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Consensus and Accuracy of Japanese GDP Forecasts

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This paper investigates the real GDP forecasts of Japanese institutional forecasters for 25 years. It finds that a consensus forecast does not exist in nine/eight years for the current-year/year-ahead forecasts. The variance of the forecast distribution is positively correlated with the absolute forecast error of its mean forecast, but the correlation is significant for the current-year forecasts only. The economy tends to hit the peak or the bottom when forecast dispersion is large, but non-parametric analysis shows that the correlation is statistically insignificant.

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1. Introduction

Many studies have regarded the mean forecast in the sample as the consensus forecast and have tested various economic hypotheses using it. Typical survey data, however, show that forecasters' cross-sectional predictions differ markedly, and that the degree of their dispersion varies over time. Therefore it is important to examine whether there exists a consensus forecast in each year that can be used to describe the entire distribution of the forecasts.

Since the seminal work of Schnader and Stekler (1991), a considerable number of studies have focused on this issue. Unfortunately, their results are somewhat mixed. Schnader and Stekler (1991) find that a consensus does not exist in eleven (fifteen) out of twenty-one years of the ASA-NBER real-GNP (GDP-deflator) forecast sets. Kolb and Stekler (1996) show that at least seven out of twenty-three semi-annual forecast sets for the 30-year Treasury bond do not have a consensus. On the other hand, Reitz and Stadtmann (2005) find that only seven out of thirty semi-annual yen-dollar forecast sets in the Wall Street Journal do not have a consensus. Dopke and Fritsche (forthcoming) find that the existence of a consensus is rejected in five (ten) out of thirty-five years of German real-GDP (inflation) forecasts.

This paper follows the methodology of Kolb and Stekler, and investigates the distribution of the real GDP forecasts made by Japanese institutional forecasters for 25 years. Section 2 explains the data, and Section 3 demonstrates that a consensus forecast does not exist in nine/eight years for the current-year/year-ahead forecasts.

Lack of a consensus among forecasters implies high level of uncertainty, and uncertainty might lead to a larger forecast error. Section 4 analyses the relation between forecast dispersion and forecast accuracy. It finds that the variance of the forecast distribution is positively correlated with the absolute forecast error of its mean forecast, but the correlation is statistically significant for the current-year forecasts only.

Section 5 examines the relationship between forecast dispersion and the business cycle. Forecasters would disagree with the strength of the economy when the economy is going to turn around. In accordance with this hypothesis, it finds that the Japanese economy tends to hit the peak or the bottom when forecast dispersion is large. Non-parametric analysis shows, however, that the correlation is statistically insignificant. Discussions and conclusions are in Section 6.

2. Data

Toyo Keizai Inc. has published the forecasts of about 60 Japanese institutions in the February or March issue of "Monthly Statistics (Tokei Geppo)" since the 1970s (Ashiya (2003, 2005, forthcoming-a, b) also uses this data). Every December, institution *i* releases forecasts of the Japanese real GDP growth rate for the ongoing fiscal year and for the next fiscal year. We call the former $f^i_{t,t}$ and the latter $f^i_{t,t+1}$. For example, the February 2005 issue contains forecasts for fiscal year 2004 (from April 2004 to March 2005) and for fiscal year 2005 (from April 2005 to March 2006). We treat the former as $f^i_{2004,2004}$ and the latter as $f^i_{2004,2005}$.

Since the participation rate was very low throughout the 1970s (on average 13.8 institutions per year), we use the forecasts published from February 1981 on. That is, we use $f^i_{t,t}$ for the fiscal years 1980 through 2004 and $f^i_{t,t+1}$ for the fiscal years 1981 through 2005. Since some forecasters did not participate in some years, the panel data set is unbalanced. The average number of observations per year is 46.56 for the current-year forecast ($f^i_{t,t}$) and 47.12 for the year-ahead forecast ($f^i_{t,t+1}$).

As for the actual growth rate g_t, Keane and Runkle (1990) argue that the revised data introduces a systematic bias because the extent of revision is unpredictable for the forecasters (see also Stark and Croushore (2002)). For this reason, we use the initial announcement of the Japanese government usually released in June.

