Do Markets Respond More to More Reliable Labor Market Data? A Test of Market Rationality

by

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Abstract

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Since 1979, the Bureau of Labor Statistics (BLS) has nearly quadrupled the size of the sample used to estimate monthly employment changes. Although first-reported employment estimates are still noisy, the magnitude of sampling variability has declined in proportion to the increase in the sample size. A model of rational Bayesian updating predicts that investors would assign more weight to the BLS employment survey as it became more precise. However, a regression analysis of changes in interest rates on the day the employment data are released finds no evidence that the bond market's reaction to employment news intensified in the late 1980s or 1990s; indeed, in the late 1990s and early 2000s the bond markets hardly reacted to unexpected employment news. For the time period as a whole, an unexpected increase of 200,000 jobs is associated with about a 6 basis point increase in the interest rate on 30 year Treasury bonds, and an 8 basis point increase in the interest rate on 3 month bills, all else equal. Additionally, unexpected changes in the unemployment rate and revisions to past months' employment estimates have statistically insignificant effects on long-term interest rates.

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Much existing work on the efficient markets hypothesis tests whether "new information" affects market valuations, and whether "old information" has no impact on market valuations. For example, Pearce and Roley (1985) find that deviations between the announced and expected money supply affect the S&P 500 on the announcement day, while the expected money supply has no effect. Related work on inflation announcements has been done by Schwert (1981), Urich and Wachtel (1985), McQueen and Roley (1993), and others. This approach to testing the efficient markets hypothesis, however, leaves open the possibility that markets may under or over react to new information.[1]

This paper uses an alternative approach to test whether markets respond efficiently to new information. The test is based on the fact that the survey the Bureau of Labor Statistics (BLS) uses to estimate payroll employment was greatly expanded and improved in the 1980s. The BLS employment survey provides the first government economic statistics each month, and is widely reported on and watched by financial players. Stevenson (1996), for example, noted, "In the markets, the monthly employment report has become the single most important indicator of economic strength, potential inflation and Fed strategy." Most importantly for our purposes, the sample size of the BLS survey increased nearly four-fold between 1979 and 1995. Because the sample size was increased, data from the survey became more reliable over time. The Root Mean Square Error (RMSE) of estimated employment fell from 121,000 in 1979 to 71,000 in 1994. The central question raised in this paper is: Did the bond market respond more to unexpected movements in the announced employment data as the data became more reliable?

Before examining the market responses to employment data, in the next section we describe the BLS Current Employment Statistics (CES) program in more detail. An unusual feature of this program is that the population mean employment is eventually revealed from a complete count of unemployment insurance payroll tax records, the so called "benchmark employment figures." A comparison of the survey results to the benchmark figures provides evidence that the reliability of the monthly releases has indeed improved as the sample size increased. Another finding is that the median prediction of

[1] Shiller (1979), of course, provides a test of whether long-term interest rates are too volatile. Other work tests for mean reversion in asset price movements, or for calendar effects, or for weather effects (for examples, see DeBondt and Thaler, 1985, Reinganum, 1981, and Saunders, 1993).

professional forecasters is highly correlated with the survey estimates and with the benchmark figures, and is close to an unbiased estimate of the actual employment change. Interestingly, the median forecast can help predict the ultimate benchmark employment numbers even after conditioning on the survey estimate. This finding suggests that analysts can derive a better estimate of true employment movements by combining the forecast and survey estimates.

The remainder of the paper examines the relationship between the employment data releases and interest rates. Section II presents a theoretical model showing that rational Bayesian investors would place more weight on the employment survey as the size of the sample increases. Another reason the employment data might cause a greater response in the market over time is that many observers believe the Federal Reserve Board shifted its focus away from money supply targets and toward employment monitoring in the mid 1980s.[2] Indeed, most forecasters did not begin making employment forecasts until 1985, and there is no "consensus" estimate of employment growth prior to 1985. If the shift in the Fed's emphasis was not motivated by improvements in the employment data, this change in monetary policy may confound the relationship between employment data and market reactions. Thus, a finding of increased market responses to the employment numbers as the sample size increased may reflect a rational response to more precise data, or a reaction to the change in the Fed's policy, or both. But a finding of a constant or declining response to employment news would present a puzzle for two reasons.

As expected, results presented in Section III and IV indicate that movements in the BLS survey data have a significant and sizable effect on the 30 year Treasury bond yield and on short term Treasury bill yields on the day the employment numbers are released. An unanticipated increase of 200,000 jobs is associated with about a 4 to 8 basis point increase in the long bond yield, and a larger increase in the short-term bond yield. *Contrary to expectations, however, the effect of reported employment changes on interest rates was at least as strong in the early 1980s as it was in the mid and late 1990s.* This finding is quite surprising in view of the widely held belief that financial markets only followed the

[2]Cook and Korn (1991) provide some evidence of a switch in the short-term interest rate's reaction to employment news after the change in Fed policy. One anomalous finding in their results, however, is that the strongest reaction to employment news occurred in the 1980-82 period.

employment releases after the Fed shifted its focus away from the money supply in the mid 1980s.

Four additional findings are noteworthy. First, interest rates are not significantly affected by announcements of revisions to past months' employment data; only the latest month employment change seems to matter. Second, announced increases in hourly pay have a statistically significant, positive impact on interest rates. Third, unexpected changes in unemployment are insignificantly related to long-term interest rates, but significantly related to 3 month rates. Fourth, the long-term interest rate is significantly related to the forecasted employment growth conditional on the deviation between the forecast and the employment survey. This latter finding results from a positive correlation between the forecast error and the employment forecast, as the forecast has an insignificant effect on the bond yield when the forecast error is not conditioned on; because investors cannot condition on the employment news in advance of the employment release, this finding is not evidence of an inefficient market.

I. Evaluation of BLS Employment Data

The BLS conducts the CES survey of business establishments each month to make timely estimates of non-farm employment, hours of work, and pay.[3] The survey pertains to the pay period covering the 12th day of each month. The CES data for the previous month are typically released at 8:30 AM on the first Friday of each month, although the data may be released on other days if the first Friday falls on a holiday (e.g., July 4th) or if there is insufficient time between the survey and first Friday of the month (e.g., March). On the release date, the BLS reports the first estimate of employment for the previous month, as well as the first revision to the employment estimate from two months ago and the second revision to the estimate from three months ago. In addition, the BLS reports information from the household survey (the Current Population Survey), which includes the monthly unemployment rate.

The sample of establishments underlying the CES survey is drawn from unemployment insurance (UI) tax records. The sample is a stratified sample, with strata consisting of geographic

[3]For a detailed description of the CES survey, see BLS (1996).

location, establishment size, and industry cells. Until recently, states were instructed to identify and survey a specified number of establishments within each strata; beginning in June 2000, in some industries a random probability sample was drawn instead of a "quota" sample. Sampled establishments remained in the survey for several years and even decades. The BLS uses the survey data to make a "linked relative" estimate of employment, in which only establishments that are in the survey in two adjacent months are used to estimate the change in employment. This method was selected to take advantage of the high month-to-month covariance in employment within establishments. To adjust for births of establishments that are not captured in the sampling scheme, the BLS adds a "bias" factor to the survey estimate each month.[4] The bias factor is based in part on a model of births of establishments. Additionally, after about a 7 month lag the BLS receives a census of employment based on the universe of UI payroll tax records. This count also is used to adjust the bias factor. Each June the complete count of employment from the UI files is used to make a "benchmark adjustment" to the previously released employment data. In practice, that may be measured with error.[5]

Beginning in the late 1970s, the BLS greatly increased the sample of establishments that were surveyed to improve geographic and industry coverage. Additionally, steps were taken to increase the response rate; most importantly, the BLS moved to an automated system in which respondents could answer the survey by pushing the buttons of a touch-tone telephone. Both of these efforts led to a higher sample size. Figure 1 shows the sample size used to estimate the first employment report each month since 1979. The sample increased from an average of 68,000 respondents in the first quarter of 1979 to an average of 239,000 in the first quarter of 1996. If there was simple random sampling, this increase in the sample size would be expected to reduce the standard error of the estimates by 47 percent.

The sample size fell slightly in the late 1990s, but was still substantially above the level in the 1980s and early 1990s. In 1997, the BLS began random sampling, called probability sampling to

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[4]The bias factor is set at the beginning of each quarter, and remains fixed for the quarter.

