ANCHORING BIAS IN CONSENSUS FORECASTS AND ITS EFFECT

ON MARKET PRICES*

Sean D. Campbell　　　　**Steven A. Sharpe**
202.452.3760　　　　　　202.452.2875

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Previous empirical studies that test for the "rationality" of economic and financial forecasts generally test for generic properties such as bias or autocorrelated errors, and provide limited insight into the behavior behind inefficient forecasts. In this paper we test for a specific behavioral bias -- the anchoring bias described by Tversky and Kahneman (1974). In particular, we examine whether expert consensus forecasts of monthly economic releases from 1990-2006 are systematically biased toward the value of previous months' releases. We find broad-based and significant evidence for such behavior, which in some cases results in sizable predictable forecast errors. Then, to investigate whether the market participants anticipate the bias, we examine interest rate reactions to economic news. We find that bond yields react only to the residual, or unpredictable, component of the surprise and not to the predictable component of the forecast error induced by anchoring, suggesting that market participants anticipate the bias embedded in expert forecasts.

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I.   Introduction

Professional forecasts of macroeconomic releases play an important role in markets, informing the decisions of both policymakers and private economic decision-makers. In light of this, and the substantial effects of data surprises on asset prices, we might expect professional forecasters to avoid making systematic prediction errors. Previous research has approached this topic by testing time series of forecasts for "rationality", an approach with a fairly long and not entirely satisfying history. Generally, such studies focus on testing for a few generic properties such as bias or autocorrelation in errors, yielding mixed results that provide limited insight into the nature of apparent bias. In addition, such studies provoke – but do not answer – the question: What are the implications of non-rational forecasts for market prices?   In particular, where persistent forecast biases exist, do the users of these forecasts take predictions at face value when making investment decisions or dispensing advice? Or do they see through the biases, which would make such anomalies irrelevant for market prices?

As noted by Tversky and Kahneman (1974), psychological studies of forecast behavior find that predictions by individuals are prone to systematic biases, which induce large and predictable forecast errors. One widely-documented form of systematic bias that influences predictions by non-professionals is "anchoring," or choosing forecasts that are too close (anchored) to some easily observable prior or arbitrary point of departure.   Such behavior results in forecasts that underweight new information and can thus give rise to predictable forecast errors.

We investigate whether anchoring influences expert consensus forecasts collected in surveys by Money Market Services (MMS) between 1991 and 2006. MMS is a widely-used source of forecasts in financial markets, which have also been subjected to tests of forecast efficiency (Aggarwal, et al., 1995; and Schirm, 2003). Our study focuses on monthly macroeconomic data releases that were previously found to have substantial effects on market interest rates (Balduzzi, et. al., 2001, Gurkaynak, et al, 2005; Goldman Sachs, 2006). We test a hunch – born of years spent monitoring data releases and market reactions – that recent past values of the data release act as an anchor on expert forecasts. For instance, in the case of retail sales, we investigate whether the forecast of January sales growth tends to be too close to the previously-released estimate of December sales growth.

We find broad-based and significant evidence that professional consensus forecasts are anchored towards the recent past values of the series being forecasted. The degree and pattern of anchoring we measure is remarkably consistent across the various data releases. Moreover, the influence of the anchor in some cases is quite substantial. We find that the typical forecast is weighted too heavily towards its recent past. These results thus indicate that anchoring on the recent past is a pervasive feature of expert consensus forecasts of economic data releases known to move market interest rates.

These findings imply that the forecast errors or "surprises" are at least partly predictable. Since data surprises measured in this way have significant financial market effects, one must wonder whether these effects represent efficient responses to economic news. If market participants simply take consensus forecasts at face value and treat the entire surprise as news, then interest rate reactions to data releases would display greater volatility, relative to a world with rational forecasts.

Our second major contribution thus involves assessing whether anchoring bias in economic forecasts affects market interest rates. Specifically, do interest rates respond to the predictable, as well as the unpredictable, component of the surprise? To answer this question, we decompose the surprise in each data release into a predictable component induced by anchoring, plus a residual that can be interpreted as the true surprise to the econometrician. We then test whether market participants anticipate the bias by regressing the change in the two-year (or ten-year) U.S. Treasury yield in the minutes surrounding the release onto these two components of the forecast error.

We find that the bond market reacts strongly and in the expected direction to the residual, or unpredictable, component of the surprises. On the other hand, interest rates do not appear to respond to the predicted piece of the surprise induced by anchoring. The results are similar for almost every release we consider. We thus conclude that, by and large, the market looks through the anchoring bias embedded in expert forecasts, so that this behavioral bias does not induce interest rate predictability or excess volatility.

The remainder of this paper is organized as follows. Section II lays out the conceptual and empirical framework for the analysis. Section III describes basic properties of the data releases and MMS consensus forecasts. Section IV estimates the proposed model of anchoring bias. Section V tests whether the anchoring bias affects the response of market interest rates to data releases. Section VI concludes.

II. Forecast Bias, Anchoring, and Research Design

A. Rationality tests and anchoring

Many psychological and behavioral studies find that, in a variety of situations, predictions by individuals systematically deviate too little from seemingly arbitrary reference points, or anchors, which serve as starting points for those predictions. As a result, those predictions underweight the forecasters' own information.[1] Tversky and Kahneman (1974) define anchoring to occur when "people make estimates by starting from an initial value that is adjusted to yield the final answer … adjustments are typically insufficient … [and] different starting points yield different estimates, which are biased towards the initial values." In this section, we characterize the relation between traditional tests of forecast rationality and our proposed model of anchoring.

Testing whether macroeconomic forecasts have the properties of rational expectations has a fairly long tradition. A variety of early studies (e.g., Mullineaux, 1978; Zarnowitz, 1985) investigated whether consensus macroeconomic forecasts were consistent with conditional expectations as measured in linear regressions on available data. Among the most recent studies, Aggarwal, Mohanty and Song (1995) and then Schirm (2003) applied this line of investigation to surveys of forecasts compiled by MMS.

While the more recent studies brought some new methodological considerations to the table, they have largely followed the basic formulation of this line of research. In particular, the typical analysis involves running regressions with the actual (realized) value of the data release, A_t, as the dependent variable on the most recent forecast, F_t, as the independent variable; that is,

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[1] One example where such behavior had actual financial ramifications is provided by Northcraft and Neale (1987), who find that professional real estate agents anchor their forecast of a home's selling price to the listing price.

$$A_t = \beta_1 F_t + \varepsilon_t. \qquad (1)$$

The hypothesis of rationality holds that β_1 is not significantly different from unity and the errors are not autocorrelated.[2] Broadly speaking, the results from such regressions tend to be mixed, with rationality being rejected in a substantial fraction of the tests. Both Aggarwal et al. (1995) and Schirm (2003) find that, when rationality is rejected, it is almost always due to a slope coefficient β_1 greater than unity. As an example of a strong rejection, Schirm (2003) estimates a slope coefficient of 1.62 in equation (1) for Durable Goods Orders, which suggests that the MMS consensus predictions are too cautious; that is, errors would be reduced if forecasted deviations (from average growth) were magnified 62 percent.

If forecasts could be improved by systematically magnifying them, the implication would be that forecasters are too slow or cautious when incorporating new information. Indeed, in a different setting, Nordhaus (1987) provides direct evidence of forecast inertia -- that forecasters "hold on to their prior view too long." That inference is drawn from an analysis of fixed-event forecasts of GDP growth, which shows that forecast *revisions* tend to be highly serially correlated.[3] That setting differs from the more conventional time series with rolling-event forecasts, including the MMS forecasts that we analyze.