3. Tests for consensus

Schnader and Stekler (1991, p.166) argues that 'a consensus would exist if the forecasts were relatively close to and resembled each other.' They point out that the distribution should be unimodal, symmetric, and relatively peaked when there is a consensus. This section follows Kolb and Stekler (1996) and tests whether there is a consensus in Japanese institutional forecasters. Figure 1 illustrates the methodology, and Tables 1 and 2 present the results.

First we test uniformity of the forecast distributions. If the distribution is relatively flat, there is no consensus. In other words, if there is a consensus, then the null hypothesis that the forecasts were generated by the uniform distribution must be rejected. We employ the Pearson chi-squared goodness of fit test to examine this null hypothesis.

Following Kolb and Stekler (1996), we classify the forecasts of year t ($f_{t,t}^{i}$) into five categories using the standard deviation of $f_{t,t}^{i}$, $StD\left(f_{t,t}^{i}\right)$. Let $\bar{f}_{t,t}$ be the mean of $f_{t,t}^{i}$. The first category contains the forecasts that are smaller than $\bar{f}_{t,t} - 1.5StD\left(f_{t,t}^{i}\right)$. The second category contains those between $\bar{f}_{t,t} - 1.5StD\left(f_{t,t}^{i}\right)$ and $\bar{f}_{t,t} - 0.5StD\left(f_{t,t}^{i}\right)$. The third category contains those between $\bar{f}_{t,t} - 0.5StD\left(f_{t,t}^{i}\right)$ and $\bar{f}_{t,t} + 0.5StD\left(f_{t,t}^{i}\right)$. The fourth category contains those between $\bar{f}_{t,t} + 0.5StD\left(f_{t,t}^{i}\right)$ and $\bar{f}_{t,t} + 1.5StD\left(f_{t,t}^{i}\right)$. The fifth category contains those that are larger than $\bar{f}_{t,t} + 1.5StD\left(f_{t,t}^{i}\right)$. Let n_t^i be the observed number of entries in the ith category, and let $n_t = \sum_{i=1}^{5} n_t^i$ be the total number of observations in year t. Then the test statistic is

$$U_t \equiv \frac{5}{n_t} \sum_{i=1}^{5} \left(n_t^i - 0.2n_t\right)^2 .$$

Under the null hypothesis that $f_{t,t}^{i}$ were generated by the uniform distribution, U_t has a chi-squared distribution with four degrees of freedom. Significantly large U_t indicates that the number of observations in each cell is uneven and hence the forecast distribution is relatively peaked.

The third column of Tables 1 and 2 shows the results. The null of uniformity is not rejected at the 0.05 significance level for the year-ahead forecast for 1982. It indicates that there is no consensus in this forecast distribution. The null is rejected for all other forecast distributions.

Next, we test normality of the forecast distributions. Since the normal distribution is unimodal, symmetric, and relatively peaked, it is reasonable to say that a consensus exists when the forecast distribution is normal. We employ the W-statistic defined by Shapiro and Wilk (1965) and the Lagrange multiplier test statistic,

$$LM_t = \frac{n_t}{24} \left(k_t^2 + 4s_t^2\right),$$

where k_t is the sample kurtosis and s_t is the sample skewness statistic, for the test of normality (The significant points of the Lagrange multiplier test are tabulated in Table 1 of Deb and Sefton (1996)).

The fourth column of Tables 1 and 2 shows the result of Shapiro-Wilk test, and the fifth column shows the result of the Lagrange multiplier test. If neither test rejects the null of normality at the 0.05 significance level, we conclude that the forecast distribution is normal and hence there is a consensus. As for the current-year forecast, the forecast distributions of 1982, 1984, 1985, 1987, 1993, 1996, 2001, 2003, and 2004 satisfy this condition. As for the year-ahead forecast, those of 1981, 1984, 1986, 1987, 1990, 1993, 1994, 1997, 1998, 1999, 2000, 2002, 2004, and 2005 satisfy the condition.

If either test rejects the null of normality, we test symmetry of the distribution. If the forecast distribution is skewed, then there is no consensus because the distribution has a long tail and hence there is wide divergence among the forecasters.

The sixth column of Tables 1 and 2 shows the results. The null of symmetry is rejected at the 0.05 significance level for the current-year forecasts for 1980, 1981, 1992, 1994, 1997, 1998, 1999, 2000, and 2002, and the year-ahead forecasts for 1983, 1985, 1989, 1991, 1995, 1996, and 2003. We conclude there is no consensus in these forecast distributions.