[5]The benchmark adjustment is made to the March data, and wedged in uniformly for the previous 12 months. In making the benchmark adjustment, the BLS also uses additional sources to count the small number of nonagricultural workers who are not covered by unemployment insurance.

replace the old quota sample. Although the new procedure was not used for the reported estimates until three years later, the sample size decreased in 1997 as the BLS diverted some of its resources to developing the new procedure. In June 2000, the BLS began phasing in the redesigned sampling procedure. The new probability sampling procedure will gradually replace the old quota sample. The probability sample was phased in starting with selected industries at various times. Due to the increased per-unit cost of the new survey, the BLS reduced the size of the sample by approximately 10 percent in industries in which the probability sample was phased in, which accounts for the drop off in the sample size in 2000.[6] Fortunately, none of our main conclusions is changed if we end the sample in 1996.

Table 1 reports summary statistics for seasonally adjusted monthly employment changes.[7] The first-reported employment change, denoted e_1, is the difference between the first report of employment for the latest month and the second report of employment for the preceding month. For example, if the data are released in September, the first-reported change would be the first estimate for August minus the second estimate for July. The second report is the revised August estimate minus the third estimate for July (denoted e_2), and this figure would be released in October. The third report would be available in November, and is the third estimate of August's employment minus the third estimate of July's (denoted e_3). The revised employment reports incorporate data from sampled establishments that responded late. The benchmark employment change is the final estimate from the UI files (denoted μ), which we take to be the population mean. The forecasted employment change (denoted f) is the median employment change forecasted by market specialists surveyed by Money Market Services International (MMS). The MMS employment data only are available from January 1985 forward. Consequently, we have constructed our own monthly forecast (denoted f_c) for 1979-2002 by recursively estimating a regression of the first-reported employment change on lags of the preceding six months of employment changes and the number of new unemployment insurance claims in the week containing the 12th of the

[6]The wholesale trade industry switched to the new survey procedures in June 2000, with mining, construction, and manufacturing following in June 2001 and transportation/public utilities, retail trade, and finance/insurance/real estate in June 2002. The phase-in will be completed in June 2003, when the service industries implement the new procedure.

[7]Because market forecasts are for seasonally adjusted data, and because most discussion focuses on the seasonally adjusted data, all of the data used in this paper are seasonally adjusted.

month. The sample used to estimate the 1979 forecasting equation consists of monthly observations from December 1969 to December 1978. The coefficients of the forecasting equation were re-estimated each year, rolling the sample forward to include the latest 12 months of data. The most current coefficients are used to forecast employment each year. The sample used to construct each month's forecast covers a time period before that month's employment data were released.

Several conclusions are evident from Table 1. First, the mean employment change is fairly close among all of the estimates. Second, the data are quite noisy. The average absolute revision between the first-reported employment change and the final benchmark figure is 86,000; the standard deviation of the revisions is 111,000. Third, over the period when the MMS data are available, the average of the median forecasts is fairly close to the average first report of employment growth, so the median forecast provides essentially an unbiased estimate. Fourth, the standard deviation of the forecast errors (i.e., the first-reported employment change minus the MMS forecast) is substantial, suggesting a good deal of news is revealed on the day the employment numbers are released.

The MMS forecast is reasonably strongly correlated with the BLS estimates of employment growth. Table 2 shows that the MMS forecast has a correlation of .68 with the first report of employment and a correlation of .73 with the final benchmark number. A regression of the first report of the employment change on the forecasted change yields the following coefficient estimates, with standard errors shown in parentheses:[8]

$$(1) \qquad \hat{e}_1 = \underset{(13.81)}{-33.48} + \underset{(.074)}{1.196} f \qquad R^2 = .56 \qquad \underset{(.07)}{\rho = .02.}$$

Although the median forecast is virtually *mean* unbiased, movements in the forecast tend to understate movements in the employment survey. This result generates a positive correlation between the forecast error and the forecast itself.

To further explore the predictive power of the MMS forecast, we regressed the benchmark employment (population mean) on the first report and MMS forecast. The results, which are presented

[8]The equation was estimated using the Cochrane-Orcutt procedure to correct for possible first-order serial correlation. The sample size is 213 monthly observations.

in equation (2) below, indicate that the forecast has surprising explanatory power, even conditional on the survey data. Combining the survey data and the MMS forecast yields a more accurate prediction of the benchmark data. Equation (2) suggests that when the survey estimate of employment growth deviates substantially from the forecasted amount, the survey data are likely to be adjusted toward the forecasted amount.[9] Indeed, in 59% of the months when the survey data exceeded the forecast the survey data were adjusted downward in the benchmark revision, and in 69% of the months when the survey data were less than the forecast, the survey data were adjusted upward.

$$(2) \qquad \hat{\mu} = \underset{(13.52)}{9.59} + \underset{(.05)}{.53}e_1 + \underset{(.09)}{.51}f \qquad R^2 = .68 \qquad \rho = \underset{(.07)}{.18.}$$

According to Table 2, the correlation between the MMS forecast and the constructed forecast is .73, suggesting that, to some extent, professional forecasters base their predictions on a model similar to the one used to derive the constructed forecast. The constructed forecast is also positively correlated with the BLS data, but not as strongly as the median of the professional forecasters. In contrast to the results for the MMS forecast, when equation (1) is estimated using the constructed forecast, the coefficient on the constructed forecast is less than 1. It is also worth noting that when equation (2) is estimated using the constructed forecast instead of the MMS forecast, the coefficient on the survey employment rises, and that on the forecast falls.[10] In sum, the constructed forecast is not as strong a predictor of employment growth as the median MMS forecast, but nonetheless is reasonably correlated with the BLS data.

Another issue concerns revisions to previous months' data. As far as we know, forecasters do not systematically try to predict BLS revisions to earlier months' employment data, even though the revisions are often substantial (see Table 1). To explore the time-series properties of the revisions, we

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[9]Further evidence that the survey may exaggerate swings in employment comes from regressing the benchmark employment change on e_1. This regression yields a coefficient of .81 on e_1, with a standard error of .03, suggesting that large movements in first reported employment growth tend to be adjusted toward the mean in the benchmark revision. This finding and the positive effect of the forecast in equation (2) may partially result from smoothing due to revised seasonal adjustment factors in the benchmark data. But a qualitatively similar set of results is found when the third reported employment change is used instead of the benchmark data, so ex-post seasonal adjustments are not the entire story.

[10]If the sample is restricted to the same months used for equation (2), the coefficient on the constructed forecast is .30.

regressed the second report of the employment change for a given month on that month's first-reported change, and the third-reported change on that month's second-reported change. In both cases, the intercept was insignificantly different from zero, and the coefficient on the previous report was very close to one.[11] Because the successive reports appear to follow a random walk, the deviation between the second and first report of employment growth (or the deviation between the third and second report) probably provides a reasonable estimate of the unanticipated revision.

Improved Precision?

Table 3 examines whether the precision of the first-reported employment data improved as the sample size increased. Although it is a simplification of the BLS's estimation procedure, the functional form used in these models was derived under the assumption that a univariate mean was estimated from a randomly selected sample. Specifically, write the variance of the mean $(\bar{x})$ of a sample of n observations, $x_1,\ldots x_n$, as $var(\bar{x}) = E(\bar{x} - \mu)^2 = \sigma^2 / n$ where μ is the population mean and σ^2 is the variance of x. Taking logarithms of each side yields:

$$(3) \quad \log E(\bar{x} - \mu)^2 = \log(\sigma^2) - \log(n).$$

Intuitively, the (proportionate) sampling variance should decline in proportion with the increase in the sample size. In the CES program, the benchmark employment can be thought of as the (time-varying) population mean, and the first report as the sample mean.

Column 1 of Table 3 presents a regression of the log of the squared deviation between the benchmark and first-reported employment change on the log of the sample size at the time of the first report. As equation (3) predicts, the coefficient on the log of the sample size is insignificantly different from -1, indicating that the sampling variability has declined at about the rate one would expect (with random sampling) as the sample size increased.[12] To check whether the results just reflect a

[11] A regression of e_2 on e_1 yields a coefficient of .98 with a standard error of .019, and a regression of e_3 on e_2 yields a coefficient of .98 with a standard error of .021.

