Do Professional Forecasters Make Use of the Phillips Curve? An Econometric Analysis of the Japanese Panel Data*

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Abstract

We test a hypothesis that in making their own forecasts, professional forecasters make use of the Phillips curve, well known as the macroeconomic structure with high predictability for inflation, using the Japanese panel data. The encompassing tests of some alternative models suggest that the professional forecasters make good use of the Phillips curve, as well as a bivariate VAR and a random walk models.

1 Introduction

Rational expectations hypothesis requires economic agents to acquire sufficient knowledge and information on economic structure to forecast in a rational way. Which models agents use in forecasting, does not matter in any univariate tests for forecast rationality. Even when agents would form current expectations in a static way of mimicking previous actual values, the univariate tests might not be able to reject such an inappropriate or primitive forecasting only if accepting the rationality.

The Phillips curve in general, has been known as a good predictor of inflation, compared with another forecasting models(Stock and Watson, 1999). It is considered as the most crucial macroeconomic structure in macroeconomics, especially by central banks which is mandated to target inflation forecasts(Akerlof, 2001).

Despite of such macroeconomic consequences of the Phillips curve, we are not aware of whether professional forecasters exploit in forecasting inflation a conventional relationship with unemployment. We empirically test a hypothesis that in making forecasts, professional forecasters make use of the Phillips curve, the macroeconomic structure. Using a panel data of forecasts by the Japanese

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professional forecasters, our empirical analysis investigates the availability of the Phillips curve in forecasting.

Some encompassing tests(Chong and Hendry, 1986; Diebold, 1998; Ericsson, 1992) suggest that actual forecasts by the professional forecasters do encompass the downward-sloping Phillips curve, as well as a simple VAR model and a random walk model. The multiple encompassing relationships imply that the professional forecasters make good use of multiple models including the conventional Phillips curve.

The structure of the paper is organized as follows. In Section 2, a few preliminaries of the Phillips curve are provided for understanding predictability and theoretical importance probably shared with professional forecasters. In Section 3, we estimate a conventional form of the Phillips curve using the Japanese monthly data, the estimates of which generate a time series of inflation forecasts for each forecaster. Similar procedures are applied to a VAR and a random walk models in Section 4. In Section 5, in order to compare these forecasts, we carry out encompassing tests for every combination of the forecasts. Finally, we conclude the paper.

2 The Phillips Curve as the Macroeconomic Structure

What is a basis in forecasting macroeconomic aggregates probably depends upon forecasters themselves. Some forecasters rely upon some simplistic charts, while others make dynamic simulations with econometric models. Among the econometric forecasters, economists who are affiliated with financial intermediaries of banks or insurance companies, might maintain different forecasting models from another economists do in trading companies or electricity ones. For instance, the former economists may intend to put more emphasis upon short-run models than long-run ones, since financial intermediaries are more interested in nominal variables such as interest rates or monetary aggregates than in real variables, unemployment rates and so forth.

In spite of the diversified views toward macro economy, there remains a shared forecasting model of the IS-LM or the AD-AS analysis, a textbook-type macroeconomic model. Among the AD-AS framework, the Phillips curve consists of the macroeconomic structure as an AS component with a micro-economic foundation. The Phillips curve, with an inverse relationship between inflation and unemployment empirically observed by Phillips(1958), was founded upon a misperception model combined with rational expectations hypothesis(Phelps, 1968; Lucas, 1972).

In the Nobel Laureate lecture, Akerlof(2001) took a stand for the Phillips curve as a representative of macroeconomic structure:

> Probably the single most important macroeconomic relationship is the Phillips Curve. The "price-price" Phillips Curve relates the rate

> of inflation to the level of unemployment, the expected rate of inflation, and variables affecting aggregate supply, such as the price of oil or food. The trade-offs between inflation and unemployment implicit in this relation define the "feasible set" for monetary policy and thus play a decisive role in its formulation.