If forecasters in the standard rolling-event setting put too little weight on new information, this raises the question: What is the prior, or anchor, on which forecasters place too much weight? One plausible scenario is that forecasters treat the value of the previous month's data as the most salient single piece of information that has come to the fore in the

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[2] These studies also typically include a constant in equation (1). Since we focus only on the conditional (i.e. time varying) component of the bias, for sake of simplicity we omit the constant term from the notation here and in later equations, but a constant is included in all the regressions.

[3] Nordhaus (1987), for example, finds that one-step-ahead professional forecasts, for some macroeconomic variables are anchored to the previous month's two step ahead forecast.

time between their previous-month and current-month forecasts. If so, then the previous month's realization might be treated as a starting point, or anchor, for the current forecast.[4] More generally, forecasters might place some weight on a few lags of the release, particularly when the forecasted series tends to bounce around from month to month (i.e., exhibits negative autocorrelation). At the extreme, forecasters might conceivably anchor their forecast on a long-run average value for the series.

To develop this set of ideas more formally, consider the following transformation of equation (1), whereby the forecast is subtracted from both sides. This yields an alternative version of the basic rationality test, where the forecast error or "surprise" (S) is regressed on the forecast:

$$S_t \equiv A_t - F_t = \beta F_t + \varepsilon_t, \tag{2}$$

Now, the canonical test of rationality examines whether the slope coefficient is significantly different from zero. Under our alternative hypothesis, we look for evidence in favor of the following model of forecast anchoring:

$$F_t = \lambda E[A_t] + (1-\lambda)\bar{A}_h, \tag{3}$$

where $E[A_t]$ represents the forecaster's unbiased prediction of next month's release and $\bar{A}_h$ represents the average value of the forecasted series over the previous h months. If $\lambda < 1$, then we would conclude that consensus forecasts are anchored to the recent past. Using the implication from equation (2) that $E[A_t] = E[S_t] + F_t$ and substituting for $E[A_t]$ in (3) yields an expression for expected surprise: $E[S_t] = \gamma(F_t - \bar{A}_h)$, where $\gamma = (1-\lambda)/\lambda$. This suggests the following regression test for anchoring bias:

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[4] Frankel and Froot (1987), for example, find evidence that professional exchange rate forecasts are anchored towards the current level of the exchange rate.

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$$S_t = \gamma\left(F_t - \overline{A}_h\right) + \varepsilon_t \qquad (4)$$

A positive coefficient estimate would imply that consensus forecasts are systematically

biased toward lagged values of the release (and $\lambda < 1$ in equation (3)).

As stated at the outset, such a finding might be interpreted as evidence in favor of the

Tversky and Kahneman (1974) "adjustment and anchoring" heuristic. However, it bears

emphasizing that a finding of forecast bias would not constitute unambiguous evidence that

forecasters are irrational or that they are inefficient data processors. Absent an analysis of

the incentive structure they face, we cannot rule out the possibility that the behavior reflects

their optimal response to a game among forecasters and the consumers of those forecasts.

For instance, Ottavani and Sorensen (2006) produce a model in which forecasters might find

it optimal to issue forecasts that underweight their own private signal while overweighting a

common prior. Moreover, actual incentive structures might give rise to non-quadratic loss

functions which would cause optimal forecasts to deviate from conditional expectations. In

our empirical analysis, we give some consideration to the robustness of our results to a non-

quadratic loss function.

B. Market relevance of economic data and consensus forecasts

Along a separate line of research, several studies have analyzed the news content of

data releases by measuring the surprise component of a release as the discrepancy between

its actual value and the consensus forecast from MMS Services. Balduzzi, Elton and Green

(2001) as well as Gurkaynak, Sack and Swanson (2005) study the impact of macroeconomic

news on interest rates using MMS consensus forecasts to gauge surprises. Aggarwal and

Schirm (1992) use the deviation between macroeconomic releases and consensus MMS

forecasts to investigate the reaction of exchange rates to innovations in the U.S. trade balance. Andersen, Bollerslev, Diebold and Vega (2003) examine the effects of this and other macroeconomic news on exchange rates. In each study, these surprises are shown to have large and significant effects on financial market prices.

In light of the strength of financial market reactions to surprises measured in this way, it would be of both academic and practitioner interest to understand how systematic biases in economic forecasts might influence financial market reactions to news. Do financial market prices react to the predictable component of the surprise, or forecast error, arising from anchoring bias in the same way that they react to the residual component of the surprise? Or do market participants anticipate the bias, and thus respond only to the residual component of the surprise?

We study this question by estimating second-stage event-study regressions in which the change in the 2-year or 10-year Treasury yield around the time of the release is regressed on the two components of equation (4):

$$\Delta i_t = \delta_1 S_t^e + \delta_2 \left(S_t - S_t^e \right) + v_t, \qquad\qquad (5)$$

where $S_t^e \equiv E(S_t)$ refers to the forecasted component of the surprise identified from OLS estimates of equation (4). If financial markets respond to the forecasted component of the surprise induced by anchoring in the same way that they respond to the residual, or unforecasted component, then we should find $\delta_1 = \delta_2$. Alternatively, if financial markets "see through" the bias in forecasts induced by anchoring, then we would expect that $\delta_1 = 0$. These two alternative hypotheses are explored in section V.

III.   Data and Sample Characteristics

A. Macroeconomic Releases, Forecasts and Surprises

Our analysis covers eight macroeconomic data releases: Consumer Confidence, Consumer Price Index (CPI), Durable Goods Orders, Industrial Production, ISM Manufacturing Index, New Homes Sales, and Retail Sales.[5] In two cases, we also examine the consensus forecasts of a key subcomponent of the top-line figure in the release -- CPI ex-Food and Energy (Core CPI) and Retail Sales ex-Auto. In both cases, these data are released simultaneously with the top line release and are considered by market participants to contain more value-relevant news than the top line.

Table I lists each release, the beginning of our sample period, the timing of the release and the reporting convention, that is, whether the release is reported as a level, a change, or a percent change. While our last observation is March 2006 in each case, the starting date varies between September 1992 and June 1996, determined by the availability of the forecast data. For each release, we define the consensus forecast, F_t, as the mean forecast from the Money Market Services (MMS) survey.[6] The surprise is measured as the difference between the release and the associated MMS mean forecast.

We focus on these eight key releases because of their previously identified and important influence on interest rate markets. Specifically, Balduzzi, Elton and Green (2001) show that each of these releases has statistically significant and economically important effects on bond yields at both the two-year and ten-year maturity; specifically, surprises explain 20 to

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[5] Previously, the Institute for Supply Management (ISM) index was known as the National Association of Purchasing Managers (NAPM) index.

[6] We also looked at the median MMS forecasts but found results to be insensitive to this choice.

60 percent of the variability in the movements of the two-year and ten-year Treasury yields in the moments surrounding each release.

In Table II we present some summary statistics for each release (A), its associated MMS forecast, (F), and forecast surprise (S). For each variable we report the sample mean, μ, standard deviation, σ, and the sum of the autoregressive coefficients from a fifth order auto-regression, $\sum \rho_j$, a measure of persistence.[7] Releases expressed in levels appear at the top of Table II, followed by the remaining releases. The mean surprise, reported in Table II, is typically close to zero, suggesting that the forecasts are unconditionally unbiased. Also, the standard deviations of the forecasts are in every case smaller than that of the releases. As one would hope, the standard deviation of the surprises is typically smaller than that for the underlying release, with Core CPI being the only exception. Not surprisingly, for data releases that are expressed in levels, which have a high degree of persistence, surprises are a lot less variable than the underlying release.