[12] In results not reported here, we estimated the model in column 1 using the log of the squared deviation between the first report and the second or third report as the dependent variable. The coefficient on the log sample size in these equations was also insignificantly different from -1, indicating a decline in the magnitude of revisions as the sample size increased.

coincidental trend toward less variable employment data, in column 2 a linear time trend is added to the model. The coefficient on the log sample size increases in magnitude in this model, although its standard error increases substantially as well. Furthermore, the coefficient on the time trend suggests that the sampling variability increased over time, although this coefficient is not statistically significant.

As a further check on these results, we regressed the squared deviation between e_1 and μ on $1/n$ and an intercept. The coefficient on $1/n$ in this regression is an estimate of σ^2, and the intercept in this regression should be 0. The coefficient on $1/n$ was large (1.24×10^9) and statistically significant, whereas the intercept was small and statistically insignificant.

If the employment survey became less noisy over time, then one would expect the forecast errors to decline. Columns 3 and 4 of Table 3 test this hypothesis with the MMS data. As expected, the results indicate that the forecast error has declined with the increase in the sample size.[13] An alternative interpretation, however, is that forecasts have improved as forecasters have become more sophisticated. This hypothesis is explored in Columns 5 and 6, which use the log of the squared deviation between the forecast and the benchmark employment numbers as the dependent variable. The motivation for estimating this model is that, if the forecasts have improved, they should do a better job predicting the population mean as well as the sample mean. Contrary to this prediction, however, the forecast errors around the population mean have actually increased as the sample size increased.

To further test the improved reliability of the data, we have re-estimated equation (2) also including an interaction between the survey employment and its underlying sample size. This interaction term was statistically significant (t=3.8) and positive, indicating that the survey data became a stronger predictor of the population mean as the sample size increased, conditional on the forecast. Taken together, these results suggest that the noise in the survey estimates declined as the sample size increased.

As a final test of our assumption that the first-report differs from the benchmark by a classical sampling error that is becoming smaller over time, we computed the correlation between the deviation between e_1 and the benchmark and the benchmark itself, separately for the first and second halves of the

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[13]Similar results were obtained using the constructed forecast instead of the MMS forecast.

sample. If the error in estimation of e_1 is classical throughout the sample period, both correlations should be zero. If the benchmark is a noisy measure of the population mean, however, the correlations would be negative. The results provided mixed support for the classical measurement error model with slightly smaller sampling variance over time. The correlation in the first half of the sample was –0.25 and in the second half was –0.21, and both were statistically significant at the 0.05 level. The negative correlations are consistent with the benchmark containing some error, which is plausible. On the other hand, the smaller correlation in the later sample suggests that the error in e_1 is behaving somewhat more like a classical measurement error more recently. Moreover, the correlational evidence for the classical measurement error model is more supportive than the corresponding evidence for the polar opposite model: that the first-report is an optimal forecast of the benchmark.[14] In this case, the correlation between $(e_1 - \mu)$ and e_1 would be zero. Instead, we find a correlation of 0.32 in the first half of the sample and 0.34 in the second half.

A regression of the first report on the benchmark data using data after 1986 yields:

$$\hat{e}_1 = \underset{(11.08)}{-9.42} + \underset{(0.04)}{0.90}\mu \qquad R^2 = .71 \qquad \rho = \underset{(.07)}{.08}\,. \tag{4}$$

Although the classical measurement error assumption of a zero intercept and unitary slope are formally rejected by an F-test, the assumptions are a reasonable approximation. Moreover, the reverse regression yields a slope (standard error) of 0.76 (0.04), qualitatively far from the unitary slope implied by an efficient forecast.

Given our understanding of the way in which the first report of the employment change is estimated – and the likelihood that the benchmark figure is a noisy measure of μ – in our view the results as a whole are consistent with the view that the error in e_1 is reasonably well approximated by classical sampling error and that the benchmark is a somewhat imperfect measure of the true employment change.

[14]See Mankiw, Runkle and Shapiro (1984) and Mankiw and Shapiro (1986) for an exposition of the classical measurement error model and efficient forecast model applied to preliminary aggregate data estimates. The former paper finds evidence that errors in preliminary money supply estimates are best characterized by the classical errors–in-variables model, while the latter paper finds that errors in initial GNP estimates are best characterized as efficient forecast errors.

II. A Model of Bayesian Investors with More Precise Data

Intuitively, one would expect rational investors to place more credence in the BLS survey of employment growth as the survey became more reliable. This intuition can easily be formalized for the case of Bayesian updating. For example, assume that the underlying employment change data are normally distributed, with variance σ^2, and unknown mean μ. Also assume that the distribution of priors about μ is normally distributed, with variance v^2 and mean f. Suppose a random sample of n observations is drawn from the population, and the average of this sample is denoted e. The mean of the posterior distribution ($\hat{\mu}$) after the sample mean is observed is:

$$(5) \qquad \hat{\mu} = \frac{\sigma^2}{\sigma^2 + nv^2} f + \frac{nv^2}{\sigma^2 + nv^2} e .$$

Equation (5) specifies the posterior estimate of the mean as a weighted average of the mean prior expectation and the sample average (see DeGroot and Schervish, 2002; pp. 339-340). For fixed values of σ^2 and v^2, the relative weight assigned to the sample mean increases as the sample size increases. Notice that one can re-write the posterior estimate as:

$$(5') \qquad \hat{\mu} = \frac{nv^2}{\sigma^2 + nv^2}(e - f) + f = \frac{1}{1 + \psi/n}(e - f) + f$$

where ψ is the ratio of σ^2 to v^2. Deviations between the survey estimate and the prior expectation receive more weight as the sample size increases, and as ψ decreases.

It seems reasonable to take the consensus estimate of professional forecasters as a measure of the mean of the prior distribution, and the first-reported employment change as the sample mean. If n were fixed, the regression results in equation (2) would provide an estimate of the optimal "Bayesian weights" to assign to the prior and to the sample average (e_1). However, n is not fixed. The optimal Bayesian weight to apply to the forecast error in equation (5') can be estimated directly by Nonlinear Least Squares (NLS). Specifically, we used NLS to estimate the parameter ψ in equation (5'), using the benchmark data as the dependent variable (μ), e_1 as the sample average, the MMS forecast as f, and the

BLS sample size as n.[15] Plugging in actual values of n, the results imply that the optimal Bayesian weight to apply to deviations between the forecast and employment survey was 0.54 in 1979, 0.61 in 1985 and 0.70 in 1996.

Next consider how the precision of the employment survey might affect the bond market. An increase in employment is typically interpreted as a sign that the labor market is tightening, and that wage-push inflation may follow. Because the bond yield is positively related to expectations of future inflation, any news raising the probability of higher inflation would be expected to increase the bond yield. Moreover, equation (5) indicates that an increase in surveyed employment growth of a given magnitude will lead investors to revise their expectations of true employment growth by a greater margin if the sample size is larger. Consequently, the bond market would be expected to react more to unexpected blips from the survey if the survey is based on a larger sample size.

Formally, assume the bond yield is a function of expected employment growth, $g(\hat{\mu})$, and that $g'>0$. The market's reaction to a given change in survey employment as the sample size increases is given by $\delta^2 g(\hat{\mu})/\delta n \delta e$, which is:

$$(6) \quad \delta^2 g(\hat{\mu})/\delta n \delta e = g''(\delta\hat{\mu}/\delta e)(\delta\hat{\mu}/\delta n) + g'(\delta^2\hat{\mu}/\delta n \delta e) > 0$$

Notice that if priors are unbiased, the first term drops out in expectation because $(\delta\hat{\mu}/\delta n) = 0$ if $e = f$. From (5), the second term is clearly positive, indicating a larger reaction of the bond yield to a given increase in the survey estimate of employment growth, when the survey estimate is based on a larger sample size. If $g(\cdot)$ is linear, the market reaction to the employment surprise would increase in proportion to $\frac{1}{1+\psi/n}$, all else equal. The next two sections test whether interest rate reactions to employment news have varied with the precision of the employment survey.

III. Estimating Market Reactions

Table 4 presents several Ordinary Least Squares (OLS) regression models simply relating the close-to-close change in the benchmark 30 year Treasury bond yield to the announced change in survey employment (e_1) on the day the employment news is released. Because a consensus forecast of

[15] The estimate of ψ equaled 169,374, with a t-ratio of 5.10.

employment growth is not available until 1985, results are first presented for a larger sample without subtracting forecasted employment growth from announced employment growth. To facilitate comparison to models that adjust for expectations, two time periods are used: February 1979 to November 2002, and February 1985 to November 2002. Although some of the employment news was anticipated, the results indicate that an increase in employment is associated with a statistically significant increase in the bond yield. In column 1, for example, an increase in employment of 200,000 jobs is associated with a 3 basis point increase in the bond yield. As shown below, the response is about twice as large if one looks at unanticipated employment changes.

