

# THE ANCHORING AND ADJUSTMENT BIAS IN FORECASTS OF U.S. EMPLOYMENT

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*The anchoring bias is prevalent in many areas of human behaviour, as auctioneers and car dealers know all too well. However, we assume that professional forecasters should be immune to its effects. In this essay, Sean Tong conducts an elegant and highly original econometric analysis of U.S employment forecasts to reveal substantial evidence of this bias. He concludes by outlining the truly tantalising prospects in the emerging field of behavioural finance.*

## Introduction

### FORECAST RATIONALITY

Given the extent to which they inform the activities of investors, expectations play a crucial role in the functioning of financial markets. When data releases differ from those that are forecasted, the effects on asset prices can be substantial (Campbell and Sharpe, 2009). It is of great interest, therefore, to investigate whether these forecasts are accurate – and the nature of the underlying bias if not.

It is typically assumed that expectations are formed rationally, and incorporate all relevant information appropriately. If this were the case, then the expectation error conditional upon the available information set should be a random variable with a mean of zero (Bofinger and Schmidt, 2003):

$$\xi_t = A_t - E_{t-1}[A_t | \Omega_{t-1}] , \quad \xi_t \sim (0, \sigma^2)$$

Tests of this hypothesis typically proceed by regressing the actual data release,  $A_t$ , on the forecasted value,  $F_t$ . If these forecasts are made rationally, then the result should be a zero intercept and slope coefficient of one:

$$A_t = \alpha + \beta_1 F_t + \varepsilon_t$$

This form of testing has a long history, and the majority of papers reject the null hypothesis of rationality with a slope estimate that exceeds one (Schirm, 2003). This suggests that

consensus estimates of future data are typically too cautious, though findings vary from market to market. At any rate, it seems that professional forecasters do not efficiently process the available information when making their estimates.

### **ANCHORING AND ADJUSTMENT**

Having established the biased nature of financial forecasts, can we make any suggestions as to the foundations of this irrationality? The answer may lie in the seminal work of Tversky and Kahneman (1974), who describe a pervasive heuristic known as anchoring and adjustment. In short, this refers to the tendency for individuals to give excessive consideration to an initial piece of information when making subsequent judgements. Adjustments made away from this “anchor” are typically insufficient, so estimates are biased towards it.

Tversky and Kahneman illustrated this by splitting participants into two groups that observed the outcome of a rigged spinning wheel. In one group the wheel was designed to stop at the number 10, while the other stopped at 65. The groups were then asked to estimate the percentage of African countries that are members of the UN – an assessment that should not have been influenced by the preceding outcome of the spinning wheel. In spite of this, participants in the second group gave significantly higher estimates than those in the first group, as their judgements were anchored to a higher initial value. Monetary reward does not reduce this bias, and neither does accountability (Brewer, Chapman, Schwartz and Bergus, 2007).

These findings have since been extended to a number of domains, using anchors of varying relevance (Ariely, Loewenstein and Prelec, 2003). The cause is simple: when a salient anchor is presented, it serves as the starting point for future estimates. Individuals then adjust away from this point until a plausible value is reached (Epley and Gilovich, 2006). Almost invariably, this point of plausibility does not deviate sufficiently from the initial anchor, and is different from the unbiased estimate that would have been produced if the anchor had not been provided.

Despite the financial and reputational importance of market forecasts, it is not implausible that analysts may produce estimates that are biased in this manner. Indeed, Northcraft and Neale (1987) have shown that experts are just as susceptible as amateurs to the anchoring heuristic, though they are less willing to admit it. The bias is particularly evident when the problem at hand is complex and opaque, as many financial estimates certainly are (Tversky and Kahneman, 1974).

Though the existing literature is relatively embryonic, the initial results are broadly supportive of this hypothesis. Evidence of an anchoring bias has been found in different markets, different countries, and across different periods of time. Bofinger and Schmidt (2003) looked at forecasts of the Euro/US Dollar exchange rate from 1999 to

2003, and found that these forecasts performed no better than a random walk. Significant evidence was found that these forecasts were influenced by past exchange rates; indeed, they were actually more strongly correlated with previous rates than with future ones.

