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Determinants of Multi-period Forecast Uncertainty Using a Panel of Density Forecasts

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Abstract

This paper examines the determinants of inflation forecast uncertainty using a panel of density forecasts from the Survey of Professional Forecasters (SPF). We show that previous studies based on aggregate time series data are biased due to heterogeneity in individual forecasts. Based on a dynamic heterogeneous panel data model, we find that the persistence in forecast uncertainty is much less than what the aggregate time series data would suggest. In addition, the strong link between past forecast errors and the current forecast uncertainty, as often is found in the ARCH literature, is largely lost in the multi-period context with varying forecast horizons. Forecasters are found to pay more attention to recent "news" about inflation than the outdated past forecast errors. We propose a novel way of estimating uncertainty of "news" using Kullback-Leibler Information, and show that it is an important determinant of the current inflation forecast uncertainty. Our results also support Friedman (1977)'s conjecture that higher inflation rate leads to higher inflation uncertainty.

Key words: Inflation forecast uncertainty; Forecast Heterogeneity; Panel data; Survey of professional forecasters; Dynamic panels.

JEL classification: E31; E37; C23; C53

1. Introduction

Inflation forecast uncertainty is central to modern macroeconomics. In his Nobel Prize lecture Milton Friedman (1977) conjectured that an increase in inflation uncertainty reduces economic efficiency and possibly output growth. The inefficiency arises from two sources. First, inflation uncertainty makes it harder for economic agents to extract signals about relative prices from the absolute prices, rendering market prices less efficient in coordinating economic activities. Second, increased inflation uncertainty shortens the optimal length of contracts and makes indexation more advantageous, which is at best an imperfect substitute for inflation stability. The economic effect of inflation uncertainty continues to be extensively studied.

Although inflation forecast uncertainty is a key economic variable, the causes of its variation are not well understood. The literature focuses mostly on the relationship between inflation rate and inflation forecast uncertainty. A substantial body of evidence indicates that there is a positive link between them.[1] Other studies, however, find little evidence of this link. For instance, Engle (1983) and Bollerslev (1986) argue informally that inflation uncertainty is highest in the late 1940s and early 1950s when inflation rate is not very high and inflation uncertainty is lower in the late 1970s and early 1980s when inflation is quite high.

The celebrated ARCH model of Engle (1982, 1983) and its extensions consider various determinants of inflation forecast uncertainty. This literature assumes that inflation forecast uncertainty could be measured as the conditional variance of inflation that, in turn, depends on past forecast errors and lagged forecast uncertainty. Based on this specification, a time-varying conditional variance can be estimated. However, it is important to investigate the robustness of ARCH-type specifications using individual data

[1] See Holland (1984), Zarnowitz and Lambros (1987), Ball and Cecchetti (1990), Evans (1991), Evans and Wachtel (1993) and Grier and Perry (1998) for some examples.

on probability density forecasts, and comparing the results from macroeconomic time series models.

This paper reexamines the sources of forecast uncertainty using panel data. The existing literature is often based on aggregate data. Forecasts and the associated forecast uncertainties for a representative agent are first constructed. A regression of forecast uncertainty on other variables is then run[2]. However, as Pesaran and Smith (1995) point out, if forecasters process available information differently, or in other words, if there is heterogeneity in forecasts, the estimation based on aggregate data may be biased[3]. This heterogeneity of forecasts has been emphasized heavily in recent literature.[4] An alternative approach is to examine the individual data directly. The use of the Survey of Professional Forecasters (SPF) data provided by the Federal Reserve Bank of Philadelphia makes this approach possible. In this survey, each forecaster reports not only their expectations of future price level, but also the probabilities with which future forecasted inflation will fall in different intervals. These probability density forecasts enable us to estimate the inflation forecast uncertainty of each forecaster directly with the aid of some minor assumptions.[5]

Compared with previous studies, this approach is expected to produce more reliable results. First, using the reported forecast uncertainty rather than its proxy avoids the problem of measurement errors. The usual proxies of inflation uncertainty in most empirical studies are based on moving variances, rolling regressions, forecast disagreements or conditional variances. Even though these proxies may have high correlations with the true forecast uncertainty, they may have large measurement errors. Second, the use of individual rather than aggregate data could avoid the problem of aggregation bias. The problem of aggregation bias has long been recognized in the

[2] In contrast to this two-step approach, some authors use GARCH-M model to simultaneously estimate inflation forecast uncertainty and examine its relationship with inflation. See, for example, Grier and Perry (1998), Baillie *et al*. (1996).
[3] Many economists have noticed that the dynamics of aggregate variables can differ from that of micro-variables substantially if there exists parameter heterogeneity. See Hsiao, Shen and Fujiki (2004).
[4] See, for example, Souleles (2002), Mankiw, Reis and Wolfers (2003), Carroll (2003) and Rich and Tracy (2003).
[5] Diebold et al. (1999) and Wallis (2003) discuss the usefulness and quality of SPF data.

forecast literature. For example, Davies and Lahiri (1995, 1999) found that tests of rationality of forecasts could be biased if researchers use average survey response data rather than individual data. They argue that the test can be biased in two ways. Researchers may falsely reject rationality of forecasts because average forecasts that are conditional on different information sets are not rational forecasts conditional on any particular information set. Furthermore, researchers may falsely accept rationality of forecasts because average forecasts mask systematic individual bias that may be randomly distributed in the population. The average bias could be zero even if all the individual forecasts are biased but positive biases cancel negative biases. Although the issue of aggregation bias has been recognized in the analysis of point forecasts, the same issue has not been addressed in the analysis of forecast uncertainty. One contribution of this paper is that our analysis is based on panel data so that the issue of aggregation bias is avoided.

The rest of the paper proceeds as follows. In section 2, we describe the model and the estimators used in the examination of the determinants of inflation forecast uncertainty. In section 3, we briefly discuss the data used in the paper. In section 4, we present the empirical results. Section 5 concludes the paper.

2. Description of the model and estimators

Traditionally most theories in macroeconomics assume that people share common information set and form expectations conditional on that information set. Recently, heterogeneity of economic forecasts has been emphasized. For example, Souleles (2002) uses data from the Michigan Index of Consumer Sentiment and documents differences across demographic groups in their inflation expectations. Mankiw, Reis and Wolfers (2003) also document substantial disagreement among economic agents about expected future inflation using data from three sources: the Michigan Survey of Consumer Attitudes and Behavior, the Livingston Survey and the Survey of Professional Forecasters. Moreover, they show that the variation of disagreement over time is closely related to the movement of other variables. Mankiw, Reis and Wolfers (2003) also propose a "sticky-information" model to explain the variation of disagreement over time. The key point of this model is that costs of acquiring and processing information and of re-optimizing lead agents to update their information sets and expectations non-uniformly. A similar model proposed by Carroll (2003) emphasizes the differential effect of macroeconomic news on household expectations. Disagreement results from the differences across demographic groups in their propensity to pay attention to news reports.

