# 9. ANCHORING EFFECT ON MACROECONOMIC FORECASTS: A HETEROGENEITY APPROACH

**Tzu-Pu CHANG**[1]
**Ray Yeutien CHOU**[2]

## Abstract

*With respect to the rational expectation hypothesis, some previous studies adopted a behavioral perspective to explain why forecast biases occur. One widely-discussed behavioral bias in forecasting is the anchoring and adjustment heuristics. This paper proposes a two-anchor heterogeneity model to simultaneously estimate the anchoring biases in individual and consensus forecasts. The results show that the previous individual forecast and consensus forecast anchor the forecasts of the U.S. macroeconomic series. Generally, forecasters slowly adjust their prior belief and behave stubbornly. Moreover, the individual forecaster also presents substantial and heterogeneous anchoring bias. A robustness analysis using Eurozone data is consistent with the findings mentioned above.*

**Keywords**: anchoring effect; macroeconomic forecast; rational expectation; heterogeneity model; consensus forecast
**JEL classification**: C23, E37

## 1. Introduction

A large and growing body of research on macroeconomic forecasts has been released over the last few decades. Most studies target the validity of Muth's (1961) rational expectation hypothesis and examine whether forecasts are systematically biased against the real world. Specifically, the previous literature has developed econometric models to test the predictability or autocorrelation in forecasting errors and provided some suggestions about a systematic improvement of forecasts (Albu *et al.*, 2015).

Some studies sequentially adopt a behavioral perspective to explain why forecast biases occur (*e.g.,* Ehrbeck and Waldmann, 1996; Welch, 2000; Ottaviani and Sørensen, 2006). One widely-discussed behavioral bias in forecasting is the anchoring and adjustment heuristics described by Tversky and Kahnemen (1974). Such behavioral bias demonstrates

*[1] Department of Finance, National Yunlin University of Science and Technology, 123, University Rd. Sec. 3, Douliou, Yunlin 64002, Taiwan.*
*[2] Institute of Economics, Academia Sinica, 128 Academia Rd., Sec. 2, Nankang, Taipei 11529, Taiwan.*

that forecasters tend to make a forecast that may underweight new information and overweight some easily observable, arbitrary, or irrelevant starting points (anchors). For example, early studies, such as Nordhaus (1987), find a first-order serial correlation of forecast revisions, meaning that current forecast revisions are anchored by previous forecast revisions. Batchelor and Dua (1992) note that participants who join in the Blue Chip Economic Indicators survey are consensus-seeking, indicating that forecasters adjust their beliefs toward the consensus by more than that which is optimal.

Campbell and Sharpe (2009) formally propose an anchoring model to estimate how much anchoring bias exists in macroeconomic forecasts and indicate that most U.S. macroeconomic forecasts are anchored by one-month lag releases. Ichiue and Yuyama (2009) conduct a similar approach and find that consensus forecasts of the U.S. federal funds rate are significantly anchored by one- and two-quarterly behind consensus forecasts. Sequentially, Nakazono (2012) and Fujiwara *et al*. (2013) apply the anchoring model to examine whether financial market forecasts are rational. Nakazono (2013) extends the above-mentioned literature through a two-anchor anchoring model.

Our study introduces a two-anchor heterogeneity anchoring model that further extends Nakazono's (2013) model, in order to more clearly realize the anchoring bias in macroeconomic forecasts. This paper studies two anchors: one is the forecaster's previous forecast and the other is the prior consensus forecast. A forecaster's previous forecast may represent how the forecaster incorporates public information, professional knowledge, and judgments. Hence, a bias toward a past forecast indicates that the revisions are smoothed and that there are slow adjustments to the rational expectation. It also implies that forecasters dislike sudden and large adjustments associated with previous forecasts in order to maintain their credibility and reputation (Stekler, 2007). Oppositely, a prior consensus forecast, measuring the average forecasts of all forecasters last month, is the outcome of all forecasters' thoughts. Thus, a bias toward past consensus describes that forecasters seek to misreport more toward the consensus. Ottaviani and Sørensen (2006) suggest that this behavior mean forecasters are trying to avoid unfavorable publicity when a forecast is wrong. Moreover, this bias can be explained by herding behavior (Welch, 2000; Beckers *et al*., 2004).

There are two perspectives for why it is necessary to consider heterogeneity. First, from a behavioral perspective, the literature addresses that forecasters with different characteristics present distinct forecasting behaviors (*e.g.,* Hong *et al*., 2000; Lamont, 2002; Brown *et al*., 2008) Hence, we believe that studying the individual behavior aspect may be more meaningful and interesting. For example, why are some forecasters rational and others not? Second, from an econometric perspective, Keane and Runkle (1990) and Davies and Lahiri (1995) argue that using consensus data creates the aggregation bias problem. Keane and Runkle (1990) illustrate that using consensus data leads to model specification error, *i.e.*, a serious upward bias. They also consider that this approach disguises individual deviations from rationality. Therefore, based on forecaster level data rather than consensus data, our proposed model can estimate the degree of overall and individual anchoring biases.

The remainder of the paper is organized as follows. Section 2 introduces the estimation methods. Section 3 describes the data. Section 4 provides an empirical analysis for a case of U.S. macroeconomic forecasts. Finally, section 5 concludes.