Similarly, Cen, Hilary and Wei (2013) found evidence of anchoring in financial analysts' estimates of firm earnings-per-share (EPS). In this case, the anchor was found to be the forecasted EPS of industry peers. This meant that analysts underestimated the future earnings of firms with forecasted EPS higher than the industry EPS, as estimates were 'dragged' down towards this anchor. Anchoring was also found by Fujiwara, Ichiue, Nakazono and Shigemi (2012), who showed that the forecasts of Japanese equity analysts were biased towards their own past forecasts. In other words, when making estimates of stock prices at some fixed point in the future, analysts showed a tendency to stay close to the forecasts they had given previously – even if material information had arisen in the interim.

In each of these cases, the anchor is one of perceived importance. It is known that the reliance of individuals on the anchoring and adjustment heuristic is directly related to the salience of the potential anchor (Czaczkes and Ganzach, 1996). Thus, values such as past prices or past forecasts are likely to represent suitable anchors in the minds of analysts.

With that in mind, this paper uses Bloomberg survey data to investigate whether there is evidence of an anchoring and adjustment bias in consensus forecasts of monthly U.S. nonfarm payroll employment data. The proposed anchor will be past realisations of these employment figures. Nonfarm payroll data is analysed because of its great significance as a monthly release: it produces the largest interest rate reaction out of all macro-economic releases, and is currently of particular significance to Federal Reserve monetary policy (Balduzzi, Elton and Green, 2001).

This paper contributes to the existing literature in two ways: firstly by incorporating a consideration of forecast standard deviations into the analysis, and secondly by proposing an alternative to the testing procedure that has typically been used.

## The Data

The change in the number of U.S. civilians employed in nonfarm industries is typically announced on the first Friday of each month by the United States Department of Labor. Consensus forecasts and actual realisations of this change were retrieved from the Bloomberg Professional service.

Monthly figures are available from December 1996 to December 2013 inclusive, representing 205 observations. Consensus forecasts are drawn from a Bloomberg survey of market professionals, with a median of 75 participants over the period being considered. The mean, median, maximum, minimum, and standard deviation of these estimates are reported.

## EMPIRICAL APPROACH

The empirical approach is comprised of two separate tasks. Firstly, the nonfarm payrolls data will be examined to determine whether the associated forecasts are rational. If they are not, the second task is to determine whether this bias can be explained by the anchoring and adjustment heuristic.

### Test of Rationality

In keeping with previous literature, the accuracy of the forecasts will be assessed by regressing the actual monthly data on the median forecasted value:

$$A_t = \alpha + \beta_1 F_t + \varepsilon_t$$

If forecasts are rational, then an intercept of zero and a slope coefficient of one are to be expected. As identified by Aggarwal, Mohanty and Song (2012), this test will be biased towards rejection if the actual or forecasted series follow a unit root process – something that many papers have overlooked. Thus, it is necessary as a preliminary measure to test for stationarity of the series using an augmented Dickey-Fuller test.

### Test of Anchoring

Within the limited existing literature, a few different approaches to testing for evidence of anchoring in financial forecasts have been proposed. When fixed-horizon forecasts are considered, as is usually the case in the foreign exchange and equities markets, the authors typically make inferences from the nature of forecast revisions. When forecasts are made on a rolling basis, however, there are no revisions from which to make these inferences, so the problem must be tackled in another manner. The prototype in this regard is the work of Campbell and Sharpe (2009), who considered forecasts of eight macroeconomic variables between 1991 and 2006.

