# FORECASTING IN A DATA-RICH ENVIRONMENT

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ABSTRACT

**Huan Zhou: Forecasting in a Data-Rich Environment**
**(Under the direction of Eric Ghysels)**

With the introduction of new macroeconomic and financial indicators and the timely publication of high frequency data, forecasters face an ever-increasing amount of information when making their predictions. It is thus a great challenge to set up parsimonious time series models that can synthesize the rich information set at hand, as well as make accurate forecasts.

I hope in my dissertation to contribute to the forecasting literature by applying newly-developed tools and methods to the empirical forecasting of macroeconomic and business indicators.

Chapter 1 examines the information contained in financial market signals can be informative regarding the state of the macro economy. In this chapter, we utilize principal component analysis and forecast combination techniques to summarize the information from a large panel of 991 financial market series. We examine the consensus GDP and CPI projections in two surveys of professional macro forecasts for their efficiency regarding the aforementioned signals. Our results show that their forecast errors correlate significantly with many financial series as well as factors extracted from these series. Using a panel of financial market data, we were able to predict professional forecasters' errors out-of-sample, indicating the potential to improve their forecasts with a rich set of financial signals. In addition, both the in-sample correlation and the out-of-sample forecast improvement were shown to strengthen during the most recent financial crisis.

In Chapter 2, we aim at designing statistical models to predict corporate earnings which either perform as well as, or even better than analysts. There are at least two challenges: (1) analysts use real-time data whereas statistical models often rely on stale data and (2) analysts use potentially large set of observations whereas models often are frugal with data series. In this chapter we introduce newly-developed mixed frequency regression methods that are able

to synthesize rich real-time data and predict earnings out-of-sample. Our forecasts are shown to be systematically more accurate than analysts' consensus forecasts, reducing their forecast errors by 15% to 30% on average, depending on forecast horizon.

In Chapter 3, we propose imposing structure on the coefficients of an autogressive (AR) model to reduce the number of parameters estimated, and show that with a finite sample, such hyper-parameterization can lead to a more parsimonious model and can thus improve the AR model's forecast performance. Monte Carlo simulations were carried out to assess under which conditions the models we propose outperform the benchmark AR model. In an empirical application of forecasting 170 monthly macroeconomic series, we found that hyper-parameterized AR models have clear advantage over the AR model, for series where the population best linear projections are long.

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CHAPTER 1

# EVALUATING MACRO FORECASTERS' USE OF FINANCIAL SIGNALS

## 1.1 Introduction

Macroeconomic forecasting is carried out extensively by both policy-makers and industry analysts. The predictions of macroeconomic performance are vital to the decisions of market participants, whether they are concerned with monetary and fiscal policies or investment positions. When making such predictions, the conditions of the financial markets are often taken into forecasters' considerations. In this study, we appraise professional macroeconomic forecasters' degree of success in reading financial market signals both in-sample and out-of-sample.

There are a number of factors that motivated this research. (1) In a data-rich environment, the benefit of a large information set could be outweighed by the noise added from using many predictors. We present econometrics methods that can synthesize financial market information and improve professional forecasters' forecast accuracy. (2) Our study complements existing literature on macroeconomic forecasters' rationality by examining their efficiency at reading financial signals. (3) The performance of most forecasts, including the predictions made by professional forecasters, as well as those generated by time series models, worsened significantly during the 2007-2008 global financial crisis. Andreou, Ghysels, and Kourtellos (2013a) documented such deterioration in forecast performance and demonstrated that their model, which combines the use of macro variables with financial series, outperforms benchmark models, which only take into account macro information. In this paper, we try to determine for professional forecasters, whether the benefits of incorporating financial variables in forecasting are magnified in tumultuous business conditions.

In this paper, the object of interest is the forecast errors of professional macro forecasters on two quarterly macroeconomic series: real GDP growth rates and CPI-based inflation rates. We carry out the study in two main steps: (1) selecting a list of publicly-available financial variables - examining their in-sample correlation with the forecast error series, and (2) developing a forecasting model based on the aforementioned financial information to predict professional forecasters' errors out-of-sample.

The idea here is straightforward: if the forecasters fully and optimally utilize financial market information, then the forecast errors should be orthogonal to such information. A non-zero correlation suggests that the tested series was not utilized optimally in the original forecast, and that a portion of the errors could potentially be predicted by exploiting such correlation and therefore reduced *ex-ante*.

Our study yields some surprisingly sharp results. A significant fraction, in many cases more than half, of the financial series are shown to be significantly correlated with GDP and inflation forecast errors. Exploiting the in-sample correlation, we are able to predict 20% to 30% of the average forecaster's errors in real-time. The financial signals tend to be more informative during the most recent financial crisis, which was substantiated by statistically higher in-sample correlation and out-of-sample predictive ability.

There is a large body of related literature on professional forecasters' rationality and efficiency, in which the two terms have been used somewhat interchangeably. To avoid confusion, we choose to use a unified definition proposed in Stekler (2002), where forecasts are evaluated on two desired properties: unbiasedness and efficiency. The former property refers to a set of forecasts being unbiased conditional on its past values, while the latter requires the forecast errors to be uncorrelated with any information known at the time of the prediction. Weak-form rationality only demands the forecasts to be unbiased. Strong-form rationality mandates both unbiasedness and efficiency.

Mincer and Zarnowitz (1969) is an important paper in this field, which proposed a popular test of conditional unbiasedness (often referred to as the Mincer-Zarnowitz test), and piqued interest in examining the weak-form rationality of available commercial forecasts. The Mincer-Zarnowitz test involves regressing actual realized values on both a constant and the projected values. If the estimated constant is zero and the slope of the projected values is one, then the forecasts are conditionally unbiased. Many papers applied the Mincer-Zarnowitz test to existing business forecasts and documented differing levels of evidence against weak-form rationality.[1] Another method of testing weak-form rationality utilizes forecast revisions. Nordhaus (1987) pointed out that in the case of fixed-event forecasts, rational forecast revisions should only be dependent on new information received since the last revision. If forecast revisions are shown to be dependent on their previous period values, then weak-form rationality can be rejected. Follow-up papers include Clements (1997); Isiklar, Lahiri, and Loungani (2006); and Ager, Kappler, and Osterloh (2009); among others.