Although the literature has focused mostly on the heterogeneity in point forecasts, some authors have raised the issue of heterogeneity in forecast uncertainty also. For example, Davies and Lahiri (1995, 1999) decompose the variance of forecast error into the variance of individual specific forecast error and the variance of aggregate shocks. They found significant heterogeneity in the former. Rich and Tracy (2003) also find evidence of statistically significant forecaster fixed effects in SPF density forecasts data. Moreover, they show that these fixed effects are related to forecasters' *ex post* inflation forecast precision fixed-effects. In other words, forecasters who are on the average more certain of their forecasts have also more precise forecasts. They take this as evidence that forecasters who have access to superior information or possess a superior ability to process information are more confident in their point forecasts. Ericsson (2003) studies the determinants of forecast uncertainty systematically. He points out that forecast uncertainty depends upon the variable being forecast, the type of model used for forecasting, the economic process actually determining the variable being forecast, the information available and the forecast horizon. If different forecasters have different information sets and use different forecast models, the anticipated forecast uncertainty will be different across forecasters even if they are forecasting the same variable at the same forecast horizon. Moreover, forecasters will make use of the same information set in different ways if they use different models[6]. Above discussion implies that, when regressing the forecast uncertainty on other variables, the coefficients should be different across forecasters. So, a natural model to study the determinants of inflation forecast

[6] Bomberger (1996) points out that forecasts differ dramatically across forecasters at any given time and it is hard to account for this heterogeneity without assuming that forecasters use different models.

uncertainty might be a dynamic heterogeneous panel data model. We start with the following EGARCH model to capture the heterogeneity in forecast uncertainty:

$$\ln(\sigma^2_{it,h}) = \alpha_{i0} + \alpha_{i1}D_1 + \alpha_{i2}D_2 + \alpha_{i3}D_3 + \beta_i \ln(\sigma^2_{it,h+1}) + \gamma_i \frac{\varepsilon^h_{it-1,1}}{\sigma_{it-1,1}} + \lambda_i \left|\frac{\varepsilon^h_{it-1,1}}{\sigma_{it-1,1}}\right| + \delta_i X_{it,h} + \upsilon_{it,h}$$

$$i = 1,2 \ldots N; h = 1,2,3,4 \tag{1}$$

where $\sigma^2_{it,h}$ is the inflation forecast uncertainty reported by forecaster i about the annual inflation rate of year t made h quarters before the end of year t. Since $\sigma^2_{it,h}$ has to be nonnegative, we adopt the EGARCH model of Nelson (1991) in (1) such that we do not need to put any restrictions on the parameters and the error distribution. These restrictions can be very complicated as lagged inflation and other exogenous variables are included[7]. For the SPF data, forecasters are asked to report their forecasts of annual inflation rate in each quarter of that year. As a result, for each targeted annual inflation rate, each forecaster reports four forecasts with the forecast horizon varying from one quarter to four quarters. Since forecast uncertainty is expected to depend on the forecast horizon, we introduce three horizon dummies $\{D_1,\ D_2,\ D_3\}$ for 3-quarter, 2-quarter, and 1-quarter ahead forecast respectively.

In model (1), $\sigma^2_{it,h+1}$ is the reported forecast uncertainty in the previous quarter[8]. The coefficient on the natural logarithm of this term captures the persistence of inflation forecast uncertainty. With multi-period forecasts for a fixed target, the appropriate definition of forecast error is not straightforward. We define $\varepsilon^h_{it-1,1}$ as the most recently known forecast error on annual inflation rate forecast of year $t-1$ made in the fourth quarter of that year. It varies over forecast horizon h because of data revisions. $\sigma_{it-1,1}$,

[7] For the same reason, several authors apply EGARCH rather than GARCH model to the time series data. See, for some examples, Fountas, Ioannidis and Karanasos (2004) and Brunner and Hess (1993).

[8] If $\sigma^2_{it,h}$ is the forecast uncertainty in the first quarter (i.e. $\sigma^2_{it,4}$), then the lagged dependent variable is the forecast uncertainty in the fourth quarter of last year, i.e. $\sigma^2_{it-1,1}$.

the square root of the reported forecast uncertainty in that quarter, is used to normalize the forecast error. For instance, for a forecaster forecasting in 2003Q3, $\varepsilon_{it-1,1}^{h}$ is the forecast error known in 2003Q3 on the annual inflation rate forecast of 2002 made in 2002Q4. To calculate $\varepsilon_{it-1,1}^{h}$, forecasters need to know the actual inflation rate of 2002 based on the known IPD values for 2002 and 2001 in 2003Q3. Because the actual IPD data go through revisions, the calculated actual inflation rate of 2002 as well as $\varepsilon_{it-1,1}^{h}$ will be different for different quarters in year 2003. For instance, the perceived $\varepsilon_{it-1,1}^{h}$ will be different in 2003Q1, 2003Q2, 2003Q3 and 2003Q4 since although the relevant past forecast is that made in 2002Q4, the perceived actual inflation rate changes over time due to data revisions.

In (1), $X_{it,h}$ is a k×1 vector that contains those variables affecting inflation forecast uncertainty other than past forecast uncertainties and forecast errors. It varies over t and h, but may or may not be the same for all forecasters.

The key assumption of model (1) is that the coefficients on all variables vary across forecasters. Let $\theta_i = (cons_i, \alpha_{i1}, \alpha_{i2}, \alpha_{i3}, \beta_i, \gamma_i, \lambda_i, \delta_i)'$ and assume it is independently normally distributed with mean $\overline{\theta}$ and covariance matrix Δ, i.e. $\theta_i \sim N(\overline{\theta}, \Delta)$. In addition, θ_i is independent of the regressors (except the lagged dependent variable). The disturbances of model (1) are assumed to be heteroscedastic and uncorrelated across different forecasters and different forecast horizons, i.e. $\upsilon_{it,h} \sim iid(0, \sigma_i^2)$ and $E(\upsilon_{it,h}\upsilon_{i't',h'}) = 0$ if $i \neq i'$ or $h \neq h'$ or $t \neq t'$. Model (1) is assumed also satisfying other assumptions specified in Hsiao, Pesaran and Tahmiscioglu (1999).

The parameters of interest are the mean coefficients, i.e. $\overline{\theta}$. Pesaran and Smith (1995) discussed how to estimate the mean coefficients of dynamic heterogeneous panel data models. After comparing four widely used procedures: pooling, aggregating, averaging group estimates and cross-section regression, they show that the pooled and aggregate estimators are not consistent in dynamic models, even for large N (the number of units) and T (the number of time periods), and the bias can be very substantial. This is because ignoring heterogeneity in coefficients creates correlation between the regressors and the error terms as well as serial correlation in the residuals. They suggest the use of group mean estimator obtained by averaging the coefficients for each group because it is consistent for large N and T. However, the group mean estimator is biased in small samples. Pesaran and Zhao (1999) and others have suggested ways to correct for the small sample bias associated with mean group estimator. Hsiao, Pesaran and Tahmiscioglu (1999) have suggested a Bayesian estimator using Markov chain Monte Carlo methods (called Hierarchical Bayes) that has better sampling properties than other estimators for both small and moderate T samples. In this study, we will report the mean group estimator, the Hierarchical Bayes estimator[9] and an Empirical Bayes estimator[10]. Detailed description of these estimators could be found in the literature mentioned above. For the purpose of comparison, the pooled OLS estimator[11] and aggregate estimator are also reported.

An alternative way to model the heterogeneity of economic forecasts is the random effects or the one-way error component model. This model assumes slope homogeneity, but allows for an individual effect, which varies across forecasters. Following the pioneering work of Balestra and Nerlove (1966), many studies discuss how to estimate this model, see, for example, Anderson and Hsiao (1981,1982), Ahn and Schmidt (1995), Arellano and Bover (1995) and Blundell and Bond (1998). Although GMM estimators are popular for this model, we would not try it here because our panel data is unbalanced and has two time dimensions – target years and forecast horizons. This makes it is very complicated to match the instrumental variables and the lagged dependent variable for consistent estimation. Instead, we will report a conditional maximum likelihood estimator with the first observation for each forecaster treated as fixed constants. This estimator is

[9] To estimate the Hierarchical Bayes estimator, we make use of parts of the GAUSS programs provided by Kim and Nelson (1998) and the BACC software described in Geweke (1999).
[10] It is just the Swamy estimator for Random Coefficient Models. In this context, it yields good results when the time dimension of the panel is sufficiently large.
[11] Pooled OLS estimator is just the OLS estimator by pooling the data for all forecasters neglecting heterogeneity of forecasts.

consistent if the number of forecasters is large. A fixed effects estimator is also reported. This estimator assumes that the individual effects are nonrandom across forecasters. But it is well known that in dynamic models, this estimator is inconsistent for fixed T when the number of forecasters tends to infinity. This result, however, assumes that the true data generating process is either the random effects or fixed effects model. If the true model is a dynamic heterogeneous panel data model, and we estimate the mean coefficients with the random effects or fixed effects estimator, the estimator will be biased even when both N and T tend to infinity.

