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Can the Disparity between GDP and GDP Forecast Cause Economic Instability? The Recent Japanese Case

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Abstract: This paper investigates the link between forecast disparity and macroeconomic instability that results from the data revision of GDP and inflation in Japan. The recent Japanese case, which reflects the unconventional monetary policy conducted since 2013, is also examined. The empirical results show that such disparities do not cause economic instability; however, they have have done so after the unconventional and drastic monetary policy was conducted. On the other hand, exchange rates impacted economic stability for the total period. For the first part of the period under study (from 2000 to 2012), currency appreciation caused instability; however, for the more recent period, depreciation has caused such instability. Recently, macroeconomic instability has been linked with exchange rate movements.

Keywords: Economic stability; Forecast; GDP; Price.

1. Introduction

Before economic data releases, markets move according to participants' (including computer program) expectations. Some data are released with the condition that there may be some change in the future, and the data actually change thereafter. The first released data tend to be unreliable compared to the final figures, especially during times of economic turmoil. Data disparities are common, and they may be large or small. When they become large, markets usually move again. Data revisions, which can be large in magnitude and are subject to an indefinite way are important to the extent that the initially released data cannot be taken at face value (Baetje and Friedrici, 2016). Even when disparities are small, market turmoil or instability sometimes occur.

Just before the first initial data are released and again when confirmation data are released, economists and private economic institutions expect each report, and when they are published, market participants (sometimes computers) see them and conduct transactions, invest, and sometimes speculate using the published data. In some cases, huge transactions occur and *wrong* one direction transactions dampen sound markets and economic development. Markets sometimes fluctuate as a result of such participants' transactions. Also, they sometimes make use of economic data disparities on purpose. However, sometimes a large variety of expectations and the transactions that are based on such expectations stabilize markets.

Market participants know quite well that disparities exist. It is quite difficult and at time nearly impossible to forecast economic data correctly; sometimes such forecasts are accurate and sometimes not, which is quite natural. However, sometimes market dispersions cause instability or turmoil. No problems result when such disparities cause market stability; however, the opposite case may cause serious situations and sometimes dampen economic growth. Such mechanisms should be examined much more but few studies have examined the relationship between forecast disparities and macroeconomic uncertainty not only in the fields of theoretical studies but also in empirical fields, despite the importance of this problem. Recent developments in ICT may accelerate economic stability or turmoil.

Mankiw and Shapiro (1986) and Faust *et al.* (2005) showed that data revisions cause uncertainty because of the reliability of economic data in real time. Zarnowitz and Lambros (1987) indicated that the relationship between survey-based dispersion and macroeconomic uncertainty depends on the assumption that forecasters have stronger effects during times of greater economic turmoil. Fair and Shiller (1990) found that the quality of economic forecasts strongly relies on the volatility of the economy. Ang *et al.* (2007) and Genre *et al.* (2013) showed that consensus forecasts outperform other forecast models closer to the initial released data. Belke and Klose (2011) found that the use of real-time instead of ex post data leads to higher estimated output gap and inflation gap. Croushore (2011) indicated that evaluation of the success of policy authority actions and forecasts is crucially linked with whether or not real-time or confirmed revised values are used. Kalckreuth and Wolff (2011) found that discretionary fiscal policy is influenced by measurements of data error. Nalewaik (2011) showed that GDI instead of GDP is useful in the analysis of the current economic situation. Neri and Ropele (2011) found that the estimated policy rule becomes more inertial and less aggressive for the case of inflation rates. Giannone *et al.* (2012) indicated that data revisions cause the economic instability that surrounds key macroeconomic ratios. Cusinato *et al.* (2013) showed that there is a difference between the revisions of GDP and adding new observations and that the latter is preponderant. Lewis (2013) found that government budget balances have a stabilizing influence on economic activity. Pedersen (2013) found that there is no improvement in nowcasting performance when historical data are supplemented. Laurent and Andrey (2014) showed that forecast accuracy of the data improves when the probability forecasts of both the coincident indicators model and the yield curve model are combined. Liebermann (2014) indicated that the precision of nowcasts increases with economic data information releases. Beradi and Duffy (2015) showed that the method of real-time parameterized expectations learning gives a plausible alternative way to use the real-time adaptive learning dynamics model. Bernoth *et al.* (2015) found that the intended discretionary response of fiscal policy to the cycle is counter-cyclical. Capek (2015) indicated that data revisions are unbiased and not autocorrelated by using the DSGE model. Leopoldo and Guilermo (2015) found that there is no reason to accept the interpretation that forecast errors have unfortunate systematic effects on fiscal procyclically. Baetje and Friedrici (2016) showed that disagreement is significantly linked with to data uncertainty. Cimadomo (2012) found that forecast errors for the government structural balance and the output gap play an important role in explaining the differences between estimates based on ex ante and ex post data. Also, Cimadomo (2016) indicated that fiscal data revisions are large and initial releases are biased estimates of final ones.

