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Abstract

Many researchers have used federal funds futures rates as measures of financial markets' expectations of future monetary policy. However, to the extent that federal funds futures reflect risk premia, these measures require some adjustment. In this paper, we document that excess returns on federal funds futures have been positive on average and strongly countercyclical. In particular, excess returns are surprisingly well predicted by macroeconomic indicators such as employment growth and financial business-cycle indicators such as Treasury yield spreads and corporate bond spreads. Excess returns on eurodollar futures display similar patterns. We document that simply ignoring these risk premia significantly biases forecasts of the future path of monetary policy. We also show that risk premia matter for some futures-based measures of monetary policy shocks used in the literature.

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1 Introduction

Predicting the future course of monetary policy is of tremendous importance to financial market participants. The current state of the art in this area is to use futures contracts on the short-term interest rate that is targeted by the central bank and to interpret the futures rate on, say, the December federal funds futures contract as the market expectation of what the federal funds rate will be in December. This procedure is widely used in the financial press (e.g., *The Wall Street Journal,* 2005, *Financial Times,* 2005), by Fed watchers (e.g., Altig, 2005, Hamilton, 2006), by central banks (e.g., European Central Bank *Monthly Bulletin,* 2005, p. 24, Federal Reserve *Monetary Policy Report to Congress,* 2005, p. 22), and in the academic literature (e.g., Krueger and Kuttner, 1996, Rudebusch, 1998, 2002, Bernanke and Kuttner, 2005).[1]

The standard practice is appealing for many reasons. First, producing the forecasts is simple—the rates on various contracts can be obtained directly from futures exchanges at any time during the day. Second, the forecasts work well—federal funds futures outperform forecasts based on alternative methods, such as sophisticated time series specifications, monetary policy rules, and forecasts derived from Treasury bills or other financial market instruments (e.g. Evans 1998, Gürkaynak, Sack and Swanson 2002). Third, previous studies generally have failed to find significant variation in risk premia in fed funds futures (e.g., Krueger and Kuttner 1996, Sack 2002, Durham 2003).

However, there is by now a large and well-accepted body of evidence in the finance literature against the expectations hypothesis for Treasury yields (e.g., Fama and Bliss 1987, Stambaugh 1988, Campbell and Shiller 1991, Cochrane and Piazzesi 2005). Over a very wide range of sample periods and bond maturities, excess returns on Treasury securities have been positive on average, time-varying, and significantly predictable. Time-varying risk premia in these markets may well carry over to related markets and therefore lead to systematic deviations of federal funds futures rates from expectations of the subsequently realized federal funds rate.

In this paper, we show that the expectations hypothesis also fails for federal funds futures. In particular, excess returns on fed funds futures contracts at even short horizons have been positive on average and significantly predictable. The R^2s depend on the forecast horizon and range from 10% at a 2-month horizon up to 39% at a 6-month horizon. We find that macroeconomic business-cycle indicators such as employment growth capture this predictability surprisingly well. We also find that financial business-cycle indicators such as corporate bond spreads and Treasury yield spreads do well at predicting excess returns. These findings stand up to a battery of robustness checks, including real-time data, subsample stability pre- and post-1994, rolling-endpoint regressions, out-of-sample forecasts, and a comparison to excess returns on eurodollar futures, for which we have a longer sample.

We exploit the significant predictability of excess returns on futures to propose a risk adjustment to forecasts of monetary policy. We find that not implementing our risk adjustment can produce very misleading results. Specifically, forecasts based on the expectations hypothesis make large mean errors and large mean-squared errors. Moreover, errors from unadjusted forecasts vary systematically over the business cycle; futures rates tend to overpredict in recessions and underpredict in booms. Non-risk-adjusted forecasts also tend to perform very poorly around economic turning points, adapting too slowly to changes in the direction of monetary policy. For example, right before recessions, when the Fed has already started easing, fed fund

[1] In some of these studies there is an allowance for a constant term premium.

futures keep forecasting high funds rates. As a consequence, forecast errors using unadjusted futures rates are more highly autocorrelated than are forecast errors using our risk-adjusted futures rates.

Our findings also suggest that monetary policy shocks may not be accurately measured by the difference between the federal funds rate target and an ex ante market expectation based on fed funds futures. Indeed, we document that the amount by which we need to adjust these shocks can be substantial, at least relative to the size of the shocks themselves. However, risk premia seem to change primarily at business-cycle frequencies, which suggests that we may be able to "difference them out" by looking at one-day changes in near-dated federal funds futures on the day of a monetary policy announcement. Indeed, our results confirm that differencing improves these policy measures.

Our findings for federal funds futures complement those in the traditional finance literature on Treasuries in several ways. First, we find that the most important predictive variables for excess returns are macroeconomic variables, such as employment growth. This finding allows us to link the predictability in excess returns directly to the business cycle, while the existing literature on Treasuries has focused mainly on predictability using financial variables such as term spreads (e.g., Cochrane and Piazzesi 2005).

Second, fed funds futures are actually traded securities, while the zero-coupon yield data used in Fama and Bliss (1987) and many other papers are data constructed by interpolation schemes. While the predictability patterns in this artificial data may not lead to profitable trading rules based on actual securities, investors can implement our results directly by trading in fed funds futures. Interestingly, we document evidence that suggests that futures market participants were aware of these excess returns in real time: Traders that are classified as "not hedging" by the U.S. Commodity Futures Trading Commission went long in these contracts precisely when we estimate that expected excess returns on these contracts were high, and they went short precisely in times when we estimate expected excess returns were very low.

Finally, fed funds futures contracts have maturities of just a few months and may therefore be less risky than Treasury notes and bonds, which have durations of several years; moreover, the holding periods relevant for measuring excess returns on fed funds futures are less than one year, while the results for Treasuries typically assume that the investor holds the securities for an entire year (an exception is Stambaugh (1988), who studies Treasury Bills). Given the short maturities and required holding periods to realize excess returns in the fed funds futures market, one might think that risk premia in this market would be very small or nonexistent. We find that this is not the case.

Throughout this paper, we will often use the label "risk premia" to refer to "predictable returns in excess of the risk-free rate." This use of language should *not* be interpreted as taking a particular stance on the structural interpretation of our results. The existing literature has proposed several appealing explanations for why excess returns on these contracts might be predictable. Some of these explanations are based on the utility function of investors: for example, investors may exhibit risk aversion which varies over the business cycle, or care about the slow-moving, cyclical consumption of items like housing. Other explanations are based on beliefs that do not satisfy the rational expectations assumption, for example because of learning or for psychological reasons. It is not easy to make the case for just one of these explanations: beliefs and other preference parameters often can often not be identified separately. We therefore set aside these issues as beyond the scope of the present paper.

The remainder of the paper proceeds as follows. Section 2 shows that measures of excess returns on fed funds futures are identical to monetary-policy forecast errors and can be predicted using business cycle indicators such as employment growth. Section 3 performs a battery of robustness checks. Section 4 presents our risk-adjustment to policy forecasts and shows that failing to implement the adjustment can lead to substantial mistakes, so that the predictability of excess returns is economically as well as statistically significant. Section 6 concludes. The Appendix investigates the approximation accuracy of our return definition for futures.

2 Excess Returns on Federal Funds Futures

Federal funds futures contracts have traded on the Chicago Board of Trade exchange since October 1988 and settle based on the average federal funds rate that prevails over a given calendar month.[2] Let $f_t^{(n)}$ denote the federal funds futures contract rate for month $t+n$ as quoted at the end of month t. We will refer to $n=1$ as the one-month-ahead futures contract, $n=2$ as the two-month-ahead contract, and so on. Let r_{t+n} denote the ex post realized value of the federal funds rate for month $t+n$, calculated as the average of the daily federal funds rates in month $t+n$ for comparability to the federal funds futures contracts.

The buyer of a federal funds futures contract locks in the contracted rate $f_t^{(n)}$ for the contract month $t+n$ on a \$5 million deposit (the \$5 million deposit is never actually made by the buyer; this is only the number that is used to compute the payoff of the contract at maturity). The contracts are cash-settled a few days after expiration, with expiration occurring at the end of the contract month. At that time, the buyer receives \$5 million times the difference between $f_t^{(n)}$ and the realized federal funds rate r_{t+n} converted to a monthly rate.[3] As is standard for futures contracts, there are no up-front costs to either party of entering into the contract; both parties simply commit to the contract rate at time t and receive their payoffs at at time $t+n$.

For the buyer of the futures contract, the amount $(f_t^{(n)} - r_{t+n}) \times \$5$ million represents the payoff of a zero-cost portfolio. Using common terminology (e.g., Cochrane, 2001, p. 11), we refer to this difference, $f_t^{(n)} - r_{t+n}$, as an "excess return." We denote the excess return for the buyer of the contract by:

$$rx_{t+n}^{(n)} = f_t^{(n)} - r_{t+n}. \tag{1}$$

Since we will consider futures contracts with maturities n ranging from 1 to 6 months, the excess returns in (1) will correspond to different holding periods for different values of n. To make excess returns on these different contracts more directly comparable, we also report statistics for annualized excess returns, which are computed by multiplying the excess returns in (1) by $12/n$. Also, we measure returns in basis points. These conventions will apply throughout the paper.

Equation (1) represents a slight simplification, because it neglects the fact that futures contracts are "marked to market" every day. This means that the two parties to a futures

[2] The average federal funds rate is calculated as the simple mean of the daily averages published by the Federal Reserve Bank of New York, and the federal funds rate on a non-business day is defined to be the rate that prevailed on the preceding business day.

[3] This means that $f_t^n - r_{t+n}$ gets multiplied by (number of days in month/360), since the quoting convention in the spot fed funds and fed funds futures markets uses a 360-day year. See the CBOT web site for additional details.

contract must post (or may withdraw) collateral every day as the contract is marked to the market price that day. (There is essentially no "alternative use of funds" or "opportunity cost" for the collateral, however, since margin requirements may be met with interest-bearing U.S. Treasury securities.) The party that receives (pays) collateral then receives (pays) interest on this collateral at the overnight interest rate all the way through to contract settlement. In the Appendix to this paper, we compute excess returns on federal funds futures contracts taking into account the effects of marking to market every day, and we show that the difference between the more complete definition and the simplification in equation (1) is extremely small and does not matter for any of our results below.

For simplicity, we therefore use equation (1) as the definition of excess returns. One advantage of this simplification is that excess returns are easily linked to forecasting. Under the expectations hypothesis, futures are expected future short rates: $f_t^{(n)} = E_t\left(r_{t+n}\right)$. Thus, equation (1) not only represents excess returns, but also minus the forecast error under the expectations hypothesis. This coincidence makes it easy to see how we can adjust futures-based forecasts for risk premia.

2.1 Average Excess Returns

To investigate whether average excess returns on federal funds futures contracts are zero, we run the regression:

$$rx_{t+n}^{(n)} = \alpha^{(n)} + \varepsilon_{t+n}^{(n)} \tag{2}$$

for different contract horizons n.

Table 1 presents results from regression (2) for the forecast horizons $n = 1, \ldots, 6$ months over the entire period for which we have federal funds futures data: October 1988 through December 2005. This period will be the baseline for all of our regressions below. We run the regression at monthly frequency, sampling the futures data on the last day of each month t.[4] We compute standard errors using the heteroskedasticity- and autocorrelation-consistent procedure from Hodrick (1992), which generalizes the Hansen-Hodrick (1988) procedure for overlapping contracts to the case of heteroskedasticity, allowing for $n-1$ lags of excess returns to be serially correlated due to contract overlap. Throughout this paper, we report HAC t-statistics based on these standard errors. To facilitate comparison across contracts with different maturities, we report annualized average excess returns in the bottom row of the table.