Compared to the volume of studies on conditional unbiasedness, there is less of an abundance of work examining efficiency, i.e. the relationship between forecast errors and information other than the forecasts themselves. Notable examples include Baghestani and Kianian (1993), where the authors tested for orthogonality between survey forecast errors and a vector of macroeconomic variables that describe the cyclical state of the economy, as well as the direction and intensity of monetary and fiscal policies; and Schuh (2001), in which forecast errors were regressed on past realized values of GDP, inflation, and interest rates. In most cases, business forecasts were found not to be efficient with regard to these exogenous variables.

Our paper relates to this literature, in particular to the aforementioned work on forecast efficiency. However, the use of newly-developed econometric tools, such as principal component analysis and forecast combination techniques, allows us to survey the efficiency of macroeconomic predictions with regard to a more extensive information set, namely financial market series. Previous studies also predominantly rely on in-sample regressions, while we appraise whether any inefficiency, if found in-sample, could be utilized to improve out-of-sample forecasts.

The remainder of the paper is organized as follows. Section 1.2 outlines macro forecasts whose errors we examine in this study, as well as the set of financial data we use as potential predictors. Section 1.3 describes the econometric methods employed in this paper. Section 1.4 discusses in-sample correlation between the forecasters' errors and financial series. Section 1.5 demonstrates that a forecaster's errors can be forecast out-of-sample by the series investigated in Section 1.4. The last section contains the conclusions reached based on the empirical results.

[1] See for instance, Zarnowitz (1985), Baghestani and Kianian (1993), Loungani (2001), Timmermann (2007).

### 1.2 Description of the Data

We examine the efficiency of two sets of professional macroeconomic forecasts, namely the Survey of Professional Forecasters and Blue Chip Economic Indicators, with regard to an extensive list of publicly-available financial market series. In particular, we choose the projections on quarterly real GDP growth rates and CPI-based inflation rates, two measures of the overall economy that have historically received the most forecast coverage. The following two subsections describe the source of the raw data, their frequency and characteristics, as well as the transformation carried out on the series.

#### 1.2.1 Professional Macroeconomic Forecasts

The Survey of Professional Forecasters (SPF) is issued quarterly by the Federal Reserve Bank of Philadelphia, documenting the predictions of GDP, inflation, and a number of other business indicators submitted by a panel of professional forecasters. The submission deadline is generally in the middle month of each quarter.[2] The forecasters are asked to report their projections on the level of surveyed macroeconomic series for various horizons ranging from the current quarter to two years ahead. We downloaded the GDP and inflation projections of the median forecaster, together with the realizations, from the website of the Federal Reserve Bank of Philadelphia. The error sequences are calculated by subtracting the median forecast from the last available vintage of realized values and span the time frame of 1985 to 2011.

Blue Chip Economic Indicators (Blue Chip) is another published survey of business forecasters. The forecasts for this compendium are submitted at the start of each month, on a number of US economic and financial variables. Compared with the Survey of Professional Forecasters, the Blue Chip forecasts are more frequent, but do not reach back as far in time. The forecasts we use in this study were made in the months ranging from January, 1992 to September, 2010. Forecast errors were calculated by subtracting the average Blue Chip forecasts from realized real GDP growth rates and inflation rates retrieved from the economic research database of the

[2] It is important to note the submission deadlines because we want to align the timing of the financial market data to only include information available to the analysts at the time their predictions were made. See http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/spf-release-dates.txt for the historical deadline dates.

Federal Reserve Bank of St. Louis.

We restrict the forecasts to the ones made for three horizons: current quarter, one quarter ahead, and one year ahead. Aside from disparities in the analysts surveyed, the two sets of professional forecasts also differ in their sampling frequency, and therefore the time series properties of the forecast error sequences. Take the current quarter forecasts of the 2000 Q1 (target quarter) inflation rate for example, the SPF dataset includes only one median prediction, which was released in the middle month of the target quarter, while the Blue Chip dataset contains three median predictions, made separately in the first, middle and last month of the target quarter. In the literature, the former is referred to as rolling-event forecasts, and the latter fixed-event forecasts. Since the fixed-event forecast errors contain a moving average structure (where the second month's error is the first month's error plus an additive term), one needs to pay attention to the econometric specification when working with such series.[3] The stationary bootstrap method we use in this paper accommodates both types of forecasts by allowing serial dependence in the forecast errors. We will discuss this further in Section 1.3.1.

We choose the last available vintages of the realized values when calculating forecast errors to achieve longer time-series, since real-time data, especially CPI data, are only available for latter years in the sample.[4] As one may be able to argue, data revisions should be independent of the financial market series, and the final vintages are more reliable and accurate estimates of the macroeconomic indicators. [5]

The use of the average (either median or arithmetic mean) of individual predictions, reflects our intention to investigate whether macroeconomic forecasters *systematically* misread financial market signals. It is well established in the literature that individual forecasters use different models and rely on varying levels of intuitive judgment to make their projections, and that

[3]For example, one should use theNordhaus test rather than the Mincer-Zarnowitz test (both discussed in Section 1.1) when testing conditional unbiasedness of fixed-event forecasts.

[4]In the SPF database, first-release CPI-based inflation rates are only available beginning in 1994.

[5]A Bureau of Economic Analysis article mentioned four reasons for macroeconomic data revision. See http://www.bea.gov/scb/account_articles/national/1093od/maintext.htm for the article.

their performance is affected by such choices.[6]. Thus, using the average may allow bias and inefficiency in individual forecasts to cancel out. In the mean time, we are aware that taking simple average or median may not be the best way to aggregate.[7] However, since the median or mean forecast is often perceived by policy makers and the private sector as the market expectations on macroeconomic conditions, we adopt this imperfect measure, rather than using other aggregation schemes.