The persistence properties of the variables listed in Table II are informative about the conditional properties of the MMS forecasts. In the case of the level variables, both the release and the forecast are highly persistent. The remaining releases and forecasts show small to moderate degrees of persistence, with the exception of Durable Goods Orders and Retail Sales. These releases exhibit a substantial and statistically significant degree of negative serial correlation; for Durable Goods Orders $\sum \rho_j = -2.08$, while for Retail Sales $\sum \rho_j = -1.41$.[8,9] However, neither of the associated forecasts exhibits a significant

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[7] Lag lengths between two and twelve were considered in the construction of $\sum \rho_j$. The results reported in Table II are not sensitive to this choice.

amount of negative serial correlation, and thus the negative serial correlation of the data

shows up in the surprises. Interestingly, these are not the only releases where the surprise

exhibits significant negative serial correlation. The surprise is negatively serially correlated

in every case except for the ISM release. It is also statistically significant in the case of the

CPI, New Home Sales, Retail Sales and Retail Sales ex-Auto, suggesting that the MMS

forecasts are conditionally biased.

The finding that the serial correlation in surprises tends to be negative rather than

positive suggests that serial correlation in surprises could be due to the anchoring of

forecasts on the most recent lagged value of the release. This can be illustrated by a simple

example in which the release is serially uncorrelated. Suppose forecasts were strongly

anchored toward the recent past – in particular, that the current forecast is set equal to the

lagged actual value, $F_t = A_{t-1}$. In this simplified setting it is easy to see that,

$$E\left[\left(A_t - F_t\right)\left(A_{t-1} - F_{t-1}\right)\right] = E\left[\left(A_t - A_{t-1}\right)\left(A_{t-1} - A_{t-2}\right)\right] = -Var(A_t) - \left(E\left[A_t\right]\right)^2, \qquad (6)$$

that is, successive surprises will be negatively correlated.

Finally, before moving on to the main results, we note the unusual empirical

properties of the Core CPI and its associated forecasts. As shown in Table II, the Core CPI

is by far the least variable of all releases; that is, both the release and the associated surprise

are significantly less volatile than any other release or surprise. Over our sample period, the

MMS forecast of Core CPI is nearly constant, equal to 0.2% (monthly inflation rate) in 117

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[8] In each case the modulus of the inverse roots of the estimated auto-regression are all smaller than one.

[9] In the case of Retail Sales the high degree of negative serial correlation can be partly explained by the presence of a few outliers occurring in the wake of 9/11/2001. In October, Retail Sales fell by 2.4%. In November, Retail Sales increased by 7.1% and in December Retail Sales fell by 3.7%. Removing these periods increases the estimate of $\sum \rho_j$ to -0.55 which is statistically significant at all conventional significance levels. In the case of Durable Goods Orders removing these three months only increases the point estimate of $\sum \rho_j$ to -1.94.

out of 176 months. Thus, in the case of the Core CPI, this sample period seems poorly

suited to conducting our tests. Still, we include the Core CPI release in our analysis because

Core CPI surprises have substantial interest rate effects, which might otherwise be

spuriously attributed to top line CPI surprises.

B. Interest Rate Reactions to Macroeconomic News Releases

We measure the reaction of the two-year and ten-year U.S. Treasury yield in the

moments surrounding each macroeconomic release using quote data from Bloomberg. For

each release and maturity we extract the quoted yield from a trade occurring both five

minutes prior and ten minutes after the release. The interest rate reaction is defined as the

difference between the post- and pre-release quote. If no quote exists five minutes before

(ten minutes after) the release, we use the last quote available between five and thirty

minutes before the release (the first quote available between ten and thirty minutes after the

release).[10]

In Table III we display the mean, standard deviation and the sum of autoregressive

coefficients of the interest rate reactions. The average interest rate response is always close

to zero, which is consistent with the near-zero mean of the associated surprises. The

standard deviations of the interest rate reactions provide some information about how much

releases affect interest rates. Consistent with the findings of Gurkaynak, et. al., (2005) the

standard deviations of the two-year and ten-year yield change are roughly similar. Also,

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[10] In unusual cases where no quote exists 30 minutes preceding the release, no yields are recorded, resulting in a missing value for the associated interest rate reaction. The number of missing values per interest rate reaction series is typically between 2 and 5. The release associated with the most missing interest rate reactions is New Home Sales. In this case there are 15 missing values for the two year reaction and 14 missing values for the ten year reaction.

consistent with the findings of Balduzzi, Elton and Green (2001) the Nonfarm Payroll

Employment release produces the largest interest rate reactions.

Looking at the persistence properties of the interest rate reactions indicates that the

degree of serial correlation in the interest rate responses is typically small, ranging from -0.3

to 0.3 in most cases. In the case of Consumer Confidence, ISM, Durable Goods Orders and

Industrial Production, however, the serial correlation is statistically significant, which

suggests that interest rate reactions might be partly predictable. In what follows we examine

whether any of the apparent predictability in these reactions can be traced to predictability of

the associated surprises.

IV. Estimates of Anchoring Bias

As discussed in section II, our test for anchoring bias in MMS consensus forecasts is

based on the regression

$$S_t = \gamma \left(F_t - \overline{A}_h \right) + \varepsilon_t \tag{7}$$

 where the dependent variable is the realized forecast error (or "surprise") and the

independent, or prediction, variable equals the difference between the forecast and the

hypothesized anchor,[11] Implementation requires specifying the history of release values (h)

used in our estimate of the anchor, $\overline{A}_h$. We focus on two cases; in the first, $\overline{A}_h$ is simply the

lagged value of the release ($h = 1$), while in the second, it equals the average value of the

release over the lagging three months ($h = 3$).[12] A positive value of the coefficient γ would

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[11] Note that while equations (4) and (7) do not include a constant term, we always include a constant term, γ_0,
in its empirical implementation.

constitute evidence that forecast errors are biased in a predictable fashion that is consistent with anchoring.

Before proceeding, it should be noted that this regression has some fairly close antecedents in the literature on rationality tests. In particular, equation (7) in Aggarwal, et. al, (1995) would look very similar if the forecast were subtracted from both sides of their equation. Otherwise, their regression differs in only two respects: (i) they effectively include only one lagged value of the release, multiplied by a constant (the autoregressive parameter of the forecasted series) and (ii) their estimation places no testable constraint on the coefficient estimates. In a sense, the main innovation here relative to that regression is interpretive, induced by a different orientation and the resulting testable constraints.[13]

We present the two alternative estimates of equation (4) for each of the macroeconomic releases listed in Table I. The results for the three releases reported (and predicted) in the form of levels are shown in the top three rows of Table IV. The results for the remaining releases follow. The first two columns show the coefficient on the forecast-anchor gap, the γ, and the R^2 for the case where the anchor is assumed to be the prior month's release, $h = 1$. The third and fourth columns show the analogous statistics when the anchor is set to the average value of the release over the prior three months, $h = 3$. For each macroeconomic release, the results from the model with the highest R^2 are shown in bold.

Broadly speaking, the results indicate a fairly consistent pattern of bias in macroeconomic forecasts. The estimated coefficient on the gap between the consensus

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[12] We examined anchors constructed from the lagged value, the average of the prior two months releases and the average of the prior three months releases. We do not report the results from using the prior two months as an anchor because they are qualitatively similar to the one and three month results and the performance of the two month anchor generally lies in between that of the one and three month anchor.

[13] Indeed, they find that lagged release values has incremental information useful for predicting the current value of the release, over and above the forecast, but take the inference no further.

forecast and the previous month's release (one-month anchoring) is positive for every release; and, in six of ten cases, it is significant at the 1% level. Considering these results together with those from the three-month anchoring model, we find that the dominant model (in bold) has a significantly positive coefficient for 8 of 10 releases. Aside from the Core CPI, which earlier was shown to be a poor candidate for this analysis, the coefficient in the dominant (bold) model fails to be significant only in the case of the ISM Manufacturing Index. The R^2 of the dominant models (again excluding the Core CPI) ranges from 1.3 to 25 percent, with an average value of around 11 percent.