As can be seen in Table 1, average excess returns on federal funds futures have been significantly positive over our sample, ranging from about 3 to 5 basis points per month (35 to 61 bp per year). For example, buying the 6-month-ahead futures contract and holding it to maturity is a strategy that generated a return of 61.4bp per year on average.[5] Longer-horizon

[4] We restrict attention to monthly data in order to avoid variations in the maturity of the contracts that would arise over the course of each month: for example, with daily data, the one-month ahead contract could have as few as 28 and as many as 61 days until maturity, which is a significant variation in the holding period required to realize the excess return on the contract. In turn, these differences in maturities and holding periods influence the size and time-variation of risk premia, as we will show below. Also, these variations would translate into different forecasting horizons when we later use our results to forecast the federal funds rate. Nonetheless, our results are all similar when we sample the data at daily rather than monthly frequency.

[5] The unannualized excess return on the six-month-ahead contract is, on average, \$5 million times .307% times (number of days in contract month/360). The annualized excess return is just double this amount (multiplying by 12/6).

contracts have had greater excess returns on average even on a per-month or per-year basis. The averages for the post-1994 period are a little lower but still significantly positive at 24.9, 27.2, 29.0, 32.7, 37.0, and 42.9 bp per year.

2.2 Time-Varying Excess Returns

Previous work using federal funds futures has typically stopped at this point, and proceeded under the assumption that risk premia in the federal funds futures market are constant. However, there is by now a large body of literature that finds excess returns on Treasury securities to be significantly predictable (e.g., Fama and Bliss, 1987, Campbell and Shiller, 1991, Cochrane and Piazzesi, 2005). To investigate the time-variation in excess returns on federal funds futures, we begin by graphing in Figure 1 the realized excess return on the 4-month-ahead federal funds futures contract, $rx_{t+4}^{(4)}$, from October 1988 through December 2005. (Each point in the graph depicts the realized excess return, $f_t^{(4)} - r_{t+4}$, at date t.) Certainly, the time-variation in these realized excess returns has been large, ranging from -315 to 413 bp at an annualized rate. The graph also suggests that there have been several periods during which fed funds futures generated particularly large excess returns: the years 1991–2, early 1995, the fall of 1998, and the years 2001–2 (these are also the periods during which the Federal Reserve lowered interest rates). Two of these periods, 1991–2 and 2001–2, coincided with the two recessions in our sample. The other two periods were not recessions, but were also periods with slower economic growth.

As a first step toward understanding the predictability of excess returns on federal fund futures, we regress these excess returns on a constant and a recession dummy D_t:

$$rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} D_t + \varepsilon_{t+n}^{(n)} \tag{3}$$

Figure 1 shows the fitted values from this regression (a step function) together with the realized excess returns. Table 2 shows that the recession dummy is significant for all contracts with maturities longer than just 1 month. The estimated coefficient on the recession dummy suggests that expected excess returns are countercyclical; expected excess returns are about 3 to 5 times higher in recessions than they are on average during other periods. (Note that annualizing the excess returns is a normalization that does not affect the t-statistics or R^2 in any of our regressions.)

Of course, recession dummies are not useful as predictive variables in real time, since the NBER's business cycle dating committee declares recession peaks and troughs as long as 2 years after they have actually occurred. In other words, recession dummies do not represent information that investors can condition on when deciding about their portfolios. Figure 1 suggests, however, that any contemporaneous business cycle indicator may be a good candidate for forecasting excess returns on these contracts. In what follows, we consider several business cycle indicators, including employment, Treasury yield spreads, and the corporate bond spread.

2.3 Employment Growth as a Predictor of Excess Returns

To investigate whether a set of variables forecasts excess returns on federal funds futures, we run predictive regressions of the form:

$$rx_{t+n}^{(n)} = \alpha^{(n)} + \beta^{(n)} X_t + \varepsilon_{t+n}^{(n)}, \tag{4}$$

where X_t is a vector of variables known to financial markets in month t. Since GDP data are only available at quarterly frequency, they do not provide a very useful variable for forecasting monthly excess returns. We therefore turn to a closely related measure of real activity: employment.

More precisely, we use the year-on-year change in the logarithm of U.S. nonfarm payroll employment. Two data issues arise if we wish to run the predictive regressions (4) with data that were available to financial market participants in real time. First, nonfarm payroll numbers for a given month are not released by the Bureau of Labor Statistics until the first Friday of the following month. Thus, to perform the predictive regressions (4) with data that were available at the end of month t, we must lag the employment numbers by an entire month. Second, nonfarm payroll numbers are revised twice after their initial release and undergo an annual benchmark revision every June, so the final vintage numbers are not available for forecasting in real time. We therefore collected the real-time nonfarm payroll numbers, and use the first release of nonfarm payrolls for month $t-1$ and the revised value for nonfarm payrolls for month $t-13$ to compute the year-on-year change.[6]

Table 3 reports the forecasting results from regression equation (4) based on these real-time nonfarm payroll numbers, which were available to market participants as of the last day of month t. The regression also includes the futures rate itself on the right-hand side, as is common practice. The results show that employment growth is a significant predictor of excess returns for contracts with two months or more to maturity. As we would expect from our results using the recession dummy, expected excess returns are countercyclical; expected excess returns. and employment growth are inversely related. The estimated slope coefficients in Table 3 increase with the maturity of the contract and lie between -0.20 and -0.73 for annualized returns.

To understand the magnitude of these coefficients, note that employment growth is measured in basis points, which means that a 1 percentage point drop in employment growth increases expected excess returns on federal funds futures by about 20 to 73 basis points per year. Over our sample, the mean and standard deviation of employment growth were 135 and 132 basis points, respectively, which means that a one-standard deviation shock to employment makes us expect around 95 bp more in annualized excess returns on the 6-month-ahead futures contract. The own futures contract rate $f_t^{(n)}$ is also a significant predictor of excess returns for these contracts, and the positive coefficient implies that, all else equal, excess returns are lower when the level of interest rates is lower.

The R^2 in Table 3 suggest that we can predict up to 39% of the variation in excess returns on federal funds futures with employment growth and the futures rate itself. This result is remarkable, since these R^2 are comparable in size to those reported in Cochrane and Piazzesi (2005), who study excess returns on Treasuries over much longer holding periods (one year, as compared to just one to six months for our fed funds futures regressions above).

Figure 2 also shows that employment growth forecasts high excess returns not only in the two recessions, but also in 1989, 1995, and 1998, and forecasts low excess returns in 1994 and 1999. The fit in the most recent recession would perhaps be even more remarkable if not for the terrorist attacks in September 2001, which led to a surprise period of high excess returns on these contracts that was not well predicted by standard business cycle indicators.

[6] Even the revised value for month $t-13$ is not quite equal to the final vintage of data for that month, because of some subsequent data revisions.

To check our regression specification, we also re-ran the predictability regressions in Table 3 using the current-month federal funds rate r_t instead of the own futures contract rate $f_t^{(n)}$. The results (not reported) are very similar to those based on the futures rate. For example, the R^2 are identical to those in Table 3. We also ran predictability regressions including both r_t and $f_t^{(n)}$. The results (also not reported) did not significantly improve upon those in Table 3, except for the 1-month-ahead contract. For $n = 1$, we obtain significant slope coefficients for all RHS variables with an R^2 of 5%. The estimated slope coefficients on $f_t^{(n)}$ and r_t almost offset each other, the former being somewhat bigger. We also ran regressions with the most recent revised vintage of the employment data, and our results are very similar: in particular, we find that employment growth predicted excess returns with R^2 values of 1, 7, 14, 20, 28 and 37%. The results are also similar if we use contemporaneous rather than lagged nonfarm payrolls growth as a regressor.

2.4 Treasury Yield Spreads and Corporate Bond Spreads as Predictors

In studies of Treasury markets, the most widely cited predictor of excess returns is the Treasury yield curve (e.g., Fama and Bliss, 1987, Cochrane and Piazzesi, 2005). For example, Cochrane and Piazzesi show that a simple tent-shaped function of 1- through 5-year forward rates explains excess returns on holding long Treasuries securities for 1 year with an R^2 of 35–40%. Of course, these findings are related to the fact that yields have been used as business cycle indicators. For example, the Stock and Watson (1989) leading index is mainly based on term spreads. A natural question is therefore whether yields also forecast excess returns on federal funds futures.

Table 4 reports results from predictions based on a set of yield spreads. We select four different term spreads based on differences of the 6 month Treasury bill rate and the 1, 2, 5, and 10 year zero-coupon Treasury yields.[7] As can be seen in Table 4, there is significant evidence that excess returns on federal funds futures contracts have been significantly predictable using yield spreads as predictors: R^2 values range from 2–26% and many t-statistics are well above 2. We consistently estimate the same pattern of coefficients for the shorter-horizon contracts as for the longer-horizon contracts, with the magnitudes of the coefficients increasing monotonically with the horizon of the contract n (except for the $n = 6$ loading on the 2–1 year spread). This pattern is not just due to differences in holding periods, as these results are obtained using annualized returns.

We also investigate whether another financial indicator of the business cycle, the spread between 10-year BBB-rated corporate bonds and 10-year Treasuries, helps predict excess returns on fed funds futures. Results are reported in Table 5, and corroborate the hypothesis that measures of business cycle risk in general may be useful predictors of excess returns in the federal funds futures market. The estimated coefficients on the corporate bond spread in these regressions are significant for federal funds futures contracts with two months or more to maturity, with R^2 of 8–22%.

Figure 3 plots realized excess returns on the four-month-ahead federal funds futures contract together with the fitted values from Table 4 and Table 5 (where realized returns have been shifted up by 500 bp and fitted values from Table 5 shifted down by 500bp to more clearly

[7] We also considered other Treasuries and the own federal funds futures contract rate, but none of these entered significantly. We also performed the analysis using 1 through 5-year forward rates, as in Cochrane and Piazzesi (2005), and got R^2 values very similar to those in Table 4.

present all three series in the same graph). Yield spreads and corporate bond spreads seem to be most successful at capturing the runups in excess returns in 1990–1993 and 2001–2002, suggesting that the predictive power of these financial indicators may be largely due to the relationship between excess returns and the business cycle.

3 Robustness and Real-Time Predictability of Excess Returns

Our results above provide substantial evidence for time variation of risk premia in federal funds futures. Surprisingly, the strongest evidence comes from conditioning on employment growth—a macroeconomic variable—instead of lagged financial data. We now perform a variety of robustness checks and sensitivity analysis of this basic result. We devote particular attention to assessing whether these excess returns were predictable in real time, looking at rolling-endpoint regressions and also some intriguing historical evidence on the actual positions taken by non-hedging traders in the federal funds futures and eurodollar futures markets.

3.1 One-Month Holding Period Excess Returns

Our sample period spans only about 17 years, which results in as few as 34 independent windows for our longest-horizon (six-month-ahead) federal funds futures contracts. A way to increase the number of independent observations in our regressions and check on the robustness of our results is to consider the excess returns an investor would realize from holding an n-month-ahead federal funds futures contract for just one month—by purchasing the contract and then selling it back as an $(n-1)$-month-ahead contract in one month's time—rather than holding the contract all the way through to maturity. By considering one-month holding period returns on fed funds futures, we reduce potential problems of serial correlation and sample size for the longer-horizon contracts, and give ourselves 206 completely independent windows of data (under the null hypothesis of no predictability of excess returns) for all contracts.

