly desirable for the design and implementation of timely policy measures. Among the macroeconomic variables, real GDP growth is one of the most important data. However, forecasting real GDP growth involves complicated calculations, and official data are often available only after at least a one-quarter delay. Due to this delay, policymakers often design and implement policies without knowing the necessary information. From this point of view, if available, the accurate forecasting of real GDP growth in advance would be highly valuable.

Forecasting macroeconomic data, such as real GDP growth, is not a simple process. To forecast data, considering the causal relationship between the dependent variable and independent variable, traditional economic forecasting models require predetermined relevant variables to make predictions and often take top-down and theory-driven approaches (Mullainathan and Spiess 2017). This process also requires economic intuition and judgment by forecasters regarding the data and methods used. If there is any flaw in the assumptions made by the forecasters, the models could produce inaccurate predictions.

In contrast to many traditional economic forecasting models, machine learning models mostly deal with pure prediction (Varian 2014). Machine learning models are more flexible than traditional economic forecasting models and can produce predictions without predetermined assumptions or judgments. In fact, in conjunction with technological development and the increase in predictive power, machine learning models have been actively applied in various fields, from forecasting transportation flows to forecasting housing prices. In fact, machine learning methods often perform better than traditional econometric models, as shown by Plakandaras et al. (2015) in the case of forecasting US housing prices. In addition, machine learning models are applied to relatively low-frequency data sets and are shown to produce sound forecasts, as demonstrated in the studies on inflation forecasting by Medeiros et al. (2019) and Inoue and Kilian (2008).

With a focus on forecasting real GDP growth in Japan, this study presents forecasts with machine learning models, specifically a gradient boosting model and a random forest model, and compares their prediction accuracy against the benchmark forecast data published by the Bank of Japan (BOJ) and the International Monetary Fund (IMF) for the years from 2001 to 2018.

This study contributes to the literature in several points. First, this study provides a comparison of the performance of machine learning models on GDP predictions in Japan, which has not been analyzed and covered sufficiently. In specific, this study focuses on gradient boosting and random forest models, as these two models have received great attention due to their outstanding performance at numerous prediction competitions, such as those hosted by Kaggle, and there has also been high demand for comparisons of their forecasting performance. In the past, Biau and D’Elia (2010) used a random forest model to forecast the GDP data of the euro area and found that the machine learning model could produce more accurate predictions than the forecasts produced by a traditional autoregressive model. Jung et al. (2018) predicted real GDP growth in the United States, the United Kingdom, Germany, Spain, Mexico, the Philippines, and Vietnam using elastic net, recurrent neural network, and super-learner models. Tiffin (2016) employed elastic net and random forest models to forecast GDP growth in Lebanon, which provides official GDP growth data only after a two-year delay. Emsia and Coskuner (2016) used support vector regression to predict the GDP growth of Turkey. However, the prediction of real GDP growth in Japan has not been sufficiently analyzed in the previous literature. Second, this study introduces a machine learning method that produces more accurate predictions of annual real GDP growth in Japan than the forecasts made by two prestigious institutions, the IMF and the BOJ, over a significant period. Lastly, this study presents a cross-validation and hyperparameter tuning process to address forecasting issues, such as overfitting problems, and provides the detailed parameters used in the prediction models, which can serve as a valuable reference for relevant research in the future.

4.2. Methodology

This study uses two machine learning models: gradient boosting and random forest models. All the models are supervised machine learning models, which means that the models perform analyses based on training data and construct a function to make predictions based on new data.

Using the data from the fourth quarter of 1981 to the second quarter of 2018, the machine learning models predict annual real GDP growth in Japan from 2001 to 2018. The machine learning models are designed to make predictions of annual real GDP growth based on data up to the second quarter of the focal year. For example, for 2001, the machine learning models train and fit their models using data up to the second quarter of that year. This means that the models do not use future data to predict past data.

The response variable for the models is the two-quarters-ahead real annual GDP growth. It should be noted that in cases where the two-quarters-ahead real annual GDP growth is predicted, the two-quarters-ahead real annual GDP is not available for the first quarter of the data; the two-quarters-ahead real annual GDP growth is available only when the third-quarter data are available. For example, for the prediction of the annual real GDP growth of 2002, the models make predictions with data up to the second quarter of 2002. However, the data set for the first quarter of 2002 cannot have two-quarters-ahead real annual GDP growth since the data become available only in the third quarter of 2002. The machine learning models make predictions of the two-quarters-ahead real annual GDP growth for the first-quarter data first. With the forecasted data in the first-quarter data, the models make final predictions of the second-quarter data and then predict the two-quarters-ahead real GDP growth.

All the machine learning algorithms used in this study are implemented with the Scikit-Learn package using Python language.

4.2.1. Machine Learning Models

<Gradient Boosting>

The gradient boosting model is an ensemble machine learning model introduced by Friedman (2001). The main idea of the gradient boosting model is to combine multiple weak learners to improve the accuracy and robustness of the final model.

The gradient boosting model starts by making a single leaf and building regression trees. A regression tree is a type of decision tree that is designed to estimate a continuous real-valued function instead of a classifier. The regression tree is constructed through an iterative process that continues to split the data into nodes or branches into smaller and smaller groups. Initially, all observations are placed in the same group. The data are then allocated into two partitions, using every possible split on every available predictor. The predictor that splits the tree is that which most clearly separates the observations into two distinct groups and minimizes the residual error, which, in this study, is measured by the Friedman MSE introduced in Friedman (2001).