## 2. Estimation: The Anchoring Model

Suppose there are *N* forecasters, *T* target years, and *H* forecast horizons. Let $F_{ith}$ be the forecast value for the U.S. GDP growth rate of the target year *t*, made by forecaster *i*, *h* months before the end of year *t*. Moreover, $A_t$ denotes the actual (realized) growth rate for year *t*. We then define the forecast error, $e_{ith}$, as $A_t$ minus $F_{ith}$. This paper follows an anchoring model developed by Campbell and Sharpe (2009) and Ichiue and Yuyama (2009) (hereafter CSIY), which is based on a rationality test:

$$e_{ith} = A_t - F_{ith} = \rho F_{ith} + \varepsilon_{ith} \tag{1}$$

where: $\varepsilon_{ith}$ is normal random noise.

CSIY suppose that the forecast follows a partial adjustment process. Accordingly, the partial adjustment of a forecast with one anchor is:

$$F_{ith} = \lambda A_{t|h} + (1-\lambda) Anchor_{ith+1}, \tag{2}$$

where: $A_{t|h}$ denotes the rational expectation conditional on the information available h months before the end of year t, assuming that each forecaster can perceive this unobservable value, and $Anchor_{ith+1}$ represents the information of the previous anchoring point. Equation (2) reveals that the formation of a current forecast includes two components: unsystematically biased expectation and anchor-induced bias. Thus, if $\lambda = 0$, then the current forecast is equal to rational expectation.

Since $A_{t|h}$ is unobservable, CSIY use a transformation - that is, $E(e_{ith}) = A_{t|h} - F_{ith}$ - and substitute it for $A_{t|h}$ in equation (2). As a result, the expected forecast error can be illustrated by $E(e_{ith}) = \gamma\,(F_{ith} - Anchor_{ith+1})$, where $\gamma = (1-\lambda)/\lambda$. Finally, the following regression expresses CSIY's anchoring model:

$$e_{ith} = \gamma(F_{ith} - Anchor_{ith+1}) + \varepsilon_{ith}. \tag{3}$$

With respect to the proposed two-anchor heterogeneity model, we assume that the forecast is adjusted simultaneously from the forecaster's previous forecast ($F_{ith+1}$) and the distance to consensus ($D_{ith+1}$). Note that $D_{ith+1}$ is equal to the difference between a specific forecast and the consensus ($F_{ith+1} - \bar{F}_{th+1}$). Accordingly, we straightforwardly modify CSIY's partial adjustment for each forecaster as:

$$F_{ith} = \lambda_{1i} A_{t|h} + \lambda_{2i} F_{ith+1} + (1-\lambda_{1i} - \lambda_{2i}) D_{ith+1}, \tag{4}$$

where: the subscript *i* in $\lambda_1$ and $\lambda_2$ indicates the heterogeneity among forecasters.[3]

Because $A_{t|h}$ is unobservable, we again use CSIY's transformation and rewrite equation (4) as:

$$E(e_{ith}) = \frac{1-\lambda_{1i}}{\lambda_{1i}}\left(F_{ith} - F_{ith+1}\right) + \frac{1-\lambda_{1i}-\lambda_{2i}}{\lambda_{1i}}\bar{F}_{th+1}. \tag{5}$$

Therefore, we estimate the following random coefficient model:[4]

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[3] *We use the term "heterogeneity" to represent the role of heterogeneous forecasters.*

[4] *The random coefficient model is also named the multilevel model, hierarchical linear model, mixed model, or nested model in different research fields.*

$$e_{ith} = \gamma_{1i}\left(F_{ith} - F_{ith+1}\right) + \gamma_{2i}\bar{F}_{th+1} + \varepsilon_{ith}$$
$$\gamma_{1i} = \gamma_{10} + u_{1i}$$
$$\gamma_{2i} = \gamma_{20} + u_{2i} \tag{6}$$

Here, $\gamma_{10}$ and $\gamma_{20}$ denote the fixed components of $\gamma_{1i}$ and $\gamma_{2i}$, respectively, which we can use to test the rationality in the aggregation level; and $u_{1i}$ and $u_{2i}$ are the random components of $\gamma_{1i}$ and $\gamma_{2i}$, respectively. If $\gamma_{1i} = \gamma_{2i} = 0$, then the forecast error is unpredictable, suggesting that the forecast is rational in the forecaster level. This two-anchor heterogeneity model is also meaningful. For instance, when $\gamma_{1i}$ is insignificantly different, but $\gamma_{2i}$ is significantly different, from zero, we interpret this case as the forecast being rational, even though the forecast is anchored by the proposed anchors. This phenomenon may occur, because human judgments provide some benefit to forecasting accuracy (Lawrence *et al.*, 2006). Finally, we estimate the best linear unbiased prediction (BLUP) for the individual random components ($u_{1i}$ and $u_{2i}$) and measure the individual slope coefficient for each forecaster (for details, please see Bryk and Raudenbush, 1992).

## 3. Data

This paper focuses on the monthly forecasts of the U.S. macroeconomic data and chooses four major macroeconomic forecasts: real GDP growth rate, industrial production growth rate, consumer price index growth rate, and unemployment rate. The data used herein come from the Consensus Forecasts database and cover the relevant information from January 1992 to December 2011 since the consensus forecasts survey the GNP growth rate rather than the GDP growth rate for each country before 1992. This database conducted by *Consensus Economics Inc.* contains worldwide surveys of 15 major macroeconomic statistics for a large number of countries since 1989.[5] Consensus Forecasts asks all participants (usually between 25 and 35 individuals) to respond to a monthly survey of macroeconomic statistics. These participants are professional forecasters among a broad array of fields, including investment banking, asset management, research institutes, non-profit institutions, etc.