If the null of normality is rejected but the null of symmetry is not rejected, we calculate the sample kurtosis of the distribution (k_t). If the forecast distribution is flat (i.e., platykurtic), then there is no consensus because forecasts are scattered. On the other hand, if the forecast distribution is peaked (i.e., leptokurtic), then a consensus exists because forecasts are clustered around the mean. The seventh column of Tables 1 and 2 shows that there is no distribution that is significantly platykurtic ($k_t < 0$). As for the current-year forecasts for 1983, 1986, 1989, and 1991, the kurtosis is insignificantly different from zero. Following the categorization of Dopke and Fritsche (forthcoming), we treat these years as having a consensus. Other forecast distributions are significantly leptokurtic ($k_t > 0$) at the 0.05 level. Hence there is a consensus in the forecast distributions of the current-year forecasts for 1983, 1986, 1988, 1989, 1990, 1991, and 1995, and the year-ahead forecasts for 1988, 1992, and 2001.

In sum, the hypothesis of a consensus among forecasters is rejected nine times (out of twenty-five years) for the current-year forecasts and eight times for the year-ahead forecasts.

4. Forecast dispersion and forecast accuracy

Zarnowitz and Lambros (1987) and Rich et al. (1992) find that dispersed forecasts indicate high level of uncertainty about the future. Since uncertainty would lead to a larger forecast error, it is natural to expect that the variance of forecasts, $\mathrm{var}\left(f_{t,t}^{i}\right)$, is positively correlated with the absolute forecast error of the mean forecast, $\left|\bar{f}_{t,t} - g_t\right|$. However, Harvey et al. (2001) and Dopke and Fritsche (forthcoming) find that their correlation is not significant.

This section reexamines this issue using the following regressions:

$$\left|\bar{f}_{t,t} - g_t\right| = \alpha + \beta \cdot \mathrm{var}\left(f_{t,t}^{i}\right) + u_{t,t} \quad (1)$$

and $$\left|\bar{f}_{t,t+1} - g_{t+1}\right| = \alpha + \beta \cdot \mathrm{var}\left(f_{t,t+1}^{i}\right) + u_{t,t+1}\,. \quad (2)$$

We also examine the relationship between the forecast accuracy and the absolute value of the skewness of the forecast distribution, $\left|\mathrm{skew}\left(f_{t,t}^{i}\right)\right|$:

$$\left|\bar{f}_{t,t} - g_t\right| = \alpha + \beta \cdot \left|\mathrm{skew}\left(f_{t,t}^{i}\right)\right| + u_{t,t} \quad (3)$$

and $$\left|\bar{f}_{t,t+1} - g_{t+1}\right| = \alpha + \beta \cdot \left|\mathrm{skew}\left(f_{t,t+1}^{i}\right)\right| + u_{t,t+1}\,. \quad (4)$$

A large value of $\left|\mathrm{skew}\left(f_{t,t}^{i}\right)\right|$ implies a long tail of the forecast distribution, i.e., the existence of super-optimists or super-pessimists.

Table 3 summarizes the results. Standard errors of estimated coefficients are in parentheses. The first and the second row show that, although the variance of the forecast distribution is positively correlated with the absolute forecast error of its mean forecast, the correlation is significant for the current-year forecast only. The third and the fourth row indicate that the skewness of the distribution is not correlated with the forecast accuracy.

5. Forecast dispersion and the business cycle

When the economy is going to make a turn, forecasters would tend to disagree with each other and consequently the degree of forecast dispersion would be larger. This section examines the relationship between forecast dispersion and the business cycle.

Let us define the following dummies:

$$\text{LargeVar}\left(f_{t,t}^{i}\right)=\begin{cases}1 & \text{if } \operatorname{var}\left(f_{t,t}^{i}\right) \text{ is larger than its average}\\ 0 & \text{otherwise}\end{cases}$$

and $$Turn_t=\begin{cases}1 & \text{if the economy hits its peak or bottom in year } t\\ 0 & \text{otherwise}\end{cases}$$

(we use the official business cycle dating released from the Economic Planning Agency to determine the turning points). If $\text{LargeVar}\left(f_{t,t}^{i}\right)=Turn_t$ is satisfied for every year, we say that $\text{LargeVar}\left(f_{t,t}^{i}\right)$ predicts the turning points of the economy perfectly.