It was also Stock and Watson(1999) who in an econometric sense focused upon high predictive power of the Phillips curve for inflation:

> This paper investigates forecasts of US inflation at the 12-month horizon. The starting point is the conventional unemployment rate Phillips curve, which is examined in a simulated out-of-sample forecasting framework. Inflation forecasts produced by the Phillips curve generally have been more accurate than forecasts based on other macroeconomic variables, including interest rates, money and commodity prices.

Since Stock and Watson(1999), there has been literature on how robust such a predictability of the Phillips curve is(Atkeson and Ohanian, 2001; Fisher, Liu and Zhou, 2002). The empirical evidence on the US economy suggests that inflation predictability of the Phillips-curve-based models are getting worse, in some cases being inferior to a naïve forecasting. As for the Japanese data, Fukuda and Keida(2001) investigates high inflation predictability of the Phillips curve à la Stock and Watson(1999).

The Phillips curve has been reevaluated in terms of firms' pricing behaviors in monopolistic competitive markets(Dennis(2007) for a recent survey). The so-called the New Keynesian Phillips curve was derived from a Calvo(1983) model with a random opportunity of price adjustment given to firms. Central banks make use of the Calvo-type Phillips curve for measuring effects of monetary policy under price stickiness. We will not, however, explicitly address a hybrid of the New Keynesian Phillips curve(NKPC), where current rates of inflation depend upon both inflation expectations and lagged realizations of inflation, as well as upon current rates of unemployment. We will deal with the NKPC as a specific form of VAR models later.

3 Estimates of a Conventional Phillips Curve

We estimate the Phillips curve as simple as possible, using the Japanese monthly data. We assume a conventional form of the Phillips curve, as in Stock and Watson(1999), an inverse relationship between contemporaneous unemployment and inflation without taking into account inflation expectations.

$$\pi_t = \text{const.} + \alpha U_t + u_t \tag{1}$$

The final term u_t is a white-noise error term.

We fit the Phillips curve in the Japanese data for two samples: January 2001 to October 2006(our full sample); and January 2001 to March 2004(before the first observation in the ESP forecast described in Section 5.1). We apply an instrumental-variables-regression to control endogeneity of unemployment rates, using as instruments lagged variables of inflation and unemployment rates. We also make standard errors adjusted to be robust to serial correlation and heteroscedasticity of error terms. Table 1 shows our estimation result, suggesting that coefficients on unemployment rate are significant and negative.

We have two alternatives of which estimates would be basis for the forecast respondents, ex ante or ex post. Our choice is to use the result of the ex post sample indicating a higher R-squared value than the ex ante sample does. The ex ante sample would also disregard any learning efforts the respondents must have made since the survey began on April 2004.

In the ESP forecast data, as detailed in Section 5.1, survey respondents make every monthly forecast upon both an inflation measure of the Consumer Price Index(total excluding fresh food; thereafter, the CPI or a notation π) and an unemployment rate(a notation U), both data of which are announced with monthly frequency. Inflation forecasts on a current t, next $t+1$ or next-to-next month $t+2$ formed on the current month t are indicated respectively,

$$\begin{aligned} E_t\pi_t &= \text{const.} + \alpha E_t U_t \\ E_t\pi_{t+1} &= \text{const.} + \alpha E_t U_{t+1} \\ E_t\pi_{t+2} &= \text{const.} + \alpha E_t U_{t+2}. \end{aligned} \tag{2}$$

Note that there is no data of current values on the CPI and the unemployment rate in information sets the respondents then possess. Therefore, a one-quarter-ahead forecast is equal to an average forecast of current, next and next-to-next month,

$$\frac{1}{3}(E_t\pi_t + E_t\pi_{t+1} + E_t\pi_{t+2}) = \text{const.} + \alpha(E_t U_t + E_t U_{t+1} + E_t U_{t+2}). \tag{3}$$

We assume for a simplicity a dichotomy of the new classical economics, where each of nominal and real variables is determined by separate structures. In particular, the Phillips curve is assumed to presume unemployment rates determined in another structure else than the Phillips curve. The unemployment expectations are thought to be predetermined for inflation forecasting.

4 Alternative Forecasting Models

For a comparison with the Phillips curve estimates, we pose alternative forecasting models, one of VAR model and the other of random walk model.