Campbell and Sharpe propose that forecasts are comprised of both an unbiased estimate and (potentially) some consideration of the previous data release:

$$F_t = \lambda E_{t-1}[A_t] + (1 - \lambda)A_{t-1}$$

If forecasts are truly unbiased then  $\lambda$  should equal one. On the other hand, anchoring would manifest itself in a  $\lambda$  of less than one. If the data “surprise” is defined as the difference between the actual release and the forecasted value, then by substitution it can be shown that the surprise is a function of the forecasted month-on-month change in nonfarm payrolls:

$$E_{t-1}[A_t - F_t] = \gamma(F_t - A_{t-1})$$

Campbell and Sharpe suggest that by estimating this regression, it is possible to infer the underlying value of  $\lambda$ . If the slope coefficient  $\gamma$  is positive, then this implies that  $\lambda$  is less than one – in other words, that forecasts are anchored to past data releases.

Though this method of testing has been used by several authors since Campbell and Sharpe, it should be noted that it makes a very strong assumption about the formation of forecasts: specifically, it assumes that forecasts are perfectly rational in the absence of anchoring. If this is not the case, then the test will be biased towards the null hypothesis. Intuitively, it can be seen that the slope of the proposed regression will be negative any time analysts incorrectly predict the direction in which next month's data will move relative to last month's: if the forecasted change is negative while the actual change is positive, then the surprise term will also be positive.

Thus, incorrect forecasts of the direction of the series are taken as evidence against anchoring, irrespective of how close the forecast is to the previous month's release. Taking even the extreme case where this month's forecast equals last month's realisation, the proposed regression would return a slope of zero and a failure to reject the null hypothesis. It is little surprise, therefore, that Campbell and Sharpe fail to find significant evidence that forecasts of U.S. nonfarm payrolls are anchored on the previous month's release.

Instead, this paper suggests an alternative approach to testing for the presence of anchoring in financial forecasts. The distribution of forecasts will first be compared to that of the actual data series so as to illustrate the pervasive herding and overconfidence that characterise these estimates.

Secondly, it will be shown that forecasts gravitate towards past data. To this end, the correlation between forecasts and previous releases will be compared with the correlation between the true data and its own past. The absolute deviation of forecasts from the previous month's release will also be compared to the absolute changes in the true series from month to month.

Finally, a regression will be run to test whether the data surprise is a function of the previous period's surprise and the change in the true series:

$$(A_t - F_t) = \alpha + \beta_1(A_{t-1} - F_{t-1}) + \beta_2(A_t - A_{t-1})$$

It is expected that both slope coefficients will be positive. In the first case this would imply that the forecast surprise is a positive function of the previous surprise – in other words, periods of excessive optimism or pessimism tend to follow one another. In the second case, this would suggest that pattern of forecast surprises is consistent with anchoring to past data.

If analysts' estimates exhibit anchoring, then increases in the true series should be associated with positive surprises, and decreases should be associated with negative surprises. Taken in isolation, none of the previous tests would be sufficient to conclude that analysts are susceptible to the anchoring and adjustment bias. As a collective, however, it is hoped that the weight of evidence will be suitably consistent so as to support or reject the underlying hypothesis.

**RESULTS**

**Test of Rationality**

The augmented Dickey-Fuller tests rejected the null hypothesis of unit root and non-stationarity for the actual data series ( $Z = -8.12, p < 0.001$ ) and the median forecast series ( $Z = -3.79, p < 0.01$ ).

Having established the stationarity of these series, the regression of actual non-farm payroll data on the median forecasted level was run. The Breusch-Pagan test suggested that heteroscedasticity may be present in the data ( $X^2 = 7.52, p < 0.01$ ), so robust standard errors were used. The results are presented in Table 1.