We thus consider regressions of the form:

$$f_t^{(n)} - f_{t+1}^{(n-1)} = \alpha^{(n)} + \beta^{(n)} X_t + \varepsilon_{t+1}^{(n)} \tag{5}$$

where $f_t^{(n)}$ denotes the n-month-ahead contract rate on the last day of month t, $f_{t+1}^{(n-1)}$ denotes the $(n-1)$-month-ahead contract rate on the last day of month $t+1$, and the difference between these two rates is the ex post realized one-month holding period return on the n-month-ahead contract.[8] Using specification (5), the residuals are serially uncorrelated under the null hypothesis of no predictability of excess returns, because all variables in equation (5) are in financial markets' information set by the start of the next period.

Table 6 presents the results of our previous analysis applied to this alternative specification, where the regressors are the own contract rate and employment growth. Although the R^2 values

[8] The investor's realized monetary return on this transaction is \$5 million times the difference in rates $f_t^{(n)} - f_{t+1}^{(n-1)}$ times (number of days in contract month/360). Since these contracts are "marked to market" essentially every day, the investor realizes the full monetary return to this transaction in month $t+1$; in particular, the investor does not need to wait until the contracts mature at the end of month $t+n$ to realize the return. As before, the opportunity cost of engaging in this transaction is negligible, so the realized return is also the realized excess return.

are uniformly lower, as is to be expected from quasi-first-differencing the left-hand side variable, our previous results are robust to this alternative specification. Results for term spreads and corporate bond spreads are similarly robust across specifications (these results are not presented to conserve space).

3.2 Excess Returns on Eurodollar Futures

Another way to increase our effective sample size is to consider Eurodollar futures, which are closely related to federal funds futures but have been available for a longer period of time (we have data for these contracts going back to March 1985). Some additional advantages of considering eurodollar futures are that eurodollar futures are more liquid (they are currently the most actively traded futures contracts in the world) and eurodollar futures have maturities that extend out to several years, providing an intermediate horizon between federal funds futures and longer-dated Treasury securities.

Eurodollar futures have traded on the Chicago Mercantile Exchange since 1981 and settle based on the spot three-month LIBOR (eurodollar time deposit) rate prevailing on the date of expiration.[9] In contrast to federal funds futures, eurodollar futures have maturities that are denominated in quarters rather than months, so we let $ef_t^{(n)}$ denote the eurodollar futures contract rate in quarter t for a contract expiring at the end of quarter $t+n$. The corresponding realized rate er_{t+n} is the spot three-month eurodollar rate that prevails on the day of expiration of the futures contract. The ex post excess return realized from holding the n-quarter-ahead contract to maturity is $ef_t^{(n)} - er_{t+n}$, and the ex post realized excess return to holding the n-quarter-ahead contract for one quarter is $ef_t^{(n)} - ef_{t+1}^{(n-1)}$. Regression equations for analyzing these excess returns are otherwise identical to equation (3) for federal funds futures.

Table 7 presents the results of our previous analysis applied to eurodollar futures contracts with maturities of $n = 1, \ldots, 8$ quarters ahead. Panel A shows that excess returns on eurodollar futures have averaged between 47 and 99 basis points per year over our sample, 1985Q2 through 2005Q4. Excess returns for eurodollar futures also display the same patterns of predictability as federal funds futures: Panel B shows that nonfarm payroll employment growth is statistically significant at all horizons, with R^2 values ranging from 25 to 43%. (Note that in these regressions, ΔNFP_{t-1} refers to year-on-year employment growth lagged one month rather than one quarter, corresponding to the data that was available to financial market participants in real time.) Results for Treasury yield spreads and corporate bond spreads (not reported) are also significant and similar to those for federal funds futures, and all of these results are robust to considering one-quarter holding periods for eurodollar futures as well as for holding the contracts all the way through to maturity.

[9] The spot three-month London Interbank Offered Rate for three-month time deposits of U.S. dollars in London is collected and published daily by the British Bankers' Association. The spot eurodollar market is a very active one, thus these rates match three-month time deposit rates in the U.S. very closely. The March, June, September, and December eurodollar futures contracts are by far the most actively traded, with expiration on these contracts near the middle of those months. Contracts are cash-settled a few days after expiration with the purchaser receiving \$1 million times the difference $ef_t^{(n)} - er_{t+n}$ times (91/360). See the CME web site for additional details.

3.3 Rolling Endpoint Regressions

We have documented that excess returns on federal funds futures were predictable using contemporaneous business-cycle indicators such as employment growth, Treasury yield spreads, and corporate bond spreads. To what extent could an investor have predicted these returns in real time, using only data that was available up to that point in time? To answer this question, we perform a set of rolling endpoint regressions.

Figure 4 shows real-time forecasts of excess returns on the 4-month-ahead federal funds futures contract together with the full-sample forecasts from Table 2 based on employment growth and the own futures contract rate. The real-time forecasts for each month t are constructed by estimating the slope coefficients with data from October 1988 up through what was available at the end of the previous month $t-1$. Figure 4 graphs these forecasts starting in October 1990, when we have only 24 months of data to estimate the three parameters of the model. The graph suggests that the real-time fitted values are quite close to the full-sample fitted values over most of the sample—indeed, the two series are essentially identical from the beginning of 1994 onward. The middle and lower panels in Figure 4 show the rolling estimates of the slope coefficients together with their full-sample counterparts (the horizontal black line), and again suggest that the rolling point estimates have largely converged to their full-sample values by 1994.

3.4 Data on Non-Hedging Market Participants' Positions

The previous section shows that excess returns on federal funds futures were potentially predictable to investors in real time using rolling regressions. In this section, we present some evidence indicating that informed investors at the time actually *did* correctly forecast the excess returns that were subsequently realized.

The U.S. Commodity Futures Trading Commission (CFTC) requires all individuals or institutions with positions above a certain size to report their positions to the CFTC each week, and the extent to which each position is hedged. In the eurodollar (federal funds) futures markets, about 90% (95%) of open interest is held by individuals or institutions that must report to the CFTC as a result of this requirement. The CFTC reports the aggregates of these data with a three-day lag, broken down into hedging and non-hedging categories and into long and short positions, in the weekly Commitments of Traders report available on the CFTC's web site.

The lower panel in Figure 5 plots the percentage of long and short open interest in eurodollar futures held by noncommercial market participants—those market participants that are classified by the CFTC as *not* hedging offsetting positions that arise out of their normal (non-futures related) business operations.[10] The number of open long positions in these contracts held by noncommercial market participants (as a percentage of total reportable open interest) is depicted in the bottom panel of the figure by the solid line (green in color), and the number of open short positions (as a percentage of reportable open interest) held by these participants is plotted by the dashed line (red in color). Analogous data are available for federal funds futures positions as well, but we focus on eurodollar futures positions here as this market is thicker

[10] The primary example of a *commercial* participant in the federal funds or eurodollar futures market would be a financial institution seeking to hedge its commercial and industrial loan portfolio. For more details on the institutional features of these markets, see Stigum (1990).

and contracts run off less frequently—only once per quarter rather than every month—which reduces some high-frequency variation in the percentage long and short series.[11] The upper panel of Figure 5 plots the difference between the noncommercial percentage long and short series as the "net long position" of noncommercial market participants.

The net long position graphed in Figure 5 displays a clear positive correlation with the excess returns in federal funds futures contracts depicted in previous figures: for example, noncommercial market participants began taking on a huge net long position in late 2000, just a few months before excess returns in these contracts began to soar, and they took on substantial long positions in mid-1990 through mid-1991 and late 1995 as well, again correctly forecasting excess returns over these periods; noncommercial market participants also took on a very substantial *short* position in late 1993 through mid-1994, correctly anticipating the low or even negative excess returns that were subsequently realized when the Federal Reserve began tightening policy in 1994.

These casual observations are confirmed by the regression results reported in Table 8. The net long position variable is a significant predictor of excess returns in the federal funds futures market at horizons of two months or more, with R^2 values from 5–25%.[12] Interestingly, the statistical significance of the net long position variable disappears if we also include any of employment growth, term spreads, or corporate risk spreads in the regression (results not reported in the table), suggesting that the information content of noncommercial market participants' net position is spanned by the business cycle indicators that we have already considered in section 2.

These results suggests that noncommercial market participants were aware of the upcoming excess returns in the market and positioned themselves accordingly, at the expense of those engaged in hedging other financial activities. The hedgers—primarily banks—essentially paid an insurance premium to noncommercial participants for providing hedging services. There are two primary explanations for why these premia were not "competed away" by the market. First, the futures market may not be perfectly competitive, with barriers to entry and noncommercial market participants facing limits on the size of the positions that they may take; commercial participants with hedging demand thus may not face a perfectly elastic supply curve for either the long or short side of these futures contracts. Second, noncommercial market participants may themselves be risk averse. For example, futures traders in these markets may be most averse to taking on large bets or risky positions precisely when their own jobs are most in jeopardy—around the times of recessions. The hypothesis that excess returns in these markets would be competed away requires both an assumption of perfectly competitive futures markets and of risk-neutral market participants, and both of these assumptions may not apply.

4 Risk-Adjusted Measures of Monetary Policy Expectations

How misleading would it be to ignore risk premia on federal funds and eurodollar futures and treat the unadjusted prices of these securities as measures of monetary policy expectations?

[11] Open interest is almost always highest in the front-month or front-quarter contract, so the running off of these contracts can create jumps. The patterns in federal funds futures noncommercial market participant holdings are very similar to those in eurodollar futures, albeit noisier for this reason.

[12] The net long position variable is also a highly significant predictor of excess returns in the eurodollar futures market at all horizons from one to eight quarters ahead, although these results are not reported to save space.

Using futures, the forecast errors are just minus the excess returns on the fed funds futures contract:

$$r_{t+n} - f_t^{(n)} = -rx_{t+n}^{(n)} \tag{6}$$

To the extent that excess returns on federal funds and eurodollar futures are forecastable, one would be making systematic forecast errors if one used unadjusted futures rates as measures of monetary policy expectations.

However, we can risk-adjust these futures rates using our previous results. To do that, we take expectations of both sides of equation (4) and solve for the expected n-month-ahead federal funds rate:

$$E_t\left[r_{t+n}\right] = f_t^{(n)} - (\alpha^{(n)} + \beta^{(n)} X_t). \tag{7}$$

From Tables 1 and 7, we know that the expected excess return, $\alpha^{(n)} + \beta^{(n)} X_t$, is on average positive. This suggests that risk-adjusted forecasts lie on average below the futures rate. Moreover, Tables 3 and 7 show that expected excess returns are countercyclical. This suggests that risk-adjusted forecasts subtract a countercyclical term from the futures rate or, equivalently, add a procyclical term to the futures rate: risk-adjusted forecasts will tend to lie above the unadjusted futures rate in booms and below the futures rate in recessions.

These features of our risk-adjustment are illustrated in Figure 6, which plots forecasts of the federal funds rate out to a horizon of 12 months on two different dates: December 1993 and December 2000. We plot a number of alternative forecasts based on federal funds and eurodollar futures rates:

1. Unadjusted futures: $\alpha^{(n)} = 0$ and $\beta^{(n)} = 0$.
2. Rule-of-thumb-adjusted futures: a constant risk adjustment of 1 bp/month, which is a rule of thumb that has been used by staff at the Federal Reserve Board for these interest rate futures,[13] so $\alpha^{(n)} = n$ and $\beta^{(n)} = 0$. For eurodollar futures, the rule of thumb is 13bp plus 3bp/quarter: $\alpha^{(n)} = 3n + 13$ and $\beta^{(n)} = 0$.
3. Risk-adjusted futures: rolling OLS estimates of $\alpha^{(n)}$ and $\beta^{(n)}$, where X_t includes the own futures rate $f_t^{(n)}$ and NFP growth ΔNFP_{t-1}, as in Table 3 for fed funds futures and Table 7 for eurodollar futures.