4.1 Bivariate VAR Model

We estimate a bivariate VAR model consisting of monthly data of inflation and unemployment.

$$\begin{pmatrix} \pi_t \\ U_t \end{pmatrix} = A(L) \begin{pmatrix} \pi_{t-1} \\ U_{t-1} \end{pmatrix} + u_t \tag{4}$$

Lag length in a VAR model is equal to 1 on a basis of the information criteria. Considering better fit of estimates, we also choose the full or ex post sample, instead of the ex ante sample until March 2004. Table 2 shows the estimation result. It is evident that auto-correlations are quite high for both variables. We can obtain each forecast as equal to the fitted values,

$$\begin{aligned} \begin{pmatrix} E_t\pi_t \\ E_tU_t \end{pmatrix} &= A(L) \begin{pmatrix} \pi_{t-1} \\ U_{t-1} \end{pmatrix} \\ \begin{pmatrix} E_t\pi_{t+1} \\ E_tU_{t+1} \end{pmatrix} &= A(L)^2 \begin{pmatrix} \pi_{t-1} \\ U_{t-1} \end{pmatrix} \\ \begin{pmatrix} E_t\pi_{t+2} \\ E_tU_{t+2} \end{pmatrix} &= A(L)^3 \begin{pmatrix} \pi_{t-1} \\ U_{t-1} \end{pmatrix}. \end{aligned} \tag{5}$$

Similarly to the Phillips curve forecast, we take a one-quarter average of these monthly forecasts.

4.2 Random Walk Model

By definition, a random walk process implies the following monthly forecasts:

$$\begin{aligned} E_t\pi_t &= E_{t-1}\pi_t \\ &= \pi_{t-1} \\ \\ E_t\pi_{t+1} &= E_t(E_{t+1}\pi_{t+1}) \\ &= E_t\pi_t \\ &= \pi_{t-1} \\ \\ E_t\pi_{t+2} &= E_t(E_{t+1}\pi_{t+2}) \\ &= E_t\pi_t \\ &= \pi_{t-1}. \end{aligned} \tag{6}$$

All the forecasts are equal to a previous realized value. It is sure that a one-quarter average is also equal to the same previous value.

5 Forecast Comparisons

5.1 Forecast Data

We use a monthly survey of professional forecasters conducted by the Economic Planning Association of Japan. The Monthly Survey of Japanese Economic Forecasts, the ESP(Economic Society Policy) forecast, covers April 2004 to the nearest present[1]. 46 survey respondents are given each ID number. The respondents' affiliations consist of general trading companies, domestic and foreign financial intermediaries including securities and insurance companies, or research institutes including subsidiaries of financial or non-financial parent companies. A list of the names is occasionally announced likewise the US SPF. Every year the Economic Planning Association evaluates ex post the forecasters participating in the ESP forecast, announcing the best 5 forecasters. Judging from the name list, their presence at mass media and practical achievements in daily newspapers, or weekly economic or financial journals, we call the respondents "professional forecasters".

The survey requires the respondents to forecast the following items: nominal and real GDP(growth rates); real personal consumption expenditure(growth rate); real non-residential investment(growth rate); real export and import(growth rates); industrial production index(growth rate); current balance(trillion yen); core consumer price index(total excluding fresh food; fluctuation in annual rate from a year earlier; %); unemployment rate(%); euro-yen TIBOR(3 months; %); JGB(10yrs.; %); Nikkei 225 average(yen); M2+CD(growth rate); yen/dollar rate(yen); and US real GDP(growth rate). The questionnaire only asks annual forecast of each item, except for three variables: real GDP(annual growth rate), core CPI(fluctuation in annual rate from a year earlier; %) and unemployment rate. As for these macroeconomic aggregates, the respondents also make forecasts with a quarter horizon.

We use the core CPI and the unemployment rate[2]. Note that there should be neither concerns about data revisions nor about a necessity of using real-time data of the variables. Figure 1 and Figure 2 indicate variations in the forecasts. It is evident that deflationary expectations subsided around the end of 2005. Note also that a variation in forecasts of unemployment rate has a downward trend, probably due to gradual settlement of increased employment uncertainty.