One key feature of *Consensus Forecasts* is that this monthly publication contains revised forecasts for the current year and next year, meaning that each forecaster provides a maximum of 24 forecasts for every target year. However, because our research period begins at January 1992, only a maximum of 12 forecasts is made by each forecaster for 1992. In fact, the participants of each survey for the U.S. may not remain the same. Over the research period (about twenty years), some forecasters are merged or acquired, some go bankrupt, and some are recently launched. Among 65 forecasters in our dataset, only six forecasters completely participated in the survey from January 1992 to December 2011.[6] As a result, our sample contains unbalanced panel data with a total of 12,021 observations.

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[5] *In fact, some surveys may include 16 statistics for several countries. For example, the survey for the U.S. macroeconomic statistics contains not only 15 basic series, but the expected probability of interest rate change at/before the next Federal Open Market Committee meeting.*

[6] *The total number of participants is originally 80. We carefully compare each forecaster's history and then combine several forecasters into a single forecaster. Finally, the total number of participants becomes 65.*

Table 1 reports summary statistics for the realized values, forecasts, and forecast errors of the four macroeconomic series. We present the sample mean, standard deviation, and minimum and maximum values for each variable. According to panel A of Table 1, the mean forecast error of the GDP growth rate is -0.08%, which is close to zero, implying that the forecasts may be unconditionally unbiased. Similarly, both panel C (CPI growth rate) and panel D (unemployment rate) present small mean forecast errors of 0.02% and 0.08%, respectively. However, if we plot realized values and forecasts for each year, then we find an interesting pattern, showing that the forecasts are behaviorally biased.

**Table 1**

**Summary Statistics of the Sample Data**

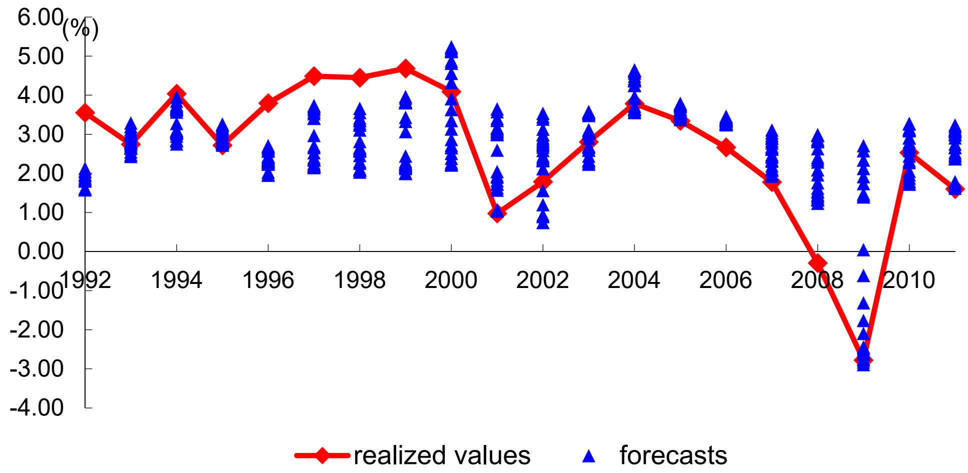
| Panel A: GDP growth rate (%) | | | | | |
|---|---|---|---|---|---|
| | N | Mean | Std. deviation | Min | Max |
| Realized values | 20 | 2.64 | 1.76 | -2.78 | 4.69 |
| Forecasts | 12,021 | 2.70 | 1.21 | -3.87 | 6.20 |
| Errors | 12,021 | -0.08 | 1.42 | -6.38 | 4.39 |
| Panel B: Industrial production growth rate (%) | | | | | |
| Realized values | 20 | 2.23 | 4.10 | -11.53 | 7.17 |
| Forecasts | 11,707 | 2.79 | 2.72 | -14.00 | 9.40 |
| Errors | 11,707 | -0.55 | 3.15 | -16.83 | 9.55 |
| Panel C: Consumer price index growth rate (%) | | | | | |
| Realized values | 20 | 2.54 | 0.90 | -0.36 | 3.84 |
| Forecasts | 11,998 | 2.53 | 0.84 | -2.25 | 5.30 |
| Errors | 11,998 | 0.02 | 0.81 | -5.16 | 2.96 |
| Panel D: Unemployment rate (%) | | | | | |
| Realized values | 20 | 6.04 | 1.66 | 4.00 | 9.80 |
| Forecasts | 12,003 | 5.93 | 1.52 | 3.50 | 10.96 |
| Errors | 12,003 | 0.08 | 0.67 | -1.70 | 4.90 |

*Note: Realized values, forecasts, and errors are $A_t$, $F_{ith}$, and $e_{ith}$ in equation (1), respectively.*

Figure 1 sketches the realized values and forecasts (consensus forecasts) of the GDP growth rate for each year. Before the recession in 2001, the consensus forecasts seem to systematically underestimate the GDP growth rate, except in 1995. Nevertheless, after 2001, the consensus forecasts typically overestimate the growth rate.

