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Bias, rationality and asymmetric loss functions☆

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HIGHLIGHTS

- Survey forecasts are often found to be biased at the individual level.
- Raises question if they are irrational or have asymmetric loss functions.
- I show that the finding is largely due to the pattern of missing observations.

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ABSTRACT

In the literature, it is a common empirical finding that survey based expectations are biased at the individual level. This has sparked a large debate if forecasters have asymmetric loss functions or the rationality assumption is violated. In this paper, I will show that the bias can in large part be explained by the pattern of missing observations in the survey. Thus the assumption of asymmetric loss functions is not required to satisfy the rationality assumption.

1. Introduction

As shown for example in Capistrán and Timmermann (2009) or Elliott et al. (2008), it is a common empirical finding that survey based expectations are biased at the individual level using symmetric rationality tests. This finding has sparked two separate strains of literature. The first strain of literature looks into specific models through which individual forecasters become optimistic and thus bias their forecasts.[1] The second strain empirically tests a specific functional form with an asymmetry parameter to test if forecasters would satisfy this specific functional form.[2]

At the same time, there are two important features of survey based forecasts, which will become important for the rest of the paper. First, there is a high correlation among forecasters as shown for example in Bürgi and Sinclair (2016) and second, there is a large number of missing observations in many surveys. In this paper, I will test if these two features can help explain the common finding.

2. Data

To test whether the high correlation among forecasters and the large share of missing observations can help explain the perceived bias in individual forecasts, I will mainly use the Bloomberg Survey for the US which is used very frequently by businesses to compare economic data releases to what economists had expected beforehand (e.g. Scotti (2013) or Chen et al. (2013)). As an additional cross check, I will also use the Survey of Professional Forecasters (SPF) which is often used in academic research (e.g. Carroll (2003) or Coibion and Gorodnichenko (2015)).

I will focus on the forecasts for CPI, GDP and unemployment at a quarterly frequency for various horizons starting with current

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[1] This literature includes for example Laster et al. (1999) or Ehrbeck and Waldmann (1996).

[2] Some of the earlier literature on this topic includes Christoffersen and Diebold (1997) or Batchelor and Peel (1998).

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Table 1
Simple bias across variables.

Horizon	Bloomberg			SPF		
	Unemployment	GDP	CPI	Unemployment	GDP	CPI
H0	−0.04	0.14	0.02	−0.04***	0.31**	−0.02
	(0.03)	(0.19)	(0.07)	(0.02)	(0.17)	(0.09)
H1	−0.07	0.28	0.00	−0.04	0.08	−0.11
	(0.06)	(0.22)	(0.39)	(0.05)	(0.23)	(0.17)
H2	−0.01	−0.44	0.14	−0.03	−0.04	−0.25
	(0.08)	(0.29)	(0.17)	(0.08)	(0.27)	(0.20)
H3	0.03	−0.56**	0.09	0.00	−0.13	−0.33
	(0.09)	(0.28)	(0.15)	(0.12)	(0.30)	(0.22)
H4	0.20	0.02	0.00	0.03	−0.09	−0.42*
	(0.26)	(0.28)	(0.06)	(0.16)	(0.31)	(0.23)

Standard errors in brackets.
* Significant at 10% level based on OLS errors (H0)/HAC errors (H1–H4).
** Significant at 5% level based on OLS errors (H0)/HAC errors (H1–H4).
*** Significant at 1% level based on OLS errors (H0)/HAC errors (H1–H4).

quarter forecasts up to four quarters ahead forecasts (H0–H4). The Bloomberg Survey uses year-over-year percentage changes for CPI, quarter-over-quarter annualized percentage change for GDP and levels for unemployment and starts for all horizons and variables in June 1993. For robustness, I also show the results for the SPF using the same three variables but start in Q1 1981.

For the actual values, I will use revised data for inflation and unemployment and the third release for GDP.