Figure 3 also indicates actual values and each forecast using the VAR estimates and the random walk model in Section 4.

5.2 Forecast Encompassing Test

We focus upon forecasts with a one-quarter forecasting horizon. We apply forecast encompassing tests of Chong and Hendry(1986) and Ericsson(1992), to

[1]This version of the paper limits the data coverage up to October, 2006.

[2]Ashiya(2009) tests homogeneity, accuracy and rationality of the CPI forecast, also using the ESP forecast data.

evaluate the professional forecasts relative to the three forecast candidates: the Phillips curve, a VAR model and a random walk model.

$$\begin{aligned}
\pi_{t,t+1} &= \text{const.} + \alpha\pi^e_{t,t+1} + \beta\pi^p_{t,t+1} + u_t \\
\pi_{t,t+1} &= \text{const.} + \alpha\pi^e_{t,t+1} + \beta\pi^v_{t,t+1} + u_t \\
\pi_{t,t+1} &= \text{const.} + \alpha\pi^e_{t,t+1} + \beta\pi^r_{t,t+1} + u_t \qquad (7)
\end{aligned}$$

In the estimated equations, we denote one-quarter-ahead inflation forecasts at a period t of the professional forecasters by $\pi^e_{t,t+1}$, the forecasts from the estimated Phillips curve by $\pi^p_{t,t+1}$, the VAR forecasts by $\pi^v_{t,t+1}$, and the random walk forecasts by $\pi^r_{t,t+1}$. The encompassing tests regress the actual inflation variable on any pairs of the candidates. In case a coefficient α(or β) is stochastically significant with a positive sign, the professional forecasts(or each forecast else than the professional ones) encompass the other forecasts(or the professional forecasts) in each equation.

5.3 Panel Data Estimations

An unbalanced panel data set covering April 2004 to October 2006, is available for us, where some missing survey items and respondents are found. Estimation equations are fitted by fixed or random effect model with AR(1) serial correlation of error term. We have 6 combinations among the 4 types of inflation forecasts.

5.3.1 Vis-à-Vis the Professional Forecasters

First, we present test results of the professional forecasts relative to alternative models. Our major interest is in the prediction performance of the survey forecasts relative to the Phillips curve estimates.

$$\pi_{t,t+1} = \text{const.} + \alpha\pi^e_{t,t+1} + \beta\pi^p_{t,t+1} + u_t$$

Table 3 is the encompassing test results for random effect model and fixed effect model, accompanied with a Hausman test statistics for a null hypothesis that all the coefficients have no differences. The statistics tells us not to reject no differences in coefficients between random and fixed effect models. The Hausman test supports the random effect model.

In the random effect model, the professional forecasts are significant with a positive sign, while neither are the Phillips curve forecasts. The asymmetry in the significance suggests that the professional forecasts contain the Phillips curve, but the opposite is not true. Thus, the professional forecasts encompass the Phillips curve in one direction.

We proceed to another alternative forecasting models.

$$\begin{aligned}
\pi_{t,t+1} &= \text{const.} + \alpha\pi^e_{t,t+1} + \beta\pi^v_{t,t+1} + u_t \\
\pi_{t,t+1} &= \text{const.} + \alpha\pi^e_{t,t+1} + \beta\pi^r_{t,t+1} + u_t
\end{aligned}$$

Comparing the professional forecasts with the bivariate VAR model, Table 4 shows a result of a random effect model, which is stipulated by the Hausman test. There are significant coefficients with positive signs on both forecasts. A result of comparing with the random walk model, as Table 5 shows, also indicates significance of the coefficients on the professional forecasts and the random walk model. Consequently, the bivariate VAR and the random walk models encompass the professional forecasters, and at the same time the forecast survey does the both parametric models.