Figure 6 illustrates that unadjusted futures forecasts are always higher than rule-of-thumb adjusted forecasts. The two panels in Figure 6 suggest that in times when the funds rate is expected to rise—such as December 1993—the higher, unadjusted futures therefore do better than rule-of-thumb-adjusted futures. However, the lower, rule-of-thumb-adjusted futures do better in times when the funds rate is expected to fall, such as December 2000. This is exactly the mechanism exploited by our time-varying risk adjustment: in December 1993, our risk-adjusted futures forecast (the blue x-line) is closer to the unadjusted futures forecast, while in December 2000, the blue x-line is closer to the rule-of-thumb-adjusted futures forecast.

[13] In private communication dated May 2004, Donald Kohn mentioned that staff at the Federal Reserve Board came up with this adjustment factor informed by their reading of the historical data on ex post errors in the federal funds and eurodollar futures markets and in interest-rate surveys. Although this adjustment factor was 1bp/month at the short end of the futures curve at the time of that communication, he noted it has not always been that and would change as events warrant.

Instead of varying the forecasting horizon for a given date, we can also fix the forecasting horizon at 4 months and vary the date. The upper panel in Figure 7 shows the realized funds rate, r_{t+4}, while the lower panel shows forecast errors made with unadjusted futures, $r_{t+4} - f_t^{(4)}$, and with risk-adjusted futures. (To focus attention on the systematic patterns in the figure rather than the high-frequency variation, we smooth the errors with a 6-month moving average.) The 1991 and 2001 recessions are both characterized by negative unadjusted forecast errors. The risk-adjustment improves upon these forecasts by adjusting the raw futures rate downward in both episodes.

Figures 6 and 7 suggest that unadjusted futures rates, or futures adjusted by a constant, can be wrong over long periods of time. The forecast errors tend to be negative during periods of falling rates and positive during periods of rate hikes. The forecast errors are largest when the funds rate changes direction, and keep being large for substantial amounts of time. The reason is that unadjusted or constant-adjusted futures rates only slowly adapt to changes in direction. As a result, these forecasts tend to *lag behind actual market expectations* around economic turning points; they generate forecast errors that are more autocorrelated than forecast errors from risk-adjusted futures.

To see this point more clearly, Table 9 reports some summary statistics for forecast errors, for each of a number of different forecasts. We compute forecast errors from futures-based forecasts and also from a simple vector autoregression (VAR) as a benchmark.[14] The VAR is computed at monthly frequency using four lags of each of the federal funds rate, the year-on-year percentage change in the core CPI, and the year-on-year percentage change in nonfarm payroll employment.[15] We compute forecasts for the n-month-ahead federal funds rate as it would have been made at each time t, using real-time data and rolling endpoint regressions. For example, when we compute forecasts for r_{t+n} using the VAR benchmark, we estimate the parameters of the VAR using only data up through time $t-1$ and then use the values of the federal funds rate, core CPI inflation, and nonfarm payrolls growth at time t as the conditioning variables for the forecast. Similarly, we use our rolling "out-of-sample" forecasts for risk premia based on nonfarm payrolls growth to make our risk adjustments. The forecast errors are computed over the October 1990 to December 2005 period, so that we have two years of data to estimate the parameters for the October 1990 forecast.

Table 9 reports mean forecast errors (ME), root-mean-squared-errors (RMSE), and the nth autocorrelation (ρ_n) for the n-month-ahead forecast. (Note that even for an efficient n-month-ahead forecasts, the forecast errors would have an MA($n-1$) autocorrelation because of forecast overlap; Table 9 therefore reports the nth autocorrelation which, ideally, should be zero.) The last column of Table 9 shows that risk-adjusted futures still made autocorrelated forecast errors over our sample, but the autocorrelation is much smaller than for any other forecast in the table. This is especially true for longer forecasting horizons. Moreover, risk-adjusted futures generate smaller average errors and lower root-mean-square errors.

Interestingly, Panel A makes a strong case for federal funds futures in general, even on a

[14] We also considered forecasts from an AR(1) and a random walk. The resulting forecasts, however, were outperformed by the VAR, so we did not include them in Table 9 to conserve space. Another alterative are Taylor-rule forecasts. For forecasts up to 3 months ahead, Evans (1998) documents that they tend to be dominated by forecasts based on (unadjusted) futures.

[15] The lag length was selected to yield good empirical forecast performance: more lags than 4 tended to lead to overfitting and poor forecast performance, while fewer lags tended to lead to overly simple dynamics and poor forecast performance.

risk-unadjusted basis. The futures-based forecasts produce lower root-mean-square errors than a VAR. However, unadjusted futures made large, negative errors on average, ranging from 3 to 31 basis points. The rule-of-thumb-adjusted futures improve upon this: average forecast errors are lower by exactly the amount of the adjustment, and the adjustment also lowers mean-square errors. However, this adjustment only represents a small improvement over unadjusted forecasts. The risk-adjusted forecasts we estimate in this paper generate forecast errors that are always smaller on average and almost always smaller in root-mean-square terms, especially for longer forecasting horizons. Panel B confirms these findings for longer-horizon forecasts using eurodollar futures.[16] Again, risk-adjusted futures do much better than unadjusted futures or the rule-of-thumb-adjusted futures.

5 Monetary Policy Shocks

Federal funds futures have also been used by a number of recent authors to separate systematic changes in monetary policy from monetary policy "shocks".[17] The idea is to use federal funds futures market forecast errors as measures of exogenous, unforecastable changes in the stance of monetary policy.[18] The federal funds futures market expectation is measured assuming the expectations hypothesis. Since we have shown in the previous section that futures rates should be adjusted for time-varying risk premia, we now investigate to what extent these risk premia might affect futures-based measures of monetary policy shocks.

Computing the futures market's forecast error of the next policy move is less straightforward than it may seem, because of some institutional features of the federal funds and federal funds futures markets. For example, the futures contract settles based on the average federal funds rate that is realized during the contract month, and not on the value of the funds rate on a particular date, such as the day following an FOMC meeting. Moreover, the Federal Reserve sets a target for the funds rate, but does not completely control the funds rate itself, and the difference between the actual funds rate and the target can be nonnegligible, even for monthly averages. In the literature, these complications have led to alternative approaches on how policy shocks are computed from futures rates.

Here, we consider the two primary approaches to measuring monetary policy shocks that have been used in the literature. First, Rudebusch (1998) suggests defining the monetary policy shock as the difference between the realized federal funds rate target and the expected federal funds rate derived from federal funds futures. While this might seem to be the most natural definition of the market's forecast error, it can suffer from the technical issues described above

[16] The VAR for the 90-day eurodollar rate uses the same variables as the monthly VAR but sampled at quarterly frequency beginning in 1990Q3 with data going back to 1985Q1. We chose a lag length of 3 since this seemed to give good empirical forecast performance: a lag length of 4 performed worse and a lag length of 2 performed better at the shortest horizons but worse at longer horizons.

[17] See, e.g., Rudebusch (1998), Cochrane and Piazzesi (2002), and Faust, Swanson, and Wright (2004) for different approaches. All of these studies treat the federal funds rate as the monetary policy instrumetn, as in Bernanke and Blinder (1992), and attempt to improve upon the earlier VAR-based identification of monetary policy shocks surveyed in Christiano, Eichenbaum, and Evans (1999).

[18] Faust, Swanson, and Wright (2004) describe the procedure in detail and test many of the required assumptions. Alternatively, Piazzesi (2005) and Cochrane and Piazzesi (2002) measure market expectations from high-frequency data on short-term interest rates instead of fed funds futures. Piazzesi (2005) computes $E_t[r_{t+1}]$ from an arbitrage-free model of the term structure of interest rates. Cochrane and Piazzesi (2002) use the change in the 1-month eurodollar rate and unrestricted regressions of r_{t+1} on a set of interest rates.

that cause the market expectation of the future realized funds rate to differ from the market expectation of the future target rate. More importantly, monetary policy shocks measured in this way will be contaminated by risk premia in the futures market even if those risk premia are constant. Our second measure of monetary policy shocks, suggested by Kuttner (2001), differences out both the technical factors in the federal funds market and any constant risk premia by using the *change* in the current-month or one-month-ahead federal funds futures rate on the day of an FOMC announcement. This approach uses daily fed funds futures data to make the interval $[t, t+1]$ around the FOMC announcement small and assumes that risk premia do not change over this small interval.[19]

We compute these two measures of monetary policy shocks over the sample period 1994 to 2005, when the Federal Reserve was explicitly announcing changes in its target for the federal funds rate. We include every FOMC meeting and every intermeeting policy move by the FOMC over this sample. Table 10 reports summary statistics for both measures of policy shocks. From Panel A it is apparent that the first measure of monetary policy shocks, labeled "actual−futures", is larger and more volatile than the second measure: the mean, standard deviation, and extremes of the shocks are all larger in the first shock series than in the second. The two shocks series do generally agree on the days of large monetary policy shocks, however—for example, the min and max of the two series both occur on the same days.

We investigate the robustness of the two monetary policy shock series to risk premia by regressing them on a set of conditioning variables that were known to financial markets right before the FOMC announcement—for this exercise, we pick Treasury yields as the regressors (as in Table 5), because we have high-frequency data on these yields.[20] Under the expectations hypothesis, each monetary policy shock measure should be unpredictable on the basis of these conditioning variables.

Results for these regressions are summarized in Panel B of Table 10, which also reports the p-values from a zero-slopes F-test that all of the coefficients (excluding the constant term) in each regression are jointly equal to zero. As can be seen in the table, our first measure of monetary policy shocks (the realized target rate minus the futures market expectation) appears to be significantly contaminated both by a constant risk premium (as evidenced by the t-statistic for the constant term) and possibly also by time-variation in risk premia (as evidenced by the zero-slopes F-test, which is borderline statistically significant). In contrast, our second policy shock measure (the one-day change in the federal funds futures rate) seems to do much better: no coefficient is statistically significant, and we do not reject the null of no contamination by time-varying risk premia.

Panel A of Table 10 also reports basic statistics for our estimated risk adjustments to each of the three monetary policy shock series. The risk adjustments for our first shock measure ("actual − futures") has a standard deviation of 3.2 bp, which seems substantial relative to

[19] This assumption is consistent with the finding by Evans and Marshall (1998) that risk premia in Treasuries show only a small response to monetary policy shocks in a VAR. It is also potentially consistent with our findings above and those of Cochrane and Piazzesi (2005) that risk premia vary substantially at business cycle frequencies but perhaps do not vary as much at higher frequencies.

[20] We reestimate the regression coefficients for the monetary policy shock series, because risk premia depend on the maturity of the contract and FOMC meetings are typically not scheduled for the end of the month. The current-month or 1-month ahead fed funds futures contract therefore has a different maturity on FOMC meeting dates than the same contract in Table 5. Moreover, the nature of the risk associated with monetary policy shocks (and therefore the risk premia associated with these shocks) may have changed after 1994, when the Fed started announcing its policy moves at FOMC meetings, as argued in Piazzesi (2005).

the standard deviation of the shock series itself of 11 bp. In contrast, the estimated risk adjustments to our second measure of monetary policy shocks are much smaller as well as statistically insignificant.

We infer from this analysis that monetary policy shocks based on the difference between the realized federal funds rate target and the unadjusted federal funds futures-based forecast, as suggested by Rudebusch (1998), are significantly contaminated by risk premia, both on average and by an amount that varies over time. The primary alternative—measuring monetary policy shocks based on the one-day change in the federal funds futures rate around FOMC announcements, as suggested by Kuttner (2001)—seems to be much more robust to the presence of risk premia in these contracts. The difference-based measure may largely "difference out" risk premia that are moving primarily at lower, business-cycle frequencies, consistent with our analysis in section 2 and the findings in Cochrane and Piazzesi (2005).