### 1.2.2 Financial Dataset

We use the same financial data as in Andreou, Ghysels, and Kourtellos (2013a) (AGK), which comprises 991 daily series categorized into five classes: equity, foreign exchange, government securities, commodities, and corporate risk. The data span the time period from 1985 to 2011.[8] Following AGK, All variables are transformed to achieve stationarity. The rule of thumb for the transformation is to take the first differences on return series and to use the log first differences on the level ones. The daily changes in financial data are summed to obtain quarterly (for SPF) or monthly (for Blue Chip) signals used in the in-sample and out-of-sample analysis.

## 1.3 Methodology

This section describes an in-sample bootstrap correlation testing method and an out-of-sample forecasting model. The former identifies inefficiencies of the consensus forecasts with regard to the financial market signals available at the times of projection, while the later uses the aforementioned signals to predict forecast errors out-of-sample.

[6] See Bathcelor and Dua (1990) for an analysis of the techniques used by professional forecasters. A more updated survey on the same topic made by the Federal Reserve Bank of Philadelphia is available at http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/spf-special-survey-on-forecast-methods.pdf

[7] Agnew (1985), among other papers, examined the issue of optimal aggregation.

[8] See the appendix for a complete list of financial variables.

### 1.3.1 In-Sample Correlation Test

We denote the h-step-ahead forecast of a stationary quarterly variable, such as GDP growth, made in period t as $\hat{Y}_{t+h|t}(I_t)$ ($I_t$ is the information used in forming the forecast). The error is then defined as the difference between the forecast and the realized value: $e_{t+h|t}(I_t) \equiv Y_{t+h} - \hat{Y}_{t+h|t}(I_t)$. If the forecast model is correctly specified, the error should be orthogonal to $I_t$.

The test of whether a set of forecasts is efficient regarding financial market information is therefore carried out by appraising the correlation between the error sequence $e_{t+h|t}(I_t)$ and the financial market information $X_t$ observable to the analysts at the time of the forecast.[9] If the correlation is not zero, there could be two causes: (1) $X_t$ is not in the information set $I_t$, or (2) the forecasting model is misspecified. Both of these indicate that the forecaster misread financial market signal $X_t$.

The statistical method we propose to test the population hypothesis $H_0$ : $corr(e_{t+h|t}, X_t) = 0$ applies the stationary bootstrap procedure proposed in Politis and Romano (1994b). We are not required to explicitly specify a data-generating process for either of the two series (apart from some mild regularity conditions), thus the method works for both rolling- and fixed-event forecast errors. The key inputs of this procedure include the average block size, and the number of bootstrap simulations. Given these inputs, the two series $e_{t+h|t}$ and $X_t$ are re-sampled by blocks of random sizes and the bootstrap generates pseudo time series $e^*_n$ and $X^*_n$ ($n = 1, \ldots, N$ where $N$ is the number of bootstrap replications). Sample correlation can be calculated from the simulated pseudo time series $\beta_n \equiv corr(e^*_n, X^*_n)$. Thus $\beta_n$ ($n = 1, \ldots, N$) form the empirical distribution of $corr(e_{t+h|t}, X_t)$, with which we can test the null hypothesis that the two series are uncorrelated in population, against $H_a : ccorr(e_{t+h|t}, X_t) < 0$ or $H_a : corr(e_{t+h|t}, X_t) > 0$.

In the aforementioned bootstrap test, $X_t$ can be either a particular financial series, or the principal components of a given cross-section of financial series. The possible outcomes of

[9] The time subscript suggests that we only test with financial market information immediately preceding the date that forecasts were made. We restrict the in-sample correlation analysis to the latest financial market information, but obviously similar tests can be carried out on any historical financial market signals such as $X_{t-1}, X_{t-2}$, etc.

the bootstrap test of correlation are positive, negative or insignificant. Since there is a large number of financial series, and we want to evaluate forecasters' efficiency regarding financial information in general, we only report the significance and not the signs of the correlation when using individual financial series as $X_t$ (see Section 1.4 for more details.)

### 1.3.2 Out-of-Sample Prediction Models

We set up a rolling-window out-of-sample forecasting model utilizing all 991 financial market series. We either use the individual series as is, or extract a certain number of factors to be used as predictors. For a given in-sample estimation window, one predictor is used in the regression model at a time, generating one forecast per series. The forecasts are then combined using a set of dynamically estimated weights to produce the final model forecast series.

## 1.3 Principal Component Analysis and Forecast Combination Methods

The challenge of using financial series to predict forecast errors lies in the dimension of the data available. With a limited degree of freedom, one cannot include hundreds of predictors in one regression. Rather than choosing a few series *ex-ante*, we opt to use newly-developed forecast combination techniques to address the issue of data proliferation.

Besides forecast combination, one of the commonly-employed strategies when dealing with a large cross-section of predictors is to extract a limited number of factors and to include only those in the regressions. Even in this case, forecast combination still has merit, as Timmermann (2006) pointed out that compared to estimating a forecast model with all predictors in one regression, carrying out the regression one predictor at a time and using forecast combination methods is more robust to model misspecification and measurement errors. The combined forecast also performs better in the presence of structural breaks and model instability.

Therefore, we take two approaches in setting up a forecast model that incorporates financial market movements. The first approach is to use individual series directly, while the second is to extract financial factors first. We do not differentiate these two in the rest of this section, and use a general term "predictor" when describing models.

Using one given predictor $X^i$, we estimate the following h-step-ahead model for the errors of the median forecaster $e_{t+h|t}$ ($t = 1, \ldots, T-h$).

$$e_{t+h|t} = c + \sum_{j=0}^{K} \beta_j X^i_{t-j} + \mu^i_{t+h|t} \tag{1.3.1}$$

All forecasts are made in a rolling fashion with the window size $W = T/2$. Model parameters, including the optimal number of lags K[10], are estimated based only on the latest $W$ observations up to the date a forecast is made, then re-estimated as the forecast date progresses. After iterating this procedure for each predictor, we obtain a set of $I$ out-of-sample forecasts $\hat{e}^i_{t+h|t}$ ($i = 1, \ldots, I$; $t = T_0, \ldots, T-h$), with $I$ equal to the total number of predictors, and $T_0$ being the first date on which a projection is made, i.e. $T_0 = W$.