To test whether the market reactions have become stronger as the CES sample size increased, the models in columns 2 and 5 also include an interaction between the first-reported employment change and the optimal Bayesian weight, defined as $e_1 \times \frac{1}{1+\psi/n}$, where ψ was estimated by NLS as previously described. Contrary to what one would expect with Bayesian updating, this interaction term is statistically insignificant and slightly negative. The Bayesian weight is a nonlinear function of the sample size. To explore the robustness of this interactive effect, we estimated two alternative functional forms: (1) interact the employment change with the linear sample size; (2) interact the employment change with the log sample size. In both specifications, the interaction was negative and statistically insignificant. Further evidence that the market reaction did not intensify as the sample size increased comes from estimating the model in column (1) on two subsamples, one covering 1979-84, and one covering 1985-2002. The coefficient (and standard error) on e_1 for the 1979-84 sample is .021 (.006), compared to .011 (.003) for the post-1984 period.

The other variables in the model are individually and jointly statistically insignificant. The change in the unemployment rate and change in the hourly wage of production/non-supervisory workers, which are also announced on the day the employment data are released, have small and statistically insignificant effects. Additionally, dummy variables indicating the day of the week the data were released and a quadratic time trend are jointly insignificant.

Only unanticipated news should affect financial markets. To adjust for expectations, results in Table 5 use the MMS data to calculate the employment change forecast error (e_1-f). The estimates are based on data for 1985 to 2002. Comparing column (1) of Table 5 to column (4) of Table 4 indicates that an unanticipated increase in employment has a larger impact on the bond yield than does the total increase in employment. An unanticipated increase of 200,000 jobs is associated with a 6.2 basis point increase in the bond yield. If the market applies the optimal Bayesian weights to the employment survey, the interaction between employment growth and the (nonlinear function of the) sample size in column (2) would be significant and positive, and the forecast error itself would be insignificant. Again, however, the interaction term is negative and statistically insignificant, providing no evidence of a stronger reaction to more precise data.[16]

Figure 2 provides a scatter diagram of the change in the bond yield versus the unexpected change in employment. An upward sloping relationship is apparent.[17] There is no obvious increase in the slope over time. A bivariate regression of the change in the interest rate on the forecast error using the 1985-89 sample yields a slope of .053 (s.e.=.011), whereas the same regression using the 1990-2002 sample yields a slope of .025 (s.e.=.005). As a rough check on the power of the estimates, suppose the effect of employment surprises had increased by 40 percent since 1985-89, i.e., to a coefficient of .074 (=1.4 x .053). The 1990-2002 estimate is statistically different from .074, so the data likely would have the ability to discriminate between effects of this magnitude.

To further explore changes in the responsiveness of interest rates to unexpected employment news over time, bivariate regressions of the 30 year bond yield on the employment surprise were estimated for each two-year period. Figure 3 illustrates the predicted change in rates associated with an unexpected increase of 200,000 jobs based on these regressions. If anything, the responsiveness of the interest rate to employment news declined over this period, and, to our surprise, changes in bond yields were completely unrelated to employment surprises in 2001-2002. But since the standard error of each of these estimates is about 3 basis points, probably too much should not be made of individual points.

McQueen and Roley (1993) and Boyd, Jagannathan, and Hu (2001) find that interest rate reactions to real economic news are invariant to the state of the business cycle, in contrast to stock

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[16] Similar results are found if the linear sample size or log of the sample size is interacted with the employment surprise.

[17] Notice that Figure 2 displays little evidence of a nonlinear relationship between the change in the interest rate and employment surprises. More formal statistical tests based on fitting a quadratic in the forecast error and a linear spline that allows for differential effects of positive or negative employment shocks also supported a linear relationship.

market returns. A similar pattern holds for employment surprises in these data: an interaction between the unemployment rate and forecast error is insignificant if it is added to the model in column 1. Thus, business cycle effects are unlikely to confound any effect of more precise data. Figure 3 is consistent with this view.

Column 3 of Table 5 indicates that deviations between the unemployment rate and the MMS consensus forecast of the unemployment rate are statistically insignificant. Previous studies that have found a significant relationship between the bond rate and unexpected changes in unemployment generally have not controlled for the effects of employment changes (e.g., Hardouvelis, 1988 and Prag, 1994). If the model in column 3 is estimated *without* the employment forecast error, the coefficient on unexpected changes in unemployment becomes –8.1, with a t-ratio of -2.5. Thus, the negative correlation between unexpected employment growth and unexpected unemployment rate changes (r = -.16) may partially drive earlier findings of a significant effect of unemployment shocks on the bond rate. As discussed below, another issue involves bond maturity: short-term rates are more sensitive to the unemployment rate.

Because forecasts of wage changes are not available before the last few years, the wage change is included as a regressor in column 3 without subtracting off expectations.[18] Announced changes in the hourly wage of production and non-supervisory workers have a statistically significant effect in these models. A 6 cent increase in the hourly wage is associated with about a 3 basis point increase in the 30 year bond rate. Notice, however, that when the employment surprise is excluded from the model (see column 7), wage changes have an insignificant and small effect.

Revisions to the two previous months' employment numbers, which are released along with the unemployment rate and the latest employment data, also have a statistically insignificant effect. Nonetheless, the magnitude of the effects of the revisions is sizable, about half the size of the effect of the latest month's data. As mentioned earlier, the second and third revisions to the employment changes appear to follow a random walk, so the revisions could be viewed as largely unanticipated.

In column (6) the MMS employment forecast is included in the model along with the forecast

[18]Experimentation with modeling wage changes as an autoregressive process, and using residuals from this process as an explanatory variable in Table 5, yielded similar results.

error. Surprisingly, the forecast has a statistically significant effect. This result is also found in the more parsimonious model in column (8). When the forecast error is omitted from the model, however, the forecast is insignificant. Thus, the positive correlation between the forecast error and the forecast drives this result.[19] Because the forecast error is not known in advance of the employment release, this finding does not conflict with the efficient markets hypothesis.

To look over a longer time period, Table 6 uses the constructed forecast in place of the MMS median forecast. The models were estimated with data from 1979 to 2002. The forecast error based on the constructed forecast has a smaller impact on the bond yield than does the MMS forecast error, but is nonetheless statistically significant.[20] An unexpected increase in employment of 200,000 jobs is associated with a 3.4 basis point increase in these models. The interaction between the constructed forecast error and the sample size again yields an insignificant effect. If the model in column 4 is estimated with a sample limited to the post-1984 period, the coefficient on the forecast error is insignificantly different from that estimated with the pre-1985 sample, though larger.

A curious result emerges when the constructed forecast is included as a regressor in columns 6 and 8. Here, the forecast has a statistically significant, positive impact on the bond yield. Recall that the MMS forecast had a negative and significant effect in this specification. The reason for the opposite signs on the two forecasts is that the constructed forecast is negatively correlated with its forecast error, while the MMS forecast is positively correlated with its forecast error. One possible explanation for the frequent statistical significance of the forecast is that the standard errors of the estimates are understated, perhaps because homoskedasticity is assumed in calculating the OLS standard errors. To explore this possibility, White (1980) standard errors were calculated for all the models in Tables 5 and 6. The heteroskedasticity-consistent standard errors for the forecast and forecast error were comparable

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[19]To see this, write $\hat{y} = bf$ and $\hat{y} = c\,(e_1\text{-}f) + df$, where constants have been suppressed for simplicity. By the omitted variable bias formula, $b = d + c\pi$, where π is the coefficient from an auxiliary regression of $(e_1 - f)$ on f. If $b = 0$, then $d = -c\pi$. In this case, d is negative because c and π are positive.

[20]Unlike in Table 5, the deviation between the announced unemployment rate and the MMS unemployment rate forecast is statistically significant in these models. This results in part because the constructed employment forecast is a weaker predictor than the MMS forecast, and in part because the unexpected unemployment rate has a smaller effect in the post-1984 period.

to the OLS standard errors, however, so OLS standard errors are reported in the tables.