6 Conclusions

We document substantial and predictable time-variation in excess returns on federal funds futures. We show that excess returns on these contracts are strongly countercyclical and can be predicted with R^2 of up to 39% using contemporaneous macroeconomic and financial business cycle indicators such as employment growth, Treasury yield spreads, and corporate bond spreads. We also present evidence that suggests that market participants could have been and in fact were aware of these excess returns in real time, as evidence by real-time rolling endpoint regressions and the observation that non-hedging futures market participants were large buyers of these contracts in times of high expected excess returns and large sellers in times of low or negative expected excess returns.

Our findings of predictable excess returns in federal funds futures contracts has important consequences for computing market expectations from these futures rates. We find that ignoring these risk premia significantly increases forecast errors, both on average and in terms of root-mean-squared error. Moreover, unadjusted futures make forecast errors that are more autocorrelated, because unadjusted futures-based forecasts lag behind our risk-adjusted forecasts around economic turning points. Finally, we show that measures of monetary policy shocks based on the realized funds rate target minus the ex ante unadjusted fed funds futures rate are significantly contaminated by risk premia. Instead, a measure of monetary policy shocks based on the one-day change in federal funds futures around FOMC announcements seems to be more robust—for instance, it may largely "difference out" risk premia that move primarily at lower, business-cycle frequencies.

Appendix: Marking to Market

Actual excess returns on fed funds futures contracts are not exactly equal to (1), because futures contracts are "marked to market" every day. This means that the two parties to a fed funds futures contract must post (or may withdraw) collateral every day as the contract is marked to the market price that day. The party that receives (pays) collateral then receives (pays) interest on this collateral at the overnight interest rate all the way through to contract settlement.

The definition of ex post realized excess returns on the n-month-ahead fed funds futures contract, including the effects of marking to market every day over the life of the contract, is thus:

$$rxmm_{t+n}^{(n)} = -\sum_{d=1}^{T} \Delta f_{t,d}^{(n)} \cdot R_{t,d}^{T} \tag{8}$$

where d indexes days from the last day of month t to the day T the contract expires (the last day of month $t+n$), $\Delta f_{t,d}^{(n)}$ is the one-day change in the contract rate on day d, and $R_{t,d}^{T} \equiv \prod_{i=d}^{T}(1 + or_{t,i})$, where $or_{t,i}$ is the risk-free overnight interest rate on day i after the end of month t. For the risk-free overnight interest rate, we used the rate on overnight repurchase agreements for U.S. Treasury securities, which is less risky, less volatile and less affected by calendar days (such as settlement Wednesdays) than the overnight federal funds rate.

Figure 8 compares the more exact definition of excess returns (8) to our baseline approximation (1). Throughout the figure, approximation (1) is plotted as the black line and excess returns including the effects of marking to market (8) is plotted as the gray line. The whole point of this figure is to demonstrate that it is very difficult to distinguish between the two lines for any of the contract horizons that we consider, which shows that our approximation (1) to excess returns is extremely good.

As a final check, we re-estimate our main equations with actual returns. We can see that the results in Panels A and B of Table A1 are almost identical to those in Tables 1 and 3, respectively. This comparison confirms that the approximation (1) works extremely well.

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TABLE 1: CONSTANT RISK PREMIA

n	1	2	3	4	5	6
$\alpha^{(n)}$	2.9	6.3	10.5	16.1	23.2	30.7
(t-stat)	(3.7)	(3.4)	(3.0)	(2.9)	(2.9)	(2.7)
annualized	35.0	38.1	42.2	48.3	55.6	61.4

NOTE: The sample is 1988:10-2005:12. The observations are from the last day of each month. The regression equation is (2). The intercept $\alpha^{(n)}$ is measured in basis points. HAC t-statistics are reported in parentheses.

Table 2: Excess Returns And Recessions

n	1	2	3	4	5	6
constant	2.3	4.4	7.2	11.1	16.5	24.7
(t-stat)	(3.3)	(2.8)	(2.3)	(2.3)	(2.3)	(2.4)
dummy	6.5	21.9	37.8	56.4	73.7	84.3
(t-stat)	(1.4)	(2.1)	(3.1)	(5.1)	(6.6)	(4.7)
R^2	0.03	0.10	0.14	0.16	0.17	0.13
			Annualized			
constant	28.2	26.6	28.8	33.3	40.0	49.4
dummy	77.8	131.3	151.2	169.3	177.0	168.6

Note: The sample is 1988:10-2005:12. The observations are from the last day of each month. The regression equation is (3), where D_t is a recession dummy. Excess returns are measured in basis points. HAC t-statistics are reported in parentheses.

Table 3: Excess Returns and Nonfarm Payrolls

n	1	2	3	4	5	6
constant	-0.0	0.3	-1.7	-5.6	-13.1	-22.8
(t-stat)	(-0.0)	(0.1)	(-0.3)	(-0.7)	(-1.3)	(-2.1)
$f_t^{(n)}$	0.01	0.03	0.06	0.11	0.16	0.22
(t-stat)	(2.1)	(2.4)	(3.1)	(4.5)	(7.0)	(10.9)
ΔNFP_{t-1}	-0.02	-0.06	-0.13	-0.21	-0.29	-0.36
(t-stat)	(-1.8)	(-3.0)	(-3.8)	(-5.1)	(-7.2)	(-11.1)
R^2	0.03	0.10	0.18	0.25	0.32	0.39
			Annualized			
constant	-0.3	1.7	-6.6	-16.8	-31.3	-45.7
$f_t^{(n)}$	0.13	0.19	0.25	0.32	0.38	0.44
ΔNFP_{t-1}	-0.20	-0.37	-0.51	-0.62	-0.70	-0.73

Note: The sample is 1988:10-2005:12. The observations are from the last day of each month. The regression equation is (4), where X_t contains $f_t^{(n)}$ and nonfarm payroll employment growth ΔNFP_{t-1} from $t-13$ to $t-1$, computed using real-time vintage of data. ΔNFP_{t-1} is measured in basis points. HAC t-statistics are reported in parentheses.

Table 4: Annualized Excess Returns and Treasury Spreads

n	1	2	3	4	5	6
constant	59.5	65.2	82.0	101.6	134.5	168.0
(t-stat)	(2.4)	(2.1)	(2.4)	(2.7)	(3.0)	(3.6)
1yr–6mo	0.30	-0.20	-0.54	-0.68	-1.38	-2.20
(t-stat)	(0.3)	(-0.2)	(-0.4)	(-0.5)	(-1.1)	(-1.8)
2–1yr	-1.46	-1.35	-1.68	-2.05	-1.97	-1.75
(t-stat)	(-1.2)	(-1.0)	(-1.2)	(-1.7)	(-1.6)	(-1.3)
5–2yr	1.84	1.95	2.68	3.50	4.19	4.56
(t-stat)	(2.1)	(2.1)	(2.9)	(4.3)	(3.9)	(3.96)
10–5yr	-1.67	-1.70	-2.38	-3.22	-4.16	-4.77
(t-stat)	(-2.7)	(-2.2)	(-3.2)	(-4.6)	(-4.4)	(-4.98)
R^2	0.02	0.03	0.07	0.11	0.18	0.26

Note: The sample is 1988:10-2005:12. The observations are from the last day of each month. The regression equation is (3), where X_t consists of yield spreads on zero-coupon Treasuries (measured in basis points). The maturities of the Treasuries are 6 months, 1 year, 2 years, 5 years, and 10 years, with spreads taken between adjacent maturities. The Treasury yield data are from the Federal Reserve Board. HAC t-statistics are reported in parentheses.

Table 5: Annualized Excess Returns and Corporate Bond Spreads

n	1	2	3	4	5	6
const.	-43.7	-67.6	-89.1	-105.4	-125.3	-142.7
(t-stat)	(-1.2)	(-1.9)	(-2.3)	(-2.6)	(-2.8)	(-2.8)
$f_t^{(n)}$	0.06	0.06	0.08	0.10	0.14	0.18
(t-stat)	(1.3)	(1.0)	(1.4)	(2.1)	(2.6)	(3.0)
BBB spread	0.34	0.52	0.62	0.69	0.75	0.80
(t-stat)	(1.8)	(2.6)	(2.9)	(2.9)	(3.0)	(2.8)
R^2	0.03	0.08	0.12	0.16	0.20	0.22

Note: The sample is 1988:10-2005:12. The observations are from the last day of each month. The regression equation is (3), where X_t consists of the own futures contract rate $f_t^{(n)}$ and the BBB-Treasury corporate bond spread. Data on BBB corporate bond yields with 10 years to maturity are from Merrill Lynch; data on 10-year Treasury par yields (the comparable Treasury yield) are from the Federal Reserve Board. HAC t-statistics are reported in parentheses.

Table 6: One-Month Holding Period Excess Returns and Nonfarm Payrolls

n	1	2	3	4	5	6
const.	0.3	6.3	-5.8	-5.4	-14.2	-69.1
(t-stat)	(0.0)	(0.2)	(-0.2)	(-0.1)	(-0.3)	(-1.2)
$f_t^{(n)}$	0.13	0.23	0.34	0.41	0.47	0.69
(t-stat)	(2.4)	(3.1)	(3.7)	(3.8)	(3.8)	(4.7)
ΔNFP_{t-1}	-0.19	-0.55	-0.76	-0.92	-1.02	-1.15
(t-stat)	(-2.0)	(-4.1)	(-4.8)	(-5.0)	(-4.9)	(-5.0)
R^2	0.03	0.08	0.10	0.11	0.11	0.14

Note: The sample is 1988:10-2005:12. The observations are from the last day of each month. The regression equation is (5), where X_t contains $f_t^{(n)}$ and nonfarm payroll employment growth ΔNFP_{t-1} from $t-13$ to $t-1$. ΔNFP_{t-1} is measured in basis points. One-month excess returns are annualized by multiplying them by 12 and measured in basis points. HAC t-statistics are reported in parentheses.

Table 7: Annualized Excess Returns in Eurodollar Futures Contracts

Panel A: Average Excess Returns

n	1	2	3	4	5	6	7	8
const.	47.2	69.5	81.3	89.4	93.5	94.4	91.3	99.2
(t-stat)	(2.2)	(2.5)	(2.5)	(2.6)	(2.6)	(2.7)	(2.7)	(3.1)

Panel B: Predictive Regressions w/Nonfarm Payrolls

const.	-35.1	-66.2	-84.0	-100.9	-108.3	-110.7	-119.0	-122.3
(t-stat)	(-0.8)	(-1.8)	(-1.9)	(-1.8)	(-1.7)	(-1.7)	(-1.8)	(-1.9)
$ef_t^{(n)}$	0.46	0.56	0.57	0.56	0.53	0.49	0.46	0.43
(t-stat)	(4.0)	(7.8)	(7.1)	(6.2)	(5.6)	(5.3)	(5.5)	(5.3)
ΔNFP_{t-1}	-1.04	-1.09	-1.01	-0.92	-0.81	-0.69	-0.59	-0.43
(t-stat)	(-5.9)	(-7.2)	(-6.3)	(-6.7)	(-8.0)	(-9.0)	(-8.2)	(-6.0)
R^2	0.25	0.37	0.42	0.44	0.45	0.43	0.42	0.43

Note: The sample is 1985Q2-2005Q4. The observations are from the last day of each quarter. The regression equations are the same as in Tables 1 and 3, but now estimated with data on Eurodollar futures. n refers to quarters, $ef_t^{(n)}$ is the eurodollar futures rate, and ΔNFP_{t-1} denotes year-on-year nonfarm payroll employment growth lagged one month. ΔNFP_{t-1} is measured in basis points. HAC t-statistics are reported in parentheses.