5.3.2 Vis-à-Vis the Phillips Curve

Second, we move to the Phillips curve forecasts in comparisons with the VAR and the random walk models.

$$\begin{aligned} \pi_{t,t+1} &= \text{const.} + \alpha\pi^{p}_{t,t+1} + \beta\pi^{v}_{t,t+1} + u_t \\ \pi_{t,t+1} &= \text{const.} + \alpha\pi^{p}_{t,t+1} + \beta\pi^{r}_{t,t+1} + u_t \end{aligned} \tag{8}$$

Table 6 indicates a relative predictability of the Phillips curve and the bivariate VAR model with an estimated random effect model. The random effect model is not rejected with a Hausman test statistics. Table 7 also shows a comparison with the random walk model. These tables suggest that the Phillips curve encompasses the VAR and random walk models, in addition to a reverse relation that the two parametric models encompass the Phillips curve.

5.3.3 A Bivariate VAR Model vs. a Random Walk Model

Third and finally, we compare two parametric models, the bivariate VAR and the random walk models.

$$\pi_{t,t+1} = \text{const.} + \alpha\pi^{v}_{t,t+1} + \beta\pi^{r}_{t,t+1} + u_t \tag{9}$$

Both of the two forecasts are time-series data, on which we regress the actual inflation variable in an encompassing test with AR(1) estimation. Table 8 shows the VAR forecast encompasses the random walk forecast in one way, though in a weak significance level.

Summing up the encompassing test results, we find relative predictability among the professional forecasts, the Phillips curve, the VAR model and the random walk model, as summarized in Table 9.

6 Conclusion

The Phillips curve is of consequence in macroeconomics. There is, however, no literature on whether the macroeconomic structure is useful especially for professional forecasters. This paper empirically analyzed the question, comparing

alternative forecasting models, bivariate VAR and random walk models. As a result of the encompassing tests for unbalanced panel data of the Japanese professional forecasters, we found the following conclusions:

1. the professional forecasts contain the Phillips curve, but the Phillips curve does not include information of the survey respondents;

2. the professional forecasts contain the bivariate VAR and the random walk models, and at the same time the two parametric models include the forecasters' information;

3. the Phillips curve contains the VAR and the random walk models, and at the same time the two parametric models do the Phillips curve; and

4. the VAR model weakly reveals encompassing the random walk model.

Thus, it turns out that the professional forecasters contain a variety of macroeconomic structure or models, one of which is the Phillips curve. So in response to the title of this paper, our answer is "Yes, they do fully well."

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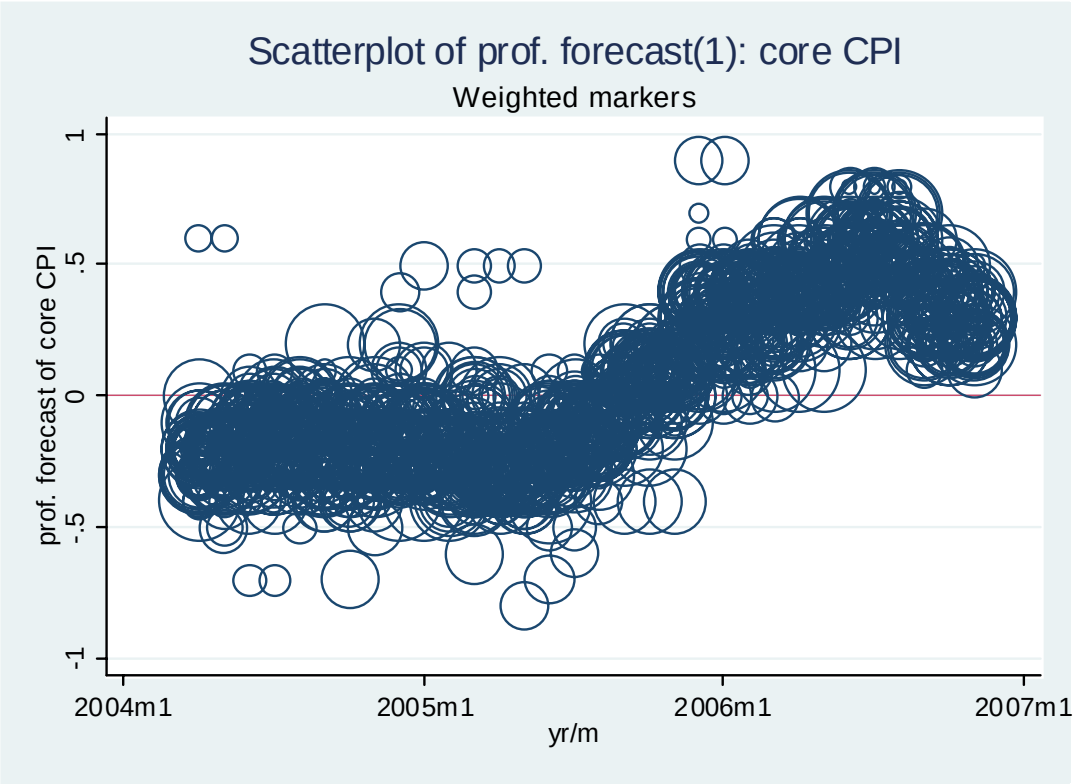
Figure 1: The ESP Forecast(1)