Then we proceed to combine the above forecasts with the discounted mean square error method, in which the combined forecast is a weighted sum of the individual ones $\hat{e}^m_{t+h|t} = \sum_{i=1}^{I} \omega_{i,t} \hat{e}^i_{t+h|t}$ and the weights $\omega_{i,t}$ are determined by the following formula:

$$\omega_{i,t} = \frac{(\lambda^{-1}_{i,t})^{\kappa}}{\sum_{j=1}^{N} (\lambda^{-1}_{j,t})^{\kappa}}$$

$$\lambda_{i,t} = \sum_{\tau=T_0}^{t-h} \delta^{t-h-\tau} (\mu_{\tau+h|\tau})^2$$

In this forecast combination scheme, the weights assigned to a predictor are tied to its historical performance, i.e., the smaller the forecast errors, the larger the weights. Performance in more recent periods is also given more consideration with the inclusion of a discounting factor $\delta = 0.9$. The historical errors are squared ($\kappa = 2$). The combined forecasts incorporate information from all financial signals, and are evaluated with tests described in the next subsection. We refer to this set of combined forecasts as "model forecasts" and denote its errors as $\mu^m_{t+h|t}$ ($\mu^m_{t+h|t} = e_{t+h} - \hat{e}^m_{t+h|t}$).

[10]The selection of K is made according to the Bayesian Information Criterion.

### 1.3 Forecast Evaluation

We appraise the performance of our model that utilizes financial market information against a benchmark with only a constant, namely $e_{t+h|t} = c + \mu^b_{t+h|t}$. If our model outperforms the benchmark, we can conclude that financial market information can improve professional forecasters' errors out-of-sample.

An intuitive measure we report is the ratio between the mean absolute error (MAE) of the model and that of the benchmark (MAE Ratio$\equiv \frac{\sum_{t=T_0}^{T-h} |\mu^m_{t+h|t}|}{\sum_{t=T_0}^{T-h} |\mu^b_{t+h|t}|}$). A ratio smaller than one suggests that the tested model outperforms benchmark.

To assess whether the forecast improvement is statically significant, we then apply the out-of-sample tests of forecast ability proposed in Giacomini and White (2006). The hypothesis evaluated can be expressed as $H_0: E_t[h_t \Delta L_{t+h|t}] = 0$. $\Delta L_{t+h|t}$ is the loss differential between the benchmark model and the tested model. We use a quadratic loss function $\Delta L_{t+h|t} \equiv (\mu^b_{t+h|t})^2 - (\mu^m_{t+h|t})^2$ in this paper. The test statistic is constructed as a Wald type test with $\chi^2$ a limiting distribution.[11]

When $h_t = \mathbf{1}$ , it is equivalent to a test of unconditional predictive ability: If the test statistic is significantly positive, that means the benchmark model performs worse on average. If $h_t \neq \mathbf{1}$, this evaluation shows whether the tested model is better than the benchmark model conditional on $h_t$.

In this paper, we use both types of tests, and have $h_t$ be a business cycle indicator in the conditional test. The data for $h_t$ were downloaded from the website of the National Bureau of Economic Research. $h_t = 0$ during expansions, while $h_t = 1$ during recessions. Following Giacomini and White (2006), we also run a regression of $\Delta L_{t+h|t} = \beta_0 + \beta_1 h_t + \epsilon_t$. The estimated slope of this regression $\hat{\beta}_1$ suggests whether the loss differentials between benchmark and the tested model are positively or negatively correlated with $h_t$. A positive correlation suggests the decrease in forecast errors achieved in our model is larger during recessions.

[11] See Giacomini and White (2006) for details regarding the construction of the multi-step conditional predictive ability test statistics.

### 1.4 In-Sample Correlation Analysis Results

The in-sample correlations between consensus forecasters' errors and financial market signals are evaluated using the stationary bootstrap procedure described in Section 1.3.1. Since the financial dataset includes a large number of series, similarly to the out-of-sample model, we take two approaches to address the dimensionality issue when implementing the analysis, and report the results of both.

The first approach is to carry out an asset-by-asset investigation using individual financial series, then summarize the results by asset class. Within each asset class, we report the percentage of series that are shown to be significantly correlated with the average forecasters' errors, under significance level 0.05. To have an idea of how large the correlations are (besides their statistical significance) within a given class, we also include the maximum and minimum simple full-sample correlation in the results tables.[12]

The second approach uses factor analysis as an intermediate step, in which the first three principal components of each asset class are extracted, then their correlations with the forecast errors are appraised with the bootstrap procedure. This approach allows us to examine whether forecasters could benefit from only using a small number of financial factors. We present each factor's simple full-sample correlation with forecast errors, as well as the significance level of this correlation.

#### 1.4.1 Correlation analysis on Survey of Professional Forecasters

In this subsection, we discuss empirical analysis regarding the correlation between the median forecast errors of Survey of Professional Forecasters and financial market information. Since forecasts are submitted in the second month of each quarter, we can safely assume that forecasters duly observe the previous quarter's market movements when making their forecasts. Therefore, the forecast errors made in the middle of a given quarter t are paired with the financial signals from quarter t-1 in the bootstrap tests.

We examine forecasts made for three different forecast horizons: current quarter, next

[12] Simple full-sample correlation is the correlation calculated with the original series, without any bootstrap procedure.

quarter and one year ahead. Since similar patterns are identified with all three sets of results, we only discuss the scenario of the current quarter forecasts in this section, while presenting the remaining two sets of results using longer horizon forecasts in the appendix.

Table 1.1 summarizes the results under the asset-by-asset approach. The analysis based on individual financial series demonstrates that a large percentage of exchange rates, commodities and equity series (45%, 37%, 33% of the respective classes) are correlated with the median forecasters' real GDP growth rate forecast errors during the period of 1985 to 2011.[13] The same three categories also have the most bearing on inflation forecast errors, with 29%, 15%, 22% showing significant correlations, respectively. Overall, we can observe a stronger linkage of financial signals with GDP forecast errors than with those on inflation.