Based on the error made by the previous tree, the gradient boosting model makes another tree, and it continues to train additional trees in this fashion until the designated number or fit cannot be improved. To avoid overfitting problems, the gradient boosting model uses a learning rate to scale the contribution from the new tree.

Based on Friedman (2001), the algorithm of the gradient boosting model takes the following steps for the input data, $\{(x_i, y_i)\}_{i=1}^{n}$, and a differentiable loss function, $L(y_i, F(x))$, which is a squared regression in this study.

Step 1: Initialize the model with a constant value:

$$F_0(x) = argmin_\gamma \sum_{i=1}^{n} L(y_i, \gamma) \quad (1)$$

where y_i is an observed value, and γ is a predicted value. $F_0(x)$ is the average of the observed values.

Step 2: For m = 1 to M:

(A) Compute

$$\gamma_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \text{ for i = 1,…,n} \quad (2)$$

(B) Fit a regression tree to the γ_{im} values and create terminal regions R_{jm} for j $= 1 \ldots J_m$

(C) For j $= 1 \ldots J_m$, compute

$$\gamma_{jm} = argmin_\gamma \sum_{x_i \in R_{ij}} L(y_i, F_{m-1}(x_i) + \gamma) \quad (3)$$

(D) Update

$$F_m(x) = F_{m-1}(x) + \nu \sum^{J} \gamma_m I(x \in R_{jm}) \quad (4)$$

where is the learning rate.

The loss functions used can be customized by setting the learning rate, ν. This feature improves the flexibility of this model while minimizing the overfitting problem by learning from the iterations performed at a slower rate (Hastie et al. 2009).

Step 3: Output:

$$\hat{F}(\mathrm{x}) = F_M(x) \quad (5)$$

After performing all M iterations and updating the $F_m(x)$ function, the final model, $\hat{F}$(x), approximates the relationship between the independent variables and the dependent variable.

<Random Forest>

The random forest model, introduced by Breiman (2001), is another ensemble method similar to boosting models. According to Dietterich (2000), the random forest is one of the most successful ensemble models in machine learning. Similar to the gradient boosting model, the random forest model uses regression trees. However, unlike the gradient boosting model, in the random forest model, using bootstrapped data, the regression trees are trained independently, and the output of trees is averaged to produce predictions.

The basic steps of the random forest model are as follows:

Step 1. For m=1 to M:

(1) Create a bootstrapped sample set, Z of size N, from the training data.

(2) Grow a random forest tree, T_m, for the bootstrapped data by repeating the following steps for each terminal node of the tree until the minimum node size, n_{min}, is reached.

i. Select x variables at random from the p variables.

ii. Pick the best variable and split point among the x variables.

iii. Split the node into two daughter nodes. The split is decided in such a way that it minimizes MSE, which is calculated as follows:

$$F_0(x) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \gamma)^2 \tag{6}$$

where y_i is an observed value and γ is a predicted value.

In addition to the bootstrapping unique data for each tree predictor, additional randomness is added at each node by randomly assigning a subset of variables to split the nodes. This random process greatly reduces the dependence between individual trees and improves flexibility against a potential overfitting problem. A fully developed tree often leads to an overfitting problem if it fits the model perfectly. In other words, a model with close to perfectly fitting trees may not produce accurate predictions when new data are added. To avoid this problem, a random forest model may prune the trees or limit the number of nodes at the expense of the in-sample fit.

Step 2. Output the ensemble of trees, $\{T_m\}_{m=1}^{M}$:

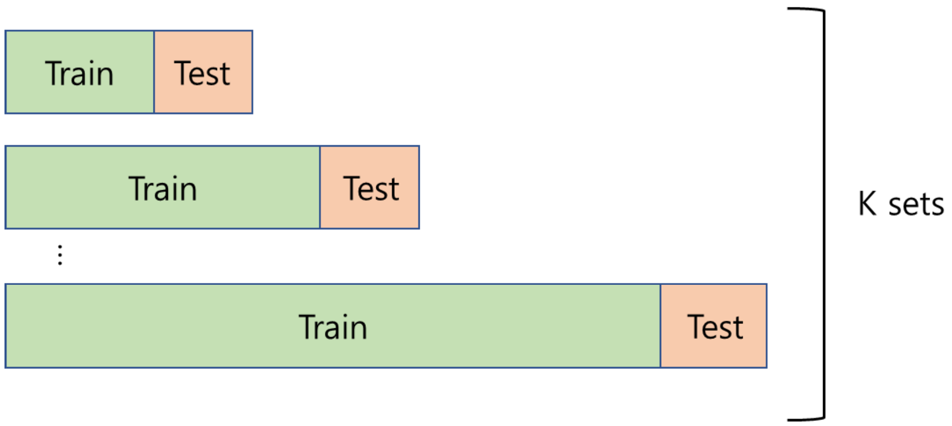
$$\hat{F}_{rf}^{M}(x) = \frac{1}{M}\sum_{m=1}^{M} T_m(x) \tag{7}$$

The final output, $\hat{F}_{rf}^{M}(x)$, is calculated by averaging the outputs of all the trees. Averaging over multiple predictions reduces the variance and stabilizes the trees' predictive performance.