**Figure 1**

**Realized GDP Growth Rate (At) and Consensus Forecasts ($\bar{F}_{th}$)**




Hence, this suggests that the forecasts are not exactly rational. In addition, this pattern appears to follow a gambler's fallacy bias, indicating that forecasters tend to underestimate (overestimate) the growth rate when the prior economic condition is booming (slumping).

# 4. Results

## Anchoring Bias in Overall Level

Table 2 presents estimation results for different anchoring models. Specifically, the results of panel A are based on Nakazono's (2013) two-anchor model. Since Nakazono's (2013) model does not consider heterogeneity among forecasters, the model can be estimated through a well-known panel data regression. Just like Nakazono's paper, we apply pooled least square to estimate the two-anchor model without heterogeneity for the four macroeconomic series. Finally, we show the results of the proposed two-anchor heterogeneity model in panel B of Table 2.

**Table 2**

**Estimation Results for the Two-anchor Heterogeneity Model**

| Panel A: without heterogeneity | | | | |
|---|---|---|---|---|
| Macroeconomic Series | GDP | Industrial Production | Consumer Price Index | Unemploy-ment |
| | | | | |
| $(F_{ith} - F_{ith+1})$ | 0.584*** (0.066) | 0.559*** (0.071) | -0.062 (0.044) | 0.622*** (0.058) |
| $\bar{F}_{th+1}$ | -0.045** (0.019) | -0.095*** (0.026) | -0.017*** (0.003) | 0.012*** (0.001) |
| $N$ | 10470 | 10164 | 10436 | 10451 |
| Pseudo $R^2$ | 0.021 | 0.024 | 0.004 | 0.039 |

| Panel B: with heterogeneity | | | | |
|---|---|---|---|---|
| Macroeconomic Series | GDP | Industrial Production | Consumer Price Index | Unemploy-ment |
| ***Fixed component*** | | | | |
| $(F_{ith} - F_{ith+1})$ | 0.377*** (0.072) | 0.351*** (0.053) | -0.038* (0.023) | 0.048 (0.036) |
| $\bar{F}_{th+1}$ | 0.016*** (0.006) | 0.024*** (0.004) | -0.018*** (0.002) | 0.012*** (0.001) |
| ***Random component*** | | | | |
| $\sigma(F_{ith} - F_{ith+1})$ | 0.280*** (0.039) | 0.369*** (0.053) | 0.089*** (0.032) | 0.216*** (0.034) |
| $\sigma(\bar{F}_{th+1})$ | 0.175*** (0.009) | 0.155*** (0.005) | 0.013*** (0.002) | 0.005*** (0.001) |
| *N* | 10470 | 10164 | 10436 | 10451 |
| *Pseudo* $R^2$ | 0.095 | 0.069 | 0.331 | 0.627 |

*Note: Dependent variable $e_{ith}$ is calculated by $A_t$-$F_{ith}$, where $A_t$ is the realized value for year t, and $F_{ith}$ is the forecast released by the $i^{th}$ forecaster h months before the end of year t. $D_{ith}$ is the distance to the consensus forecast and is measured by $F_{ith}$-$\bar{F}_{th+1}$. Pseudo $R^2$ is computed via McFadden's approach. *, **, and *** denote significance levels at 0.1, 0.05, and 0.01, respectively.*

With respect to panel A, all macroeconomic forecasts, excluding the consumer price index, present significantly positive coefficients for $(F_{ith} - F_{ith+1})$. It means that a forecaster's revision is irrational and anchored by two anchors. In terms of the magnitude of the anchoring effect, the coefficient for $(F_{ith} - F_{ith+1})$ ranges from 0.559 to 0.622, which implies that forecasters may place 36%-38% of the weight on anchors and only 62% (1/1.622×100%) to 64% (1/1.559×100%) on the rational expected value. However, the existing two-anchor model's $R^2$ ranges from 0.4% to 3.9%, indicating that the goodness of fit is not well indeed.

Regarding the proposed model in panel B, the forecasts of GDP and industrial production show significant and positive coefficients for $(F_{ith} - F_{ith+1})$ and $\bar{F}_{th+1}$, confirming that forecasts are behaviorally biased again. However, the coefficients for $(F_{ith} - F_{ith+1})$ and $\bar{F}_{th+1}$ of the consumer price index are significantly negative, which we will discuss later. In terms of the forecasts for unemployment, the coefficient for $(F_{ith} - F_{ith+1})$ is insignificant, while the coefficient for $\bar{F}_{th+1}$ is significantly positive, implying that the forecast at the aggregation level may be unbiased, but forecasters are still behavioral. Moreover, all random components, i.e., $\sigma(F_{ith} - F_{ith+1})$ and $\sigma(\bar{F}_{th+1})$, are quite significant in the heterogeneity anchoring model, indicating that the behavior of each forecaster is heterogeneous indeed. Incidentally, the pseudo $R^2$ of the heterogeneity model, ranging from 6.9% to 62.7%, are much higher than those of the model without heterogeneity. Since the effect of the forecaster level can substantially change an empirical conclusion, we suggest employing a heterogeneity approach. This also verifies the concerns of Keane and Runkle (1990) and Davies and Lahiri (1995), *i.e.*, the aggregation bias problem.