3. Data

Basically two data sources are used in this paper. One is the Survey of Professional Forecasters (SPF), which provides data on the inflation forecasts. The other is the real time macro data, which can be used to reconstruct the information set when forecasters make forecasts in real time. Both of them are available from the Federal Reserve Bank of Philadelphia.

SPF was started in the fourth quarter of 1968 by American Statistical Association and National Bureau of Economic Research and was taken over by the Federal Reserve Bank of Philadelphia in June 1990. The respondents are professional forecasters from academia, government, and business. The survey is mailed four times a year, the day after the first release of the NIPA (National Income and Product Accounts) data for the preceding quarter. Most of the questions ask for the point forecasts on a large number of variables for different forecast horizons. A unique feature of the SPF data set is that forecasters are also asked to provide density forecast for aggregate output and inflation. In this paper, we will focus on the latter.

To use this data set appropriately, several issues related to it should be considered, including:

(1) The number of respondents changes over time. It is about 60 at first and decreased in mid 1970s and mid 1980s. In recent years, the number of forecasters was around 30. So, we have an unbalanced panel data.

(2) The number of intervals and their length has changed over time. From 1968Q4-1981Q2 there were 15 intervals, from 1981Q3-1991Q4 there were 6 intervals, and from 1992Q1 onward there are 10 intervals. The length of each interval was 1 percentage point prior to 1981Q3, then 2 percentage points from 1981Q3 to 1991Q4, and subsequently 1 percentage point again.

(3) The definition of inflation in the survey has changed over time. It was defined as annual growth rate in GNP implicit price deflator (IPD) from 1968Q4 to1991Q4. From 1992Q1 to 1995Q4, it was defined as annual growth rate in GDP IPD. Presently it was defined as annual growth rate of chain-type GDP price index.

(4) The base year for price index has changed. For surveys from 1968Q4 to 1975Q4, the base year is 1958. From 1976Q1 to 1985Q4 the base year is 1972. From 1986Q1 to 1991Q4 the base year is 1982. From 1992Q1 to 1995Q4 the base year is 1987. From 1996Q1 to 1999Q3 the base year is 1992. Since 1999Q4, the base year is 1996.

(5) The forecast periods to which the SPF questions refer have changed over time. Prior to 1981Q3, the SPF asked about the annual growth rate of IPD only in the current year. Subsequently it asked the annual growth rate of IPD in both the current year and the following year. However, there are some exceptions. In certain surveys, the density forecast referred to the annual growth rate of IPD in the following year, rather than the current year[12]. Moreover, Federal Reserve Bank of Philadelphia is uncertain about the years referred to in the surveys of 1985Q1 and 1986Q1.

To deal with problem (1), the observations for infrequent respondents are deleted. We keep only the observations of forecasters who forecast 20 or more surveys so that we can run regression for each forecaster and the small sample bias is not too severe. Problem (2)

[12] The surveys for which this is true are 1968Q4, 1969Q4, 1970Q4, 1971Q4, 1972Q3 & Q4, 1973Q4, 1975Q4, 1976Q4, 1977Q4, 1978Q4, and 1979Q2 - Q4.

can be handled by using appropriate intervals although it may cause the procedure of extracting forecast uncertainty from density forecasts a little more complicated. Such a procedure is discussed in detail in the rest of this section. Problem (3) and (4) cause no trouble in this study because the actual inflation is calculated using real time macro data, in which price index and base years are consistent with the SPF data. To avoid problem (5), we use only the density forecasts for the current year[13]. Since the survey is conducted quarterly, we will have four consecutive forecasts for the same target with forecast horizon equal to 1, 2, 3, 4 quarters respectively.

To estimate model (1), we need to calculate the mean and variance from individual density forecasts. The standard approach in the literature is as follows[14] :

$$E(F) = \sum_{j=1}^{J} F_j \Pr(j) \quad \text{and} \quad Var(F) = \sum_{j=1}^{J} [F_j - E(F)]^2 \Pr(j) \tag{2}$$

where F_j and Pr(j) are the midpoint and probability of interval j, respectively. The lowest and highest intervals, which are open, are typically taken to be closed intervals of the same width as the interior intervals.

This approach implicitly assumes that all probability mass is concentrated at the interval midpoints. However, it will lead to the so-called "grouping data error". To solve this problem, Sheppard correction may be used. An alternative approach proposed by Giordani and Soderlind (2002) is to fit a normal distribution to each histogram and the mean and variance are estimated by minimizing the sum of the squared difference between the survey probabilities and the probabilities for the same intervals implied by the normal distribution. We will follow their approach in this paper[15]. However, the results of this paper are not sensitive to this choice.

[13] The remaining panel after deleting observations for infrequent respondents and for the following target year is unbalanced. It has 25 forecasters and 125 quarters with a total of 840 observations due to missing data. The number of surveys each forecaster participates ranges from 20 to 69.

[14] See, for instance, Lahiri and Teigland (1987) and Lahiri, Teigland and Zaporowski (1988).

[15] We are grateful to Giordani and Soderlind for kindly providing their program.

To examine the sources of inflation forecast uncertainty, we need to know the information sets of forecasters. Theoretically, we should not use the most recent data because that was not available to forecasters when they made forecasts in real time. The real-time data set provided by the Federal Reserve Bank of Philadelphia can be used to reconstruct the information sets of forecasters in real time[16]. This data set reports values as they existed in the middle of each quarter from November 1965 to the present. Thus, for each vintage date, the observations are identical to those one would observe at that time. Fortunately, this is also approximately the date when forecasters of SPF are asked to submit their forecasts. The real time data set includes information on some key macroeconomic variables including Real GDP, GDP Price Index, Import Price Index, Money Supply, 3-month T-bill Rate, and 10-year T-bond rate.

However, the number of variables in this data set is limited. It is possible that some important variables that affect the inflation forecast uncertainty are not included. Thus we also make use of revised data of some variables in the hope that data revision will not cause serious problem. Description of these variables can be found in section 4 and the data appendix. The variables considered have different sample frequency. We will use monthly observations if they are available. Otherwise quarterly observations are used.

4. Empirical Results

In this section we want to address three questions. First, do past forecast errors or lagged forecast uncertainty affect current forecast uncertainty, as is assumed by ARCH models? Second, we want to test if there is any link between the level of inflation rate and the forecast uncertainty, as suggested by Friedman (1977). Finally, we want to investigate if there is any other variable that affects the inflation forecast uncertainty.

[16] A description of this data set can be found in Croushore and Stark (2001).

Before answering these questions, let us first look at the estimated inflation forecast uncertainty. Figure 1 shows the distribution of estimated forecast uncertainty across forecasters[17]. In the figure, the bottom and top of the box are the 25% and 75% percentiles, the interior line is the median, the bottom point of the vertical line is the 10% percentile, and the top point of the vertical line is the 90% percentile. Several features of the graph are noteworthy. First, the distributions are often quite dispersed, which conveys a strong impression that the heterogeneity of forecast uncertainty is quite substantial. Second, the dispersion of forecast uncertainty across forecasters varies over time. Roughly the higher is the inflation rate, the more dispersed is the distribution. Secondly, the position of the median roughly confirms Friedman's conjecture. From middle 1970s to early 1980s when inflation rate was high, the median forecast uncertainty is also high. During 1990s when inflation rate is low, the median forecast uncertainty is also very low.