Some studies have examined data dispersions including GDP; however, there are not enough of these in spite of their importance. In particular, few studies have examined the Japanese case. Using macroeconomic data, this study focuses on predicted real output and inflation rates. Also, the current study focuses on the recent Japanese unconventional monetary policy.

This paper is structured as follows. Following this section, theoretical aspects of data dispersions are explained. Section 3 provides data description and empirical methods for the conduct of the empirical analyses the follow. Section 4 shows the empirical analyses and analyzes the results. Finally, this paper ends with a brief summary.

2. Theoretical Analysis

If initially released data are not accurate or biased, later revisions may reflect large data uncertainty. On the other hand, if the initial data are correct, revisions would tend to be small in general. The disparities between the initial and final figures may have negative effects on the economy or sometimes dampen economic growth. This study starts with this point of view.

Several studies have examined the link between initial and final data releases to determine whether revisions can be characterized as news or noise. Under the news view, data revisions occur as additional information becomes available. Accordingly, initial data are efficient and rational forecasts for the final data. On the other hand, if the preliminary announcement equals the final data plus some measurement errors, revisions reduce noise, which implies that they tend to be predictable. The present study mainly considers the latter case. The equation used in this study examines the relationship between data disparities and economic stability as explained in the next section.

Data revision errors are defined as $\text{DIFFERENCE}^{l}_{t} = A^{F}_{t} - A^{l}_{t}$, where the announced data at real-time vintage l and y^{F}_{t} denotes the true or final, revised data. A in the equation means GDP and inflation in this study. This study's measurement of data uncertainty is defined by the standard deviation of revision errors over a preselected revision window with length of quarters or months. The length is shown in the next section. Whether or not forecast dispersions of GDP and inflation that reflect data uncertainty impact economic stability is examined. Detailed data and empirical methods are also explained in the section 3. The recent Japanese unconventional monetary policy also is considered.

3. Data and Empirical Methods

This study uses the predicted real GDP rate and predicted inflation rate, both as measured by the GDP price index. The *real GDP growth rate* is defined as the annualized quarter-over-quarter percentage change using forecast horizons of four quarters (one year) and eight quarters (two years). *Inflation rate* is defined as the annualized month-over-month percentage change using forecast horizons of three (one quarter) or six months (a half year). The proxy for economic stability, such as macroeconomic uncertainty, is the standard deviation among individual forecast. The sample period for GDP is from 2000Q1 to 2016Q1 and the sample period for inflation is from 2013M1 to 2016M6. The data are from the Japanese Statistical Bureau and the Bank of Japan.

Since April, 2013, a new, unconventional monetary policy has been conducted in Japan. To check the difference between the periods before and after implementation of this police would be interesting and necessary; however, not enough time has passined since this policy was first introduced, so the problem of the amount data would occur especially for quarterly data (i.e., GDP). So examination of the differences between the period before the unconventional monetary policy and the period of after its implementation is applied to the case of inflation, which can be determined from monthly data. GDP data are usually quarterly.

Whether or not forecast disparities reflect instability of the Japanese economy is assessed using the following regression (1).

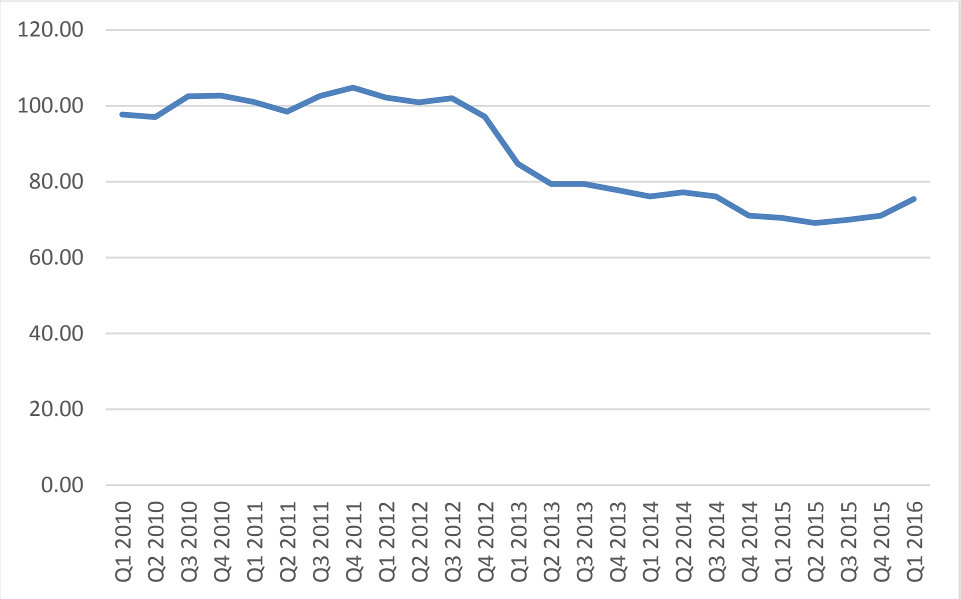
$$\log(\sigma_t) = \alpha + \beta \log(\text{DIFFERENCE}_{t-h}) + \varepsilon_t \tag{1}$$