4.2.2. Cross Validation

The machine learning models used in this study utilize several hyperparameters. This study uses k-fold cross-validation, which is a popular technique for tuning hyperparameters. The k-fold cross-validation separates the training data into k-pieces and separately tests each piece to fit the model. Due to the temporal dependencies among the data, the k-fold cross-validation is designed to set the first k-folds as the training set and the data after the folds as the test set. This ensures that future data are not used to test past data since the forecasting model should exclude all data about events that occur chronologically after the events used to fit the model (Tashman 2000). In this study, following previous literature, including Molinaro et al. (2005), k is set to 10, and the training data are set to 10 subsets to train and fit the model. Fig. 1 illustrates the concept behind the cross-validation process used in this study.

Figure. 4.1 Cross-validation process



Some may argue that the cross-validation process is not needed for the random forest models as the random forest models use trees created from the bagging process. It is true that the out-of-bag process of the random forest model is similar to the cross-validation process, and the cross-validation may not be needed. However, one of the main aims of this study is to compare the performance of the gradient boosting model and the random forest model. To make this comparison as fair as possible, this study applies the cross-validation process to the random forest model. In addition, the out-of-sample data are set to be the same for both the gradient boosting model and the random forest model to ensure a fair comparison of the models.

The cross-validation process is designed to select an optimal set of hyperparameters that produces the lowest average mean squared errors based on the tests of 10 subsets. In other words, the set of hyperparameters suggested by the cross-validation process will be used to make forecasts based on the test data set. The hyperparameter tuning strategy that this study uses is grid search, in which all possible combinations of the hyperparameters given are tested (Probst et al. 2019). Regarding the number of predictors, all predictors are considered, and the depth of trees is controlled with the number of splits for both the gradient boosting model and the random forest model. The cross-validation is designed to find a combination of the hyperparameters that minimizes the average of MSE. The hyperparameters determined by the cross-validation are presented in Table 4.1.

Table 4.1. Description of the hyperparameter test

Machine Learning Model	Hyperparameter	Hyperparameter Test Set
Gradient Boosting	No. of boosting stages	100, 500, 1000
	Learning rate	0.0001, 0.001, 0.01, 0.1, 0.3
	Max. depth of the tree	1, 3, 5, 7, 9, 11, 13, 15, 17, 19
Random Forest	No. of trees	100, 500, 1000
	Max. depth of the tree	1, 3, 5, 7, 9, 11, 13, 15, 17, 19

For the forecast of real GDP growth in year x, the same cross-validation will be conducted twice. The first process will be for the forecast of the two-quarters-ahead forecast of year-to-year real GDP growth in the first-quarter data. The second process will be repeated for the second quarter of the data for the final forecast.

4.2.3 Data

The prediction models use the traditional economic indicators related to national account, employment, monetary, trade, and inflation statistics as the regressors. The inflation variables include the consumer price index and GDP deflator. The national account variables include real government consumption, real private consumption, current account of balance of payments, real annual GDP, real GDP growth (quarter to quarter), real GDP growth (year over year), government balance as share of GDP, gross government debt as percent of GDP, foreign exchange reserves, real stockbuilding, total external debt, and foreign direct investment. The employment variables include total employment and the unemployment rate. The monetary variables include exchange rate against US dollar, exchange rate against euro, and 10-year government bond yields.

The data are chosen based on the availability and previous literature, including Jung et al. (2018) and Richardson et al. (2018). All variables are quarterly data from the fourth quarter of 1981 to the second quarter of 2018. In this study, real GDP growth (year over year) is set as the dependent variable, and other variables are set as independent variables. The number of observations is 147 for each variable. More details on the variables are available in Table 4.A.1 in Appendix.