Next tests of random coefficients as assumed in (1) are conducted. If we are interested in whether the slopes are the same across individuals, the usual F test for the null hypothesis that the intercepts are heterogeneous but the slopes are homogeneous against the alternative hypothesis that all coefficients are heterogeneous can be used. The F test rejects the null hypothesis strongly at 1% significance level for all specifications considered in this study. If we are interested in estimating the average effects, Hausman type tests can be applied. For example, the Hausman test can be based on a comparison of the mean group estimator and fixed effects estimator. The former is consistent under both the null and alternative hypotheses while the latter is efficient under the null hypothesis but inconsistent under the alternative hypothesis. Pesaran, Smith and Im (1996) derived the Hausman test for this case. Applying this test to our model, the null hypothesis of slope homogeneity is rejected for most specifications (especially the final specification in table 3) considered in this paper at the significance level of 5%. So, the tests for slope homogeneity justify the use of random coefficients model, which concurs with previous findings of heterogeneity of forecast uncertainty.

[17] In figure 1, the observations of infrequent forecasters are kept.

4.1. Do past forecast uncertainty and forecast errors matter?

The ARCH literature assumes that forecast uncertainty can be proxied by the conditional variance, which depends on past forecast uncertainties and/or past forecast errors. Table 1 shows the result of a regression of the natural logarithm of current forecast uncertainty on the natural logarithm of past forecast uncertainty, the level and absolute value of standardized forecast errors and the variance of news (to be explained later). Several findings are worth mentioning here.

First, the horizon effect is highly significant. The longer the forecast horizon, the higher is the forecast uncertainty. This is evident from the negative signs on the horizon dummies and is consistent with previous findings in the forecasting literature. See, for example, the Bank of England's fan chart in Wallis (2003).

Second, the forecast uncertainty seems to be somewhat persistent. The estimated coefficient on the natural logarithm of past forecast uncertainty is around 0.3 for those estimators that are known to be consistent when both N and T tend to infinity, i.e., the Mean Group Estimator, the Swamy Estimator and the Hierarchical Bayes Estimator. Moreover, the comparison of different estimators reveals that the estimators that ignore the heterogeneity of coefficients altogether have severe biases on the estimates of the lagged dependent variable. For example, the estimated coefficient on the natural logarithm of the past forecast uncertainty is 0.6 for the pooled OLS estimator, and 0.75 for the aggregate estimator[18]. Both are seriously overestimated. This finding is robust for other specifications of model (1) (see tables 2 and 3). The result on the direction of bias is consistent with the finding in Hsiao, Pesaran and Tahmiscioglu (1999). In a Monte Carlo experiment, they find that the pooled OLS estimator overestimates the coefficient on the lagged dependent variable while the mean grouped estimator without correction for small sample bias is downward biased. The latter is also confirmed in our study by comparing the estimated coefficient on the lagged dependent variable for the mean group estimator

[18] Aggregate estimator is the OLS estimator based on the aggregate time series data. The dependent variable is the logarithm of the average forecast uncertainty over forecasters. The forecast error is defined as the difference between the actual inflation rate and the consensus forecast.

and Hierarchical Bayes estimator. Thus, our study casts doubt on results based on aggregate data. For example, Giordani and Soderlind (2003) examine the determinants of inflation forecast uncertainty using only first-quarter data. In a regression similar to ours[19] in Table 1, they estimate the coefficient on the lagged inflation forecast uncertainty to be 0.73, similar to the estimate of our aggregate estimator[20].

Third, the bias of the pooled estimators is not very large although they are known to be inconsistent even when both N and T tend to infinity (cf., Pesaran and Smith (1995)). Both the fixed effect estimator and the MLE estimator tend to underestimate the coefficient on the lagged dependent variable. But the bias is less than that of the pooled OLS estimator and aggregate estimator. It seems that, in the current context, if heterogeneity of forecasts is considered somehow, the estimation bias will not be too severe.

Finally, the estimates of coefficients on the level and absolute value of standardized past forecast error are insignificant, which is contrary to the assumption of ARCH literature[21]. We would like to interpret this as evidence that the past forecast errors are not important when forecasters evaluate the uncertainty associated with their multiperiod point forecasts. One reason is that in the ARCH models, the past forecast errors are used to capture the new information about the process of inflation forecast uncertainty. The forecast error is a piece of such new information for one period ahead forecast. However, for the SPF data, as forecasters go through a year, new information affecting inflation uncertainty in current year is gradually revealed, but not in the form of forecast error because actual inflation of the current year will not be available until the next year. One way to capture this new information about inflation uncertainty is to use the data on fixed-target forecast revisions. As we know, forecasters forecast the same annual inflation rate in each quarter of that year with forecast horizon varying from one quarter

[19] We pool forecasts of different horizons.

[20] They do not take the logarithm of forecast uncertainty. Since the forecast uncertainty is nonnegative, the error in their model is truncated – a problem they ignore. We also estimate our model without taking logarithm of the forecast uncertainty and find that the aggregate estimator still substantially overestimates the coefficient on the lagged dependent variable.

[21] For the Hierarchical Bayes Estimator, we examine the estimated 95% posterior interval. If it covers zero, we interpret it as evidence of insignificance.

to four quarters. So, for the same target, there are four forecasts. The revision of forecast in each quarter from previous quarter reflects perceived news about inflation that befell in that quarter. Although forecasters revise their forecasts based on this perceived news, they are not sure about the effect of this news on annual inflation rate in current year. Therefore the perceived uncertainty on the news should be an important determinant of inflation forecast uncertainty.

One problem is that we do not observe forecasters' uncertainty on news. One way is to use forecasters' disagreement on news as a proxy, which is defined as the standard error of the revision of point forecast across forecasters. The underlying assumption is that with higher uncertainty about the effect of news in the current quarter, the disagreement amongst the respondents will be greater. This follows the same logic as the use of the forecast disagreement as a proxy for forecast uncertainty, a common practice in applied research.

The drawbacks of using forecasters' disagreement on news as a proxy of forecasters' uncertainty on news are many. First, it is an indirect measure and its effectiveness relies on auxiliary assumptions, which may or may not be reasonable. Second, we have to assume that all forecasters have the same uncertainty on the news at each point in time. This contradicts with the observed heterogeneity of forecasts. Due to the differences in information sets and the differential ability to process information, the perceived news and uncertainty on news should differ across forecasters. Finally, only the revision of point forecast is used when computing disagreement on news. However, for SPF data, forecasters revise the whole distribution of forecasts, not just point forecasts. Thus, forecast disagreement on news does not make full use of the information in the data.

An alternative approach to measuring the uncertainty on news is based on the concept of Kullback-Leibler Information. This method measures the uncertainty on news directly. It also avoids the issues of disagreement on news as mentioned above. The logic of this approach is as follows.

Suppose in one quarter the density forecast of the annual inflation rate is $f(\pi)$. In the following quarter, the density forecast for the same target is revised to $g(\pi)$. Then, a measure of information gain from one quarter to the next can be defined as $\log(g(\pi)/f(\pi))$. This information gain actually measures the perceived effect of news occurring between two quarters on the annual inflation rate. Since π is a random variable, so is the information gain. The Kullback-Leibler Information defined as

$$\mu_\pi = \int_{-\infty}^{\infty} \log(g(\pi)/f(\pi))g(\pi)d\pi \tag{3}$$

is the expected information gain with respect to $g(\pi)$. It is the posterior expectation of the effect of news between two quarters. The variance of this information gain measures naturally the uncertainty of the effect of news on inflation, which is

$$\sigma_\pi^2 = \int_{-\infty}^{\infty} (\log(g(\pi)/f(\pi)) - \mu_\pi)^2 g(\pi)d\pi \tag{4}$$

Table 1 shows that, the estimated coefficient on the uncertainty on news[22, 23] is highly significant for all except the aggregate estimator. [24, 25] This suggests that uncertainty of

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[22] We calculated the variance of news for each forecaster. One practical issue is that $f(\pi)$ or $g(\pi)$ may be equal to zero for some intervals so that their natural logarithms are not defined. To circumvent this issue, we assign a small positive probability (0.001) to those intervals subject to the constraint that probabilities over all bins add up to one.