**Table 3**

**The Weights of the Rational Expected Value and Anchors**

| Weights | Macroeconomic forecasts | | | |
|---|---|---|---|---|
| | GDP | Industrial Production | Consumer Price Index | Unemployment |
| Rational expected value | 0.726<br>[0.663, 0.817] | 0.740<br>[0.690, 0.804] | 1.040<br>[0.995, 1.092] | 0.955<br>[0.894, 1.020] |
| Previous forecast | 0.262<br>[0.168, 0.325] | 0.242<br>[0.176, 0.294] | -0.021<br>[-0.072, 0.024] | 0.034<br>[-0.033, 0.095] |
| Distance to consensus | 0.012<br>[0.005, 0.022] | 0.017<br>[0.012, 0.024] | -0.019<br>[-0.023, -0.015] | 0.012<br>[0.010, 0.013] |

*Note: The weights of the rational expected value, previous forecast, and distance to consensus are derived via equation (4). Simulated 95% confidence intervals are presented in brackets.*

In order to understand the magnitude of the anchoring effect on macroeconomic forecasts, we transform the estimated parameters in equation (5) into equation (4) and show the weights on the rational expected value and anchors in Table 3. The forecasts for the GDP growth rate indicate that the forecasts place only a 72.6% weight on the rational expected value, 26.2% weight on their prior forecasts, and 1.2% weight on the distance to the consensus forecast. The results of the industrial production growth rate present a similar pattern with GDP forecasts, implying that forecasters behaviorally underweight their own information when they forecast GDP and industrial production growth rates. The weights on the rational expected value for CPI and unemployment are 1.040 and 0.955, respectively, while those weights do not significantly differ from unity at the 0.05 significant level. This finding reveals that the forecasts for CPI and unemployment are unbiased regarding the rational expected value. However, we still suggest that the forecasts for CPI and unemployment are behavioral, because the weights on distance to consensus significantly deviate from zero, echoing Lawrence *et al.* (2006) and Stekler (2007) who consider that human judgement can improve forecasting performance.

According to Table 3, the four macroeconomic series seem to exhibit two groups: one consisting of GDP and industrial production that presents a higher anchoring bias, whereas the other one consisting of CPI and unemployment shows a slight anchoring effect. It should be meaningful to find out what is the determinant of the above-mentioned finding. We suppose that if a macroeconomic series is more volatile, then it is more difficult for forecasters to make a forecast. As a result, forecasters have to highly rely upon human adjustments and refer to their past forecasts as well as consensus. To examine our supposition, we calculate the coefficient of variation for each macroeconomic series based on its yearly realized value. Unsurprisingly, the industrial production growth rate presents the highest coefficient of variation (1.83), followed by GDP growth rate (0.67), CPI growth rate (0.35), and unemployment rate (0.28). Using a simple non-parametric correlation, we find that the coefficient of variation positively correlates with the magnitude of the anchoring effect, confirming our supposition.

We thus conclude that forecasters are anchored simultaneously by their previous forecasts and consensus forecasts in most cases. On the one hand, forecasters are inclined to refer to their previous forecasts when they make new forecasts. This indicates that new forecasts are smoothed and exhibit slow adjustments to the rational expectation. This finding is in accordance with the works of Ichiue and Yuyama (2009) and Fujiwara *et al.* (2012). On the other hand, forecasters tend to retain the distance to consensus when they revise forecasts. For example, an optimistic (pessimistic) forecaster continually reports an overestimated (underestimated) forecast. This result implies that forecasters are not consensus-seeking and do not present herding behavior. We suggest that, in general, forecasters are obstinate in order to maintain their credibility and reputation and can also explain this bias by their overconfidence behavior.

## Anchoring Bias in the Forecaster Level

This paper further estimates the magnitude of the two anchoring biases for each forecaster by computing BLUPs, so that we can analyze the differences between forecasters' behaviors more thoroughly. First, in order to examine whether a forecaster's behavior is consistent in the four macroeconomic forecasts, panel A of Table 4 reports the correlations of the weights on rational expectation ($\lambda_{1i}$) among the four series. As shown in panel A, $\lambda_{1i}$'s for the four macroeconomic series positively correlate to each other, and the correlation coefficients are significant in most cases. This illustrates that a forecaster who provides a higher/lower biased forecast for one series tends to also give a higher/lower biased forecast for the other three series. For instance, based on our computation, Dun & Bradstreet is the most unbiased forecaster regarding both GDP and industrial production forecasts. Therefore, we confirm that a forecaster's behavior is consistent, even if forecasting different macroeconomic series.

This paper would also like to know how a forecaster's behavior is anchored by previous consensus. Hence, panel B of Table 4 lists the correlations of the anchoring effect from distance to consensus ($1-\lambda_{1i}-\lambda_{2i}$) among the four series. According to the correlation matrix, ($1-\lambda_{1i}-\lambda_{2i}$) for the GDP forecast is highly and positively related to the industrial production forecast, while it is negatively related to the consumer price index and unemployment rate. This result reveals that a forecaster tends to report GDP and industrial production forecasts with numbers higher than the consensus, while also providing consumer price index and unemployment rate forecasts with numbers lower than the consensus. Actually, this result is quite reasonable in that, for example, an optimistic forecaster prefers higher GDP and industrial production growth rate and lower inflation and unemployment rate. The significant coefficients imply that the aforementioned behavior frequently exists among the consensus participants.