IV. Short-term Treasury Bills

Although the focus of this paper is mainly on responses to announced employment news in the long-term bond market, we have also examined responses in the market for short-term Treasury bills. Figure 4 displays the change in interest rates associated with an unexpected increase of 200,000 jobs from a bivariate regression of the 3 month T-bill rate on the employment forecast error every 2 years, analogous to Figure 3. Table 7 presents results using as the dependent variable the yield change for 3 month or 1 year Treasury bills. The sample covers 1985-2002, and the estimated models are comparable to those in Table 5 in that they use the MMS employment change forecast.[21]

The interest rate changes associated with unanticipated employment news is greater for the short-term maturities than for the 30 year bond. An unexpected increase of 200,000 jobs is associated with a 7.6 basis point increase in the interest rate for 3 month bills, and a 12 basis point increase for 1 year bills. There is no evidence that the market reaction to unanticipated employment changes has increased as the BLS sample size increased; indeed, for both the 3 month and 1 year Treasury bill the interaction term between the (nonlinear function of the) sample size and the employment forecast error is negative and statistically significant. Figure 4 is also consistent with this view. If the constructed forecast is used to look at a longer time period, this interaction term is negative but insignificant. Thus, like long-term interest rates, short-term rates do not exhibit a more intense reaction to employment news after the news became more precise.

The most notable difference between the results for the short term markets and the long term market is the statistically insignificant and small effect of the MMS forecast on the yield of the short term Treasury bills. This finding is consistent with the findings of Cook and Korn (1991). In addition, unexpected changes in the unemployment rate have a boarder-line statistically significant effect on 3 month yield rates: a 0.5 percentage point increase in unemployment is associated with a decrease in the 3 month yield of approximately 2.5 basis points.

[21] The one year Treasury bill was discontinued in mid-2001, so columns 4-6 have 17 fewer observations.

V. Extensions

A number of extensions of the basic results were explored. First, to test whether bond markets react to the employment news with a lag, the effect of the employment announcement on the change in the next trading day's yield was examined. Specifically, we estimated the models in Tables 4-6 using as the dependent variable the change in the bond yield for the next trading day. These results provided no indication that the employment news had a lagged effect on long-term bond yields: neither the employment numbers nor their deviation from forecasts had a statistically significant impact on bond yields in these models. Curiously, however, the change in the hourly wage had a statistically significant, positive effect in these models.

Second, it is often alleged that markets over react to the employment data on the day the data are released, and then correct for this over reaction on the following trading day. Although the results described in the previous paragraph are inconsistent with this view, to further test this hypothesis we correlated the residuals from the models in Tables 4-6 with the next day's yield changes. If larger than predicted movements in yields on announcement days are corrected the next day, this correlation would be negative. The results of this exercise yielded numerically small, statistically insignificant and typically positive correlations, however.

Third, if some market participants have advance knowledge of the BLS data, the news may affect the markets prior to the announcement date. To test for this possibility, we regressed the change in the yield *on the day before* the employment announcement on the forecast errors.[22] When the models in Table 5 were estimated using the post-1984 sample, the unexpected soon-to-be-announced changes in employment and unemployment had statistically insignificant and small effects. Surprisingly, however, when the models in Tables 4 and 6 were estimated for the 1979-2002 sample using the previous day's yield change as the dependent variable, the changes in the unemployment rate, employment and hourly wage often were statistically significant. These findings do not necessarily imply that the BLS data were leaked to some investors prior to their announcement date, however. It is possible, for example, that the Fed -- which is notified of the employment data prior to their release --

[22]The employment data typically are known to the BLS only one or two days before the announcement date.

acts on this information, and that the markets respond to the Fed's actions without direct knowledge of the BLS employment data.

Fourth, it is worth comparing our results to those in Jones, Lamont, and Lumsdaine (1996), who examine the effect of CES announcement dates on volatility in the 30-year-bond market from 1977 to 1993, and in the 5- and 10-year-bond markets from 1969 to 1993. They find that the variance of the daily excess return is about 50 percent greater in all three markets on announcement days than on non-announcement days. Our results indicate that the R^2 of the employment surprises, revisions to past months data, wage change and unemployment rate, is about 25 percent (using the MMS forecast data) for long term bonds, and about 40 percent for short-term bills, suggesting that the news conveyed by the employment report can account for a good deal of the excess volatility on announcement dates.

Figure 5a displays the average absolute change in the 30-year-bond interest rate on announcement days and on all other days, each year from 1979 to 2002. Figure 5b displays the difference in volatility between announcement days and non-announcement days. There is no tendency for volatility to have increased on announcement days over time, either in isolation or relative to non-announcement days. Moreover, the correlation between the excess volatility on announcement days and the average sample size at first closing is only 0.13, which is not significantly different from zero (p-value=0.56). Because it is unnecessary to make assumptions about the functional relationship between employment surprises and the sample size, at one level this examination of volatility provides a more robust test than our earlier regressions. On the other hand, because volatility can arise from several sources and because the variability of underlying shocks to employment could change over time – and because we suspect that assuming linearity of employment surprises does not impose a severe constraint in the yield equations – we consider the earlier evidence to be a stronger test. Nevertheless, it is reassuring that both tests point in the same direction.

VI. Summary and Conclusion

The three main findings of this paper are: (1) the precision of the BLS's first estimate of nonfarm employment growth improved as the sample size increased; (2) announcements of unanticipated employment changes strongly affected daily interest rate movements from 1979 to 2002;

(3) the effect of unanticipated employment changes on interest rates does not appear to have increased over time, as the BLS employment data became more reliable and as the Federal Reserve Board shifted its focus to employment indicators. Although the latter finding may seem surprising, there is additional evidence suggesting that financial markets paid at least some attention to the BLS employment announcements before the mid 1980s. Table 8 reports the percent of times an article in the *New York Times* cited the BLS employment release data the day after the announcement date in a story regarding the bond or stock market. After 1983, the employment data were noted as influencing the financial markets virtually every day after they were released. In the 1979-83 period, the employment news was cited as influencing the financial markets less frequently, but was still mentioned on 45 percent of post-announcement days. Interestingly, the dip in references to the employment report in stories related to the bond market in 1999-2002 is consistent with the declining importance of employment news for interest rates in recent years evident in Figure 3.

One possible explanation for the apparent constant market reaction to more precise news is that the markets were not aware of the increased precision of the BLS employment survey. This is certainly possible, but there were news articles written about the improvements in the BLS data in the 1980s. Moreover, the BLS reports the sample size and sampling variability of the employment survey in every issue of *Employment and Earnings*, so it is not difficult to learn that the series improved. Market forecasters have a tremendous amount of information regarding the construction of the BLS data; for example, many are knowledgeable of the magnitude of the quarterly bias adjustment. It would be somewhat surprising if they were not aware of the expansion of the survey.

Another possibility is that the amount of additional information available to market participants increased during the same time period the precision of the employment survey increased, so the employment survey provided less new information than otherwise would be the case.[23] There is scant evidence that the quantity or quality of other labor market data improved over this period, however. For example, the BLS's closely watched survey of manufacturing turnover was eliminated in the early 1980s, and the sample size of the CPS was cut from 65,500 to 53,600 households in the 1980s. More

[23] In terms of equation (5), this hypothesis is equivalent to a decrease in v^2.

generally, Abraham (1996) reports that the BLS's budget was constant in real terms since 1978, so it is unlikely that there was a major increase in other labor market data in this period. Finally, the finding that MMS employment forecasts have not improved relative to the benchmark data suggests that private forecasters were unable to make more precise forecasts over time.

At this stage, it seems anomalous that the bond market did not respond more to more reliable employment data. Kahneman and Tversky (1982) document that, compared to optimal Bayesian updating, it is common for individuals to place too much weight on recent information and too little weight on their prior data. The findings of this study may reflect this broader phenomenon. From the present results, however, it is not possible to determine if the market over or under reacts to employment news. It is possible that the market over reacted to the news initially, and that the current reaction is efficient. Alternatively, it is possible that the market over reacted initially, and continues to over react today. But in either scenario, the results suggest that investors did not rationally respond to changes in the precision of relevant information.

Before the conclusion that financial markets do not rationally respond to more accurate information is generally accepted, it would be useful to see this hypothesis tested further by examining the effects of changes in other data series. For example, there have been (or are planned) changes in the quality of other U.S. government surveys, including the Employment Cost Index, Consumer Price Index, Produce Price Index, Capacity Utilization, and National Income and Product Accounts. And the sample size of the University of Michigan's consumer sentiment survey was drastically cut in recent years.