Table 8: Annualized Excess Returns and Non-Hedging Market Pariticipant Positions

n	1	2	3	4	5	6
const.	-4.2	-8.6	-22.2	-36.4	-53.4	-73.9
(t-stat)	(-0.2)	(-0.3)	(-0.8)	(-1.3)	(-1.9)	(-2.6)
$f_t^{(n)}$	0.08	0.08	0.11	0.15	0.19	0.25
(t-stat)	(1.6)	(1.3)	(1.6)	(2.1)	(2.7)	(3.5)
Net Long Pos	1.18	2.61	3.76	4.70	5.37	6.15
(t-stat)	(1.1)	(2.1)	(2.5)	(2.8)	(3.1)	(3.3)
R^2	0.02	0.05	0.09	0.13	0.18	0.25

Note: The sample is 1988:10-2005:12. The observations are from the last day of each month. The regression equation is (3), where X_t consists of the own futures contract rate $f_t^{(n)}$ and the net long position of noncommercial (non-hedging) eurodollar futures market participant positions, as a percentage of total reportable open interest (see text for details). Data on futures market participant positions are from the U.S. Commodities and Futures Trading Commission. HAC t-statistics are reported in parentheses.

Table 9: Forecasts Of The Federal Funds Rate

A: Federal Funds Rate Forecasts

	Benchmark			Federal Funds Futures-Based Forecasts								
	VAR(4)			Unadjusted Futures			Rule-of-Thumb Adjusted Futures			Risk-Adjusted Futures		
n	ME	RMSE	ρ_n	ME	RMSE	ρ_n	ME	RMSE	ρ_n	ME	RMSE	ρ_n
1	−1.4	27	.67	−3.2	11	.10	−2.2	11	.06	−0.5	12	.08
2	−1.1	36	.57	−7.6	19	.28	−5.6	18	.23	−2.1	19	.19
3	−1.9	47	.39	−12.4	29	.37	−9.4	28	.33	−4.3	29	.20
4	−2.6	57	.24	−18.2	41	.39	−14.2	40	.34	−7.0	38	.16
5	−3.6	66	.13	−24.7	54	.40	−19.8	52	.40	−8.7	46	.14
6	−5.2	75	.08	−30.8	66	.49	−24.8	64	.45	−8.9	50	.16

B: Eurodollar Rate Forecasts

	Benchmark			Eurodollar Futures-Based Forecasts								
	VAR(3)			Unadjusted Futures			Rule-of-Thumb Adjusted Futures			Risk-Adjusted Futures		
n	ME	RMSE	ρ_n	ME	RMSE	ρ_n	ME	RMSE	ρ_n	ME	RMSE	ρ_n
1	15	120	.80	−17	44	.40	−1	40	.29	−7	38	.07
2	27	135	.45	−43	89	.56	−24	81	.48	−21	64	.28
3	31	144	.10	−73	134	.57	−51	123	.51	−37	90	.17
4	25	161	−.22	−105	182	.47	−80	169	.39	−54	116	.04
5	11	180	−.34	−135	223	.38	−107	207	.30	−68	138	.05
6	−17	198	−.26	−163	256	.31	−132	238	.22	−83	159	.16
7	−45	209	−.13	−181	281	.26	−147	260	.16	−86	179	.16
8	−72	206	.17	−200	297	.25	−163	274	.15	−92	195	.06

Note: n is the forecasting horizon in months (quarters for eurodollar rate). ME denotes the mean forecast error (in basis points), RMSE the root-mean-squared error (in bp), and ρ_n is the nth autocorrelation of the forecast error, all over the period 1990:10 through 2005:12 at monthly frequency (1990Q3 throuh 2005Q4 at quarterly frequency for eurodollars). VAR(4) is a monthly VAR forecast based on 4 lags of each of the federal funds rate, the year-on-year percentage change in the core CPI, and the year-on-year percentage change in nonfarm payrolls. VAR(3) is a quarterly VAR based on 3 quarterly lags of the 90-day eurodollar rate, the year-on-year percentage change in the core CPI, and the year-on-year pecentage change in nonfarm payrolls. The risk-adjusted futures-based forecast adjusts the fed funds futures rate for risk premia using the own futures rate and the year-on-year percentage change in nonfarm payrolls. Coefficients of the VAR and the risk-adjustment regression are recomputed at each date t using data only up through month $t-1$, so all forecasts are pseudo-out-of-sample.

Table 10: Risk-adjusting Measures of Monetary Policy Shocks

Panel A: Summary statistics of Policy Shocks

	Actual − Futures		Change in FF Futures	
	original	adjustment	original	adjustment
mean	-3.0	-3.0	-1.2	-1.2
std dev	11.0	3.2	8.2	2.0
min	-43.8	-12.6	-42.5	-6.4
max	17.1	4.1	14.5	15.2

Panel B: t-statistics from regressions on Treasury spreads

	const.	1yr–6mo	2–1 yr	5–2 yr	10–5 yr	R^2	p-value
Actual − Futures	-2.0	-1.7	2.6	-2.5	2.2	0.09	.054
Change in FF Futures	-1.5	-0.6	1.8	-1.6	1.3	0.06	.431

Note: Daily observations on days of FOMC meetings and intermeeting policy moves, 1994-2005.

Table A1: Annualized Excess Returns, Marking to Market

Panel A: Constant Risk Premia

n	1	2	3	4	5	6
$\alpha^{(n)}$	35.1	38.3	42.5	48.8	56.2	60.4
(t-stat)	(3.7)	(3.4)	(3.0)	(2.9)	(2.8)	(2.7)

Panel B: Excess Returns And Nonfarm Payrolls

n	1	2	3	4	5	6
constant	-0.3	1.7	-6.8	-17.2	-32.2	-45.8
(t-stat)	(-0.0)	(0.1)	(-0.3)	(-0.7)	(-1.4)	(-2.1)
$f_t^{(n)}$	0.13	0.19	0.25	0.32	0.39	0.44
(t-stat)	(2.1)	(2.4)	(3.1)	(4.5)	(7.0)	(13.1)
$\Delta \mathrm{NFP}_{t-1}$	-0.20	-0.37	-0.51	-0.62	-0.71	-0.74
(t-stat)	(-1.8)	(-3.0)	(-3.8)	(-5.0)	(-7.2)	(-11.5)
R^2	0.03	0.10	0.18	0.25	0.32	0.40

Note: The sample is 1988:10-2005:12. The observations are from the last day of each month. The regression equations are those from Tables 1 and 3, but now returns are defined by equation (8). HAC t-statistics are reported in parentheses.

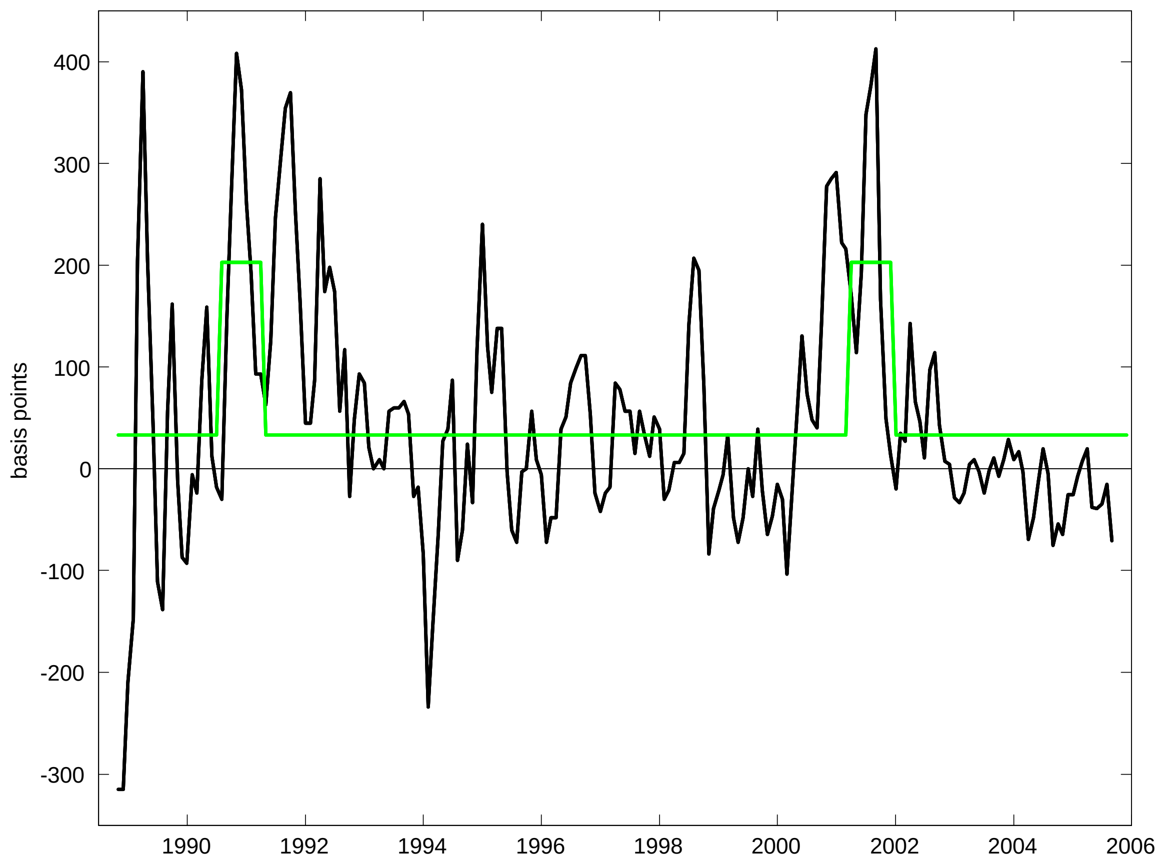

Figure 1: Annualized excess returns on the federal funds futures contract 4 months ahead. The step function represents the fitted values from a regression of $rx_{t+4}^{(4)}$ on a constant and a recession dummy.