Figure 4.2. Correlation matrix of the variables

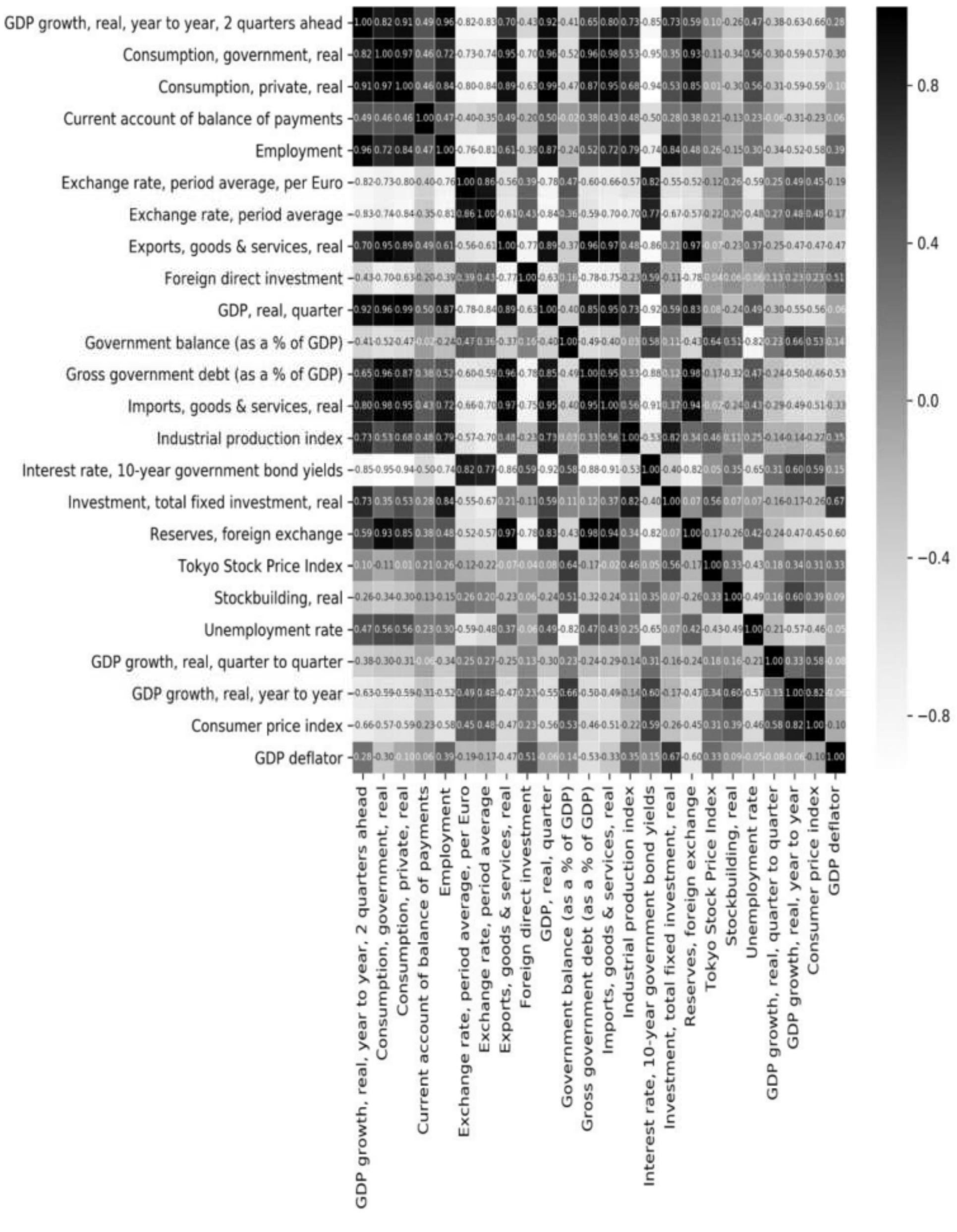


Figure 4.2 presents the matrix for the correlation between the dependent variable and the independent variables for the two-quarters-ahead forecast. According to the correlation matrix, correlations among the regressors can be observed. Multiple regressors have correlations with other regressors above 0.5. For traditional linear

regression models that focus on the interpretation of the impact of regressors, high correlations may lead to multicollinearity problems; however, ensemble models that focus on prediction, such as the gradient boosting and random forest models, are designed to handle multicollinearity problems using decision trees, which, instead of using all the predictors, choose certain regressors to maximize prediction accuracy and are robust to multicollinearity problems (Sandri and Zuccolotto, 2008).

As benchmarks, this study uses the forecast data published by the IMF and the BOJ from 2001 to 2018 to check the performance of the machine learning models used in this study. Although the details of the previous forecast models used by the IMF and BOJ are not available to the public, the results of their models are used as benchmarks in this study, as they are widely accepted and quoted in both the public and private sectors. The forecasts that the IMF and the BOJ publish are the main forecasts on annual real GDP growth in spring and fall. In the case of the BOJ, this study uses the median values of the forecasts by the majority of policy board members.

4.3. Results

This study presents a method for forecasting the annual real GDP growth[11] of Japan from 2001 to 2018. The machine learning models produce predictions of annual real GDP growth in Japan for each year from 2001 to 2018, using data from the fourth quarter of

[11] The data on the annual real GDP growth of Japan refer to those published by the World Bank and are obtained from https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=JP

1981 up to the second quarter of the year of prediction. For example, for the prediction of annual real GDP growth in Japan in 2018, the machine learning models use data up to the second quarter of 2018.

Table 4.2 presents the hyperparameters used by the machine learning models, which are selected by the cross-validation process. As Table 4.2 shows, since the training data receive new data for each new year, the hyperparameters change accordingly to adjust to the new data set.

Table 4.2. Hyperparameters by year

Year	GB			RF	
	Max. depth of the tree	No. of boosting stages	Learning rate	Max. depth of the tree	No. of trees
2001	1	100	0.1	5	1000
2002	1	1000	0.1	5	100
2003	1	500	0.3	9	100
2004	3	100	0.1	9	100
2005	3	100	0.1	9	100
2006	3	100	0.1	5	100
2007	3	500	0.1	5	500
2008	1	1000	0.01	11	100
2009	1	500	0.1	3	1000
2010	1	1000	0.01	7	500
2011	3	500	0.1	9	500
2012	9	1000	0.01	11	500
2013	5	500	0.3	7	500
2014	1	1000	0.1	9	500
2015	1	500	0.1	11	100
2016	1	1000	0.01	7	500
2017	7	100	0.1	9	100
2018	1	500	0.1	7	500

* GB and RF are gradient boosting and random forest, respectively.