Other countries also have changed the quality of their economic statistics over time. For example, France's National Institute of Statistics and Economic Studies (INSEE) introduced a new method for determining the monthly unemployment rate in 1996. Their new method links the Labor Force Survey with month-end numbers of job seekers and temporary employees, and then applies an econometric model to simulate seasonally adjusted monthly unemployment. Germany has likewise introduced new statistical techniques for seasonally adjusting several economic time series. The United Kingdom's Office for National Statistics has implemented a new system of weighting, known as "chain-linking," to improve its estimates of output growth. New European Union regulations for availability, quality, and timeliness of short term statistics agreed upon in 1998 and scheduled for enforcement beginning in mid-2003 could also have an impact on financial markets. The present type of analysis can be performed using the experiments provided by changes in these and other data series for a number of countries and by examining responses in the corresponding financial markets.

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Table 1: Descriptive Statistics for Monthly Employment Changes

Variable	Mean Value	Mean Absolute Value	Std. Dev.	Period
Employment Change, First Report (e_1)	134.4	203.1	200.4	1979:1-2002:10
Employment Change, Second Report (e_2)	131.9	205.9	207.0	1979:1-2002:9
Employment Change, Third Report (e_3)	152.9	222.2	216.9	1979:1-2002:8
Employment Change, Benchmark (μ)	163.5	217.1	190.2	1979:1-2001:2
MMS Median Forecast (f)	150.8	168.1	110.7	1985:1-2002:10
Constructed Forecast (f_c)	129.8	161.3	126.0	1979:1-2002:10
First Report - Second Report	3.0	48.0	65.2	1979:1-2002:9
First Report - Third Report	-17.3	68.9	106.6	1979:1-2002:8
First Report - Benchmark	-13.3	86.3	110.6	1979:1-2001:2
First Report - MMS Median Forecast	-3.4	91.2	118.7	1985:1-2002:10
First Report - Constructed Forecast	4.3	122.4	167.6	1979:1-2002:10

Notes: All numbers are in thousands. MMS forecast is the median of professional forecasters. The constructed forecast is predicted employment change from a recursive regression of the first-reported employment change on six of its lags and seasonally adjusted initial unemployment insurance claims for the week including the 12th of each month. All employment data are seasonally adjusted.

Table 2: Correlations Among Measures of Employment Change

	1st Rept (e_1)	2nd Rept (e_2)	3rd Rept (e_3)	Benchmark (μ)	MMS Forecast (f)	Constr. Forecast (f_c)
Employment Change, First Report	1.00					
Employment Change, Second Report	.94	1.00				
Employment Change, Third Report	.86	.92	1.00			
Employment Change, Benchmark	.81	.85	.83	1.00		
MMS Median Forecast	.68	.69	.64	.73	1.00	
Constructed Forecast	.47	.50	.51	.53	.73	1.00

Notes: Sample size is 194 months. MMS forecast is the median of professional forecasters. Constr. forecast is the constructed employment forecast from a recursive regression equation based on six lags of e_1 and seasonally adjusted initial unemployment insurance claims for the week including the 12th of each month; see text.

Table 3: Tests of Employment Data Reliability as Sample Size Grows

Explanatory Variable	Dependent Variable: $\log(e_1 - \mu)^2$ (1)	(2)	$\log(e_1 - f)^2$ (3)	(4)	$\log(f - \mu)^2$ (5)	(6)
Constant	21.12	27.03	26.01	18.86	-4.33	-11.18
	(3.51)	(8.35)	(8.63)	(10.76)	(8.05)	(13.58)
Log *n*	-1.09	-1.61	-1.47	-0.83	1.01	1.61
	(0.29)	(0.74)	(0.71)	(0.91)	(0.66)	(1.17)
Trend (months)	….	.003	….	-.003	….	-.003
		(.004)		(.003)		(.005)
R^2	.05	.05	.02	.03	.01	.01
Sample Size	265	265	214	214	192	192

Notes: e_1 is the first employment change report; μ is the final benchmark employment change; *f* is the median forecast of the employment change from MMS. Log *n* is the log of the number of establishments used by BLS to estimate the first employment change. Sample period is 1979:1-2001:2 in columns 1 and 2, 1985:1-2002:10 in columns 3 and 4, and 1985:1-2001:2 in columns 5 and 6.

Table 4: OLS Estimates of Effect of Employment Releases on Bond Yields
Dependent Variable: Change in 30 Year T-Bond Yield (times 100)

Explanatory Variable	1979:2 to 2002:11			1985:2 to 2002:11		
	(1)	(2)	(3)	(4)	(5)	(6)
e_1	.015 (.003)	.038 (.012)	.035 (.013)	.011 (.003)	.037 (.036)	.049 (.037)
$e_1 \dfrac{1}{1+\psi/n}$	….	-.051 (.026)	-.047 (.027)	….	-.050 (.068)	-.070 (.068)
Change in Hourly Wage Rate	….	….	35.664 (21.077)	….	….	34.533 (22.547)
Change in Unemployment Rate	….	….	-1.646 (3.082)	….	….	3.578 (3.708)
p value for F-test of year, year squared, Wednesday and Thursday dummies	.197	.082	.229	.172	.169	.292
p value for F-test of e_1 and $e_1 \dfrac{1}{1+\psi/n}$	….	.000	.000	….	.008	.003
R^2	.113	.124	.135	.076	.079	.093
Sample Size	281	281	279	211	211	211

Notes: Standard errors are in parentheses. e_1 is the first-reported employment change, n is the underlying BLS sample size, and ψ is an estimate of σ^2/v^2 (see test for details). All equations also include year, year squared, a dummy indicating whether the release date is a Wednesday, and a dummy indicating whether the release date is a Thursday.

Table 5: OLS Estimates of Effect of Deviations from Median Forecast on the Long Bond Yield, Feb 1985 through Nov 2002
Dependent Variable: Change in 30 Year T-Bond Yield (times 100)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$e_1 - f$	.031 (.005)	.097 (.046)	.034 (.005)	.034 (.005)	.116 (.046)	.036 (.005)	….	.033 (.005)	….
$(e_1 - f)\frac{1}{1+\psi/n}$	….	-.124 (.086)	….	….	-.155 (.086)	….	….	….	….
Revision of last month's employment change	….	….	….	.011 (.010)	.012 (.010)	.014 (.010)	.008 (.011)	….	….
Revision of 2 months ago employment change	….	….	….	.003 (.007)	.004 (.007)	.003 (.007)	.007 (.008)	….	….
Change in hourly wage	….	….	50.619 (20.854)	48.872 (20.968)	51.715 (20.912)	51.443 (20.517)	21.403 (22.741)	….	….
Deviation of unemployment rate change from MMS forecast	….	….	1.782 (3.462)	2.040 (3.478)	2.748 (3.481)	1.729 (3.402)	-1.501 (3.813)	….	….
Median Employment Forecast	….	….	….	….	….	-.016 (.005)	-.010 (.006)	-.015 (.005)	-.009 (.006)
p value for F-test of year, yr squared Wed, Thurs dummies	.250	.283	.505	.442	.561	.361	.120	.273	.109
p value for F-test of $e_1 - f$ and $(e_1 - f)\frac{1}{1+\psi/n}$	….	.000	….	….	.000	….	….	….	….
p value for F-test of the two employment revisions	….	….	….	.460	.385	.318	.448	….	….
R^2	.201	.209	.224	.230	.243	.268	.061	.234	.047
n	211	211	211	211	211	211	211	211	211

Notes: e_1 is the first employment change; f is the MMS median employment forecast; n is the sample size of the BLS employment survey; and ψ is an estimate of σ^2/v^2(see text for details). Standard errors are in parentheses.