The results in Table 1.2 show that factors extracted from the large cross-sections of financial data are also correlated, in many cases significantly, with the forecast errors. The first principal component of the equity class, for example, has a statistically significant correlation of 0.3 with GDP forecast errors and -0.19 with CPI-based inflation projection errors.

### 1.4.2 Correlation analysis on Blue Chip Economic Indicators

Similar to the previous subsection, we performed tests on the average Blue Chip Economic Indicators forecasts from January,1992 to September,2010. In this set of surveys, predictions on quarterly real GDP growth rates and CPI-based inflation rates are collected at the start of each month. The forecasts are thus of the fixed-event variety. For example, there are three monthly forecasts of current quarter GDP in the first quarter of 2000, made in early January, February and March of 2000. Since forecasts are submitted at the start of each month, we select financial market information from the previous month as the object of testing. Same as the case of Survey of Professional Forecasters, we report the results using current quarter forecast errors in this section, and show those on one-quarter ahead and one-year ahead forecast errors in the appendix.

[13] Note that not all financial series are available throughout the entire time span, thus the testing period varies with each series.

## 1.4 Analysis over the Entire Sample Period

As far as individual series go, in Table 1.3, we see that equity, government securities, and commodities are the classes that have high percentages of assets that significantly correlate with consensus GDP and CPI Blue Chip forecast errors, with the percentages ranging from 33% to 69%. In the case of CPI forecasts, a faction of exchange rates (27%) and corporate securities (20%) were shown to correlate with the forecast errors as well. The pattern roughly resembles that seen in Survey of Professional Forecasters (Table 1.1), in the classes of assets identified to have the largest percentages that significantly correlate with the forecast errors. Our conjecture is that the discrepancies, in particular regarding the exchange rates' correlation with GDP forecast errors[14], may be due to the sampling frequencies. At a monthly level, changes in exchange rates may be less indicative of the real side of the economy, but rather reflect nominal fluctuations, evidenced by their stronger link to inflation.

Table 1.4 presents the correlation between Blue Chip Economic Indicator consensus forecast errors and financial factors. The first principal components of equity, government securities and commodities correlate significantly with real GDP growth rate forecast errors; the first component of equity also shows a moderate but significant correlation with CPI-based inflation rate forecast errors. When comparing this with the numbers on SPF errors (in Table 1.2), we can identify some interesting similarities between the two sets of results. For instance, the first principal component of the equity class correlates positively with GDP forecast errors, and negatively with those on inflation, regardless of whether SPF or Blue Chip series are used.

As stated in the introduction, the 2007-2008 global financial crisis posed, and continues to pose, a great challenge to macroeconomic forecasting. The performance of most forecasting models and of professional forecasters suffered significantly during and after the crisis. Therefore, one of the motivations for this paper is to examine the role of financial market information during the most recent economic recession. The more frequent (monthly) observations of the Blue Chip forecasts allow the correlations on two subsamples to be estimated by the bootstrap procedure; namely a precrisis period of January, 1992 to December, 2007, and a crisis (and

[14]Many quarterly exchange rate series were shown to be correlated with GDP forecast errors significantly in the SPF results, but such is not the case with monthly exchange rates and Blue Chip GDP errors.

post-crisis) period of January, 2008 to September, 2010.

### 1.4 Correlation Pre-Crisis and Crisis Periods

The results using individual financial assets, summarized in Table 1.5, suggest that a higher percentage of assets from all categories correlate significantly with GDP and CPI forecast errors during the recent financial crisis. The classes that saw the biggest increases are equity, exchange rates, and corporate securities. Sub-sample analysis results using financial factors, presented in Table 1.6, reveal that the first principal component of corporate securities became significantly correlated with forecast errors during the financial crisis. Besides corporate securities, the first principal component of commodities also became significant in the case of GDP growth rate forecasts during the crisis, and the first principle component of government securities became significant in the case of CPI-based inflation rate forecasts. The correlations between forecast errors and the first principal component of equity class are significant in both periods, but increased in levels during and after the crisis.

The aforementioned observations confirm that, in general, the linkage between forecast errors and financial market movements strengthened during the crisis, whether one chooses to use individual assets or financial factors. Such a pattern complements the analysis in AGK, and implies that financial market signals, may help improve forecasts during crisis periods where traditional models tend to fail.

## 1.5 Out-of-Sample Predictive Ability of Financial Market Information

The in-sample correlations identified in the previous section suggest a statistically significant relationship between the forecast errors and financial series. However, if such a relationship cannot improve the forecasts out-of-sample, then it is of limited use for practitioners. Therefore, we further test whether financial market information has predictive ability for the forecast errors. In other words, we aim at showing how to forecast forecasters' errors with financial signals.

We choose the Blue Chip Consensus Forecasts to implement the forecasting model described in Section 1.3. The reason is that compared with Survey of Professional Forecasters, Blue Chip forecasts are released more frequently, allowing more observations for in-sample estimation and out-of-sample forecasts evaluation (We have 225 monthly observations in total, so T=225.)

For each of the two target macroeconomic indicators and three forecast horizons, we appraise the performance of two models (1) utilizing all 991 financial series (2) including only 15 factors, relative to the naive benchmark regression. We report two measurements of the forecast improvement. The mean absolute error (MAE) ratio, if smaller than one, indicates the average size of reduction in the out-of-sample errors when the financial predictors are included. Giacomini-White (GW) test assesses whether the reduction is statistically significant, and whether it is more evident during the financial crisis. The larger the test statistics, the more our model outperforms the benchmark. If the GW test statistics have a p-value smaller than the significance level required[15], then the improvement is statistically significant. We carry out the GW test both unconditionally and conditionally on the binary NBER business cycle indicator $h_t$ ($h_t = 1$ stands for recession). We also show the constant $\hat{\beta}_0$ and the slope coefficient $\hat{\beta}_1$ estimates from regressing the loss differentials on $h_t$ as discussed in section 1.3.2.2. Since $h_t$ is binary, $\hat{\beta}_0$ is essentially the average size of the loss differentials pre-crisis, and $\hat{\beta}_0 + \hat{\beta}_1$ is that during the financial crisis.[16] Therefore, if $\hat{\beta}_1 > 0$ then the advantage of the model is more evident during the financial crisis.