Let n_{ij} be the number of years in which $\text{LargeVar}\left(f_{t,t}^{i}\right)=i$ and $Turn_t=j$ ($i, j \in \{0,1\}$), and $n \equiv n_{00}+n_{01}+n_{10}+n_{11}$. Let $A\left(f_{t,t}^{i}\right)$ be the proportion of times that $\text{LargeVar}\left(f_{t,t}^{i}\right)$ correctly predicts $Turn_t$. Then, by definition,

$$A\left(f_{t,t}^{i}\right)\equiv\frac{n_{11}+n_{00}}{n}.$$

To test whether $\text{LargeVar}\left(f_{t,t}^{i}\right)$ has an ability to predict $Turn_t$, we can use the Fisher's (1922) exact test (see Henriksson and Merton, 1981). Let us define

$$P\left(f_{t,t}^{i}\right)\equiv\sum_{x=n_{11}}^{n^*}\binom{n_{10}+n_{11}}{x}\binom{n_{00}+n_{01}}{n_{01}+n_{11}-x}\Big/\binom{n}{n_{01}+n_{11}}$$

where $n^*\equiv\min\{n_{10}+n_{11}, n_{01}+n_{11}\}$.

Then the null hypothesis that $\text{LargeVar}\left(f_{t,t}^{i}\right)$ and $Turn_t$ are independent is rejected when $P\left(f_{t,t}^{i}\right)$ is sufficiently small. We also define $A\left(f_{t,t+1}^{i}\right)$ and $P\left(f_{t,t+1}^{i}\right)$ in the same way and test whether $\text{LargeVar}\left(f_{t,t+1}^{i}\right)$ and $Turn_{t+1}$ are independent.

Table 4 shows the result. Although the accuracy rates ($A\left(f_{t,t}^{i}\right)$ and $A\left(f_{t,t+1}^{i}\right)$) are higher than 0.625, $P\left(f_{t,t}^{i}\right)$ and $P\left(f_{t,t+1}^{i}\right)$ are much larger than the critical value of 0.05. Therefore the variance of the forecast distribution is not a good predictor of the turning points of the economy.

6. Discussions and conclusions

This paper has examined the real GDP forecasts of Japanese institutional forecasters and has found that a consensus forecast does not exist in nine/eight out of twenty-five years (36%/32%) for the current-year/year-ahead forecasts. Our result is somewhat between that of the U.S. and Germany. Schnader and Stekler (1991) find that the existence of a consensus is rejected in eleven out of twenty-one years (52%) of the distributions of the ASA-NBER real GNP forecasts. In contrast, Dopke and Fritsche (forthcoming) find that the existence of a consensus is rejected in only five out of thirty-five years (14%) of German real GDP forecasts.

One question remains: why the U.S. forecasters tend to disagree with each other? Why the German forecasters tend to have a consensus? A possible answer is the strategic behavior of the forecasters. Ashiya and Doi (2001, p.345) argue that an economist takes two opposing effects into account in forecasting. First, a person can reduce the risk of an extremely low reputation by making a similar forecast to others. Second, a person can signal confidence in his or her own ability by making a forecast different from others. The incentive to signal own confidence is stronger when forecasting ability is more heterogeneous.

According to this argument, the U.S. forecasters would be sufficiently heterogeneous in their abilities and hence some forecasters intentionally release extreme forecasts to signal own ability. This leads to a dispersed forecast distribution and rejection of the null hypothesis of a consensus. On the other hand, the German forecasters would be homogeneous enough and hence they mimic each other in order not to be singled out as an incompetent forecaster. As a result, the forecast distribution is peaked so that we find a consensus. The heterogeneity of the Japanese forecasters would be moderate and hence the proportion of the forecast sets which have a consensus is between that of Germany and the U.S. In support of this argument, Ashiya (forthcoming-b) finds that the accuracy rankings of the Japanese forecasters are not significantly different from those that might be expected when all institutions had equal forecasting ability. To test the homogeneity of the forecasters' ability in Germany and the U.S. is a future topic of research.