Table 6: OLS Estimates of Effect of Deviations from Constructed Forecasts on the Long Bond Yield, Feb 1979 through Nov 2002
Dependent Variable: Change in 30 Year T-Bond Yield (times 100)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$e_1 - f_c$	.017 (.003)	.031 (.015)	.017 (.003)	.017 (.003)	.023 (.016)	.017 (.003)	….	.018 (.003)	….
$(e_1 - f_c)\frac{1}{1+\psi/n}$	….	-.030 (.032)	….	….	-.014 (.033)	….	….	….	….
Revision of last month's employment change	….	….	….	-.009 (.009)	-.009 (.009)	-.009 (.009)	-.008 (.009)	….	….
Revision of 2 months ago employment change	….	….	….	.006 (.007)	.006 (.008)	.006 (.007)	.007 (.008)	….	….
Change in hourly wage	….	….	43.045 (20.906)	44.712 (20.986)	42.90 (21.48)	43.468 (20.988)	41.088 (21.913)	….	….
Deviation of unemployment rate change from MMS forecast	….	….	-6.808 (3.195)	-6.881 (3.202)	-6.76 (3.22)	-6.061 (3.265)	-7.748 (3.391)	….	….
f_c	….	….	….	….	….	.006 (.005)	.003 (.005)	.008 (.005)	.006 (.005)
p value for F-test of year, yr squared Wed, Thurs dummies	.064	.066	.129	.112	.112	.218	.214	.135	.136
p value for F-test of $e_1 - f_c$ and $(e_1 - f_c)\frac{1}{1+\psi/n}$	….	.000	….	….	.000	….	….	….	….
p value for F-test of the two employment revisions	….	….	….	.465	.463	.463	.454	….	….
R^2	.112	.114	.140	.145	.145	.150	.069	.122	.036
n	281	281	279	279	279	279	279	281	281

Notes: e_1 is the first employment change; f_c is the MMS median employment forecast; n is the sample size of the BLS employment survey; and ψ is an estimate of σ^2/v^2 (see text for details). Standard errors are in parentheses.

Table 7: Effect of Deviations from Forecasts on the Short Term Bond Market, February 1985 to November 2002
Dependent Variable: Close-to-Close Change in T-Bill Yield (times 100)

Variable	3 Month T-Bill Yield (1)	(2)	(3)	1 Year T-Bill Yield (4)	(5)	(6)
$e_1 - f$	.038 (.004)	.218 (.039)	.037 (.004)	.061 (.006)	.239 (.056)	.062 (.006)
$(e_1 - f)\frac{1}{1+\psi / n}$	….	-.339 (.072)	….	….	-.333 (.104)	….
Revision of last month's employment change	.011 (.009)	.012 (.008)	.010 (.009)	.018 (.013)	.020 (.012)	.019 (.013)
Revision of 2 months ago employment change	.004 (.006)	.006 (.006)	.004 (.006)	.007 (.010)	.010 (.009)	.007 (.010)
Change in hourly wage	34.693 (18.374)	40.907 (17.534)	33.903 (18.378)	69.325 (26.100)	76.840 (25.579)	69.225 (26.160)
Deviation of unemployment rate change from MMS forecast	-5.250 (3.048)	-3.703 (2.919)	-5.154 (3.048)	-3.090 (4.517)	-1.388 (4.440)	-3.158 (4.530)
Median employment forecast	….	….	.005 (.004)	….	….	-.003 (.007)
p value for F-test of year, year squared, Wednesday and Thursday dummies	.451	.766	.479	.887	.901	.902
p value for F-test of $e_1 - f$ and $(e_1 - f)\frac{1}{1+\psi / n}$	….	.000	….	….	.000	….
p value for F-test of the two employment revisions	.372	.186	.415	.232	.135	.224
R^2	.341	.406	.345	.395	.427	.395
n	211	211	211	196	196	196

Notes: e_1 is the first employment change; *f* is the MMS median employment forecast; *n* is the sample size of the BLS employment survey; and ψ is an estimate of σ^2 / v^2 (see text for details). Standard errors are in parentheses.

Table 8: Percent of times the *New York Times* cited the BLS employment release in connection to the bond or stock market on the day after the release

Period	Bond Market	Stock Market	Either Bond or Stock Market
1979-1983	27%	33%	45%
1984-1988	97	78	98
1989-1993	100	92	100
1994-1998	95	95	97
1999-2002*	70	98	98

*1999-2002 data are through November of 2002. Source: Authors' calculations from Lexis-Nexis.