**Table 4**

**Correlations among the Anchoring Effects of Macroeconomic Forecasts**

| Panel A: Weight on rational expectation ($\lambda_{1i}$) | | | | |
|---|---|---|---|---|
| Series | GDP | Industrial production | Consumer price index | Unemployment |
| GDP | - | **0.628** | **0.219** | **0.312** |
| Industrial production | **0.626** | - | 0.121 | **0.431** |
| Consumer price index | **0.235** | 0.186 | - | **0.266** |
| Unemployment | **0.223** | **0.315** | 0.175 | - |
| Panel B: Anchoring effect from distance to consensus ($1-\lambda_{1i}-\lambda_{2i}$) | | | | |
| GDP | - | **0.748** | **-0.318** | -0.204 |
| Industrial production | **0.731** | - | **-0.283** | **-0.367** |
| Consumer price index | **-0.328** | **-0.326** | - | -0.138 |
| Unemployment | -0.090 | **-0.366** | -0.138 | - |

*Note: Pearson's and Spearman's rank correlation coefficients are shown under and above the diagonal, respectively. Coefficients at the 0.1 significance level appear in bold.*

This paper finally looks to test whether a forecaster's characteristics may influence the forecasting behavior. Thus, the paper categorizes all forecasters based on two criteria: one is forecaster's background and the other is response rate. Table 5 presents the average weights on the rational expectation for different types of forecasters. According to the first criteria, forecasters are divided into three groups: financial institutions, industrial institutions, and research institutions. The result shows that financial institutions are more unbiased than both industrial institutions and research institutions in terms of GDP and industrial production forecasts. We suggest that financial institutions, which invest or manage funds in global financial markets, are more sensitive to economic environments around the world. Therefore, financial institutions can more efficiently forecast those two direct prosperity indicators, while noting that they still underweight their information by over 20%. However, based on mean comparison testing, none of the three groups is significantly superior in any macroeconomic series.

The second grouping criterion is the response rate that denotes how many forecasts a forecaster provides during the whole research period. This paper equally divides two groups according to the response rate. Hence, the group with a high response rate indicates it has taken part in the Consensus Forecasts survey for a longer time and can be deemed as being more sophisticated forecasters versus the other group. As shown in Table 5, however, the group with a high response rate presents more serious anchoring bias in all series except the consumer price index. Specifically, for GDP and industrial production forecasts, the weights on the rational expectation for the high response group are significantly lower than those of the low response group, even though both groups underweight the rational expectation. With respect to the anchoring behaviors among the two groups, it is interesting that the low response group tends to keep its distance to consensus ($1-\lambda_{1i}-\lambda_2$ is positive), while the high response group typically eliminates the distance to consensus when they revise forecasts ($1-\lambda_{1i}-\lambda_2$ is negative). This finding implies that the high response group may seek to be closer to the consensus forecast and make conservative forecasts. We leave explanations about the strategies behind the above-mentioned behavior for future research.

**Table 5**

### Average Weights of the Rational Expectation for Different Types of Forecasters

| Groups | GDP | Industrial production | Consumer price index | Unemployment |
|---|---|---|---|---|
| 1. Background | | | | |
| Financial institutions | **0.757** | **0.778** | 1.043 | 0.977 |
| Industrial institutions | 0.699 | 0.731 | 1.065 | **0.989** |
| Research institutions | 0.711 | 0.737 | **1.025** | 0.982 |
| 2. Response rate | | | | |
| High | 0.706 | 0.726 | **1.040** | 0.972 |
| Low | **0.766#** | **0.793#** | 1.044 | **0.988** |

*Note: For each macroeconomic series, the most unbiased forecaster group appears in bold. # denotes that the group is significantly better than the other groups at the 0.05 significance level.*

## Robustness: Using the Eurozone Dataset

In order to obtain a robust conclusion, we further use the same four macroeconomic series data of the Eurozone.[7] The Consensus Forecasts database started to report consensus forecasts for the Eurozone in December 2002. Thus, we collect corresponding data covering from January 2003 to December 2011 for a total of 6,097 observations.

The proposed heterogeneity anchoring model again fits the Eurozone data better than the existing model. The $R^2$ for the four macroeconomic series ranges from 13.3% to 46.6% using the heterogeneity model. Table 6 lists the magnitude of anchoring effects on the Eurozone forecasters. Similar to the U.S. data, the forecasters severely present anchoring biases and only place 51% and 74% weights on rational expectations of GDP and industrial production growth rate, respectively. They not only slowly adjust their belief, but also adjust their forecast away from the consensus, especially for the GDP forecast. In terms of the consumer price index and unemployment rate, the anchoring biases are minor, although the weights on rational expectations differ significantly from unit.

In the forecaster level, just like panel A of Table 4, the weights on rational expectation ($\lambda_{1i}$) for GDP and industrial production are highly and positively correlated. However, other pairwise correlation coefficients are not significant, indicating forecasters present the same behavior or strategies only if they forecast GDP and industrial production growth rate. Moreover, among 41 participants for the Eurozone data, most of them are financial institutions, with only five research institutions and one industrial institution. Therefore, we just compare the behaviors between financial institutions and research institutions in the forecaster level. The result for the Eurozone data echoes the U.S. data, whereby financial institutions show slighter anchoring biases in GDP and industrial production forecasts than research institutions. In short, no matter whether using U.S. or Eurozone forecast data, the conclusions are very close in both aggregation and forecaster levels.