3. Methodology

To test whether forecasters are biased, I run a simple Holden and Peel (1990) regression assuming symmetric loss functions of the form

$$A_t - F_{t,t-i} = \alpha + \varepsilon_{t,t-i}; \qquad i = 0, 1, \dots, 4, \tag{1}$$

where $F_{t,t-i}$ is the simple average of all forecasts for period t, made in period $t-i$, A_t is the revised actual value and $\varepsilon_{t,t-1}$ is the error term, which is autocorrelated for $i > 0$. Due to this autocorrelation, I will use HAC errors for H1–H4. If forecasts are unbiased, the constant α should be not significantly different from zero.

At the individual level, I have to deal with missing values. Just estimating Eq. (1) without any adjustments may lead to overestimating the share of biased forecasters. This is due to gaps in the survey. For example, a forecaster might only have contributed to the survey during periods where most forecasters tended to over predict the underlying variable. This forecaster will be identified as being overall biased, even if this might only be due to the pattern of missing observations.

The most common approach taken in the literature to avoid this sample bias is to require individual forecasters to have made at least a minimum number of predictions. For example, Capistrán and Timmermann (2009) or Elliott et al. (2008) require forecasters to have made at least 30 and 20 predictions respectively. This requirement does not directly address the potential sample bias. However, one would assume that forecasters who made quite a few forecasts are less likely to only have predicted during periods when most forecasters tended to over (under) predict the underlying variable if the pattern of missing data is random. At the same time, this method substantially reduces the sample to institutions which could cause small sample biases.

To test whether the above approaches indeed reduce the number of biased forecasters, I also estimate Eq. (1) at the individual level, requiring forecasters to have contributed a varying number of forecasts. I report the share of biased forecasters based at the 5% level for OLS errors.[3] While I cannot directly measure the share of biased forecasters controlling for missing data, I can introduce a new approach to identify forecasters that are likely to be affected by the identification issue provided the simple average is unbiased over the entire sample. In particular, I can replace the forecasts made by a specific forecaster by the simple average. This will leave in place the pattern of missing observations, but replace the potentially biased forecasts with overall unbiased values. In addition, the simple average is likely to have the same systemic biases that cancel out over time due to the high correlation among forecasts. If I then estimate Eq. (1) based on this data, I either find that the simple average is biased for this specific sub sample or that it is unbiased. If it is unbiased, the biased forecasters are correctly identified. If it is biased, it is quite likely that it is simply due to the pattern of missing observations and he will likely be identified as biased. This is independent from him actually being biased or not. Reporting the share of forecasters for whose sample the simple average is biased as well can thus provide an upper bound to the share of forecasters being falsely identified as being biased.[4]

4. Empirical application

Table 1 presents the results from this regression. If the constant is positive, forecasters tend to over predict the underlying variable and if it is negative, forecasters tend to under predict the underlying variable.

The simple mean of all forecasters is broadly unbiased by this measure and thus one can conclude that the simple average is rational as well for those variables.[5] The exceptions are found in three cases. If the rationality assumption is to hold for this case as well, it would require asymmetric loss functions.

In Table 2, I report the share of biased forecasters for the Bloomberg survey and for the SPF for CPI forecasts. While it is the case that the numbers are broadly decreasing when the number or required contributions is increased, the decreases are not very large. What is more, the share of biased forecasters even increases sometimes when the number of required forecasts to be included is increased. For example, the 30 period restriction reduces the share of biased forecasters only by 5% for H2 and H4 relative to the

[3] Due to missing observations, HAC errors are not feasible.

[4] Provided the simple average is overall unbiased and assuming that the share of forecasters being biased is independent from the simple average being biased for their sample or not, this method could be used to directly estimate the share of biased forecasters in two steps. In the first step, one would check if the simple average is unbiased for a given forecaster. If it is biased, the forecaster is dropped from the analysis as a second step. If it is unbiased, one can check if the forecaster is biased and obtain the overall share of biased forecasters in the second step. This approach would cut the share of biased forecasters roughly in half as compared without this extra step.

[5] Similar results can be obtained using the Mincer and Zarnowitz (1969) approach, where the actual value is regressed on the forecast and a constant.