IV (2SLS); dep. var. inf. π_t				
sample	Jan/01-Oct/06		Jan/01-Mar/04	
indep. vars.	const.	unem. U_t	const.	unem. U_t
coef.	2.42***	-0.57***	2.00*	-0.49**
(std. error)	(0.38)	(0.08)	(1.17)	(0.23)
t-value	6.35	-6.83	1.70	-2.16
number of obs.	70		39	
R-squared	0.44		0.12	
F-value	46.70		4.66	
Notes: Instruments are lagged variables. Standard errors are robust to heteroscedasticity and serial correlation of error term. *** refers to significance at 1%, ** at 5%, and * at 10% level.				

Table 1: Estimate of a Conventional Phillips Curve

Bivariate VAR (π_t, U_t)				
sample	Feb/01-Oct/06		Feb/01-Mar/04	
	dep. var.		dep. var.	
indep. vars.	inf. π_t	unem. U_t	inf. π_t	unem. U_t
const.				
coef.	0.01	0.82***	-0.72	1.81***
(std. error)	(0.24)	(0.32)	(0.53)	(0.58)
z-value	0.06	2.60	-1.36	3.11
lagged inf. π_{t-1}				
coef.	0.93***	-0.17**	0.94***	-0.10
(std. error)	(0.06)	(0.08)	(0.07)	(0.08)
z-value	15.34	-2.08	12.95	-1.21
lagged unem. U_{t-1}				
coef.	-0.01	0.82***	0.13	0.64***
(std. error)	(0.05)	(0.07)	(0.10)	(0.11)
z-value	-0.13	11.92	1.28	5.65
number of obs.	69		38	
Log likelihood	43.67		21.49	
R-squared	0.86	0.82	0.82	0.53
Notes: Lag length is fixed due to the information criteria. *** refers to significance at 1%, ** at 5%, and * at 10% level.				

Table 2: Bivariate VAR Model

Encompassing Test(1): the Prof. Forecasts vs. the Phillips Curve				
models	random effect		fixed effect	
	coef.(std.error)	z-value	coef.(std.error)	t-value
const.	-0.03***(0.01)	-3.10	-0.02***(0.004)	-5.39
prof. forecasters	0.45***(0.03)	17.41	0.45***(0.03)	16.26
Phillips curve est.	0.03(0.02)	1.63	0.03(0.02)	1.34
number of obs.	1060		1022	
R-squared	0.51		0.22	
AR(1) coef.	0.63			
Hausman	χ^2stat.[p-value]=0.20[0.90]			
Notes: Estimate of random effect model is a GLS regression with AR(1) disturbance, and fixed effect(within) a regression with AR(1) disturbance. Hausman test of H_0: diff. in coef. not systematic shows χ^2stat. and the p-value.				