where DIFFERENCE_{t-h} is defined as the forecast disparity for the target quarter or month at point t, observed h quarters or months ago, depending on the forecast horizon.

Moreover, a new explanatory variable, *exchange rate*, is added to the equation. The reason that exchange rates should be included in the equation is that especially since 2013, the unconventional monetary policy began to be conducted and exchange rates moved greatly as a result. Significant depreciation of the Japanese yen has occurred and may cause economic fluctuations.

In Japan, a drastic new policy, called *Abenomics* (for Abe, the prime minister), was adopted in April 2013 to combat deflation. Japan has been under severe economic conditions (i.e., deflation). Moreover, by strengthening coordination between the Japanese central bank (Bank of Japan; BOJ) and the government, since April 2013, the Japanese government has implemented measures to achieve a new fiscal structure to ensure the credibility of the fiscal condition. At that time, BOJ introduced an unprecedented and unconventional aggressive monetary policy that expands the volume of government bond purchases to pour money into markets for consumption, investment, and so on. As a result of this policy, exchange rates depreciated and stock prices rose. The movement of exchange rates (real effective exchange rate) are shown in Figure 1.

Figure-1. Exchange rate



For the analysis that includes exchange rates, this equation (2) instead of the equation (1) is regressed.

$$\log(\sigma_t) = \alpha + \beta \log(\mathrm{DIFFERENCE}_{t-h}) + \gamma \log(\mathrm{EXCHANGE}_{t-h}) + \varepsilon_t \qquad (2)$$

Empirical methods are OLS (ordinary least squares) and robust estimation. Robust estimation is unlike maximum likelihood estimation. OLS estimates for regression are sensitive to the observations that do not follow the pattern of the other observations. This is not a problem if the outlier is simply an extreme observation from the tail of a normal distribution; however, if the outlier is from non-normal measurement error or some other violation of standard OLS, it compromises the validity of the regression results if a nonrobust regression method is employed. In this study, there are not enough sample numbers, so along with the usual OLS, robust estimation is used.

4. Empirical Results and Analyses

First, GDP is regressed. The empirical results of equation (1) are reported in Table 1 and the results of the equation (2) are reported in Table 2.

Table-1. Difference of GDP and Economic Stability.

Horizon = 4 or 8	Horizon = 4	Horizon = 4	Horizon = 8	Horizon = 8
Method	OLS	Robust Estimation	OLS	Robust Estimation
C	0.899*** (11.765)	0.702*** (14.469)	0.835*** (10.542)	0.664*** (13.368)
DIFFERENCE	0.024 (0.131)	0.094 (0.790)	0.064 (0.329)	0.049 (0.402)
Adj.R2	-0.016		-0.015	
Adj.Rw-squared		0.013		0.003
F-statistic	0.017 (0.895)		0.108 (0.743)	
Rn-squared statistic		0.624 (0.429)		0.162 (0.687)

Note. Figures in parentheses are t-statistics for OLS, z-statistic robust estimation, and probability for F-statistic and Rn-squared statistic. ***, **, and * denote 1%. 5%, and 10% significance levels respectively.