The pattern of results is also sensible in light of the time series properties of the releases. The top three data releases, each of which is expressed in levels, were shown in Table III to display a high degree of persistence. In all three of these cases, we find that the model with the one-month lag as the anchor clearly dominates the model based on the three-month anchor. Although anchoring itself may or may not be rational, the forecasters seem sophisticated enough to treat further lags of these three releases as largely redundant.

In the case of Consumer Confidence and New Home Sales, looking at the point estimates of γ suggests the anchoring bias is not only statistically significant but that its influence also can be sizable. In the case of Consumer Confidence, the point estimate of 0.71 suggests that, to minimize the mean squared error, the average forecast would have to be shifted by 71 percent *further* from the lagged release value (in the direction indicated by the sign of the gap). In terms of the framework laid out it equations (3) and (4), forecasters are placing roughly 40 percent of the weight on the previous month's release and only 60 percent on the expected value. $(1-\lambda) = \gamma \backslash (1+\gamma) = 0.71 \backslash 1.71 \approx 0.40$. The R^2 statistics of 11.5 percent for Consumer confidence and 4.9 percent for New How Sales are also notable.

Given the importance of these releases for bond markets and the relatively large variance of surprises, an R^2 of even 5 percent represents a substantial amount of predictability with potentially noticeable implications for interest rate responses to these releases.

The remaining releases in the table are expressed in terms of changes or percent changes. Among these, the evidence for anchoring is pretty strong for both the one-month and the three-month anchoring models. In three of the six cases (again leaving aside the Core CPI), the one-month anchoring model yields the best fit. And in four cases (Durable Goods Orders, Industrial Production, Retail Sales and Retail Sales ex-Auto), the null hypothesis of no anchoring is rejected at all conventional significance levels regardless of whether a one- or three-month anchor is employed. For the CPI and Nonfarm Payroll Employment, anchoring is significant in the case of the three month anchor but not the one month anchor.

The magnitude of anchoring in the MMS forecasts of the change variables is generally somewhat less than that of the level variables, though it appears to be economically meaningful in most cases. The magnitude for Retail Sales falls close to middle of the pack; the coefficient of 0.25 in the one-lag model for Retail Sales implies forecasters place roughly 20 percent ($0.25/1.25 = 0.20$) of the weight on that anchor. In addition, the forecast errors for Retail Sales appear to be unusually predictable: the R^2 suggests that the forecast-anchor gap explains 25 percent of the variance in surprises. Among the other change variables, the R^2 covers a range comparable to that of the level variables.

An implicit assumption of the OLS framework, is that the professional forecasters' goal is to minimize the squared forecast errors. But they might face incentives under which

this goal is not optimal, making our evidence potentially misleading. As an alternative, Basu and Markov (2004) suggest the use of a linear loss function, which is implemented vis-à-vis median regression, based on the notion that a 3 percent forecast error may only be three times more costly than a 1 percent error rather than nine times as costly. Indeed, in a study of earnings forecasts, they find that evidence of bias is significantly weakened when the median regression approach is adopted.

We examine the robustness of our results by estimating equation (7) using the median regression approach and find remarkably consistent results to those in Table IV.[14] Specifically, we find significant evidence of anchoring (t-stat in excess of 2.0) in all but one case where the OLS produced significant evidence of anchoring, the exception being New Home Sales (the 3-month case). Moreover, median regression estimates also resulted in statistically significant anchoring in two specifications where the OLS results did not -- the ISM Index and Nonfarm Payrolls. In addition, point estimates are remarkably similar across the OLS and median regressions. The average difference (in absolute value) between the estimates of γ, across all the specifications, is only 0.06. Thus, the finding of anchoring does not rely on the assumption of a quadratic loss function.

The results in Table IV indicate that the gap between the current forecast and the anchor predicts future surprises in almost every release we consider. In those tests, the alternative hypothesis is that forecast errors are unpredictable, that is, orthogonal to all known information. A more demanding test of our model would involve testing it against a more general model, for instance, a model where the forecast error might be related to the current forecast for some unspecified reason. To implement this, we test whether the

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[14] We do not report the results of the median regression because of their similarity to the OLS results in Table IV. The results, however, are available upon request.

coefficient on the hypothesized anchor is opposite in sign and equal in magnitude to the coefficient on the current forecast.

In Table V we show estimates of the following unrestricted anchoring model,

$$S_t = \gamma_f F_t + \gamma_A \overline{A}_h + \varepsilon_t. \tag{7}$$

For these regressions, we choose the anchor from the best-fitting model in Table IV. The first column in Table V denotes the choice of anchor. The next two columns display the point estimates of γ_f and γ_A. The final two columns display the Wald test that $\gamma_f = -\gamma_A$ and the model R^2.

A quick perusal of the point estimates reveals a pattern of coefficients on forecasts and anchors that is remarkably consistent with our model of anchoring bias. In particular, in every case aside from the Core CPI, the estimate for γ_f is positive while that for γ_A is negative. In most cases, both the current forecast and the anchor are statistically important for predicting future surprises. What is more, the difference in the coefficients' magnitudes is often remarkably small. For instance, for Consumer Confidence, $\gamma_f = 0.76$ and $\gamma_A = -0.74$.

The Wald tests reported in the fourth column of Table V show that only in the aberrant case of Core CPI is the null hypothesis that $\gamma_f = -\gamma_A$ rejected at all conventional significance levels. Elsewhere, the Wald statistic provides scant evidence against the null hypothesis. The possible exceptions are Industrial Production and Nonfarm Payroll Employment, where the null hypothesis can be rejected at the 10%, but not the 5%, level. Even there, the discrepancies between γ_f and γ_A are relatively small. Finally, comparing the fit of the unrestricted and restricted (Table IV, bold) models reveals only a small

deterioration in fit when we impose the $\gamma_f = -\gamma_A$ restriction (in the original specification); the decline in R^2 is typically on the order of a percentage point.

Our model of anchoring bias assumes that forecasters always tilt their forecast toward the value of the previous month's (or few months') release by a similar proportion. On the other hand, it is plausible that the extent to which forecasters treat a lagged release as reasonable starting point for current-month forecasts could depend on whether that lagged release is viewed as representative or normal. For instance, when lagged realizations are far out of line with recent trends or broader historical experience, they may have less influence on current forecasts. Of course, the opposite might be true; that is, it might be that most of the anchoring occurs on the heels of outliers or trend-breaking observations, while very little anchoring occurs in normal times.

In principle such considerations would suggest that a more complex specification than our simple anchoring model might be informative, but there is no clear a priori case for any particular alternative. Thus, rather than postulate a more complicated anchoring model, we simply re-estimate equation (4) on a sub-sample of observations that excludes outliers. Specifically, we exclude observations in which the change in the release from month $t-2$ to $t-1$ is larger than 1.5 standard deviations of the historical monthly change in the release. The results are contained in Table VI.

As with the model restriction tests in Table V, we report results only for the best-fitting model (1-month or 3-month anchoring) based on the Table IV regressions. The second and third columns report the estimates of γ and the R^2 statistics from the full sample, while the final two columns report the same for the sample that excludes the outliers. Broadly speaking, the outlier exclusion does not substantially alter the picture. The

estimates of γ are all still positive; in most cases, the estimated degree of anchoring appears to increase somewhat. The most notable change is in the case of the ISM Manufacturing Index release, where the coefficient doubles to 0.44 and becomes statistically significant, while the R^2 rises to 5%. The Nonfarm Payrolls release is the only case showing a notable decline in the coefficient estimate when outliers are excluded, from 0.25 to 0.17, reducing its significance.