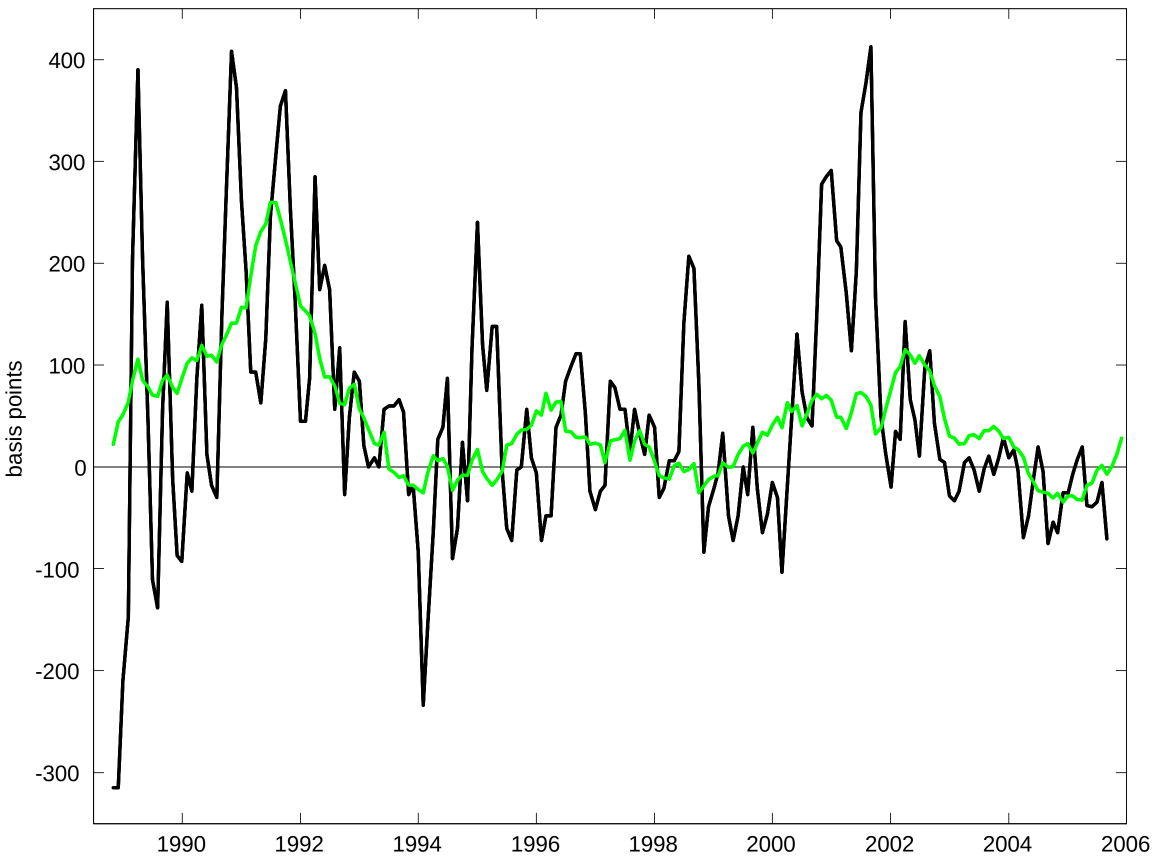

Figure 2: Annualized excess returns on the federal funds futures contract 4 months ahead. The gray (green in color) function represents the fitted values from a regression of $rx_{t+4}^{(4)}$ on a constant, employment growth and $f_t^{(4)}$ itself.

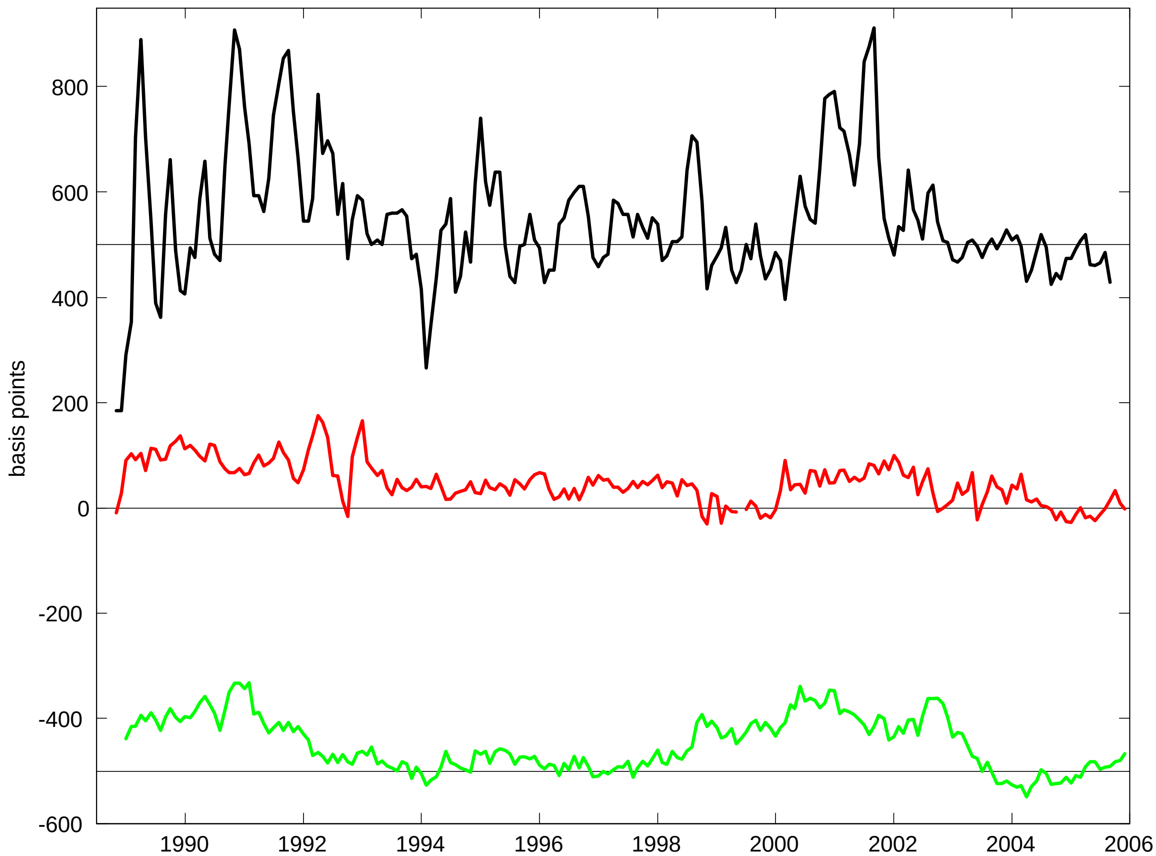

Figure 3: The top line are annualized excess returns $rx_{t+4}^{(4)}$ on the 4-month ahead futures contract (shifted up by 500 bp), the middle line are fitted values from the regression on Treasury yield spreads (Table 4) and the bottom line are fitted values from the regression on the corporate bond spread (Table 5, shifted down by 500 bp).

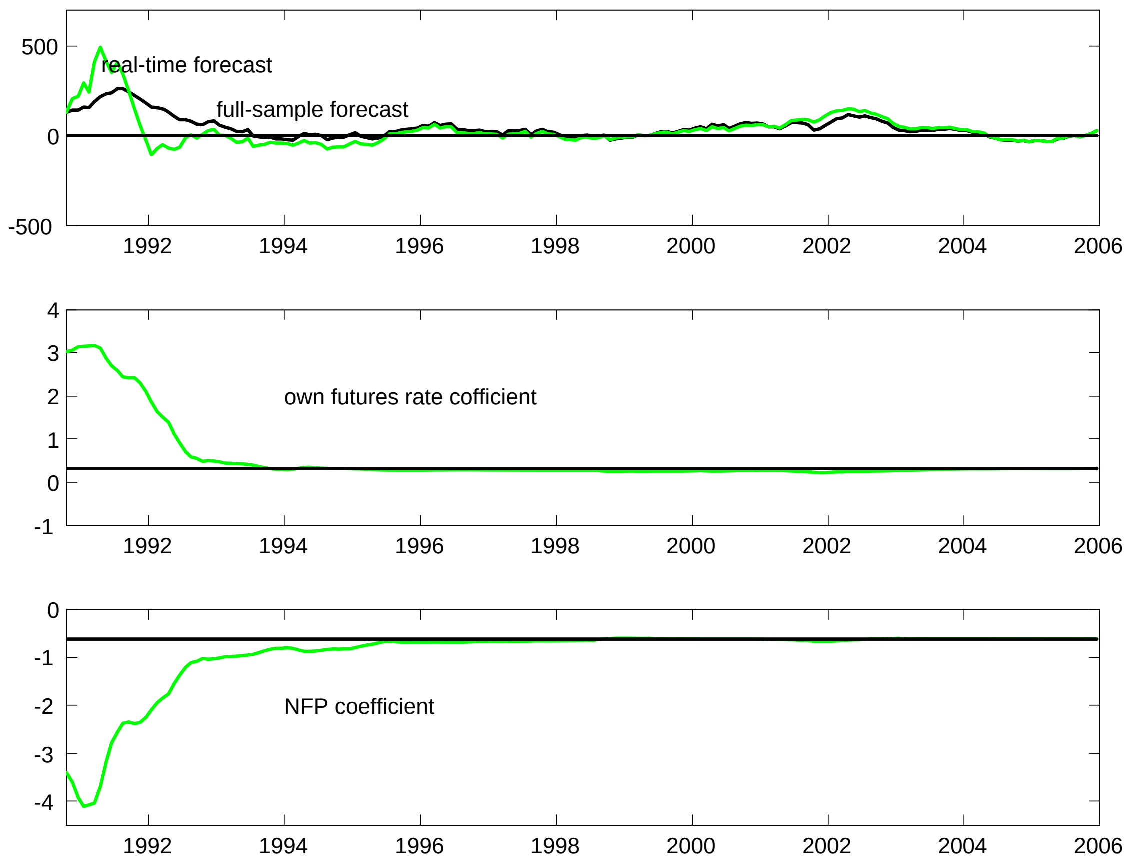

Figure 4: The top panel shows real-time and full-sample forecasts of $rx_{t+4}^{(4)}$. The middle panel shows the rolling estimates of the coefficient on the own futures rate $f_t^{(4)}$. The flat line is the full-sample coefficient from Table 2. The lower panel shows the rolling estimates of the coefficient on employment growth. Again, the flat line is the full-sample coefficient from Table 2.

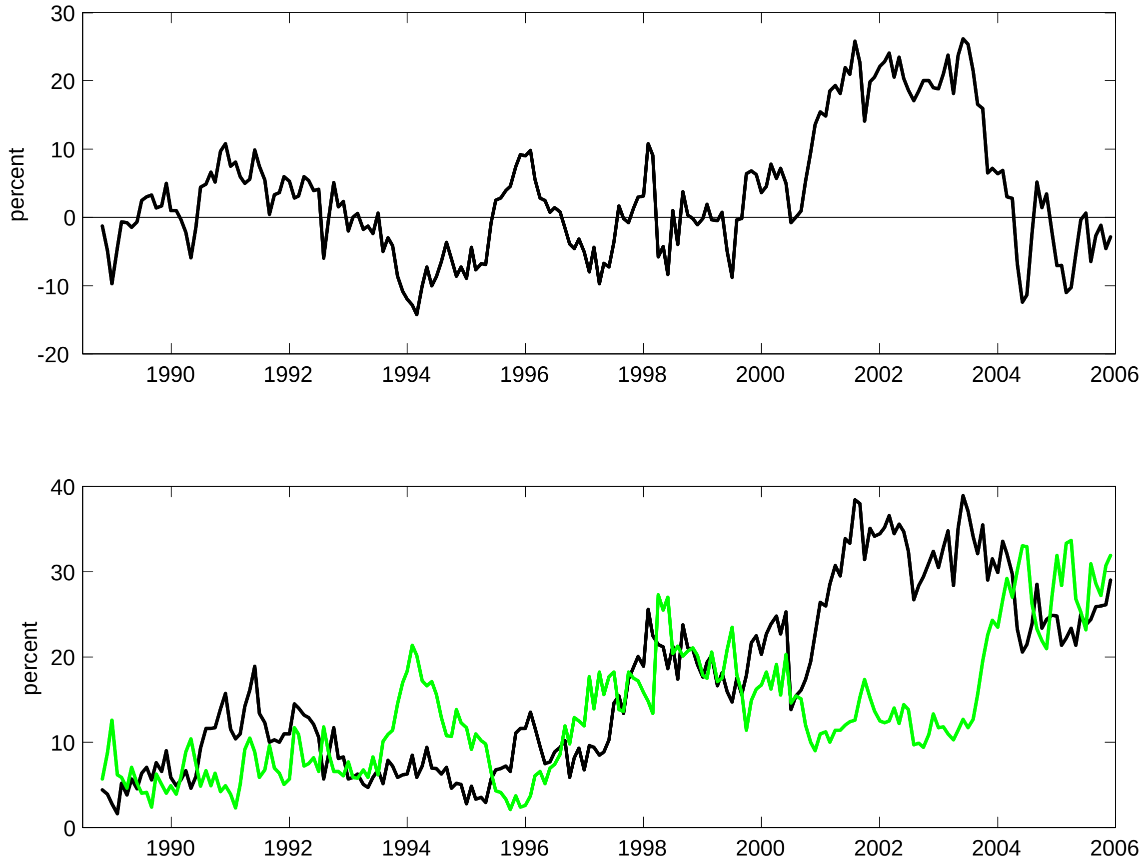

Figure 5: The upper panel shows net positions in eurodollar futures. The lower panel shows long and short positions (in gray/green) separately.