Table 1.7 outlines the forecast performance of the model using all 991 financial assets. On average, the inclusion of financial signals reduces the forecast errors by 20% to 30%, depending on the target series and the horizon, with the only exception being the one-year-ahead inflation forecasts, where the improvement is minimal (2%). All reductions are statistically significant in the case of real GDP growth rate projections, evidenced by the positive signs of the unconditional WG test statistics, and the corresponding p-values being smaller than 0.01. The predictive ability of the model on inflation forecast errors, however, is slightly below significance, where the WG test statistics are positive, but p-values are between 0.11 and 0.35. The conditional WG test results and the positive signs on both $\hat{\beta}_0$ and $\hat{\beta}_1$ suggest that the benefit of incorporating financial series exists throughout the sample, but is stronger during the financial

[15]We require a significance level of 0.05 in this paper.

[16]When using a rolling window of half the size of the entire sample, the forecasts are made in and after June 2002, a period only containing one recession according to the NBER indicator, namely the Janurary 2008 to June 2009 one.

crisis period (January 2008- June 2009).

Similar patterns can be identified using a model of 15 financial factors, as shown in Table 1.8. There is a reduced number of equations to be estimated, increasing the speed of the algorithm. However, since factors are extracted in order to explain the cross-sectional variations, not to achieve best forecast performance, one would expect and does see with Table 1.8 a loss in predictive ability compared with the more labor-intensive method of using each and every financial series.

To shed some light on which class of assets contributed more when forecasting forecasters' errors, we sum the weights by class, and plot in Figure 1.1 and 1.2, with the x-axis being the dates on which forecasts are made. Both figures show that during the economic expansion period of 2004-2006, the equity series are the most relevant. However, there is a peak in the weights assigned to corporate securities during the 2008-2009 crisis, which is consistent with our in-sample analysis from the previous section. When we switch to using 15 financial factors, the weights are quite close to equal weighting across asset classes, as shown in Figures 1.3 and 1.4.

To sum up, financial assets do seem to have predictive ability on forecast errors. Using individual assets yields better results than extracting financial factors, at least in the cases we examined. Another observation is that the out-of-sample performance of our models fares better with GDP than with CPI forecast errors. This could indicate either that financial assets are not as effective indicators of CPI, or that the existing CPI forecasts utilize financial information better. We leave this question to further study.

## 1.6 Conclusions

The main question we address in this paper is whether financial market signals have been used optimally in professional macroeconomic forecasts. The analysis is implemented by examining both the in-sample correlation and the out-of-sample predictive ability of the financial series on the consensus forecast errors.

In-sample correlation tests performed on both Survey of Professional Forecasts and Blue Chip Consensus forecasts, show that the forecast error sequences correlate not only with a significant portion of all asset classes, but also with a number of factors extracted from financial market movements. Such correlations strengthened during the recent economic crisis. Out-of-sample predictive ability tests on Blue Chip Consensus forecasts further establish that financial series and factors can be used to predict forecaster errors, especially during recessions.

Table 1.1: In-Sample Correlations Between SPF Errors and Individual Financial Series

| Real GDP Growth Rate Forecasts | | | | |
|---|---|---|---|---|
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 32.82% | -0.44 | 0.51 |
| Government Securities | 239 | 21.34% | -0.30 | 0.30 |
| Commodities | 269 | 37.17% | -0.49 | 0.58 |
| Exchange Rates | 88 | 44.83% | -0.35 | 0.31 |
| Corporate Securities | 119 | 10.08% | -0.21 | 0.30 |
| CPI-based Inflation Rate Forecasts | | | | |
| Asset Class | No. of Assets | Percentage | Max Corr. | Min Corr. |
| Equity | 268 | 22.05% | -0.32 | 0.24 |
| Government Securities | 239 | 2.93% | -0.33 | 0.36 |
| Commodities | 269 | 15.24% | -0.39 | 0.30 |
| Exchange Rates | 88 | 28.74% | -0.26 | 0.37 |
| Corporate Securities | 119 | 10.08% | -0.38 | 0.46 |

Note: The column ”Percentage” denotes the percentages of assets within each class that significantly correlate with SPF forecast errors under significance level 0.05. The Column ”Min (Max) Corr.” reports the minimum (maximum) simple full sample correlation between an asset and the forecasting errors within each class.

Table 1.2: In-Sample Correlations Between SPF Errors and Financial Factors

| Real GDP Growth Rate Forecasts | | | |
|---|---|---|---|
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | 0.30 ** | -0.11 | 0.07 |
| Government Securities | 0.06 | -0.18 ** | -0.08 |
| Commodities | 0.49 *** | -0.04 | -0.19 |
| Exchange Rates | 0.07 | -0.03 | -0.08 * |
| Corporate Securities | 0.03 | 0.01 | -0.03 |
| **CPI-based Inflation Rate Forecasts** | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | -0.19 ** | -0.03 | 0.07 |
| Government Securities | -0.19 * | -0.01 | 0.19 *** |
| Commodities | -0.11 | 0.01 | 0.05 |
| Exchange Rates | -0.02 | 0.07 | 0.01 |
| Corporate Securities | 0.11 *** | 0.04 | 0.10 ** |

Note: The numbers are full-sample correlations between the principal components and the SPF forecast errors. * denotes the significance level under which we can reject the hypothesis that population correlation is zero by stationary bootstrap. (* means $p < 10\%$; ** means $p < 5\%$; *** means $p < 1\%$)