The broad picture that emerges from Tables IV, V and VI is one in which anchoring plays a statistically and economically meaningful role in determining MMS forecasts of key macroeconomic releases. In some cases the estimates imply that the anchor receives as much as a 40 percent weighting (Consumer Confidence) in the current forecast and the anchoring variable can account for up to 25 percent (Retail Sales) of the variance in future surprises. The pattern in the results is remarkably uniform. Accordingly, anchoring appears to be an important and robust feature of the MMS forecast data. These findings thus raise the question that we examine in the second part of our analysis: How does anchoring bias in these forecasts affect market reactions to the measured surprises?

V. Testing Market Reactions

A. The Framework

This section examines the implications of anchoring bias in macroeconomic forecasts for bond market reactions to the data releases. A large literature uses MMS forecasts to measure surprises in macroeconomic releases, which are then used to gauge the effect of macroeconomic news on asset prices (Aggarwal and Schirm, 1992; Balduzzi, et al., 2001; Andersen, et al., 2003, Gurkaynak, et al 2005). These studies examine the reaction

of equity prices, exchange rates, and interest rates to differences between macroeconomic

releases and the associated forecasts in the minutes surrounding the releases. The typical

specification in these studies takes on the following form:

$$\Delta i_t = \delta S_t + v_t , \qquad (8)$$

where Δi_t represents the change in the asset price in a small window surrounding the release

and the coefficient δ measures the sensitivity of the asset price to the surprise, $S_t \equiv A_t - F_t$.

The results above imply that these surprises-- or forecast errors, to be precise -- are

partly predictable due to anchoring bias in the MMS forecasts. If markets are

informationally efficient and market participants understand the nature of this bias, then

market prices should anticipate this component of the forecast error. In particular, market

interest rates should not respond to the predictable component of the forecast error. We

investigate this hypothesis using the model laid out in equation (5) of Section II,

$\Delta i_t = \delta_1 S_t^e + \delta_2 \left(S_t - S_t^e \right) + v_t$. Again, Δi_t represents the change in either the two-year or ten-

year U.S. Treasury bond yield in the moments surrounding the release and $S_t^e = \gamma \left(F_t - \bar{A}_h \right)$

represents the predicted component of the surprise induced by anchoring. We thus refer to

the second regressor as the residual component of the surprise – the true surprise from the

econometrician's point of view.

We focus on two hypotheses concerning how market participants react to the

predicted and residual components of the surprise. If market participants take the forecasts

at face value and are unaware of the predictability in surprises then we would expect to find

no difference in the response to the predicted and residual components of the surprise, or

$\delta_1 = \delta_2$. Finding $\delta_1 = \delta_2$ would indicate that the bond markets are not informationally

efficient in the sense that data known at the time of the forecast can help predict movements in bond prices. Alternatively, if market forecasts are informationally efficient -- market participants are aware of the predictability induced by anchoring in the MMS forecasts -- then we would expect to find no response of interest rates to variation in the predictable component of the surprise, or $\delta_1 = 0$.

Our investigation of the response of interest rates to the predicted and residual components of surprises in macroeconomic releases is related to the previous work of Mishkin (1981). Mishkin examines whether the surprise implied by the reaction of interest rates to inflation news is consistent with the unpredictable component of inflation identified from an autoregressive specification. Specifically, Mishkin estimates the following system,

$$\Delta i_t = \alpha + \delta \left(\pi_t - b_0 - \sum_{i=1}^{q} b_i \pi_{t-i} \right) + v_t$$
$$\pi_t = c_0 + \sum_{i=1}^{q} c_i \pi_{t-i} + \varepsilon_t$$

$$\tag{9}$$

and tests whether $b_i = c_i$.[15] Mishkin argues that finding $b_i = c_i$ constitutes support for the hypothesis that market forecasts are informationally efficient. Our analysis differs in that our measure of news is constructed using professional forecasts, which presumably incorporate a wealth of information beyond the lags of the series being forecasted. Moreover, our analysis differentiates between forecasters and trader/investors.

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[15] Mishkin (1981) actually examines the return on long term bonds over short term bonds rather than the change in the yield.

B. Empirical Results

Before reviewing the empirical results, we first introduce two variations on the basic

specification of equation (5) that apply to some of the releases. First, we control for

revisions to previously released data that are announced along with the current month's data.

This is done by including the value of the revision as an additional regressor. Revisions are

announced with the release of Industrial Production, Nonfarm Payrolls and Retail Sales

(both the top-line and ex-Auto release). For Nonfarm Payrolls and Retail Sales, revisions to

two previous months of data are released and included as regressors; but to conserve space,

we only report the parameter estimate for the most recent month's revision. In the Nonfarm

Payrolls regression, we also include a control for the surprise to the unemployment rate

(based on the MMS survey), which is released simultaneously but generally with less market

impact than the payroll numbers. Thus, our general event-study regression can be written

as:

$$\Delta i_t = \delta_1 S_t^e + \delta_2 \left(S_t - S_t^e \right) + \phi R_t + v_t.$$ (10)

The second variation, used for Retail Sales and the CPI, is to include the surprise

decompositions of two forecasted releases, the top-line release, S_t^e, and its key sub-

component, SX_t^e (Retail sales ex-Auto or Core CPI, ex-Food and Energy):

$$\Delta i_t = \delta_1 S_t^e + \delta_2 \left(S_t - S_t^e \right) + \delta_1' SX_t^e + \delta_2' \left(SX_t - SX_t^e \right) + \phi R_t + v_t.$$ (11)

Here, $\left(\delta_1, \delta_2 \right)$ are the coefficients on the predicted surprise and the residual for the top-line

release, whereas $\left(\delta_1', \delta_2' \right)$ are the coefficients on the key sub-components.

The model is estimated via GMM. In particular, note that the terms $S_t^e (SX_t^e)$ that

appear in equation (10) and (11) are not directly observed and must be estimated from the

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first stage anchoring model in equation (4). These generated regressors influence the

sampling distribution of the interest rate response coefficients $(\delta_1, \delta_2, \delta_1', \delta_2')$. In particular,

the sampling variability induced by using generated regressors tends to increase the amount

of sampling variability in the second stage coefficients. We follow the approach of Newey

(1984) by including the first stage anchoring model, equation (4), along with the second

stage event-study regressions, equations (10) and (11), in the GMM system.[16] The resulting

variance-covariance matrix fully accounts for the use of generated regressors in equations

(10) and (11).

The results from GMM estimation of equations (10) and (11) are contained in Table

VII. The parameter estimates have been scaled so that they reflect the effect on yields, in

basis points, of a change in the independent variable equal to one standard deviation of the

(total) surprise, S_t. The first three columns report the parameter estimates. The fourth

column reports the Wald test of the null hypothesis that bond yields react symmetrically to

the predictable and unpredictable component of the MMS surprise, $\delta_1 = \delta_2$.[17] The fifth

column reports the model R^2.

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[16] Note that the system defined by equations (4), (10) and (11) is exactly identified so that the point estimates are numerically identical to those obtained from first estimating equation (4) by OLS and then using the predicted surprises, $S_t^e(SX_t^e)$, in OLS estimates of equation (10) and (11). Including equations (4), (10) and (11) in the GMM system only affects the variance-covariance matrix of the estimates. Details of the GMM system are contained in an appendix.