Table 3: Forecast Encompassing Test(1): The Professional Forecasts vs. the Phillips Curve

Encompassing Test(2): the Prof. Forecasts vs. VAR Model		
random effect model	coef.(std.error)	z-value
const.	-0.04***(0.01)	-4.17
prof. forecasters	0.37***(0.03)	14.28
VAR model	0.21***(0.03)	6.65
number of obs.	1158	
R-squared	0.51	
AR(1) coef.	0.66	
Hausman	χ^2stat.[p-value]=0.49[0.78]	
Notes: Estimate of random effect model is a GLS regression with AR(1) disturbance, and fixed effect(within) a regression with AR(1) disturbance. Hausman test of H_0: diff. in coef. not systematic shows χ^2stat. and the p-value.		

Table 4: Forecast Encompassing Test(2): The Professional Forecasts vs. VAR Model

Encompassing Test(3): the Prof. Forecasts vs. Random Walk Model		
random effect model	coef.(std.error)	z-value
const.	-0.04***(0.01)	-3.62
prof. forecasters	0.36***(0.03)	13.98
random walk model	0.18***(0.03)	6.80
number of obs.	1158	
R-squared	0.50	
AR(1) coef.	0.66	
Hausman	χ^2stat.[p-value]=0.80[0.67]	
Notes: Estimate of random effect model is a GLS regression with AR(1) disturbance, and fixed effect(within) a regression with AR(1) disturbance. Hausman test of H_0: diff. in coef. not systematic shows χ^2stat. and the p-value.		

Table 5: Forecast Encompassing Test(3): The Professional Forecasts vs. Random Walk Model

Encompassing Test(4): the Phillips Curve vs. VAR Model		
random effect model	coef.(std.error)	z-value
const.	-0.02**(0.01)	-2.16
Phillips curve	0.08***(0.02)	3.78
VAR model	0.40***(0.03)	12.70
number of obs.	1069	
R-squared	0.43	
AR(1) coef.	0.61	
Hausman	χ^2stat.[p-value]=3.94[0.14]	
Notes: Estimate of random effect model is a GLS regression with AR(1) disturbance, and fixed effect(within) a regression with AR(1) disturbance. Hausman test of H_0: diff. in coef. not systematic shows χ^2stat. and the p-value.		

Table 6: Forecast Encompassing Test(4): The Phillips Curve vs. VAR Model

Encompassing Test(5): the Phillips Curve vs. Random Walk Model		
random effect model	coef.(std.error)	z-value
const.	-0.01(0.01)	-1.24
Phillips curve	0.07***(0.02)	3.41
random walk model	0.33***(0.03)	12.47
number of obs.	1069	
R-squared	0.42	
AR(1) coef.	0.62	
Hausman	χ^2stat.[p-value]=4.37[0.11]	
Notes: Estimate of random effect model is a GLS regression with AR(1) disturbance, and fixed effect(within) a regression with AR(1) disturbance. Hausman test of H_0: diff. in coef. not systematic shows χ^2stat. and the p-value.		

Table 7: Forecast Encompassing Test(5): The Phillips Curve vs. Random Walk Model

Encompassing Test(6): VAR Model vs. Random Walk Model		
AR(1)	coef.(std.error)	t-value
const.	-0.01(0.00)	-1.36
VAR model	0.22*(0.12)	1.94
random walk model	0.13(0.10)	1.36
number of obs.	31	
R-squared	0.12	
AR(1) coef.	0.64	
Note: AR(1) estimate for both time-series data.		

Table 8: Forecast Encompassing Test(1): VAR Model vs. Random Walk Model

Encompassing	Prof. Forecasts	Phillips Curve	VAR Model	Random Walk
Prof. Forecasts	—	Y	Y	Y
Phillips Curve	N	—	Y	Y
VAR Model	Y	Y	—	Y
Random Walk	Y	Y	N	—
Note: "Y" means a forecast in a row encompasses another in a column. "N" means otherwise.				