Figure 1: Sample Size at First Closing: 1979:1-2002:10

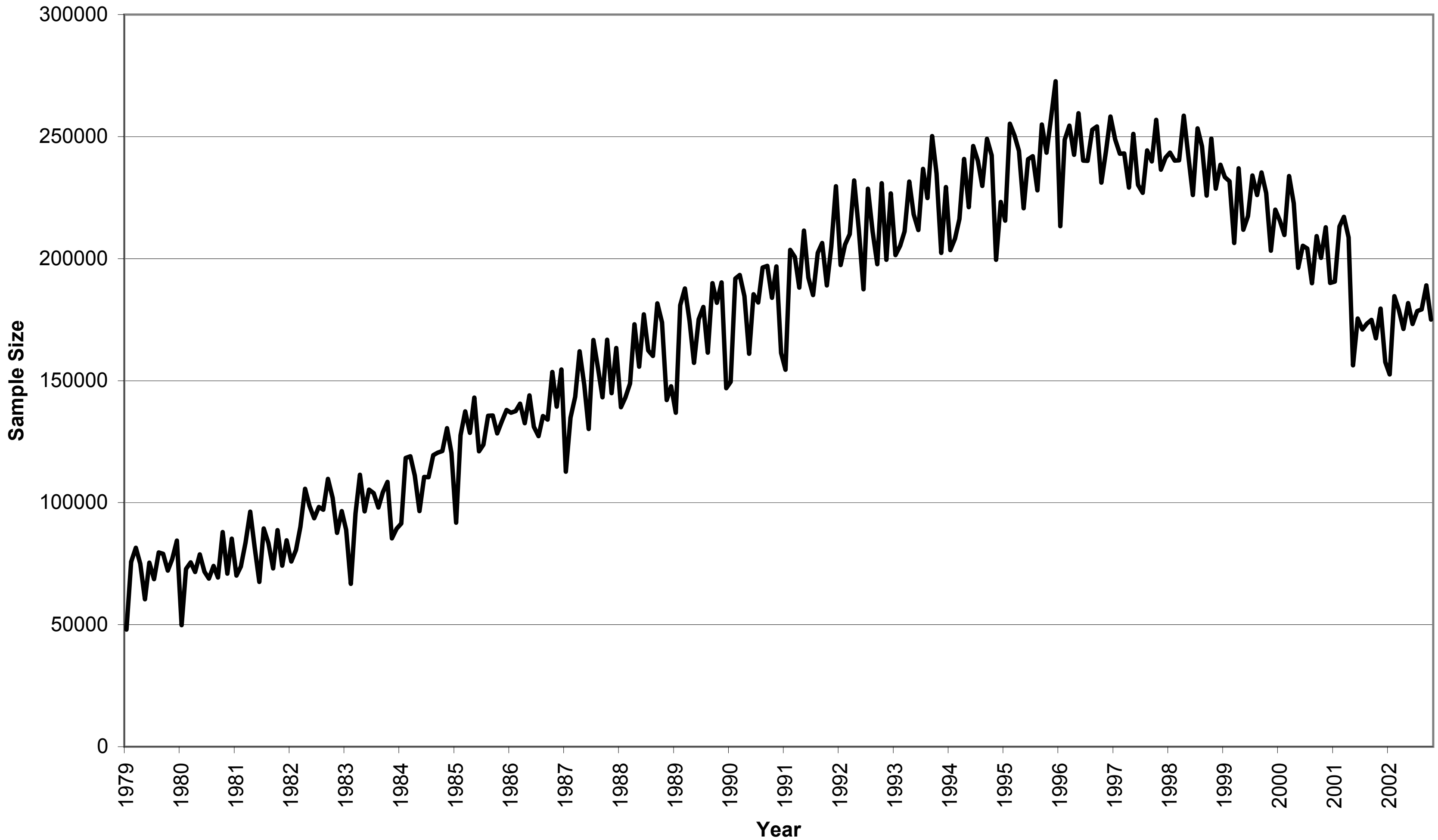

Figure 2: Change in 30 Year Treasury Bond Yield vs. Forecast Error

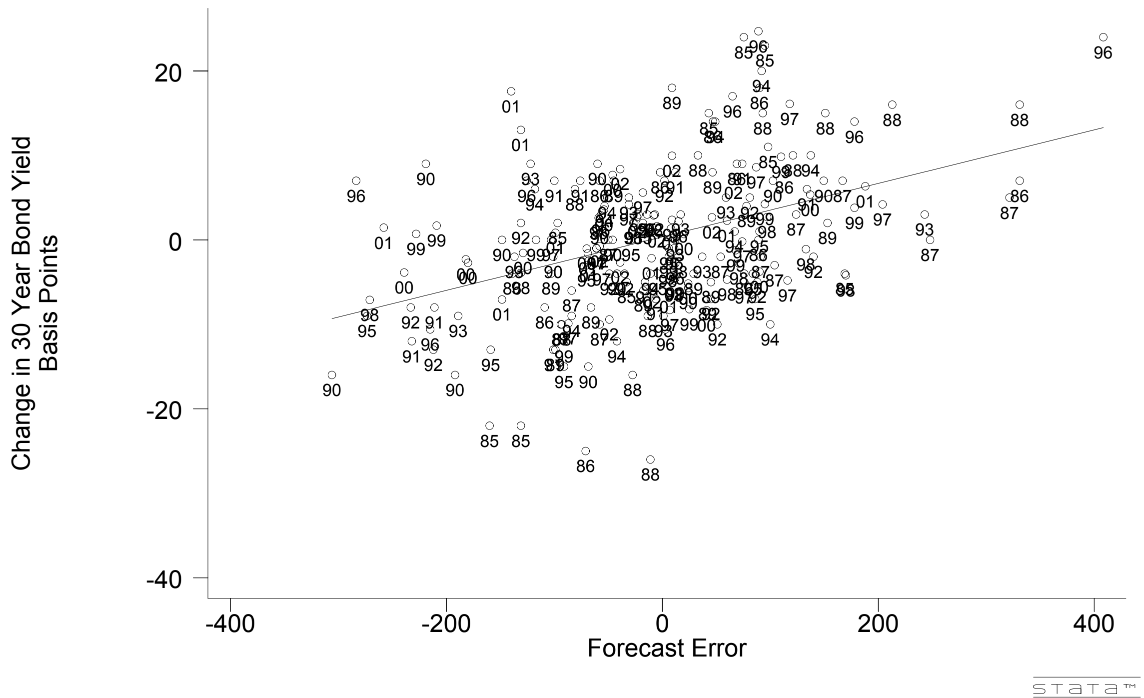

Figure 3: Long Bond Market Response to Forecast Error

Figure 4: 3 Month T-Bill Response to Forecast Error

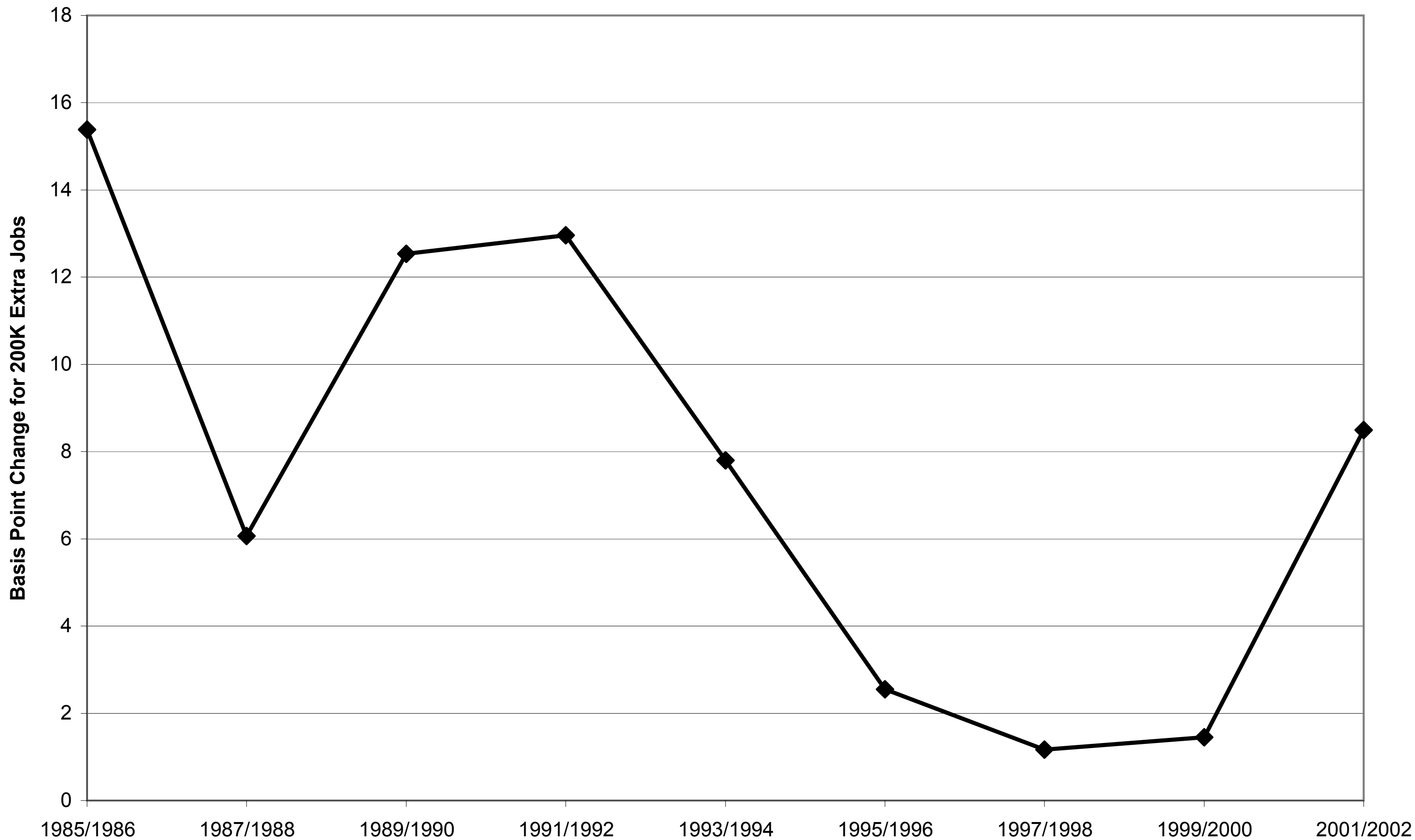

Figure 5a: Annual Average Absolute Yield Change for 30 Year Treasury Bond Interest Rate (x 100)

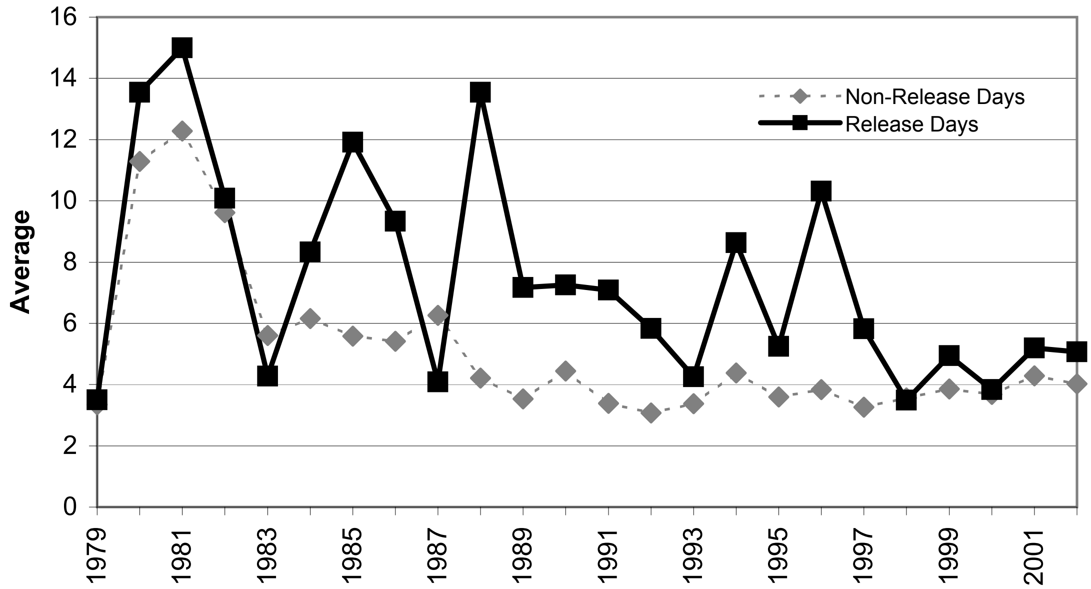

Figure 5b: Volatility on Release Days Minus Non-Release Days