[17] In the case of Retail Sales ex-Auto and Core CPI we report the results for (δ_1', δ_2') in the columns labeled (δ_1, δ_2) rather than introduce two more columns to the table. Also, the associated joint Wald test and R^2 that are discussed in the text are reported in the row relating to the top line release. Finally, in the case of Retail Sales and Retail Sales ex-Auto, the reported ϕ parameter reflects the effect of a revision to Retail Sales and Retail Sales ex-Auto, respectively.

Looking down the columns of Table VII reveals three broad findings. First, consistent with previous research, we find that the releases account for a significant fraction of bond yield movements, ranging from roughly 20 to 50 percent, as measured by the R^2. Second, the estimate of δ_2, the coefficient on the unexpected component of the surprise on bond yields, is significant at the 1% level for every release except the CPI. Third, δ_1, the effect of the expected component of the surprise on bond yields, is about as often negative as it is positive, is typically an order of magnitude smaller than δ_2; and it is insignificant in every case. Moreover, the results are quite similar across the short and long end of the yield curve. The Wald test of the null hypothesis that bond yields react symmetrically to the unexpected and expected components of the surprise is rejected at the 10% level or lower in 5 out of 8 cases.[18] This is notable since the Wald test fully accounts for the extra variability in the measurement of δ_1 resulting from S_t^e being a generated regressor.

Focusing on the results for individual releases indicates that the exceptions to the broad pattern of results can largely be rationalized as special situations. First, for the (top line) CPI, both the expected and unexpected components of the surprise are not significant; and so we obviously would be unable to reject the hypothesis that the components have the same effect. But this owes to the finding that, conditional on Core CPI, shocks to the total CPI (including Food and Energy) have little incremental effect on bond yields.[19] The market perceives the Core CPI as a better indicator of future inflation and Federal Reserve

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[18] Note that Retail Sales, Retail Sales ex-Auto and CPI, Core CPI are each treated as a single case since the reported Wald test is the appropriate joint test, $\delta_1 = \delta_2, \delta_1' = \delta_2'$.

[19] To the contrary, the results in Table IV indicate that surprises to total CPI contain a significant predictable component due to predictability in CPI: Food and Energy surprises. Unfortunately, however, we are not able to identify whether bond market participants react to the predictable component of Food and Energy surprises since this component of CPI is largely ignored by bond market participants.

policy. The other obvious exception is in the Core CPI results. Here, we find that the

estimated magnitude of δ_2 is large and not significantly different from δ_1. But this result

presumably owes to the poor performance of the anchoring model for the Core CPI, which

explains less than 1 percent of the variation in the surprise. As argued already, this could be

attributable to the granularity of Core CPI and its resultant lack of time-series variation in

our sample period.

A few other aspects to our findings in Table VII are notable, even if not central to

our main hypotheses. First, we are comforted by the finding -- consistent with previous

research findings and views on Wall Street -- that the employment release shows the largest

interest rate effects and has the most explanatory power of all the releases (in the event study

window). It is also interesting to note that in every case where it is available, the revision to

the previous month's data (ϕ) also has a significant positive effect on interest rates.

Surprisingly, in most of these cases, the coefficient on the revision is almost as large as the

coefficient on the current month (residual) surprise.

Finally, for comparison purposes, column 6 shows R^2 statistics from the standard

event study regression model of data surprises, equation (8), which does not split up the

forecast error into the two pieces. Comparing these statistics to those in column 5 provides

one quantitative measure of how much better our anchoring model explains interest rate

movements compared to that benchmark. Comparing columns (5) and (6) reveals that

adjusting for the predictable component of the surprise increases the explanatory power of

the releases for interest rate movements in every case that we consider.[20] In some cases such

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[20] One could argue that the appropriate comparison to be made is between the reported R^2 in column (6) and
the R^2 from a regression of interest rate changes on only the unpredictable component if the surprise, $S_t - S_t^e$.
The difference between this regression R^2 and the one reported in column (5) is minor due to the very small

as Consumer Confidence, Durable Goods and Retail Sales the increase in R^2 can be substantial, on the order of 25 percent, while in the case of other releases the improvement is more modest, ranging between 1 and 10 percent.

Summing up, the results in Table VII suggest that market participants do react to the unpredictable component but not to the predictable component of the MMS surprises. Moreover, focusing on the unpredictable component of the surprise uniformly increases the explanatory power of the releases for interest rate changes. Accordingly, these results suggest that the informational inefficiency of MMS forecasts identified in Tables IV, V and VI does not lead to any important source of inefficiency in interest rate markets. Market participants apparently anticipate the anchoring behavior of professional forecasters.

VI. Conclusions

We find that professional economic forecasts are biased in a manner consistent with a specific behavioral model of forecasting behavior: the anchoring and adjustment hypothesis of Kahneman and Tversky (1974). Specifically, we find that forecasts of any given release are anchored toward recent months' realized values of that release, thereby giving rise to predictable surprises. In some cases, such as Retail Sales, we find that up to 25% of the surprise in the macroeconomic release is predictable, due to a substantial weight being placed on the anchor by professional forecasters. Moreover, the evidence in favor of anchoring is remarkably consistent across each of the key releases that we study and is robust to the exclusion of outliers.

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point estimates of δ_1. Typically, the difference between these two measures is on the order of 0.1-0.2 percentage points.

In light of the significant evidence of systematic bias in professional forecasts, we examine the implications for market prices of U.S. Treasury bonds. Specifically, we examine whether yields on 2-year and 10-year Treasury yields react to the predictable component of forecast surprises induced by anchoring behavior. Across the board, we find that interest rates only respond to the unpredictable component of the surprise. Estimates of the market reaction to the predictable component of data surprise in every case are small and insignificant, whereas the estimated reaction to the unpredictable component is large and significant.

We thereby conclude that market participants do not take professional forecasts at face value when responding to macroeconomic news. To the contrary, at least some influential market participants are apparently able to parse the component of these forecasts due to anchoring from the component of the forecasts containing useful information about the expected future path of these macroeconomic variables. As a result, the behavioral bias displayed by the forecasts does not translate into a similar behavioral bias in market reactions to macroeconomic news.

These findings suggest a variety of directions for future research. We identify a source of forecast bias consistent with a particular behavioral hypothesis; however, one cannot conclude that forecasters are irrational or that they are inefficient data processors based on this evidence alone. There could well be important professional considerations that induce forecasters to issue "conservative" forecasts relative to some naïve prior. For instance, investors might see these monthly economic forecasts as signals of the forecaster's perception of the underlying trend. In that case, minimizing mean squared or absolute error would not necessarily be the optimal strategy.

A related point is that our findings only provide a characterization of the bias of a "representative forecaster", and this ignores the likelihood that there are substantial cross-sectional differences in ability. What is more, individual forecasts are likely to be influenced by strategic considerations, as suggested by Ehrbeck and Waldmann (1996) or Ottaviani and Sorensen (2006). Indeed, the latter study models circumstances in which forecasters might find it optimal to issue forecasts that underweight their own private signals.

Finally, our findings raise the question of whether other markets are as adept as the U.S. Treasury market at processing the information in professional forecasts. In particular, we wonder whether biases in professional forecasts are a source of inefficiency in markets that are commonly perceived to be less efficient than the U.S. Treasury market, such as markets for individual stocks.