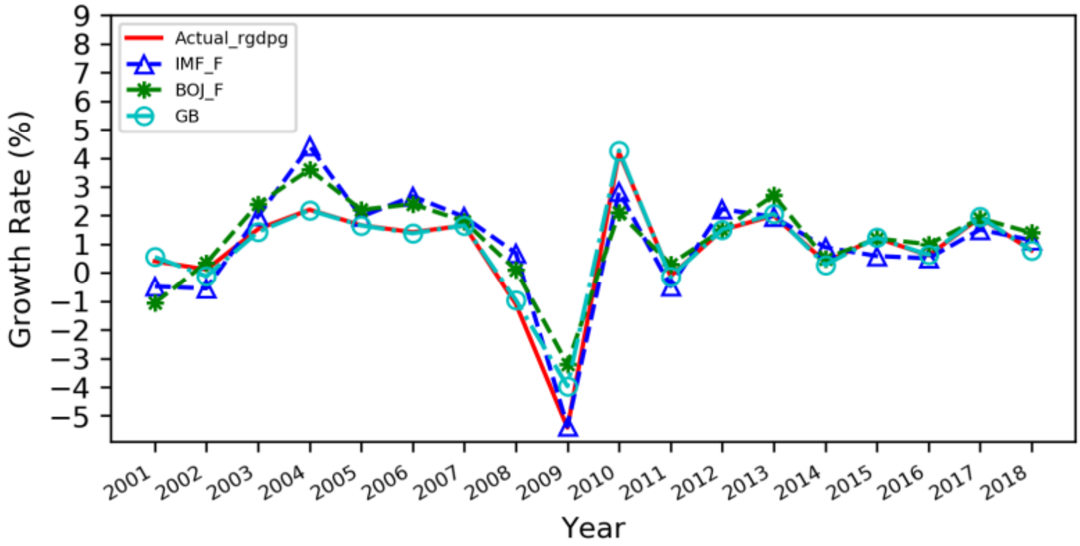
For benchmark points, this study uses the forecast data generated by the IMF and the BOJ. The IMF and the BOJ provide annual real GDP growth biannually: once in the spring and again in the autumn. Table 4.3 presents the forecasted real GDP growth of Japan, including that from the machine learning models, the IMF and the BOJ, along with the actual real GDP growth.

Table 4.3. Actual and predicted real GDP growth of Japan (%)

Year	Actual real GDP growth	Forecasted real GDP growth					
		GB	RF	IMF_F	IMF_S	BOJ_F	BOJ_S
2001	0.41	0.55	0.50	-0.48	0.60	-1.05	0.55
2002	0.12	-0.12	0.04	-0.55	-0.97	0.35	-0.20
2003	1.53	1.43	1.51	1.98	0.82	2.40	1.00
2004	2.20	2.18	2.14	4.42	3.35	3.60	3.10
2005	1.66	1.66	1.67	1.96	0.81	2.20	1.30
2006	1.42	1.38	1.41	2.67	2.80	2.40	2.20
2007	1.65	1.66	1.60	1.95	2.34	1.80	2.10
2008	-1.09	-0.96	-0.85	0.69	1.43	0.10	1.50
2009	-5.42	-3.97	-2.32	-5.37	-6.20	-3.20	-3.10
2010	4.19	4.27	4.66	2.82	1.90	2.10	1.80
2011	-0.12	-0.15	-1.20	-0.47	1.40	0.30	0.60
2012	1.50	1.51	1.50	2.22	2.04	1.50	2.30
2013	2.00	2.06	2.05	1.95	1.58	2.70	2.90
2014	0.38	0.28	0.15	0.89	1.35	0.50	1.10
2015	1.22	1.23	1.28	0.59	1.04	1.20	2.00
2016	0.61	0.63	0.62	0.51	0.49	1.00	1.20
2017	1.93	1.96	1.96	1.51	1.25	1.90	1.60
2018	0.79	0.77	0.88	1.14	1.21	1.40	1.60

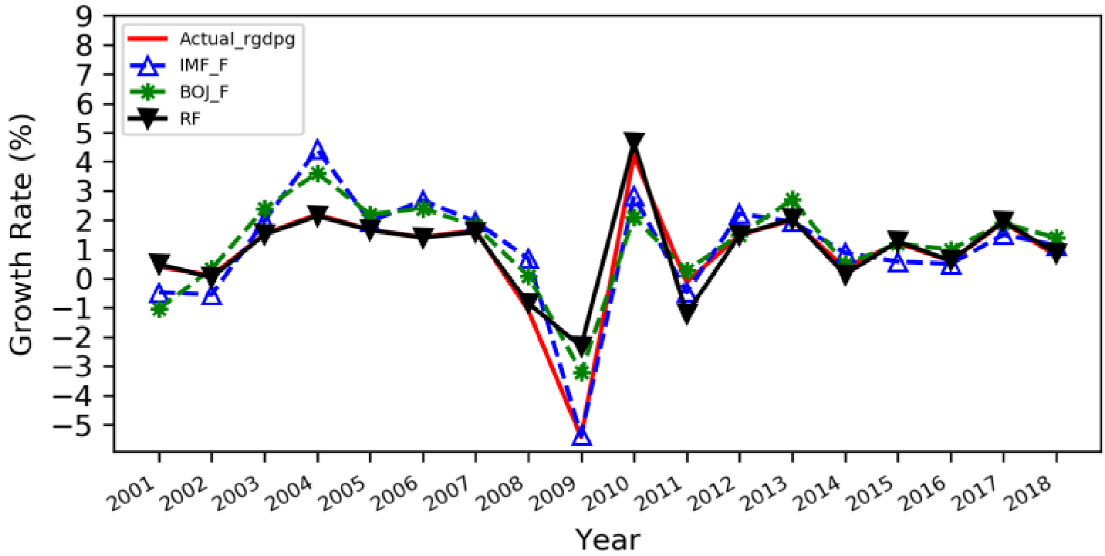
* GB and RF are gradient boosting and random forest, respectively, and represent the forecasts based on the out-of-sample tests. IMF_F and IMF_S are the IMF forecasts made in fall and spring, respectively. BOJ_F and BOJ_S are the BOJ forecasts made in fall and spring, respectively.