**Table 6**

**The Weights of Rational Expectation and Anchors using Eurozone Data**

| Weights | Macroeconomic forecasts | | | |
|---|---|---|---|---|
| | GDP | Industrial Production | Consumer Price Index | Unemployment |
| Rational expected value | 0.510 [0.489, 0.533] | 0.740 [0.679, 0.820] | 0.913 [0.870, 0.960] | 1.174 [1.072, 1.297] |
| Previous forecast | 0.409 [0.382 0.433] | 0.227 [0.145, 0.293] | 0.063 [0.015, 0.107] | -0.211 [-0.338, -0.105] |
| Distance to consensus | 0.081 [0.076, 0.086] | 0.032 [0.020, 0.045] | 0.024 [0.021, 0.027] | 0.037 [0.031, 0.043] |

*Note: The weights of rational expected value, previous forecast, and distance to consensus are derived via equation (4). Simulated 95% confidence intervals are presented in brackets.*

An interesting question now arises: if a forecaster participates in both U.S. and Eurozone forecasting surveys, is the behavior consistent beyond national boundaries? According to the datasets, twelve forecasters are involved in both the U.S. and Eurozone surveys.[8] To deal with the aforementioned question, this paper collates these forecasters' BLUPs for $u_{1i}$

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[7] *The authors heartily thank the reviewers' comments.*

[8] *Twelve forecasters include Barclays Capital, Citigroup, Credit Suisse, Econ Intelligence Unit, Global Insight, Goldman Sachs, JP Morgan, Lehman Brothers, Merrill Lynch, Morgan Stanley, Oxford Economics, and UBS.*

of each macroeconomic series in two datasets. A higher $u_{1i}$ indicates a higher $\gamma_{1i}$, lower $\lambda_{1i}$, and higher anchoring bias versus the average within a certain survey data. Table 7 reports the correlations of the weight on the rational expectation of each series among 12 forecasters.

**Table 7**

## Correlations of Weight of the Rational Expectation among 12 Forecasters

| | $GDP_E$ | $IP_E$ | $CPI_E$ | $UNE_E$ | $GDP_U$ | $IP_U$ | $CPI_U$ | $UNE_U$ |
|---|---|---|---|---|---|---|---|---|
| $GDP_E$ | | + | + | + | **+** | + | - | + |
| $IP_E$ | **+** | | - | + | + | + | + | + |
| $CPI_E$ | + | - | | + | + | **+** | + | **+** |
| $UNE_E$ | + | + | + | | + | + | - | - |
| $GDP_U$ | **+** | + | + | + | | **+** | + | + |
| $IP_U$ | **+** | + | **+** | + | **+** | | + | **+** |
| $CPI_U$ | - | + | + | - | + | + | | + |
| $UNE_U$ | + | + | **+** | + | + | **+** | + | |

*Note: Symbols + and – indicate the signs of the correlation coefficient are positive and negative, respectively. Signs of Pearson's and Spearman's rank correlation are shown under and above the diagonal, respectively. Subscripts E and U denote the forecasts for the Eurozone and U.S. datasets, respectively. Significant coefficients at the 0.1 significance level appear in enlarged and bold symbols.*

We use two dashed lines to separate this table into four rectangles. The meaning of the upper left and lower right rectangles is equivalent to panel A of Table 4, showing that these 12 forecasters who present a relatively higher anchoring bias in one series also provide higher biased forecasts for other series within each survey. The lower left and upper right rectangles of Table 7 show the correlations between different surveys by the Pearson and Spearman correlations, respectively. In terms of the lower left rectangle, almost all pairwise correlations are positive. Specifically, a forecaster who gives a higher anchoring biased forecast for Eurozone GDP growth will also report higher biased forecasts for U.S. GDP and industrial production growth rates. One more example is that the anchoring bias in U.S. industrial production forecasting is significantly positively correlated to Eurozone GDP and consumer price index forecasting. As a result, we conclude that those forecasters who both participate in U.S. and Eurozone surveys behave consistently beyond national boundaries.

In summary, using the proposed two-anchor heterogeneity anchoring model, we simultaneously estimate the consensus (aggregation) and forecaster (individual) level anchoring biases. Compared to existing anchoring models, the proposed model can deal with multiple anchors and fit the empirical data better. Furthermore, analyzing the anchoring effects on the forecaster level allow us to estimate each forecaster's behavior and to gain fruitful findings. This model also improves the consensus forecasts on macroeconomic forecasting. Because this model detects the efficient degree of each forecaster, we are able to reorganize the consensus forecast based on the top 5 efficient forecasters' reports. This provides a way to construct a "smart" conditional consensus rather than simple/unconditional consensus data. Additionally, based on the estimation at the forecaster level, we can easily adjust each forecaster's forecast toward the rational expectation value ($A_{t|h}$) and gain a rationally conditional consensus forecast.

## 5. Conclusion

Most studies in the existing literature have documented that macroeconomic forecasts do not follow the rational expectation hypothesis. Specifically, they usually attribute this problem to behavioral biases, such as anchoring and adjustment heuristics. This paper introduces a two-anchor heterogeneity anchoring model that estimates anchoring bias in the overall and individual forecaster levels at the same time.