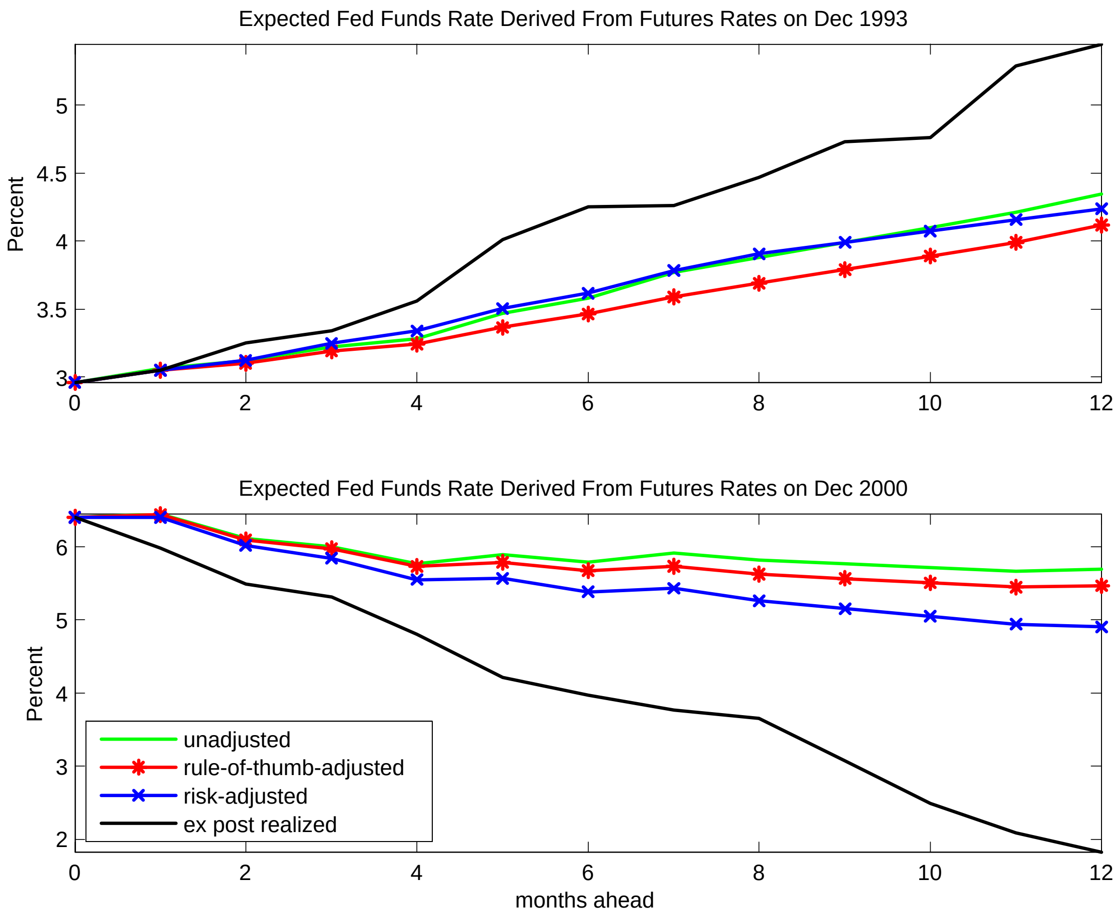

Figure 6: Federal funds rate forecasts on two illustrative dates, and subsequent realized funds rate. Funds rate forecasts are constructed from unadjusted and risk-adjusted futures rates, and using three different risk adjustments: an estimated constant adjustment, a rule-of-thumb constant adjustment, and a time-varying risk adjustment based on employment growth.

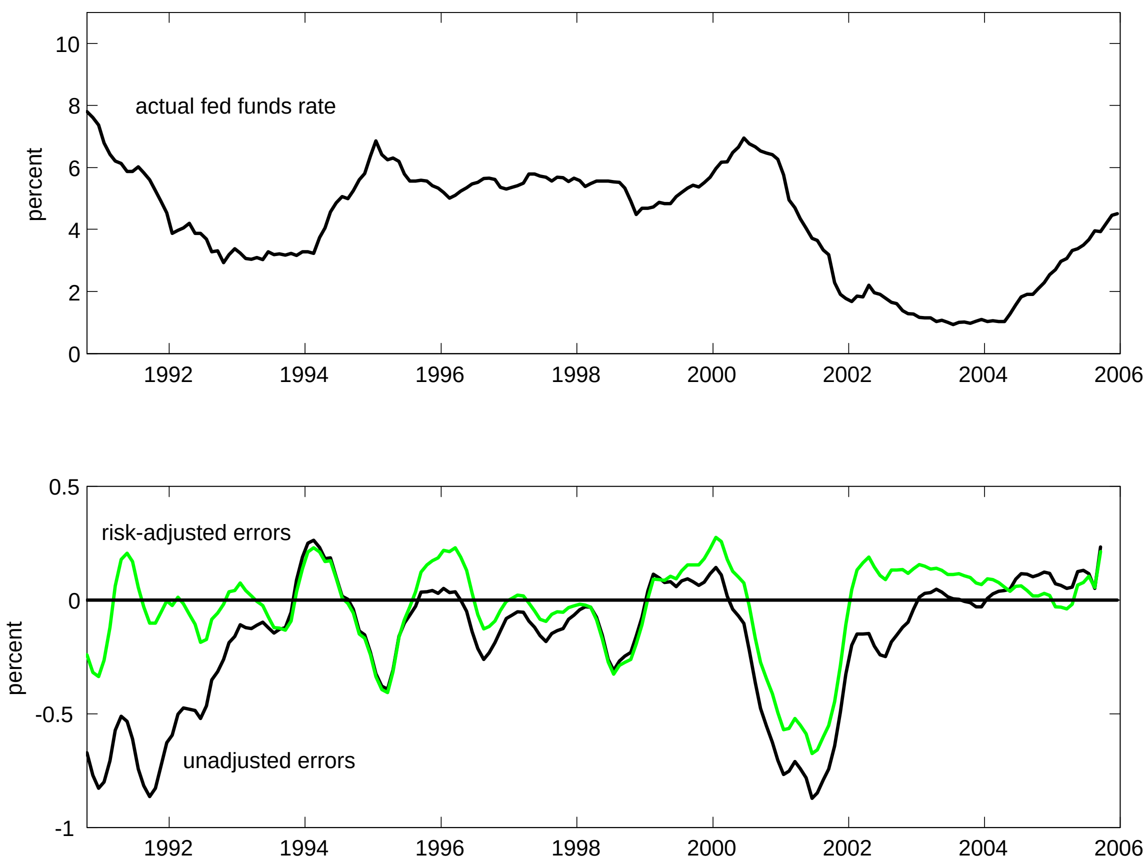

Figure 7: The upper panel shows the actual federal funds rate. The lower panel shows the 4-month ahead forecast error using the unadjusted and the risk-adjusted federal funds rate. Forecast errors are smoothed using a 6 month moving average.

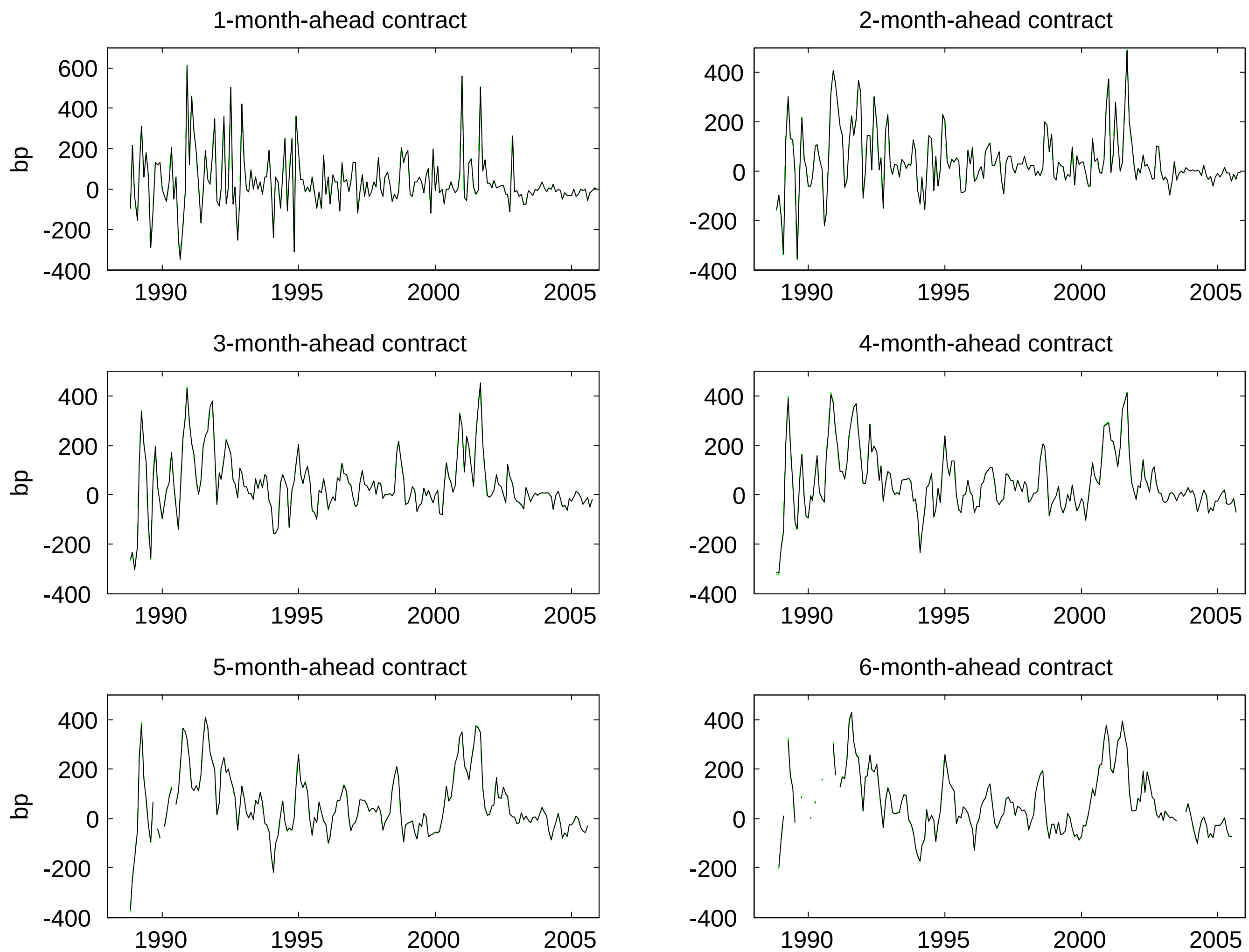

Figure 8: Each panel plots the actual annualized excess returns on the n-month ahead federal funds futures contract as black line and our return definition (1) as dashed gray line (green in color).