Table-2. Difference of GDP, Exchange Rate and Economic Stability

Horizon = 4 or 8	Horizon = 4	Horizon = 4	Horizon = 8	Horizon = 8
Method	OLS	Robust Estimation	OLS	Robust Estimation
C	2.864*** (5.826)	2.165*** (5.864)	2.472*** (4.625)	1.580*** (4.238)
DIFFERENCE	0.028 (0.170)	0.045 (0.363)	0.067 (0.369)	0.066 (0.523)
EXCHANGE	-0.018*** (-4.035)	-0.012*** (-3.758)	-0.015*** (-3.091)	-0.008** (-2.340)
Adj.R2	0.192		0.113	
Adj.Rw-squared		0.247		0.117
F-statistic	8.153 (0.0007)		4.839 (0.011)	
Rn-squared statistic		14.271 (0.0007)		5.766 (0.055)

Note. Figures in parentheses are t-statistics for OLS, z-statistics for robust estimation, and probability for F-statistic and Rn-squared statistic. ***, **, and * denote 1%. 5%, and 10% significance levels respectively.

The empirical results are clear. They show that disparities in GDP data do not cause instability. The coefficients are positive as expected; however, they are not significant even at the 10% level. On the other hand, exchange rates have caused economic instability. It is interesting to note that exchange rate movements instead of disparities in GDP cause economic instability.

For inflation, the empirical results are reported in Tables 3 and 4.

Table-3. After Abenomics

Horizon = 3 or 6	Horizon = 3	Horizon = 3	Horizon = 6	Horizon = 6
Method	OLS	Robust Estimation	OLS	Robust Estimation
C	26.342*** (6.310)	28.632*** (5.691)	0.716*** (11.654)	0.679*** (10.164)
DIFFERENCE	3.636* (1.733)	4.113* (1.748)	0.127*** (4.143)	0.139*** (4.142)
Adj.R2	0.046		0.282	
Adj.Rw-squared		0.090		0.392
F-statistic	3.003 (0.090)		17.166 (0.0001)	
Rn-squared statistic		3.058 (0.080)		17.164 (0.000)

Note. Figures in parentheses are t-statistics for OLS, z-statistics for robust estimation, and probability for F-statistic and Rn-squared statistic. ***, **, and * denote 1%. 5%, and 10% significance levels, respectively.

Table-4. After Abenomics.

Horizon = 3 or 6	Horizon = 3	Horizon = 3	Horizon = 6	Horizon = 6
Method	OLS	Robust Estimation	OLS	Robust Estimation
C	57.626 (1.596)	60.896 (1.495)	-1.312*** (-3.085)	-1.342*** (-2.758)
DIFFERENCE	3.803* (1.799)	4.277* (1.794)	0.138*** (5.573)	0.140*** (4.939)
EXCHANGE	0.285 (0.872)	0.314 (0.850)	0.018*** (4.800)	0.018*** (4.291)
Adj.R2	0.040		0.537	
Adj.Rw-squared		0.113		0.604
F-statistic	1.873 (0.167)		24.838 (0.000)	
Rn-squared statistic		3.698 (0.157)		39.296 (0.000)

Note. Figures in parentheses are t-statistics for OLS, z-statistics for robust estimation, and probability for F-statistic and Rn-squared statistic. ***, **, and * denote 1%. 5%, and 10% significance levels, respectively.

The empirical results reveal some interesting points: Disparities do cause instability since implementation of the drastic, unconventional monetary policy. On the other hand, depreciation has caused economic instability. It is difficult to judge; however, recent depreciation of the yen has been significant (see Figure 1) and has caused large fluctuations in economic conditions. Of course this condition entails both pros and cons for the economy.

Policy authorities should take these findings into account in some cases. Surely, data disparities should be avoided, especially for the case of *noise*. Forecasts should be performed as accurately as possible and at least should be able to account for the reasons for the disparities as market participants could understand and agree. In such cases, markets would rely on the authorities, and market turmoil would be avoided. However, along with improvements in the accuracy of forecasts, authorities should consider the movements of exchange rates. In some cases, markets (e.g., foreign exchange markets and stock markets, etc.), go out of control. Such situations should be avoided as much as possible.

5. Conclusions

This paper empirically examined the relationship between forecast disparities and macroeconomic instability that resul from data revisions of GDP and inflation figures in Japan. The recent Japanese case, for which unconventional monetary policy has been conducted since 2013, was also examined. The empirical results showed that disparities in GDP forecasting do not cause instability; however, inflation figure disparities, after the unconventional and drastic monetary policy was conducted, have caused instability. On the other hand, exchange rates impacted economic instability for the total period. For the first part of the sample period (from 2000 to 2012), appreciation caused instability; also, for the more recent period, depreciation has caused economic instability. Recently, disparities in GDP and inflation data have been linked with macroeconomic instability. Exchange rates should be taken into account along with the some kinds of data dispersions.

Finally, data accumulation seems necessary. Further study is necessary.

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