Figure 4.3. Actual and predicted real GDP growth in Japan (including the gradient boosting model)



* Actual_rgdpg is actual annual real GDP growth of Japan. IMF_F, BOJ_F, and GB are the forecasts made by the IMF in fall, the BOJ in fall and the gradient boosting model (out-of-sample tests)

Figure 4.4. Actual and predicted real GDP growth in Japan (including the random forest model)



* Actual_rgdpg is actual annual real GDP growth of Japan. IMF_F, BOJ_F, and RF are the forecasts made by the IMF in fall, the BOJ in fall and the random forest model (out-of-sample tests)

Figure 4.3 and Figure 4.4 present the graphs of the actual real GDP growth of Japan and those forecasted by the machine learning models, the IMF, and the BOJ.

As shown in Table 4.3 and Figures 4.3 and 4.4, the machine learning models produce forecasts that are overall more accurate than those produced by the IMF and the BOJ. However, for 2009, a year during which the global economic crisis was on-going, the machine learning models do not predict the extreme drop in real GDP growth, which was forecasted by the IMF. The actual real GDP growth in 2009 is -5.42 %. The rates forecasted by the gradient boosting and random forest models are -3.97 % and -2.32 %, respectively. The rate by forecasted by the IMF is -5.37 %.

To compare forecast accuracy, MAPEs (mean absolute percentage errors) and RMSEs (root mean squared errors) are calculated for each model and compared. MAPE is a measure strongly preferred and frequently used by both practitioners and academics to assess the accuracy of forecasting models. MAPE is calculated by using the following formula.

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{O_i - P_i}{O_i} \right| \tag{8}$$

P is a predicted value, and O is an observed value. n is the total number of observations. Table 4.4 presents MAPEs for the machine learning models of this study, the gradient boosting and random forest models, and for the forecasts by the IMF and the BOJ in the spring and fall for each year from 2001 to 2018.

Table 4.4. MAPEs for the machine learning models and forecasts by the IMF and the BOJ (%)

Period	GB	RF	IMF_F	IMF_S	BOJ_F	BOJ_S
2001	36.04	23.38	217.18	46.84	358.62	35.47
2001-2002	118.78	43.32	390.08	482.91	277.62	152.48
2001-2003	81.34	29.26	269.81	337.32	204.1	113.17
2001-2004	61.25	22.66	227.43	265.99	168.89	95.03
2001-2005	49.08	18.18	185.51	223.1	141.57	80.39
2001-2006	41.35	15.29	169.28	202.08	129.48	76.14
2001-2007	35.5	13.57	147.68	179.13	112.24	69.12
2001-2008	32.64	14.66	149.62	185.61	111.85	90.12
2001-2009	31.99	19.38	133.09	166.59	103.97	84.86
2001-2010	28.97	18.55	123.04	155.41	98.57	82.08
2001-2011	29.03	102.6	139.73	260.91	122.41	131.14
2001-2012	26.72	94.08	132.15	242.2	112.24	124.7
2001-2013	24.9	87.02	122.16	225.16	106.3	118.57
2001-2014	24.99	85.06	123.27	227.66	101.09	123.91
2001-2015	23.36	79.68	118.5	213.46	94.47	119.88
2001-2016	22.11	74.84	112.11	201.38	92.58	118.45
2001-2017	20.91	70.54	106.78	191.62	87.22	112.49
2001-2018	**19.86**	**67.23**	**103.31**	**183.97**	**86.69**	**111.96**

* GB and RF are gradient boosting and random forest, respectively. The first two columns indicate the results from the out-of-sample tests. IMF_F and IMF_S are the IMF forecasts made in fall and spring, respectively. BOJ_F and BOJ_S are the BOJ forecasts made in fall and spring, respectively.

According to Table 4.4, for the 2001-2018 period, the gradient boosting model appears to have more predictive power than the random forest model. In addition, both the gradient boosting (19.86 %) and random forest (67.23 %) forecasts are shown to be more accurate than the IMF (103.31 % in fall and 183.97 % in spring) and the BOJ (86.69 % in fall and 111.96 % in fall) forecasts. Some may question whether the in-sample forecast models could overfit, and there could be an overfitting problem. Regarding the overfitting problem, Table 4.A.2 in Appendix presents MAPEs calculated for the in-sample tests.

MAPEs for in-sample tests are calculated using the forecast values from the cross-validation process. The average values for the in-sample tests of the gradient boosting model (39.61%) and random forest model (73.13%) for the 2001-2018 period suggest the lack of overfit for the models. In addition, to avoid potential overfitting problems, this study adopts an expanding window method. This method creates a new model for each period using cross-validation and hyperparameter tuning and introduces a certain level of bias into the model to reduce variance. For example, if the model used for the annual real GDP growth of Japan in 2015 is used again for the prediction in 2017, the performance could be significantly low. However, the methodology used in this study creates a new model for the prediction in 2017 using the sample available up to the second quarter of 2017. As a result, the out-of-sample forecasts consistently outperform the those made by the IMF and the BOJ; the MAPEs for the out-of-sample forecasts are lower than those for the IMF and the BOJ. Based on the performance shown by the out-of-sample forecast models, the overfitting problem should not be significant.