[23] To calculate the news and variance on news, the prior density forecast and the posterior density forecast should have the same target. In the first quarter of each year, the posterior density forecast is the reported density forecast for current year whereas the prior density forecast should be the reported density forecast for next year in the fourth quarter of last year. So, to keep the targets the same, we make use of density forecasts of both the current year and the next year when calculating news and variance on news. We match data on forecast uncertainty and variance on news by year, quarter and forecaster identification number.

[24] People may worry about the problem of endogeneity since the calculation of current forecast uncertainty and variance on news both make use of the reported density forecast of the current quarter. To test for the endogeneity of the variance of news, we first projected this variable on a set of instrument variables including lagged news, disagreement on news by random coefficients estimation, then the prediction is augmented in model (1) for different specifications. We found that the estimated coefficient of the instrumental variable is not significant in our estimations. The reason could be due to the complicated method of calculating the variance of news. In addition, this variable is based on the revision of the density forecasts whereas the forecast uncertainty is based on the variance of the probability distribution of forecasts.

the latest news is an important determinant of inflation forecast uncertainty. The last year's forecast error is no longer important because it is out dated. The incorporation of news may be taken as an extension of ARCH models in the context of multi-period forecasts with varying forecast horizons.

Our findings that past forecast errors have only a weak influence on the forecast uncertainty are consistent with the study of Rich and Tracy (2003). They find that there is only a weak relationship between the *ex post* consensus forecast error and *ex ante* forecast uncertainty, though their study is based on aggregate data. Instead they show that there is a significant link between observed heteroskedasticity in the consensus forecast errors and forecast disagreement. They conclude that conventional model-based measures of uncertainty may be capturing not the degree of confidence that individuals attached to their forecasts but rather the degree of disagreement across individual forecasters. Bomberger (1996) and Giordani and Soderlind (2003), however, find that (G)ARCH effects are significant for inflation forecasts. But both of these studies use aggregate data rather than individual data so that aggregation bias cannot be ruled out.

4.2 Does higher inflation leads to higher inflation uncertainty?

In this section we examine if there is a positive link between inflation uncertainty and lagged inflation rate as suggested in Friedman (1977). Table 2 shows the regression of the natural logarithm of the inflation forecast uncertainty on the natural logarithm of the lagged inflation uncertainty, lagged inflation rate and expected change in inflation rate. The coefficient on the lagged inflation rate is positive and significant for all estimators. This result implies that higher inflation is associated with higher inflation uncertainty. This is not surprising since most other studies with survey data also get similar results. The positive link between inflation forecast uncertainty and the level of inflation rate still

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[25] The estimated coefficient of disagreement on news is insignificant when the variance of news was replaced by the disagreement on news. This implies that disagreement on news is not a good proxy of variance of news.

holds if we replace lagged inflation rate with current expected inflation rate. Diebold et al. (1999) also found a similar relationship using aggregate SPF data.

Table 2 also reveals that there is an asymmetry in the effect of expected change in inflation rate on current inflation forecast uncertainty. The estimated coefficient on the negative expected change in inflation rate is insignificant for the mean group and empirical or hierarchical Bayesian estimators while the estimated coefficient on the positive expected change in inflation rate is positive and significant for all estimators except aggregate estimator. The implication of this finding is that, if people expect inflation rate in current year to rise, they will raise the uncertainty associated with this forecast, but if inflation rate in current year is expected to fall, they will not reduce the uncertainty associated with this forecast immediately. They will wait to see if that expectation comes to be true or not.

Ball (1992) provides an explanation why there is a positive link between the inflation uncertainty and the level of inflation rate. According to him, there are two types of policymakers. They alternate in power stochastically. The public knows that only one type of policymaker is willing to bear the economic costs of a recession to disinflate. When inflation is low, both types of policymakers try to keep it low. As a result, the uncertainty about future inflation will also be low. However, when inflation is high, the public is uncertain about how the monetary authority will respond because they do not know which type of policymakers is in office. Our empirical finding not only supports the Friedman-Ball view that people will increase inflation uncertainty when inflation is high, but also reveals the speed of people’s response when facing possible increase or decrease in inflation rate. They will respond quickly in the former situation, but slowly in the latter situation.

4.3. Other Determinants of inflation forecast uncertainty

Table 3 reports the result of the full regression including all the variables found statistically significant so far. All variables are still significant in the full regression based on the Hierarchical Bayesian estimator. From the estimates of the Hierarchical Bayesian estimator, we could calculate the horizon effects after controlling for other variables. We find that three, two and one quarter ahead forecast uncertainty are only 59.46%, 51.71% and 39.43% of four quarters ahead forecast uncertainty respectively[26]. Thus, on the average, there is a sharp drop in uncertainty from 4-quarter ahead to the 3-quarter ahead forecasts, afterwards the uncertainty tapers off slowly. Table 3 also reveals that 1% change in lagged forecast uncertainty is associated with a 0.31% change in current forecast uncertainty while one percentage point change of lagged inflation rate will change current forecast uncertainty by 17.15%, indicating that lagged inflation has a strong effect on current forecast uncertainty. Variance on news and expected positive change in inflation are also significant determinants of current forecast uncertainty. One unit change of the former will change the current forecast uncertainty by 8.46% while one percentage point increase of the latter will raise the current forecast uncertainty by 31.46%.

We are also interested to see if other macroeconomic variables have information for forecast uncertainty, above and beyond that contained in variables in table 3. Stock and Watson (1999, 2003) examine extensively the predictors of inflation. Based on macroeconomic theories, four broad categories of variables are often considered as potential useful predictors. First, according to the Phillips curve or its generalizations, some measures of real economic activities or output gap such as real GDP, unemployment rate, should help predict future inflation rate. Secondly, the expectations hypothesis of the term structure of interest rates suggests that spreads between interest rates of different maturities incorporate market expectations of future inflation. Thirdly, the quantity theory of money suggests that the growth rate of money supply should be positively related with the inflation rate. Finally, the change in prices of important inputs, such as oil prices, commodity prices, nominal wages and so on, predicts future inflation

[26] Based on the estimates of Hierarchical Bayesian estimator, $\ln\left(\sigma_{it,3}^2 / \sigma_{it,4}^2\right) = -0.5198$, which implies that $\sigma_{it,3}^2 / \sigma_{it,4}^2 = 59.46\%$. Other numbers are calculated similarly.

rate. If forecasters do use these variables to predict future inflation rate, we expect that volatility of these variables may help explain the uncertainty associated with the point forecasts. We examine the effect of volatility of the following variables:[27]

- Variance of (annualized) quarterly growth rate of real GDP in the most recent four quarters calculated with data available in the current quarter (real time data).
- Variance of monthly total civilian unemployment rate in the most recent six months calculated with data available in the current quarter (real time data).
- Variance of (annualized) monthly growth rate of M1 in the most recent six months calculated with data in the current quarter (real time data).
- Variance of (annualized) monthly growth rate of M2 in the most recent six months calculated with revised data available in 2003Q4. Although the data source is still the real time data from the Federal Reserve Bank of Philadelphia, we choose to use revised data rather than real time data for the latter is incomplete.
- Variance of (annualized) monthly growth rate in the crude oil price in the most recent six months calculated with revised data available in June 2004.
- Variance of (annualized) monthly growth rate in the nominal wage in the most recent six months calculated with revised data available in December 2003.
- Variance of (annualized) monthly growth rate in the commodity prices in the most recent six months calculated with revised data available in June 2004.
- Variance of (annualized) monthly growth rate in the stock prices in the most recent six months calculated with revised data available in June 2004.
- Variance of monthly spread between the 10-year T-bond and 3-months T-bill rates in the most recent six months.