Appendix
Specification of GMM System Reported in Table VII

Following Newey (1984), we account for the generated regressors in equations (10) and (11) by including the specification of the anchoring model, equation (4), in the GMM system. Specifically, we estimate the following exactly identified GMM system for each data release (row) contained in Table VII.

$$g_T(\theta) = \frac{1}{T} h_t(\theta) = \frac{1}{T} \sum_{t=1}^{T} \begin{bmatrix} \left(S_t - \gamma_0 - \gamma_1\left(F_t - \overline{A}_h\right)\right) \\ \left(S_t - \gamma_0 - \gamma_1\left(F_t - \overline{A}_h\right)\right)\left(F_t - \overline{A}_h\right) \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \phi R_t\right) \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \phi R_t\right)S_t^e \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \phi R_t\right)\left(S_t - S_t^e\right) \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \phi R_t\right)R_t \end{bmatrix} \tag{A.1}$$

in the case of Consumer Confidence, ISM index, New Homes Sales, Durable Goods, Industrial Production and Nonfarm Payroll employment. In the case of Retail Sales and CPI we estimate the system,

$$g_T(\theta) = \frac{1}{T}\sum_{t=1}^{T} h_t(\theta) = \sum_{t=1}^{T} \begin{bmatrix} \left(S_t - \gamma_0 - \gamma_1\left(F_t - \overline{A}_h\right)\right) \\ \left(S_t - \gamma_0 - \gamma_1\left(F_t - \overline{A}_h\right)\right)\left(F_t - \overline{A}_h\right) \\ \left(SX_t - \gamma_{0,x} - \gamma_{1,x}\left(F_{x,t} - \overline{A}_{x,h}\right)\right) \\ \left(SX_t - \gamma_{0,x} - \gamma_{1,x}\left(F_{x,t} - \overline{A}_{x,h}\right)\right)\left(F_{x,t} - \overline{A}_{x,h}\right) \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \delta_1'SX_t^e - \delta_2'\left(SX_t - SX_t^e\right) - \phi R_t\right) \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \delta_1'SX_t^e - \delta_2'\left(SX_t - SX_t^e\right) - \phi R_t\right)S_t^e \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \delta_1'SX_t^e - \delta_2'\left(SX_t - SX_t^e\right) - \phi R_t\right)\left(S_t - S_t^e\right) \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \delta_1'SX_t^e - \delta_2'\left(SX_t - SX_t^e\right) - \phi R_t\right)SX_t^e \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \delta_1'SX_t^e - \delta_2'\left(SX_t - SX_t^e\right) - \phi R_t\right)\left(SX_t - SX_t^e\right) \\ \left(\Delta i_t - \delta_0 - \delta_1 S_t^e - \delta_2\left(S_t - S_t^e\right) - \delta_1'SX_t^e - \delta_2'\left(SX_t - SX_t^e\right) - \phi R_t\right)R_t \end{bmatrix} \tag{A.2}$$

in the case of Retail Sales and the CPI. In each case the GMM system is estimated by minimizing, $g_T(\theta)'g_T(\theta)$, over θ and note the omission of a weighting matrix due to the just identified nature of the system. Finally, the variance-covariance matrix is estimated by:

$$V = D_T^{-1}S_T D_T^{-1}, \tag{A.3}$$

where,

$$S_T = \Gamma_{0,T} + \sum_{v=1}^{q}\left(1 - \frac{v}{q+1}\right)\left(\Gamma_{v,T} + \Gamma'_{v,T}\right)$$

$$\Gamma_{v,T} = \sum_{t=v+1}^{T} h_t(\theta) h_t(\theta)' \tag{A.4}$$

and,

$$D'_T = \frac{\partial g_T(\theta)}{\partial \theta'}. \tag{A.5}$$

Finally, we note that a separate system is estimated for each release and each bond maturity (2 and 10 year).

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Table I
Economic Release Summary and Schedule

Release	Beginning of Sample	Release Day (Next Month)	Release Time (AM)	Reporting Convention
Consumer Confidence	09/1992	Final Tuesday*	10:00	Level
Consumer Price Index (CPI)	01/1993	3rd Wednesday	08:30	% Change
Core CPI	01/1993	3rd Wednesday	08:30	% Change
Durable Goods Orders	12/1992	4th Thursday	08:30	% Change
Industrial Production	12/1992	3rd Week	09:15	% Change
ISM Index	10/1992	1st Business Day	08:30	Level
Nonfarm Payroll Employment	10/1992	1st Friday	08:30	Change
New Home Sales (in thousands)	06/1996	4th Wednesday	10:00	Level
Retail Sales	01/1993	2nd Week	08:30	% Change
Retail Sales ex-Auto	01/1993	2nd Week	08:30	% Change

* Released in current month

Notes: We report each data release, the month and year in which our sample period begins, the period in the following month when it is released, the time of the release and whether the release is reported as a level, change or percent change.

Table II
Summary Statistics
Macroeconomic Releases, Forecasts and Surprises

	Release (A)			Forecast (F)			Surprise (S)		
	μ	σ	$\sum \rho_j$	μ	σ	$\sum \rho_j$	μ	σ	$\sum \rho_j$
Consumer Confidence	104.73	22.40	0.96***	104.24	21.87	0.96***	0.50	4.97	-0.14
ISM Index	52.92	5.07	0.88***	53.02	4.64	0.89***	-0.10	2.06	0.18
New Home Sales	986.70	167.33	0.94***	970.47	160.68	0.98***	16.23	68.35	-0.94***
Consumer Price Index (CPI)	0.20	0.22	-0.05	0.23	0.13	0.34*	-0.02	0.13	-0.60**
Core CPI	0.20	0.10	0.28	0.21	0.05	0.81***	0.00	0.10	-0.25
Durable Goods Orders	0.42	3.36	-2.08***	0.28	1.25	0.01	0.14	2.73	-1.34***
Industrial Production	0.22	0.48	0.42**	0.20	0.34	0.59***	0.02	0.27	-0.10
Nonfarm Payroll Employment	130.64	164.84	0.70***	145.43	106.76	0.87***	-14.78	111.00	-0.13
Retail Sales	0.33	0.95	-1.41***	0.35	0.54	-0.13	-0.02	0.60	-0.58***
Retail Sales ex-Auto	0.35	0.49	-0.25	0.37	0.20	0.36	-0.01	0.40	-0.45*

Notes: We report the sample mean (μ), standard deviation (σ) and the sum of the autoregressive coefficients from an AR(5) ($\sum \rho_j$) for the underlying release (A), its forecast (F) and the surprise ($S = A - F$). In the case of the sum of the autoregressive coefficients ($\sum \rho_j$), * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Table III
Summary Statistics
Interest Rate Reactions to Macroeconomic Releases

	2 Year Response (Δi_2)			10 Year Response (Δi_{10})		
	μ	σ	$\sum \rho_j$	μ	σ	$\sum \rho_j$
Consumer Confidence	0.00	0.02	0.27**	0.00	0.03	0.37***
ISM Index	0.00	0.03	0.37***	0.00	0.03	0.28**
New Home Sales	0.00	0.02	0.38	0.00	0.02	-0.27
Consumer Price Index (CPI)	0.00	0.03	-0.05	0.00	0.03	-0.05
Core CPI	0.00	0.03	-0.05	0.00	0.03	-0.05
Durable Goods Orders	0.00	0.03	-0.69***	0.00	0.02	-0.33**
Industrial Production	0.00	0.02	0.27**	0.00	0.02	0.29**
Retail Sales	-0.01	0.04	0.17	-0.01	0.03	0.12
Retail Sales ex-Auto	-0.01	0.04	0.17	-0.01	0.03	0.12
Nonfarm Payroll Employment	0.00	0.09	-0.18	0.00	0.07	-0.28

Notes: We report the sample mean (μ), standard deviation (σ) and the sum of the autoregressive coefficients from an AR(5) ($\sum \rho_j$) for the change in the two year U.S. Treasury yield, (Δi_2), and the ten year U.S. Treasury yield, (Δi_{10}), in the moments surrounding each release. In the case of the sum of the autoregressive coefficients ($\sum \rho_j$), * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