Table 1.3: In-Sample Correlations Between Blue Chip Errors and Individual Financial Series

| Real GDP Growth Rate Forecasts | | | | |
|---|---|---|---|---|
| Asset Class | No. of Assets | Percentage | Max Corr. | Min Corr. |
| Equity | 268 | 69.23% | -0.43 | 0.46 |
| Government Securities | 239 | 38.91% | -0.30 | 0.20 |
| Commodities | 269 | 32.71% | -0.47 | 0.49 |
| Exchange Rates | 88 | 6.90% | -0.14 | 0.21 |
| Corporate Securities | 119 | 10.08% | -0.19 | 0.25 |
| CPI-based Inflation Rate Forecasts | | | | |
| Asset Class | No. of Assets | Percentage | Max Corr. | Min Corr. |
| Equity | 268 | 34.36% | -0.38 | 0.22 |
| Government Securities | 239 | 53.14% | -0.30 | 0.24 |
| Commodities | 269 | 41.64% | -0.54 | 0.28 |
| Exchange Rates | 88 | 27.59% | -0.25 | 0.32 |
| Corporate Securities | 119 | 20.17% | -0.25 | 0.39 |

Note: The column ”Percentage” denotes the percentages of assets within each class that significantly correlate with Blue Chip forecast errors under significance level 0.05. The Column ”Min (Max) Corr.” reports the minimum (maximum) simple full sample correlation between an asset and the forecasting errors within each class.

Table 1.4: In-Sample Correlations Between Blue Chip Errors and Financial Factors

Real GDP Growth Rate Forecasts

| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
|---|---|---|---|
| Equity | 0.45 ** | 0.02 | 0.28 ** |
| Government Securities | -0.24 ** | 0.12 ** | -0.16 |
| Commodities | 0.40 *** | -0.21 ** | -0.12 |
| Exchange Rates | -0.02 | -0.06 | -0.05 |
| Corporate Securities | -0.06 | 0.06 | 0.05 |

CPI-based Inflation Rate Forecasts

| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
|---|---|---|---|
| Equity | -0.21 ** | -0.01 | 0.02 |
| Government Securities | -0.02 | 0.24 *** | 0.07 |
| Commodities | -0.10 | 0.01 | 0.05 |
| Exchange Rates | 0.01 | -0.02 | -0.05 |
| Corporate Securities | -0.05 | 0.05 | 0.16 *** |

Note: The numbers are full-sample correlations between the principal components and the Blue Chip forecast errors. * denotes the significance level under which we can reject the hypothesis that population correlation is zero by stationary bootstrap. (* means $p < 10\%$; ** means $p < 5\%$; *** means $p < 1\%$)

Table 1.5: In-Sample Correlations Between Blue Chip Errors and Individual Financial Series: Sub-Samples

Real GDP Growth Rate Forecast

| Pre-crisis | | | | |
|---|---|---|---|---|
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 41.03% | -0.46 | 0.42 |
| Government Securities | 239 | 10.46% | -0.24 | 0.19 |
| Commodities | 269 | 34.20% | -0.49 | 0.46 |
| Exchange Rates | 88 | 14.94% | -0.30 | 0.16 |
| Corporate Securities | 119 | 3.36% | -0.14 | 0.11 |
| Crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 73.85% | -1.00 | 1.00 |
| Government Securities | 239 | 29.29% | -0.50 | 0.52 |
| Commodities | 269 | 54.28% | -0.72 | 0.62 |
| Exchange Rates | 88 | 71.26% | -0.54 | 0.68 |
| Corporate Securities | 119 | 27.73% | -0.43 | 0.67 |

CPI-based Inflation Rate Forecast

| Pre-crisis | | | | |
|---|---|---|---|---|
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 24.62% | -0.32 | 0.17 |
| Government Securities | 239 | 54.39% | -0.23 | 0.17 |
| Commodities | 269 | 51.30% | -0.44 | 0.26 |
| Exchange Rates | 88 | 8.05% | -0.07 | 0.16 |
| Corporate Securities | 119 | 42.02% | -0.21 | 0.09 |
| Crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 38.46% | -1.00 | 1.00 |
| Government Securities | 239 | 21.76% | -0.51 | 0.48 |
| Commodities | 269 | 31.97% | -0.75 | 0.47 |
| Exchange Rates | 88 | 49.43% | -0.57 | 0.71 |
| Corporate Securities | 119 | 10.08% | -0.37 | 0.62 |

Table 1.6: In-Sample Correlations Between Blue Chip Errors and Financial Factors: Sub-Samples

| Real GDP Growth Rate Forecast | | | |
|---|---|---|---|
| Pre-crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | 0.43 *** | 0.01 | -0.34 *** |
| Government Securities | -0.17 | 0.07 | -0.14 |
| Commodities | 0.31 *** | -0.25 ** | 0.09 |
| Exchange Rates | -0.04 | 0.05 | -0.08 |
| Corporate Securities | -0.03 | -0.04 | -0.05 |
| Crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | 0.49 ** | -0.29 | -0.08 |
| Government Securities | 0.24 | 0.10 | 0.52 ** |
| Commodities | 0.42 ** | -0.36 * | -0.22 |
| Exchange Rates | 0.11 | -0.10 | -0.03 |
| Corporate Securities | 0.49 *** | 0.38 | -0.12 |
| CPI-based Inflation Rate Forecast | | | |
| Pre-crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | -0.19 * | -0.00 | 0.01 |
| Government Securities | 0.07 | 0.19 *** | 0.09 |
| Commodities | -0.15 * | 0.13 | -0.08 |
| Exchange Rates | 0.06 * | -0.00 | 0.05 |
| Corporate Securities | 0.04 | 0.03 | -0.18 *** |
| Crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | -0.52 *** | -0.37 * | 0.26 ** |
| Government Securities | 0.36 ** | -0.14 | 0.06 |
| Commodities | -0.10 | -0.21 | -0.36 *** |
| Exchange Rates | -0.05 | -0.01 | -0.05 |
| Corporate Securities | 0.47 * | 0.38 | -0.02 |