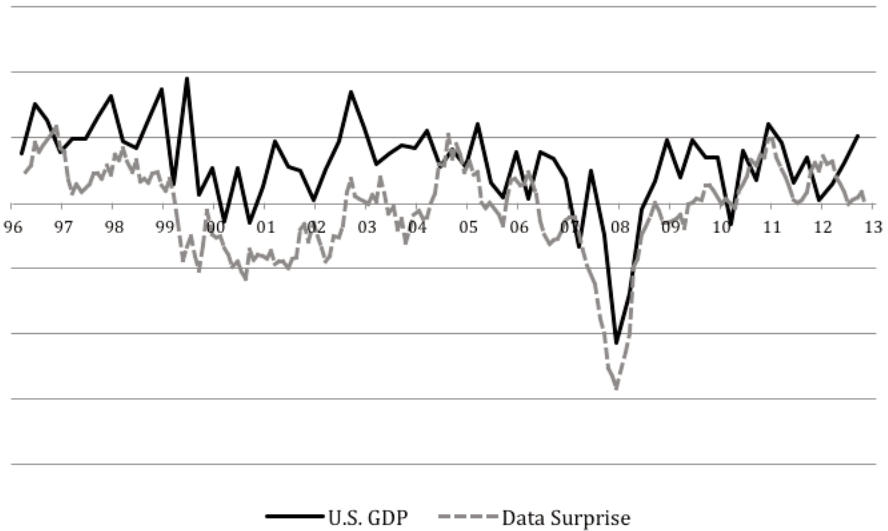
| $Y = A_t$ | Coefficient | Standard Error | <i>t</i> -statistic | <i>p</i> -value |
|-----------|-------------|----------------|---------------------|-----------------|
| $F_t$     | 1.1826      | 0.0512         | 23.10               | < 0.001         |
| Constant  | -25.0414    | 9.3265         | -2.68               | < 0.01          |

*Table 1: Regression of actual data on median forecast*

Consistent with previous research, the null hypothesis of rational forecasts was overwhelmingly rejected at the 5% significance level. The slope coefficient exceeds one, as Schirm (2003) suggested was typical. The next task is to establish whether this bias is consistent with anchoring and adjustment, as hypothesised.

**Tests of Anchoring**

A brief inspection of the available data is enough to suggest that some degree of forecast inertia is present. Data surprises seem highly persistent: during the financial crisis, for instance, analysts' forecasts were overly optimistic for sixteen consecutive months. Indeed, the relationship between average forecast errors and GDP is quite striking, as illustrated in Figure 1.



*Figure 1: Average data surprise vs. quarterly GDP*

The persistent periods of optimism and pessimism depicted in this chart are a reflection of the herding that is prevalent in analysts' estimates. The distribution of estimates across the many analysts who are surveyed by Bloomberg is very narrow, and implies a degree of confidence that is not warranted by the available information set.

To illustrate this, Table 2 reports the percentage of monthly observations for which the associated forecast error is greater than the indicated number of survey standard deviations. Half of the consensus forecasts were more than two standard deviations away from the true release, and a third were greater than three standard deviations away. Incredibly, almost 40% of actual nonfarm payroll releases were larger than the maximum estimate or smaller than the minimum estimate in the survey that month. If nothing else, this illustrates the "strength in numbers" mentality of financial analysts.

| Size of Forecast Error            | Percentage of Observations |
|-----------------------------------|----------------------------|
| <i>&gt; 1 standard deviation</i>  | 67.20%                     |
| <i>&gt; 2 standard deviations</i> | 50.00%                     |
| <i>&gt; 3 standard deviations</i> | 33.33%                     |
| <i>&gt; 4 standard deviations</i> | 22.04%                     |
| <i>&gt; 5 standard deviations</i> | 15.59%                     |
| <i>Outside max-min range</i>      | 38.83%                     |

*Table 2: Forecast errors and standard deviations*

As well as being biased, therefore, it is clear that analysts' forecasts can often deviate substantially from the true change in unemployment. Are these deviations consistent with reliance on the anchoring and adjustment heuristic? In order to test this, the relationship between the true, forecasted and previous values were analysed.