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Figure 1: The methodology

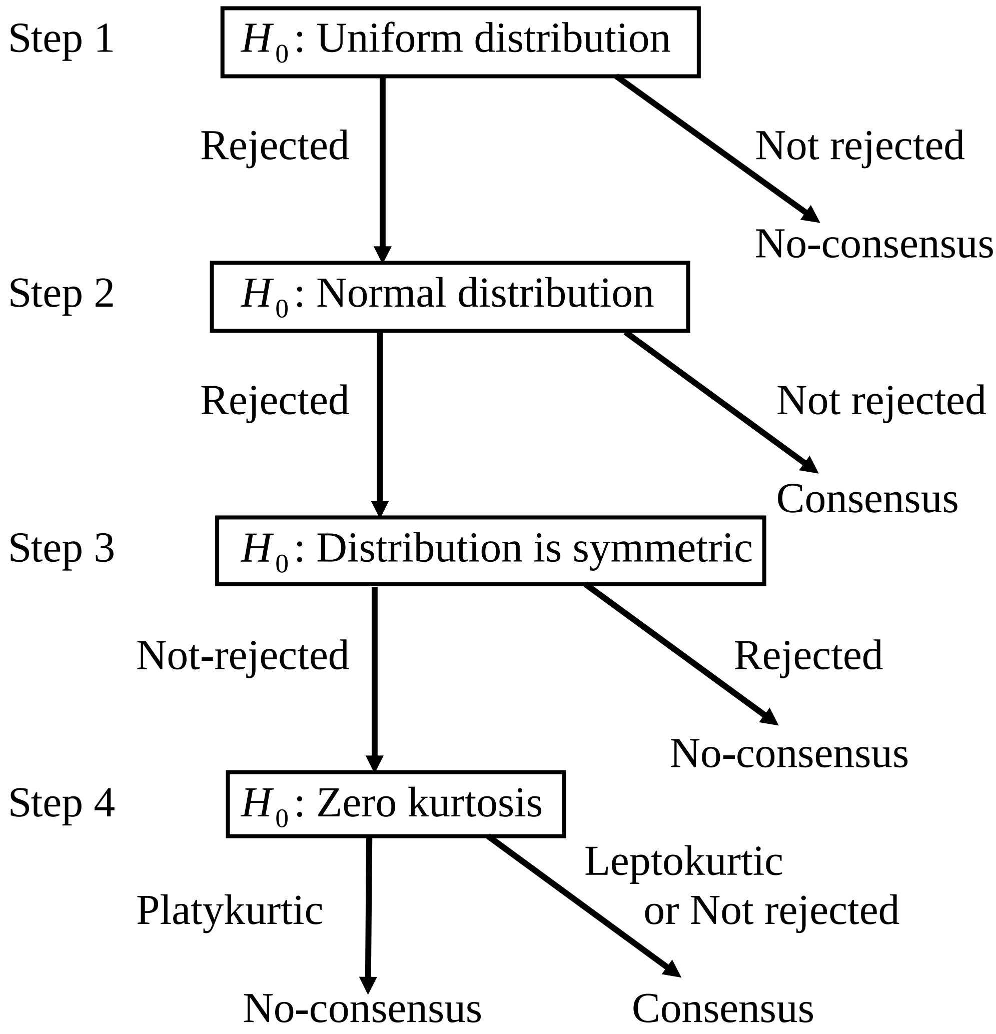

Table 1: Current-year forecasts

		Step 1	Step 2		Step 3	Step 4	
Year	Obs.	U_t	SW	LM	Sym.	Kurt.	Result
1980	22	R	R	R	R		NC
1981	30	R	R	R	R		NC
1982	37	R	NR	NR			C
1983	38	R	R	NR	NR	NR	C
1984	42	R	NR	NR			C
1985	45	R	NR	NR			C
1986	48	R	R	NR	NR	NR	C
1987	37	R	NR	NR			C
1988	52	R	R	NR	NR	Lept.	C
1989	54	R	R	NR	NR	NR	C
1990	56	R	R	NR	NR	Lept.	C
1991	58	R	R	NR	NR	NR	C
1992	56	R	R	NR	R		NC
1993	56	R	NR	NR			C
1994	55	R	R	NR	R		NC
1995	57	R	R	R	NR	Lept.	C
1996	56	R	NR	NR			C
1997	56	R	R	R	R		NC
1998	52	R	R	R	R		NC
1999	55	R	R	R	R		NC
2000	56	R	NR	R	R		NC
2001	48	R	NR	NR			C
2002	27	R	R	NR	R		NC
2003	35	R	NR	NR			C
2004	36	R	NR	NR			C

Notes
R/NR: reject/not reject (at the 0.05 significance level).
Lept.: leptokurtic (at the 0.05 significance level).
C/NC: consensus/non-consensus.
U_t : Pearson chi-squared goodness of fit test for uniformity.
SW: Shapiro-Wilk test for normality.
LM: Lagrange multiplier test for normality.
Sym.: test for symmetry.
Kurt.: test for zero-kurtosis.