Table 9: Binomial Relationships between Forecasting Models

Figure 2: The ESP Forecast(2)

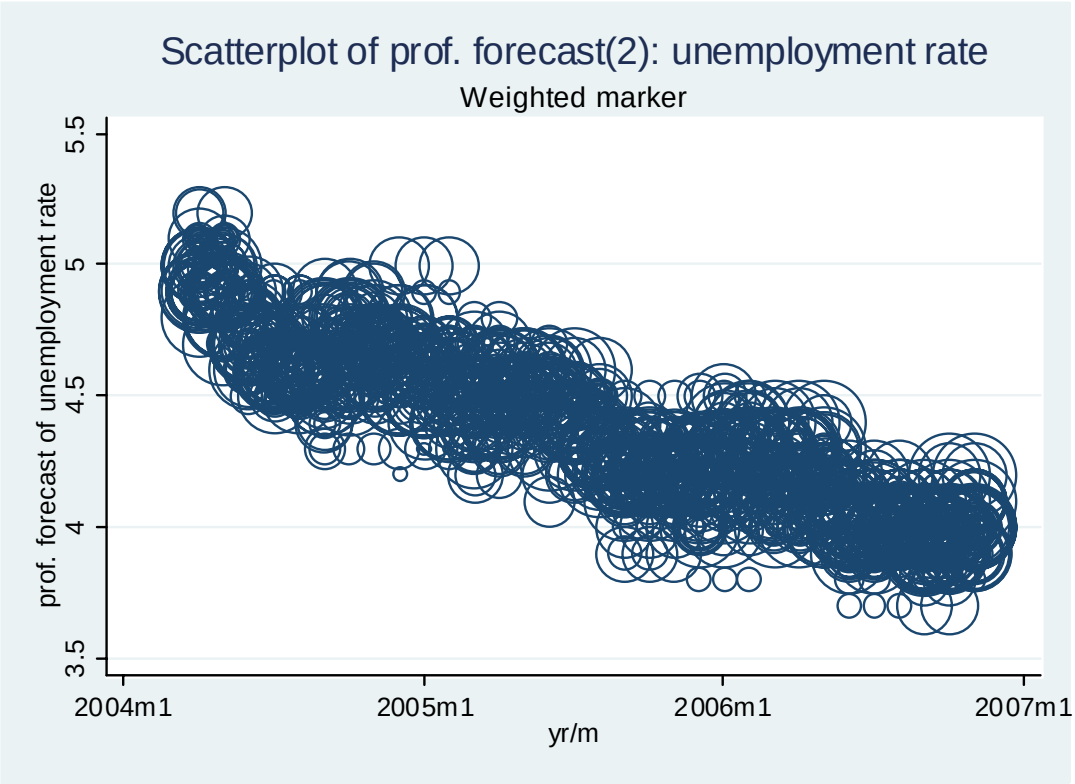
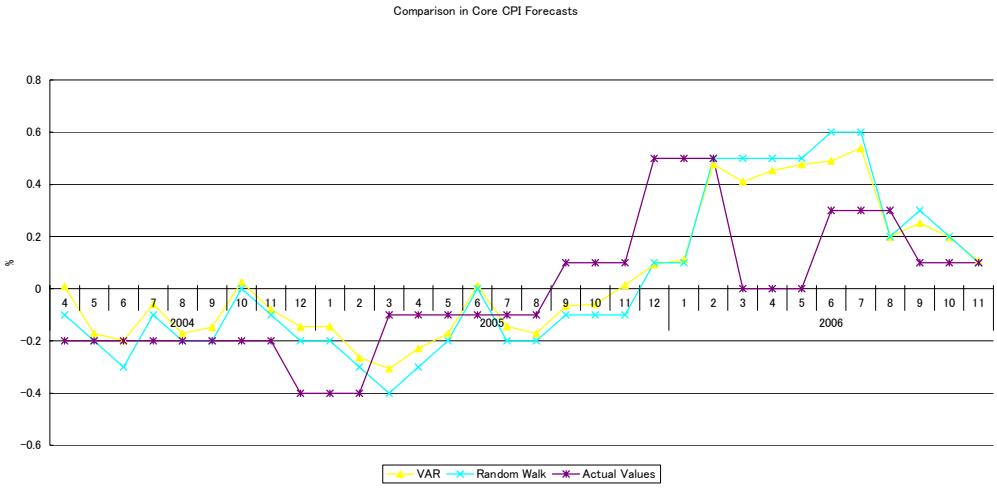



Figure 3: Comparison in the Core CPI Forecasts: VAR and Random Walk Models