It was first found that analysts' forecasts are more highly correlated with the previous month's data release ( $r = 0.8650$ ) than the actual data series was with its own past ( $r = 0.7136$ ). This difference was significant at the 5% level ( $Z = 4.69, p < 0.001$ ), suggesting that the relationship between forecasts and previous realisations is stronger than would be the case if these forecasts were unbiased.

The second consideration was the extent to which analysts' estimates deviate from the previous month's release. Comparing the mean absolute value of this deviation ( $F_t - A_{t-1}$ ) with the mean absolute change in the data series itself ( $A_t - A_{t-1}$ ), it was found that analysts' forecasts are too closely tied to past changes in employment ( $\mu_1 = 90.5, \mu_2 = 109.9, t = 2.22, p < 0.05$ ). In other words, the estimates seem to gravitate towards the observable data rather than deviating to the extent that the true series does.

The final aspect of the testing procedure is to regress the current data surprise on the previous month's surprise and the month-on-month change in nonfarm payrolls, as described previously. Heteroscedasticity was once again deemed to be a concern ( $X^2 = 33.78, p < 0.001$ ), so robust standard errors were used. The results are presented in Table 3.

| $Y = (A_t - F_t)$     | Coefficient | Standard Error | <i>t</i> -statistic | <i>p</i> -value |
|-----------------------|-------------|----------------|---------------------|-----------------|
| $(A_{t-1} - F_{t-1})$ | 0.5971      | 0.0621         | 9.61                | < 0.001         |
| $(A_t - A_{t-1})$     | 0.5801      | 0.0838         | 6.92                | < 0.001         |
| <i>Constant</i>       | -3.6117     | 4.7838         | -0.75               | > 0.05          |

Table 3: Regression of surprise on previous surprise and monthly change

The model was significant at the 5% level ( $F = 46.22, p < 0.001, R^2 = 0.60$ ), and the Variance Inflation Factor values were substantially below those that would indicate a multicollinearity problem. As expected, both slope estimates were found to be significantly positive.

The relationship between the current surprise and the previous one is consistent with the persistence of forecast errors that was previously depicted in Figure 1. It implies that positive surprises follow one another, as do negative surprises. This is a reflection of the apparent inertia of analysts' expectations, as they are slow or unwilling to incorporate new information.

The positive relationship between the surprise term and the change in the true series is also consistent with anchoring. It suggests that forecasts are typically too low



when this month's change in nonfarm payrolls is greater than that of the previous month, and are too high when the series is declining. In conjunction with the previous findings, this suggests that analysts' estimates are biased towards the previous realisation.

## **Conclusion**

Consistent with the existing literature, it has been found that professional forecasts of U.S. employment data are significantly biased. This bias is such that estimates do not deviate sufficiently from past observations, and their error terms are a function of the observable data. In both these respects, the evidence is supportive of the hypothesis that financial analysts are susceptible to the anchoring and adjustment heuristic, as described by Kahneman and Tversky.

Though the empirical testing of this hypothesis is complex, the weight of evidence presented here is certainly consistent with it. In isolation, the alternative tests described in this paper are insufficient to conclude the precise form and foundation of the forecasting bias; in conjunction, however, they certainly provide a basis for such a claim. Given the complexity of the problem, there is little doubt that the appropriate testing methodology could be further refined and modified. Future research may concern itself with the possibility of alternative anchors, such as a moving average of past data realisations or the forecasts of peers.

It is also surprising that the existing studies focus almost exclusively on the relationship between data forecasts and the 'true' values that are initially announced. Given that these initial releases are often mere estimates that are subsequently revised and updated by the relevant institutions, it would be interesting to investigate whether forecasts are similarly biased with respect to these more final data announcements.

As one of the more recent endeavours within behavioural finance (itself a relatively new field), the search for causes of expectation biases is far from complete. Indeed, there is much still to be discovered: as new concepts and methods are unearthed, it will be exciting to see how these are applied to long-standing issues within the study of finance as a whole.

## References

Aggarwal, R., Mohanty, S., and Song, F., 1995. Are survey forecasts of macroeconomic variables rational?. *The Journal of Business*, 68(1), pp.99-119.