RMSE is another measure that is popular among practitioners and academics for assessing the accuracy of forecasting models. RMSE measures the differences between observed and predicated values and is calculated using the following formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{9}$$

P is a predicted value, and *O* is an observed value. *n* is the total number of observations. In the formula, it should be noted that by squaring the difference between the predicted and observed values, the RMSE penalizes large errors.

Table 4.5 presents the RMSEs for the machine learning models of this study, the gradient boosting and random forest models, and the forecasts by the IMF and the BOJ in spring and fall for each year from 2001 to 2018.

Table 4.5. RMSEs for the machine learning models and the forecasts by the IMF and the BOJ

Period	GB	RF	IMF_F	IMF_S	BOJ_F	BOJ_S
2001	0.15	0.09	0.88	0.19	1.46	0.14
2001-2002	0.20	0.09	0.78	0.78	1.04	0.25
2001-2003	0.17	0.07	0.69	0.75	0.99	0.37
2001-2004	0.15	0.07	1.26	0.87	1.10	0.55
2001-2005	0.13	0.06	1.13	0.87	1.02	0.52
2001-2006	0.12	0.06	1.15	0.97	1.01	0.57
2001-2007	0.11	0.06	1.07	0.94	0.94	0.55
2001-2008	0.12	0.10	1.19	1.25	0.97	1.05
2001-2009	0.50	1.04	1.12	1.21	1.18	1.26
2001-2010	0.47	0.99	1.15	1.36	1.30	1.41
2001-2011	0.45	1.00	1.10	1.37	1.24	1.36
2001-2012	0.43	0.96	1.07	1.32	1.19	1.33
2001-2013	0.41	0.92	1.03	1.28	1.16	1.30
2001-2014	0.40	0.89	1.00	1.26	1.12	1.27
2001-2015	0.39	0.86	0.98	1.21	1.08	1.24
2001-2016	0.37	0.83	0.95	1.18	1.05	1.21
2001-2017	0.36	0.81	0.93	1.15	1.02	1.18
2001-2018	**0.35**	**0.79**	**0.90**	**1.13**	**1.00**	**1.16**

* GB and RF are gradient boosting and random forest, respectively. The first two columns indicate the results from the out-of-sample tests. IMF_F and IMF_S are the IMF forecasts made in fall and spring, respectively. BOJ_F and BOJ_S are the BOJ forecasts made in fall and spring, respectively.

Table 4.5 presents RMSEs for the predictions of the annual real GDP growth of Japan made by the machine learning models two quarters ahead. The RMSEs for all the machine learning models are lower than those of the IMF and the BOJ for the 2001-2018 period. Based on the RMSEs for the 2001-2018 period, the gradient boosting model appears to have more predictive power than the random forest model. Similar to MAPEs, Table 4.A.2 in Appendix presents the RMSEs for in-sample tests. The average values for the in-sample tests of the gradient boosting model (0.39) and random forest model (0.57) for the 2001-2018 period show that the overfit should not be significant.

Although the machine learning models made worse forecasts for the crisis year of 2009, both the MAPEs and the RMSEs of the machine learning models suggest that the machine learning models produce predictions that are more accurate than those produced by the IMF and the BOJ for multiple years, including the 2001-2018 period.

4.4. Conclusion

The results of this study advocate the use of machine learning techniques in forecasting macroeconomic data. Based on the customized cross-validation process, the machine learning method employed in this study, which creates gradient boosting and random forest models for the 2001-2018 period, produces forecasts that are more accurate than those made by the IMF and the BOJ. Accuracy is measured by MAPE and RMSE.

Traditional econometric models focus on explanations of causal relationships, whereas machine learning models focus on predictions. Machine learning models may not be a good choice for determining the impact of independent variables on the dependent variable or analyzing a causal relationship. However, as shown in this study and in multiple previous studies, machine learning models often show high prediction power.

Since there is no model or methodology that produces the best result for every type of data set, this study contributes to the literature by empirically testing and comparing predictions of real GDP growth in Japan using popular machine learning models based on real data. This study further proposes a recursive method that combines cross-validation and hyperparameter tuning to create accurate models, which can be accurate even with low-frequency macroeconomic data. From this point of view, the method suggested in this study should serve as an effective analysis option for predicting economic variables that could lead to more effective economic policy design and implementation, especially when only low-frequency data are available. Finally, based on the validated result, this study also supports and encourages further research on and use of machine learning models to forecast economic variables and to answer economic