Regressions of current forecast uncertainty on all the variables in table 3 and logarithm of each of the above 9 volatility variables reveal that none of time series volatility variables is significant. One possible explanation may be the instability of the underlying indicators in predicting inflation. As found in Stock and Watson (2003), finding an indicator that predicts inflation well in one period is no guarantee that it will predict well in another

[27] See Data Appendix for a detailed description of these variables.

period or another country. It is hard to find a single variable that is a reliable (potent and stable) predictor of inflation over multiple time periods. This implies that forecasters often need to select a subset of predictors from a huge number of candidate predictors. If forecasters have many predictors to choose from, very possibly they may choose different set of variables at different times. As a result when we estimate a panel data model with inflation forecasts, any single variable may become statistically insignificant. Of course, our experimentation with macro variables is tentative because there could be other time series variables that we did not consider.

We adopted a different strategy to check if we omitted any important determinants of forecast uncertainty from our specification. If there are any relevant macroeconomic variables that we failed to consider, the error term of model (1) will have a common factor structure. More specifically, we will have

$$\upsilon_{it,h} = \lambda_i F_{t,h} + e_{it,h} \tag{5}$$

in which $F_{t,h}$ are the common macroeconomic variables that forecasters consider when evaluating the uncertainty associated with their point forecasts but we failed to include in our model, λ_i are the factor loadings and $e_{it,h}$ are the individual-idiosyncratic errors. Recently much attention has been focused on the effect of cross section dependence in the form of common factors on the estimation of panel data models. See, Robertson and Symon (2000), Coakley, Fuertes and Smith (2002), Pesaran (2002), Phillips and Sul (2002) for some examples. However, one basic question that one needs to answer first is how many factors there are. To find the number of factors, the usual likelihood ratio test can be used if the error follows the classical factor model, which means that N is fixed and much smaller than T (number of time periods), the factors are independent of the individual-idiosyncratic errors $e_{it,h}$, and the covariance of $e_{it,h}$ is diagonal. If instead the error follows the "approximate factor model" which was first introduced by Chamberlain and Rothschild (1983) to allow for a non-diagonal covariance matrix of $e_{it,h}$, the likelihood ratio test will be inappropriate and other methods should be used.[28]

In our model, the cross section dependence between individual forecasters comes from the omitted common macro variables. We ignore the spread of panic or confidence among our panel of forecasters for two reasons. First, unlike point forecasts, data on forecast uncertainty is rarely collected and released. Therefore it is hard for a forecaster to know how uncertain other forecasters are for their forecasts and adjust his forecast uncertainty accordingly. Furthermore, even if we observe a widespread panic of high inflation or confidence of low inflation, that is more likely due to some commonly observed indicators of the economy than the interaction between forecasters. Second, forecasters in the SPF data are professional forecasters. They are less likely to be affected by others than ordinary people who do not have the necessary professional knowledge. Based on the above argument, we believe that the covariance matrix of $e_{it,h}$ is diagonal. So, we test the number of factors using the likelihood ratio test. The null hypothesis is that there is one common factor; the alternative hypothesis is that there is no common factor. The likelihood ratio test strongly rejects the null hypothesis.[29]

An alternative strategy is to allow the cross section dependence to be more general than the common factor structure so that cross section dependence due to other reasons can be accommodated. Then we first test if there is any cross section dependence. If there is no cross section dependence, we can conclude that there is no common factor and that no significant macroeconomic variable is omitted.

[28] See Connor and Korajczyk (1993), Stock and Watson (1998) and Bai and Ng (2002) for some examples.

[29] We first get OLS residuals for the full regression in table 3 individual by individual. The OLS residuals should provide consistent estimates of $\upsilon_{it,h}$ and could be used as "observed data" to test for the number of factors. Under the null hypothesis of one common factor, we could estimate the factor and factor loading by maximum likelihood estimation in principle. Since we have a lot of missing values, it is more convenient to use the principal component estimator that is asymptotically equivalent to MLE. Stock and Watson (1998) discuss how to estimate the principal component estimator using an EM algorithm to deal with the problem of missing values. We follow the procedure outlined in that paper.

To test for cross section dependence, the Lagrange multiplier (LM) test proposed by Breusch and Pagan (1980) can be used. However, this test is valid only when N is relatively small and T sufficiently large. The test over rejects the null when $N \rightarrow \infty$ (cf., Pesaran (2004)). Recently, Pesaran (2004) proposes tests that are applicable to a variety of panel data models, including stationary and unit root dynamic heterogeneous panels with short T and large N. These tests are based on average of pair-wise correlation coefficients of the OLS residuals from the individual regressions in the panel and have a standard normal distribution as $N \rightarrow \infty$. Pesaran also compares this test (called CD test) with the LM test and shows that the CD test has the correct size in small samples and satisfactory power while the LM test tend to over-reject the null hypothesis of cross section independence when T is small and N is large. Since our data set has a relatively large N and small T, the CD test seems more suitable than the LM test.[30] Applying the CD test to the specification in table 3, we get the value of test statistic equal to 1.43 and p-value equal to 0.15. For the LM test, the value of test statistic is equal to 275.06, which has chi-square distribution with degree of freedom equal to 241. The p-value of this test is 0.07. So both tests accept the null hypothesis of cross section independence at the significance level of 5%[31]. Thus, the absence of cross sectional correlation rules out the possibility of inconsistency of our estimators.[32]

In summary, our analysis of the SPF data shows that the inflation forecast uncertainty tends to:

- Rise with lagged inflation rate.
- Rise if people expect inflation rate will rise in current year.
- Rise with uncertainty on news.

[30] We have an unbalanced panel data with N=25 and T varying from 20 to 69, whereas the number of common observations between each pair of forecasters varies from 1 to 39.

[31] Since the LM test is known to over reject with large N, we interpret p-value of 0.07 as very little evidence in favor of cross-sectional dependence.

[32] As a robustness check of model (1), we also investigate another assumptions about the error term, i.e. if there is any autocorrelation of the error term in model (1). To test for autocorrelation, the modified Breusch-Godfrey test is applied to each forecaster. The null hypothesis of no autocorrelation is not rejected for all forecasters at the significance level of 1% and not rejected for all except 4 forecasters at the significance level of 5%.

- Show no clear relationship with macroeconomic variables such as the variability of recent growth rates of real output or money supply, the variability of recent inflation rate of oil and the variability of spread between the 10-year T-bond and 3-months T-bill rates and so on.
- Show no clear relationship with past forecast errors as is typically assumed in ARCH models.

5. Conclusion

This paper examines the determinants of inflation forecast uncertainty. Compared to previous studies that have extensively used aggregate time series data, we utilize panel data on density forecasts. The model we estimate is a heterogeneous dynamic panel data model that recognizes the importance of the heterogeneity in forecasts. Our study shows that ignoring the heterogeneity of forecasts will lead to severe bias, as pointed out by Pesaran and Smith (1995).