Ariely, D., Loewenstein, G., and Prelec, D., 2003. Coherent arbitrariness: stable demand curves without stable preferences. *The Quarterly Journal of Economics*, 118(1), pp.73-106.

Balduzzi, P., Elton, E. J., and Green, T. C., 2001. Economic news and bond prices: evidence from the U.S. Treasury market. *Journal of Financial and Quantitative Analysis*, 36(4), pp.523-543.

Bofinger, P. and Schmidt, R., 2003. On the reliability of professional exchange rate forecasts: an empirical analysis for the €/US-\$ rate. *Financial Markets and Portfolio Management*, 17(4), pp.437-449.

Brewer, N. T., Chapman, G. B., Schwartz, J. A., and Bergus, G. R., 2007. The influence of irrelevant anchors on the judgments and choices of doctors and patients. *Medical Decision Making*, 27, pp.203-211.

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.

Cen, L., Hillary, G., and Wei, K. C. J., 2013. The role of anchoring bias in the equity market: evidence from analysts' earnings forecasts and stock returns. *Journal of Financial and Quantitative Analysis*, 48(1), pp.46-76.

Czaczkes, B., and Ganzach, Y., 1996. The natural selection of prediction heuristics: anchoring and adjustment versus representativeness. *Journal of Behavioral Decision Making*, 9, pp.125-139.

Epley, N., and Gilovich, T., 2006. The anchoring-and-adjustment heuristic. *Psychological Science*, 17(4), pp.311-318.

Fujiwara, I., Ichiue, H., Nakazono, Y., and Shigemi, Y., 2012. Financial markets forecasts revisited: are they rational, herding or bold?, *Globalization and Monetary Policy Institute Working Paper 106*, Federal Reserve Bank of Dallas.

Northcraft, G. B., and Neale, M. A., 1987. Experts, amateurs and real estate: an anchor-

ing-and-adjustment perspective on property pricing decisions. *Organizational Behavior and Human Decision Processes*, 39, pp.84-97.

Schirm, D. C., 2003. A comparative analysis of the rationality of consensus forecasts of U.S. economic indicators. *The Journal of Business*, 76(4), pp.547-561.

Tversky, A. and Kahneman, D., 1974. 'Judgment under uncertainty: heuristics and biases'. *Science*, 185(4158), pp.1124-1131.

Aggarwal, R., Mohanty, S., and Song, F., 1995. Are survey forecasts of macroeconomic variables rational?. *The Journal of Business*, 68(1), pp.99-119.

Ariely, D., Loewenstein, G., and Prelec, D., 2003. Coherent arbitrariness: stable demand curves without stable preferences. *The Quarterly Journal of Economics*, 118(1), pp.73-106.

Balduzzi, P., Elton, E. J., and Green, T. C., 2001. Economic news and bond prices: evidence from the U.S. Treasury market. *Journal of Financial and Quantitative Analysis*, 36(4), pp.523-543.

Bofinger, P. and Schmidt, R., 2003. On the reliability of professional exchange rate forecasts: an empirical analysis for the €/US-\$ rate. *Financial Markets and Portfolio Management*, 17(4), pp.437-449.

Brewer, N. T., Chapman, G. B., Schwartz, J. A., and Bergus, G. R., 2007. The influence of irrelevant anchors on the judgments and choices of doctors and patients. *Medical Decision Making*, 27, pp.203-211.

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.

Cen, L., Hillary, G., and Wei, K. C. J., 2013. The role of anchoring bias in the equity market: evidence from analysts' earnings forecasts and stock returns. *Journal of Financial and Quantitative Analysis*, 48(1), pp.46-76.

Czaczkes, B., and Ganzach, Y., 1996. The natural selection of prediction heuristics: anchoring and adjustment versus representativeness. *Journal of Behavioral Decision Making*, 9, pp.125-139.