Appendix

Table 4.A.1. Description of the variables

Variable	Unit	Scale	Number of Observations	Sources
Consumer price index	Index	1990=100	147 (4Q of 1981 – 2Q of 2018)	Ministry of Internal Affairs a Japan, Oxford Economics
Consumption, government, real	Yen	Billions: 1990 prices	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics
Consumption, private, real	Yen	Billions: 1990 prices	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics
Current account of balance of payments	%		147 (4Q of 1981 – 2Q of 2018)	Bank of Japan/Ministry of Finance, Oxford Economics
Employment	Person	Thousands	147 (4Q of 1981 – 2Q of 2018)	Ministry of Internal Affairs a Oxford Economics
Exchange rate, period average, per euro	Yen per euro		147 (4Q of 1981 – 2Q of 2018)	Haver Analytics, Oxford Economics
Exchange rate, period average	Yen per US dollar		147 (4Q of 1981 – 2Q of 2018)	Federal Reserve Board, Oxford Economics
Exports, goods & services, real	Yen	Billions: 1990 prices	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics
External debt, total	US dollar	Millions	147 (4Q of 1981 – 2Q of 2018)	Ministry of Finance/Federal Reserve Board, Oxford Economics
Foreign direct investment	US dollar	Millions	147 (4Q of 1981 – 2Q of 2018)	Bank of Japan/Ministry of Finance Japan, Oxford Economics
GDP deflator	Index	1990=100	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics
GDP, real, q	Yen	Billions: 1990 prices	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics
GDP growth, real, quarter to q	%	Base year=1990	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics, Author's calculation
GDP growth, real, year over year	%	Base year=1990	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics, Author's calcula
GDP growth, real, year over year, 2 quarters a	%	Base year=1990	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics, Author's calcula
GDP growth, real, year over year, 3 quarters a	%	Base year=1990	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics, Author's calculation

Government balance (as a % of GDP)	%		147 (4Q of 1981 – 2Q of 2018)	Organization for Economic Cooperation & Development/Cabinet Office of Japan, Oxford Economics
Gross government debt (as a % of GDP)	%		147 (4Q of 1981 – 2Q of 2018)	Bank of Japan/Cabinet Office of Japan, Oxford Economics
Imports, goods & services, real	Yen	Billions: 1990 prices	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics
Industrial production index	Index	1990=100	147 (4Q of 1981 – 2Q of 2018)	Ministry of Economy, Trade a Oxford Economics
Interest rate, 10-year government bond yields	%		147 (4Q of 1981 – 2Q of 2018)	Ministry of Finance of Japan, Oxford Economics
Investment, total fixed investment, real	Yen	Billions: 1990 prices	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics
Reserves, foreign exchange	US dollar	Millions	147 (4Q of 1981 – 2Q of 2018)	Ministry of Finance of Japan, Oxford Economics
Tokyo Stock Price Index	Index	Jan-04-1968=100	147 (4Q of 1981 – 2Q of 2018)	Financial Times/Nihon Keizai Shinbun (Nikkei), Oxford Economics
Stockbuilding, real	Yen	Billions: 1990 prices	147 (4Q of 1981 – 2Q of 2018)	Cabinet Office of Japan, Oxford Economics
Unemployment rate	%		147 (4Q of 1981 – 2Q of 2018)	Ministry of Internal Affairs a Japan, Oxford Economics

Table 4.A.2. MAPEs and RMSEs for the in-sample tests of the machine learning models

Forecast Year	MAPE (%)		RMSE	
	GB (In-sample)	RF (In-sample)	GB (In-sample)	RF (In-sample)
2001	80.67	196.11	0.44	0.59
2002	24.04	35.15	0.52	0.78
2003	28.86	39.12	0.30	0.40
2004	27.31	33.94	0.43	0.65
2005	28.06	44.06	0.30	0.42
2006	20.76	23.89	0.31	0.66
2007	8.27	15.92	0.19	0.35
2008	22.35	25.93	0.39	0.50
2009	27.80	48.44	0.35	0.50
2010	61.05	210.95	0.39	0.55
2011	11.36	25.62	0.73	0.83
2012	26.96	46.06	0.21	0.58
2013	9.89	15.39	0.10	0.24
2014	79.98	287.14	0.74	0.87
2015	24.26	24.14	0.73	0.96
2016	9.03	18.61	0.21	0.44
2017	208.40	208.43	0.41	0.50
2018	13.95	17.37	0.26	0.47
Average (2001-2018)	**39.61**	**73.13**	**0.39**	**0.57**

* MAPEs and RMSEs are calculated using the forecast values from the cross-validation process used for each forecast year.

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Chapter 5 Conclusion

This dissertation presents various applied econometric and machine learning methods ranging from system GMM to machine learning models including Random Forest and Gradient Boosting models. In addition, the detailed analysis results are presented to answer questions on empirical economic issues that cover firm productivity, monetary policy, and macroeconomic forecasting by machine learning models with focus on the Japanese data.

The first essay in Chapter 2, titled "Impact of Foreign Ownership on Firm Productivity: Evidence from the Japanese Manufacturing Firms, confirms the positive impact of foreign ownership on firm productivity in the case of manufacturing firms in Japan. The second essay in Chapter 3, titled "Physical investment of Japanese firms during QE and QQE periods: Did the transmission mechanism work?," concludes that the neoclassical transmission channel worked during the QE and QQE periods with the confirmation of the positive impact of Tobin'q on the firm investment and the non-neoclassical transmission channel did not work during QE and QQE periods. It is also confirmed that the debt ratio turns out to have negative impacts on investment only for the QE period. The third essay in Chapter 4, titled "Forecasting of Real GDP Growth of Japan Using Machine Learning Models," presents machine learning models, including Gradient Boosting and Random Forest model, that produce more accurate forecasts on real GDP growth of Japan for the periods between 2001 and 2018 than those by International Monetary Fund (IMF) and Bank of Japan (BOJ).

I strongly believe that the results and implications from this dissertation could make meaningful contribution to the current literature of applied econometrics and machine learning. I also sincerely hope that the essays in this dissertation would serve as stepping-stones for advancement of related applied econometric and machine learning research in the future.

- The End -