Our empirical results also confirm the Friedman-Ball view that there is a positive relationship between the level of inflation rate and inflation forecast uncertainty. But we find that past forecast errors have no significant influence on forecast uncertainty in a multi-period context. This is because in the multi-period forecast context where a number of forecasts have to be made before the target variable is known, the information contained in past forecast errors is often outdated. Forecasters would pay more attention to the most recent information. This conjecture is supported by the strong effect of uncertainty of news on the current inflation forecast uncertainty, which is estimated directly from the revision of density forecasts based on the concept of Kullback-Leibler Information. Other factors that may contain information about current inflation forecast uncertainty are also examined. We find that the expected change in inflation affects forecast uncertainty asymmetrically - positive changes affect uncertainty positively but negative changes have no significant effect. It seems that people are more sensitive to the pressure of inflation than deflation. In addition, the volatility of most inflation predictors seems to have no effect on forecast uncertainty. The reason may be that forecasters have numerous predictors to choose from and any single predictor becomes insignificant over a long time series.

Absent from this study is the feedback of inflation forecast uncertainty on the level of inflation rate. Some studies[33] emphasize that greater forecast uncertainty causes higher average inflation. The famous GARCH-M model and its application to inflation data is a good example. How to incorporate this effect into a heterogeneous dynamic panel data model and study the simultaneous determination of inflation and inflation uncertainty may be an interesting direction for future research.

Data Appendix.

Data on real GDP, total civilian unemployment rate, M1 and M2, 10-year T-bond and 3-months T-bill rates are from the real time data set provided by the Federal Reserve Bank of Philadelphia. Data on Real GDP are quarterly data. Data on other variables are monthly data.

Data on crude oil prices are from Bureau of Labor Statistics (series ID: wpu0561. Not Seasonally Adjusted. 1982=100). Monthly data. 1947:1-2003:12

Data on nominal wage are the average hourly earnings of production workers: total private sector from Bureau of Labor Statistics (series ID: CES0500000006, $, Seasonally Adjusted). Monthly data. 1964:1-2003:11

[33] See, for some examples, Grier and Perry (1998, 2000), Cukierman and Meltzer (1986) and Cukierman (1992).

Data on commodity prices are from Bureau of Labor Statistics (Series ID: wpu000000. Not Seasonally Adjusted. 1982=100). Monthly data. 1947:1-2004:5

Data on stock prices are S&P 500 common stock price index: composite (1941-1943=10). Monthly data. 1950:1-2003:12

The growth rate of all variables is calculated as log difference.

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Table 1. Regression evidence on the link between current inflation forecast uncertainty and past forecast uncertainties, past forecast errors and variance of news.

	Constant	D_1	D_2	D_3	$\ln(\sigma^2_{it,h+1})$	Variance on news	$\varepsilon^h_{it-11}/\sigma_{it-11}$	$\lvert\varepsilon^h_{it-11}/\sigma_{it-11}\rvert$
Pooled OLS estimator	-0.041 (0.091) (-0.451) (0.652)	-0.8416 (0.099) (-8.517) (0.000)**	-0.9125 (0.097) (-9.444) (0.000)**	-1.0654 (0.097) (-11.031) (0.000)**	0.5986 (0.028) (21.33) (0.000)**	0.0571 (0.019) (3.032) (0.003)**	-0.0417 (0.02) (-2.108) (0.035)*	-0.0139 (0.021) (-0.661) (0.509)
Fixed effect estimator	-	-0.5467 (0.091) (-5.998) (0.000)**	-0.734 (0.088) (-8.334) (0.000)**	-0.9966 (0.087) (-11.41) (0.000)**	0.2803 (0.034) (8.351) (0.000)**	0.0434 (0.017) (2.508) (0.012)*	-0.0197 (0.018) (-1.076) (0.282)	-0.0019 (0.019) (-0.100) (0.92)
Mean group estimator	-0.7575 (0.171) (-4.425) (0.000)**	-0.5156 (0.098) (-5.262) (0.000)**	-0.7687 (0.119) (-6.473) (0.000)**	-0.99 (0.154) (-6.424) (0.000)**	0.3238 (0.047) (6.823) (0.000)**	0.1314 (0.039) (3.367) (0.001)**	-0.1431 (0.157) (-0.912) (0.362)	-0.1417 (0.163) (-0.869) (0.385)
Swamy Estimator	-0.6693 (0.198) (-3.38) (0.001)**	-0.5449 (0.13) (-4.176) (0.000)**	-0.7128 (0.146) (-4.875) (0.000)**	-0.9784 (0.177) (-5.539) (0.000)**	0.3583 (0.058) (6.145) (0.000)**	0.105 (0.045) (2.356) (0.018)*	-0.0529 (0.164) (-0.323) (0.746)	-0.0411 (0.173) (-0.238) (0.812)

Hierarchical bayes estimator	**-0.6013** **(0.153)** **(-0.889)** **(-0.6042)** **(-0.3005)**	**-0.5673** **(0.108)** **(-0.7771)** **(-0.5598)** **(-0.3673)**	**-0.6722** **(0.103)** **(-0.8698)** **(-0.6702)** **(-0.4795)**	**-0.9547** **(0.14)** **(-1.2354)** **(-0.9483)** **(-0.6747)**	**0.3845** **(0.047)** **(0.2918)** **(0.3852)** **(0.481)**	**0.0894** **(0.028)** **(0.0379)** **(0.0879)** **(0.148)**	**-0.0341** **(0.042)** **(-0.1263)** **(-0.0349)** **(0.0588)**	**-0.0244** **(0.047)** **(-0.1154)** **(-0.0264)** **(0.061)**
Conditional MLE	-0.6149 (0.145) (-4.236) (0.000)**	-0.5819 (0.091) (-6.387) (0.000)**	-0.7542 (0.088) (-8.583) (0.000)**	-1.0037 (0.087) (-11.532) (0.000)**	0.3185 (0.034) (9.267) (0.000)**	0.0452 (0.017) (2.628) (0.009)**	-0.0228 (0.019) (-1.23) (0.219)	-0.0039 (0.02) (-0.196) (0.844)
Aggregate estimator	0.3597 (0.144) (2.499) (0.014)*	-0.8909 (0.129) (-6.893) (0.000)**	-0.9377 (0.12) (-7.831) (0.000)**	-1.0762 (0.12) (-8.999) (0.000)**	0.7484 (0.057) (13.108) (0.000)**	0.1142 (0.061) (1.883) (0.063)	-0.0068 (0.006) (-1.174) (0.244)	-0.0069 (0.006) (-1.203) (0.232)

Note:

1. For hierarchical bayes estimator, the first row shows the means of coefficients, the second row shows the standard errors of coefficients, the third row shows the 2.5% percentiles of coefficients, the fourth row shows the medians of coefficients, and the fifth row shows the 97.5% percentile of coefficients. For other estimators, the first row shows the estimated coefficients, the second row shows the standard errors of coefficients, the third row shows the t-statistic of coefficients, and the fourth row shows p value.

2. * indicates significance at 5% level. ** indicates significance at 1% level.

3. Sample period is from 1968Q4 to 2003Q4

4. Other tables in this paper follow the same format as this table.

Table 2. Regression evidence on the link between inflation forecast uncertainty and lagged inflation rate and expected change in inflation rate.