In the case of the U.S. real GDP and industrial production, the results show that macroeconomic forecasts are anchored by previous forecasts and the consensus forecast, implying that forecasters usually adjust their belief too slowly and behave stubbornly. We also show that substantial and heterogeneous anchoring biases are found among forecasters. For instance, financial institutions present the slightest anchoring bias in their forecasts. In addition, we find that each forecaster's behavior is consistent for U.S. and Eurozone macroeconomic forecasts. These conclusions cannot be attained without the heterogeneity anchoring model.

It is noteworthy that our model assumes forecaster $i$'s behavior is consistent over time. One could argue that this assumption may hold for the short term, but fail over the long term. To deal with this concern, in future works we suggest constructing a three-level random coefficient model to incorporate the time effect. Moreover, this model is constructed based on a fixed-event forecasting target rather than a rolling-event target used in the existing model. Some macroeconomic series in the survey, such as 10-year government bond yield in the future three or twelve months, are a rolling-event target that may not be suitable for our model. We suggest establishing a more flexible model for future improvement in this area.

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## References

Albu, L.L. Jiménez, C.M. and Simionescu, M., 2015. The Assessment of Some Macroeconomic Forecasts for Spain using Aggregated Accuracy Indicators. *Romanian Journal of Economic Forecasting*, 18(2), pp.30-47.

Batchelor, R. and Dua, P., 1992. Conservatism and Consensus-Seeking among Economic Forecasters. *Journal of Forecasting*, 11(2), pp.169-181.

Beckers, S. Steliaros, M. and Thomson, A., 2004. Bias in European Analysts' Earnings Forecasts. *Financial Analysts Journal*, 60(2), pp.74-85.

Brown, L.D. Gay, G.D. and Turac, M., 2008. Creating a "Smart" Conditional Consensus Forecast. *Financial Analysts Journal*, 64(6), pp.74-86.

Bryk, A.S. and Raudenbush, S.W., 1992. *Hierarchical Linear Models: Applications and Data Analysis Methods*. CA: SAGE Publications.

Campbell, S.D. and Sharpe, S.A., 2009. Anchoring Bias in Consensus Forecasts and Its Effect on Market Prices. *Journal of Financial and Quantitative Analysis*, 44(2), pp.369-390.

Davies, A. and Lahiri, K., 1995. A New Framework for Analyzing Survey Forecasts using Three-Dimensional Panel Data. *Journal Econometrics*, 68(1), pp.205-227.

Ehrbeck, T. and Waldmann, R., 1996. Why are Professional Forecasters Biased? Agency versus Behavioral Explanations. *Quarterly Journal of Economics*, 111(1), pp.21-40.

Fujiwara, I. Ichiue, H. Nakazono, Y. and Shigemi, Y., 2013. Financial Markets Forecasts Revisited: Are They Rational, Stubborn or Jumpy? *Economics Letters*, 118(3), pp.526-530.

Hong, H. Kubik, J.D. and Solomon, A., 2000. Security Analysts' Career Concerns and Herding of Earning Forecasts. *RAND Journal of Economics*, 31(1), pp.121-144.

Ichiue, H. and Yuyama, T., 2009. Using Survey Data to Correct the Bias in Policy Expectations Extracted from Fed Funds Futures. *Journal of Money, Credit and Banking*, 41(8), pp.1631-1647.

Keane, M.P. and Runkle, D.E., 1990. Testing the Rationality of Price Forecasts: New Evidence from Panel Data. *American Economic Review*, 80(4), pp.714-735.

Lamont, O.A., 2002. Macroeconomic Forecasts and Microeconomic Forecasters. *Journal of Economic Behavior and Organization*, 48(3), pp.265-280.

Lawrence, M. Goodwin, P. O'Connor, M. and Önkal, D., 2006. Judgmental Forecasting: A Review of Progress over the Last 25 years. *International Journal of Forecasting*, 22(3), pp.493-518.

Muth, J.F., 1961. Rational Expectations and the Theory of Price Movements. *Econometrica*, 29(3), pp.315-335.

Nakazono, Y., 2012. Heterogeneity and Anchoring in Financial Markets. *Applied Financial Economics*, 22(21), pp.1821-1826.

Nakazono, Y., 2013. Strategic Behavior of Federal Open Market Committee Board Members: Evidence from Members' Forecasts. *Journal of Economic Behavior and Organization*, 93, pp.62-70.

Nordhaus, W.D., 1987. Forecasting Efficiency: Concepts and Applications. *Review of Economics and Statistics*, 69(4), pp.667-674.

Ottaviani, M. and Sørensen, P.N. 2006. The Strategy of Professional Forecasting. *Journal of Financial Economics*, 81(2), pp.441-466.

Stekler, H.O., 2007. The Future of Macroeconomic Forecasting: Understanding the Forecasting Process. *International Journal of Forecasting*, 23(2), pp.237-248.

Tversky, A. and Kahneman, D., 1974. Judgment under Uncertainty: Heuristics and Biases. *Science*, 185(4157), pp.1124-1131.

Welch, I., 2000. Herding among Security Analysts. *Journal of Financial Economics*, 58(3), pp.369-396.