Table IV
Anchoring in Macroeconomic Forecasts

	1 Month Anchoring		3 Month Anchoring	
	γ	$R^2(\%)$	γ	$R^2(\%)$
Consumer Confidence	**0.71** **(6.10)**	**11.52**	0.11 (1.60)	1.38
ISM Index	**0.22** **(1.26)**	**1.34**	0.09 (0.88)	0.75
New Home Sales	**0.53** **(2.75)**	**4.85**	-0.11 (0.57)	0.36
Durable Goods Orders	0.16 (4.51)	6.61	**0.49** **(5.74)**	**13.28**
Industrial Production	**0.14** **(3.24)**	**7.30**	0.19 (2.92)	6.81
Nonfarm Payroll Employment	0.06 (0.75)	0.48	**0.25** **(1.91)**	**3.36**
Retail Sales	**0.25** **(4.74)**	**25.09**	0.34 (2.82)	17.79
Retail Sales ex-Auto	**0.29** **(4.04)**	**15.36**	0.37 (3.12)	7.50
Consumer Price Index (CPI)	0.06 (1.52)	1.49	**0.26** **(4.89)**	**15.36**
Core CPI	**0.04** **(0.67)**	**0.18**	-0.06 (0.41)	0.10

Notes: We report estimated slope coefficient, γ, and R^2 from the model, $S_t = \gamma_0 + \gamma\left(F_t - A_{-h}\right) + \varepsilon_t$. The results that equate the previous month's value of the release with $\overline{A}_h$, $h = 1$, are contained in the first two columns. The results that equate the average of the three previous month's release with $\overline{A}_h$, $h = 3$, are contained in the final two columns. Newey-West (1987) t-statistics are reported in parentheses. Results from the model with the highest R^2 appear in bold.

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Table V
Anchoring in Macroeconomic Forecasts
Predicting Surprises with Forecasts and Lagged Releases

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	h	γ_f	γ_A	Wald	$R^2(\%)$
Consumer Confidence	1	0.76	-0.74	0.27	12.00
		(5.92)	(6.03)		
ISM Index	1	0.25	-0.24	0.72	1.43
		(1.29)	(1.31)		
New Home Sales	1	0.46	-0.50	0.38	5.40
		(2.14)	(2.50)		
Durable Goods Orders	3	0.55	-0.42	0.68	13.38
		(3.35)	(2.00)		
Industrial Production	1	0.23	-0.11	0.06	9.42
		(3.11)	(2.47)		
Nonfarm Payroll Employment	3	0.36	-0.23	0.08	4.92
		(2.18)	(1.77)		
Retail Sales	1	0.31	-0.23	0.43	25.43
		(2.59)	(5.80)		
Retail Sales ex-Auto	1	0.36	-0.27	0.61	15.53
		(2.11)	(3.48)		
Consumer Price Index (CPI)	3	0.35	-0.15	0.07	17.22
		(6.81)	(1.58)		
Core CPI	1	-0.34	-0.09	0.00	5.05
		(2.54)	(1.47)		

Notes: We report estimates from the model, $S_t = \gamma_f F_t + \gamma_A A_{-h} + \varepsilon_t$. The number of months ($h$) used in constructing the anchor, $\bar{A}_h$, is selected from the best fitting model in Table IV and is reported in the first column. The second and third column report γ_F and γ_A. The fourth column reports the asymptotic p-value of the Wald test of the restriction $\gamma_f = -\gamma_A$ and the fifth column reports the R^2. Newey-West (1987) t-statistics appear in parentheses.

Table VI
Anchoring in Macroeconomic Forecasts
Excluding Outliers

	Lags	All Observations		Outliers Excluded	
	h	γ	$R^2(\%)$	γ	$R^2(\%)$
Consumer Confidence	1	0.71 (6.10)	11.52	0.79 (5.48)	13.16
ISM Index	1	0.22 (1.26)	1.34	0.44 (2.17)	4.89
New Home Sales	1	0.53 (2.75)	4.85	0.54 (2.01)	3.41
Consumer Price Index (CPI)	3	0.26 (4.89)	15.36	0.21 (1.41)	10.54
Core CPI	1	0.04 (0.67)	0.18	0.03 (2.24)	0.03
Durable Goods Orders	3	0.49 (5.74)	13.28	0.61 (3.67)	17.98
Industrial Production	1	0.14 (3.24)	7.30	0.17 (2.19)	4.89
Nonfarm Payroll Employment	3	0.25 (1.91)	3.36	0.17 (1.83)	1.68
Retail Sales	1	0.25 (4.74)	25.09	0.23 (3.78)	15.59
Retail Sales ex-Auto	1	0.29 (4.04)	15.36	0.41 (3.33)	15.86
Consumer Price Index (CPI)	3	0.26 (4.89)	15.36	0.21 (1.41)	10.54
Core CPI	1	0.04 (0.67)	0.18	0.03 (2.24)	0.03

Notes: We report estimates from the model, $S_t = \gamma(F_t - A_{-h}) + \varepsilon_t$, using the full sample and a sub-sample that excludes observations in which the change in the previous month's release over the prior month is large (see text for details). The first column reports the number of months (h) used in constructing the anchor ($\bar{A}_h$). The second and third column report the parameter estimate, γ, and R^2 from the full sample. The fourth and fifth column report the parameter estimate, γ, and R^2 from the sub-sample. Newey-West (1987) t-statistics appear in parentheses.

Table VII
Interest Rate Reactions to Macroeconomic Releases

	δ_1	δ_2	ϕ	$\delta_1 = \delta_2$	$R^2(\%)$	$R_S^2(\%)$
Consumer Confidence						
2 Year	0.19	1.69***	--	0.00	46.9	38.1
10 Year	0.07	1.60***	--	0.00	44.0	39.4
ISM Index						
2 Year	-2.33	2.31***	--	0.23	52.4	49.6
10 Year	-3.45	2.09***	--	0.21	51.9	47.4
New Home Sales						
2 Year	0.09	0.85***	--	0.21	17.3	16.6
10 Year	0.10	0.82***	--	0.23	17.6	17.0
Durable Goods Orders						
2 Year	-0.25	1.39***	--	0.00	22.6	18.5
10 Year	-0.45	1.16***	--	0.00	19.4	14.4
Industrial Production						
2 Year	-0.12	0.76***	0.55***	0.07	20.7	19.2
10 Year	0.00	0.74***	0.49***	0.09	19.2	18.2
Nonfarm Payroll Employment						
2 Year	1.06	6.27***	1.65***	0.08	57.3	56.3
10 Year	0.97	4.96***	1.08***	0.07	50.8	49.8
Retail Sales: Auto						
2 Year	0.03	1.44***	1.62***	0.17	30.4	25.4
10 Year	0.09	1.31***	1.02**	0.12	29.2	23.5
Retail Sales: ex-Auto						
2 Year	-0.20	3.28***	1.23**	0.02	30.4	25.4
10 Year	-0.32	2.80***	1.08***	0.01	29.2	23.5
CPI: Food and Energy						
2 Year	-0.32	-0.38	--	0.96	28.8	28.5
10 Year	-0.74	-0.36	--	0.71	28.6	28.3
Core CPI						
2 Year	7.43	2.29***	--	0.68	28.8	28.5
10 Year	6.50	2.14***	--	0.69	28.6	28.3

We report GMM estimates of the model, $\Delta i_t = \delta_1 S_t^e + \delta_2 \left(S_t - S_t^e \right) + \phi R_t + v_t$. *** denotes statistical significance at the 1% level and ** denotes significance at the 5% level. We also report the p-value of the Wald test that $\delta_1 = \delta_2$, the model's R^2 and the R^2 from a regression of the interest rate change on the total surprise, R_S^2, in the final three columns .