Table 2: Year-ahead forecasts

		Step 1	Step 2		Step 3	Step 4	
Year	Obs.	U_t	SW	LM	Sym.	Kurt.	Result
1981	22	R	NR	NR			C
1982	30	NR					NC
1983	37	R	R	R	R		NC
1984	38	R	NR	NR			C
1985	42	R	R	R	R		NC
1986	45	R	NR	NR			C
1987	48	R	NR	NR			C
1988	51	R	NR	R	NR	Lept.	C
1989	52	R	R	NR	R		NC
1990	54	R	NR	NR			C
1991	56	R	R	R	R		NC
1992	58	R	NR	R	NR	Lept.	C
1993	56	R	NR	NR			C
1994	56	R	NR	NR			C
1995	55	R	R	R	R		NC
1996	57	R	R	R	R		NC
1997	56	R	NR	NR			C
1998	56	R	NR	NR			C
1999	52	R	NR	NR			C
2000	55	R	NR	NR			C
2001	56	R	NR	R	NR	Lept.	C
2002	48	R	NR	NR			C
2003	27	R	R	R	R		NC
2004	35	R	NR	NR			C
2005	36	R	NR	NR			C

Notes
R/NR: reject/not reject (at the 0.05 significance level).
Lept.: leptokurtic (at the 0.05 significance level).
C/NC: consensus/non-consensus.
U_t : Pearson chi-squared goodness of fit test for uniformity.
SW: Shapiro-Wilk test for normality.
LM: Lagrange multiplier test for normality.
Sym.: test for symmetry.
Kurt.: test for zero-kurtosis.

Table 3: Forecast dispersion and forecast accuracy

Dependent variable: $\left|\bar{f}_{t,t} - g_t\right|, \ \left|\bar{f}_{t,t+1} - g_{t+1}\right|$

		α (s.e.)	β (s.e.)	$\bar{R}^2$
(1)	$\operatorname{var}\left(f^i_{t,t}\right)$	0.242 (0.155)	4.096 (2.124)*	0.102
(2)	$\operatorname{var}\left(f^i_{t,t+1}\right)$	0.862 (0.518)	2.741 (2.581)	0.006
(3)	$\left|\operatorname{skew}\left(f^i_{t,t}\right)\right|$	0.467 (0.099)***	0.056 (0.087)	-0.025
(4)	$\left|\operatorname{skew}\left(f^i_{t,t+1}\right)\right|$	1.422 (0.314)***	-0.121 (0.530)	-0.043

Notes
Standard errors are in parentheses.
*: Significant at the 0.10 level.
***: Significant at the 0.01 level.

Table 4: Forecast dispersion and the business cycle

Current-year	$A\left(f_{t,t}^{i}\right) = 0.640$	$P\left(f_{t,t}^{i}\right) = 0.222$
Year-ahead	$A\left(f_{t,t+1}^{i}\right) = 0.625$	$P\left(f_{t,t+1}^{i}\right) = 0.260$

Notes

$A\left(f_{t,t}^{i}\right)$: the proportion of times that $\mathrm{LargeVar}\left(f_{t,t}^{i}\right)$ correctly predicts $Turn_t$.

$A\left(f_{t,t+1}^{i}\right)$: the proportion of times that $\mathrm{LargeVar}\left(f_{t,t+1}^{i}\right)$ correctly predicts $Turn_{t+1}$.

$P\left(f_{t,t}^{i}\right)$: the *P*-value of the null hypothesis that $\mathrm{LargeVar}\left(f_{t,t}^{i}\right)$ and $Turn_t$ are independent.

$P\left(f_{t,t+1}^{i}\right)$: the *P*-value of the null hypothesis that $\mathrm{LargeVar}\left(f_{t,t+1}^{i}\right)$ and $Turn_{t+1}$ are independent.