	Constant	D_1	D_2	D_3	$\ln(\sigma^2_{it,h+1})$	Lagged annual inflation	Expected negative change in inflation	Expected positive change in inflation
Pooled OLS estimator	-0.6919 (0.127) (-5.466) (0.000)**	-0.8129 (0.096) (-8.428) (0.000)**	-0.8822 (0.094) (-9.358) (0.000)**	-1.0515 (0.095) (-11.094) (0.000)**	0.5056 (0.028) (17.984) (0.000)**	0.1762 (0.028) (6.363) (0.000)**	0.2221 (0.082) (2.722) (0.007)**	0.2548 (0.075) (3.394) (0.001)**
Fixed effect estimator	-	-0.5222 (0.088) (-5.914) (0.000)**	-0.7052 (0.085) (-8.268) (0.000)**	-0.9673 (0.085) (-11.346) (0.000)**	0.2063 (0.032) (6.418) (0.000)**	0.2027 (0.03) (6.864) (0.000)**	0.2245 (0.075) (2.99) (0.003)**	0.2121 (0.07) (3.019) (0.003)**
Mean group estimator	-1.4833 (0.254) (-5.844) (0.000)**	-0.5087 (0.096) (-5.28) (0.000)**	-0.7255 (0.099) (-7.314) (0.000)**	-1.0567 (0.154) (-6.854) (0.000)**	0.1806 (0.047) (3.873) (0.000)**	0.201 (0.051) (3.968) (0.000)**	0.1091 (0.117) (0.935) (0.35)	0.3202 (0.134) (2.388) (0.017)*
Swamy Estimator	-1.4204 (0.295) (-4.814) (0.000)**	-0.5294 (0.127) (-4.165) (0.000)**	-0.6894 (0.129) (-5.362) (0.000)**	-1.0118 (0.175) (-5.783) (0.000)**	0.2293 (0.058) (3.956) (0.000)**	0.2045 (0.064) (3.179) (0.001)**	0.111 (0.145) (0.764) (0.445)	0.3287 (0.16) (2.059) (0.039)*

Hierarchical bayes estimator	**-1.3082** **(0.213)** **(-1.7491)** **(-1.3017)** **(-0.9051)**	**-0.5576** **(0.101)** **(-0.7628)** **(-0.5555)** **(-0.3688)**	**-0.6784** **(0.096)** **(-0.8641)** **(-0.6794)** **(-0.4862)**	**-0.9743** **(0.143)** **(-1.2743)** **(-0.9666)** **(-0.6978)**	**0.2783** **(0.045)** **(0.1886)** **(0.2792)** **(0.367)**	**0.1943** **(0.042)** **(0.1113)** **(0.1934)** **(0.274)**	**0.1131** **(0.099)** **(-0.0645)** **(0.106)** **(0.2978)**	**0.2667** **(0.103)** **(0.0695)** **(0.2678)** **(0.456)**
Conditional MLE	-1.311 (0.168) (-7.801) (0.000)**	-0.5549 (0.088) (-6.289) (0.000)**	-0.7237 (0.085) (-8.51) (0.000)**	-0.9746 (0.085) (-11.476) (0.000)**	0.2398 (0.033) (7.321) (0.000)**	0.2029 (0.029) (7.014) (0.000)**	0.2271 (0.075) (3.047) (0.002)**	0.2207 (0.07) (3.165) (0.002)**
Aggregate estimator	0.1734 (0.196) (0.883) (0.38)	-0.9009 (0.128) (-7.019) (0.000)**	-0.9348 (0.118) (-7.933) (0.000)**	-1.126 (0.114) (-9.885) (0.000)**	0.6614 (0.072) (9.164) (0.000)**	0.0551 (0.026) (2.08) (0.041)*	0.0752 (0.083) (0.904) (0.369)	0.0975 (0.113) (0.859) (0.393)

Table 3. Inflation forecast uncertainty and its determinants.

	Constant	D_1	D_2	D_3	$\ln(\sigma^2_{it,h+1})$	Lagged annual inflation	Variance on news	Expected positive change in inflation
Pooled OLS estimator	-0.6187 (0.123) (-5.011) (0.000)**	-0.7994 (0.097) (-8.266) (0.000)**	-0.8831 (0.094) (-9.372) (0.000)**	-1.0438 (0.095) (-10.98) (0.000)**	0.5261 (0.029) (18.374) (0.000)**	0.1165 (0.021) (5.568) (0.000)**	0.0513 (0.018) (2.79) (0.005)**	0.306 (0.072) (4.272) (0.000)**
Fixed effect estimator	-	-0.5174 (0.089) (-5.832) (0.000)**	-0.7126 (0.085) (-8.336) (0.000)**	-0.9749 (0.086) (-11.387) (0.000)**	0.223 (0.033) (6.767) (0.000)**	0.1386 (0.023) (6.057) (0.000)**	0.0339 (0.017) (2.011) (0.045)*	0.2592 (0.068) (3.801) (0.000)**
Mean group estimator	-1.4465 (0.28) (-5.169) (0.000)**	-0.4851 (0.094) (-5.151) (0.000)**	-0.7354 (0.102) (-7.222) (0.000)**	-1.004 (0.147) (-6.845) (0.000)**	0.2303 (0.049) (4.669) (0.000)**	0.17 (0.06) (2.843) (0.004)**	0.1437 (0.034) (4.282) (0.000)**	0.4034 (0.119) (3.382) (0.001)**
Swamy Estimator	-1.3905 (0.316) (-4.398) (0.000)**	-0.5035 (0.125) (-4.04) (0.000)**	-0.689 (0.13) (-5.316) (0.000)**	-0.9612 (0.168) (-5.729) (0.000)**	0.2667 (0.06) (4.444) (0.000)**	0.1726 (0.07) (2.477) (0.013)*	0.1089 (0.039) (2.776) (0.005)**	0.3752 (0.145) (2.587) (0.009)**

Hierarchical bayes estimator	**-1.3026**	**-0.5198**	**-0.6595**	**-0.9306**	**0.3116**	**0.1715**	**0.0846**	**0.3146**
	(0.211)	**(0.098)**	**(0.103)**	**(0.135)**	**(0.047)**	**(0.041)**	**(0.027)**	**(0.095)**
	(-1.7445)	**(-0.7256)**	**(-0.873)**	**(-1.1862)**	**(0.222)**	**(0.098)**	**(0.0336)**	**(0.1394)**
	(-1.2996)	**(-0.5218)**	**(-0.6591)**	**(-0.9352)**	**(0.3118)**	**(0.171)**	**(0.0848)**	**(0.3147)**
	(-0.8982)	**(-0.3335)**	**(-0.4629)**	**(-0.647)**	**(0.4017)**	**(0.2508)**	**(0.1385)**	**(0.5099)**
Conditional MLE	-1.2093	-0.5501	-0.7311	-0.9812	0.258	0.1385	0.0358	0.2691
	(0.165)	(0.089)	(0.085)	(0.085)	(0.034)	(0.022)	(0.017)	(0.068)
	(-7.327)	(-6.206)	(-8.576)	(-11.503)	(7.676)	(6.186)	(2.136)	(3.985)
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.033)*	(0.000)**
Aggregate estimator	0.2019	-0.8814	-0.9316	-1.0797	0.7017	0.0228	0.0856	0.1221
	(0.193)	(0.127)	(0.116)	(0.117)	(0.075)	(0.024)	(0.051)	(0.107)
	(1.044)	(-6.92)	(-8.004)	(-9.266)	(9.329)	(0.947)	(1.693)	(1.138)
	(0.3)	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.346)	(0.094)	(0.258)

Note: 1. For the F test for slope homogeneity, the value of test statistic is 1.96, the degree of freedom is 224 and 854, p-value of the test is 0.000;

2. For the Hausman test for slope homogeneity, the value of test statistic is 15.87, which has a chi-square distribution with the degree of freedom equal to 7. p-value of this test is 0.026;

3. For the CD test that has standard normal distribution as the number of forecasters tend to infinity, the value of test statistic equal to 1.43 and p-value equal to 0.15. For the LM test, the value of test statistic is 275.06, which has chi-square distribution with degree of freedom equal to 241. The p-value of this test is 0.07. Both tests cannot reject the null hypothesis of cross section independence at the significance level of 5%.

4. The likelihood ratio test for H0: one common factor has the value of the statistic equal to 2361.21. The degree of freedom for the test equal to 275 (=$\frac{1}{2}\times\left((25-1)^2-25-1\right)$). The p-value of the test is 0.000. So we reject H0 significantly and accept the alternative hypothesis that there is no common factor.

Figure 1. Distribution of Forecast Uncertainty across Forecasters