Table 1.7: Can Financial Series Predict Blue Chip Forecast Errors

| Real GDP Growth Rate Forecast Errors | | | | | |
|---|---|---|---|---|---|
| Forecast Horizon | MAE Ratio | Uncond.(P Value) | Cond.(P Value) | $\hat{\beta}_0$ | $\hat{\beta}_1$ |
| Current Quarter | 0.82 | +8.04 (0.00) | +13.94 (0.00) | 0.37 | 0.36 |
| One Quarter Ahead | 0.76 | +10.37 (0.00) | +12.41 (0.00) | 0.46 | 1.30 |
| One Year Ahead | 0.69 | +9.73 (0.00) | +8.85 (0.01) | 0.92 | 1.99 |
| CPI-based Inflation Rate Forecast Errors | | | | | |
| Forecast Horizon | MAE Ratio | Uncond.(P Value) | Cond.(P Value) | $\hat{\beta}_0$ | $\hat{\beta}_1$ |
| Current Quarter | 0.73 | +2.61 (0.11) | +6.21 (0.04) | 0.16 | 4.39 |
| One Quarter Ahead | 0.78 | +2.20 (0.14) | +5.59 (0.06) | 0.16 | 5.09 |
| One Year Ahead | 0.98 | +0.86 (0.35) | +1.71 (0.43) | 0.09 | 0.17 |

Note: "MAE Ratio" is the ratio between the mean absolute error of the model and that of the benchmark. An MAE ratio smaller than 1 suggests the tested model outperforms the benchmark. The columns Uncond.(P Value) and Cond.(P Value) report the results of the WG unconditional and conditional tests. A positive test statistic combined with a p-value smaller than 0.05 means the tested model significantly outperforms benchmark. $\beta_0$ and $\beta_1$ are the constant and the coefficient from regressing the loss differentials on the business cycle indicator $h_t$. A positive $\beta_1$ means the forecast improvement over the benchmark is more evident during recessions.

Table 1.8: Can Financial Factors Predict Blue Chip Forecast Errors

| Real GDP Growth Rate Forecast Errors | | | | | |
|---|---|---|---|---|---|
| Forecast Horizon | MAE Ratio | Uncond.(P Value) | Cond.(P Value) | $\hat{\beta}_0$ | $\hat{\beta}_1$ |
| Current Quarter | 0.84 | +8.51 (0.00) | +10.11 (0.01) | 0.40 | 0.05 |
| One Quarter Ahead | 0.75 | +8.42 (0.00) | +10.42 (0.01) | 0.43 | 1.60 |
| One Year Ahead | 0.64 | +5.82 (0.02) | +7.60 (0.02) | 0.65 | 4.43 |
| CPI-based Inflation Rate Forecast Errors | | | | | |
| Forecast Horizon | MAE Ratio | Uncond.(P Value) | Cond.(P Value) | $\hat{\beta}_0$ | $\hat{\beta}_1$ |
| Current Quarter | 0.96 | +0.97 (0.33) | +1.39 (0.50) | 0.01 | 0.73 |
| One Quarter Ahead | 0.97 | +1.10 (0.30) | +1.24 (0.54) | 0.04 | 0.65 |
| One Year Ahead | 0.96 | +1.42 (0.23) | +3.06 (0.22) | 0.11 | 0.48 |

Note: "MAE Ratio" is the ratio between the mean absolute error of the model and that of the benchmark. An MAE ratio smaller than 1 suggests the tested model outperforms the benchmark. The columns Uncond.(P Value) and Cond.(P Value) report the results of the WG unconditional and conditional tests. A positive test statistic combined with a p-value smaller than 0.05 means the tested model significantly outperforms benchmark. $\beta_0$ and $\beta_1$ are the constant and the coefficient from regressing the loss differentials on the business cycle indicator $h_t$. A positive $\beta_1$ means the forecast improvement over the benchmark is more evident during recessions.

Figure 1.1: Asset-By-Asset Model Weights - Forecasting Real GDP Growth Rate Forecast Errors

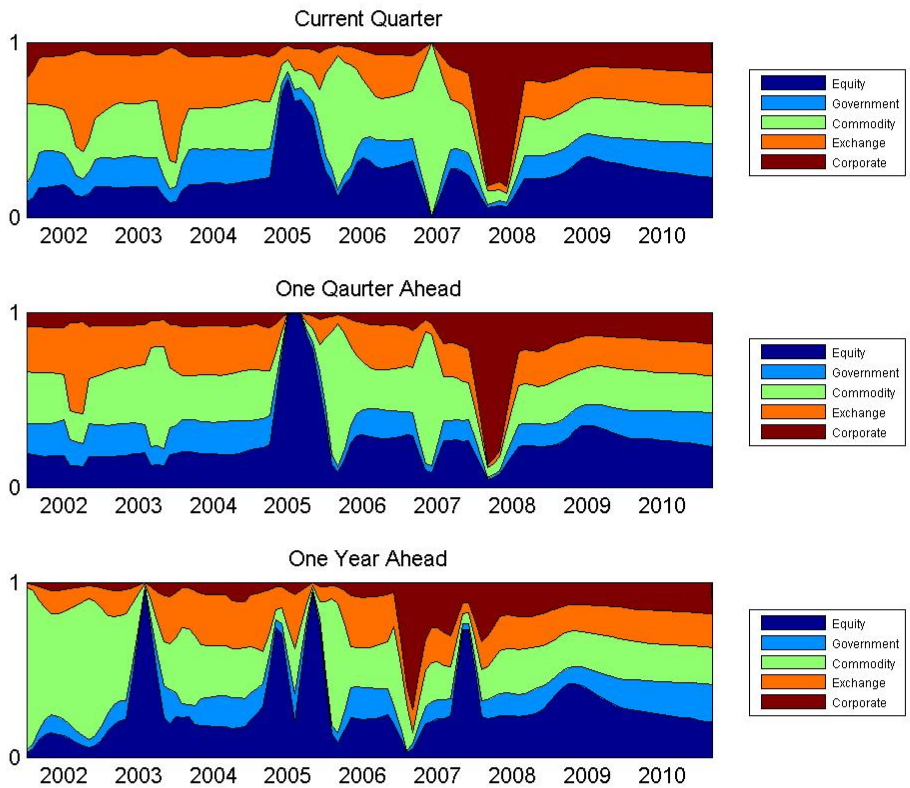


Figure 1.2: Asset-By-Asset Model Weights - Forecasting CPI-based Inflation Rate Forecast Errors

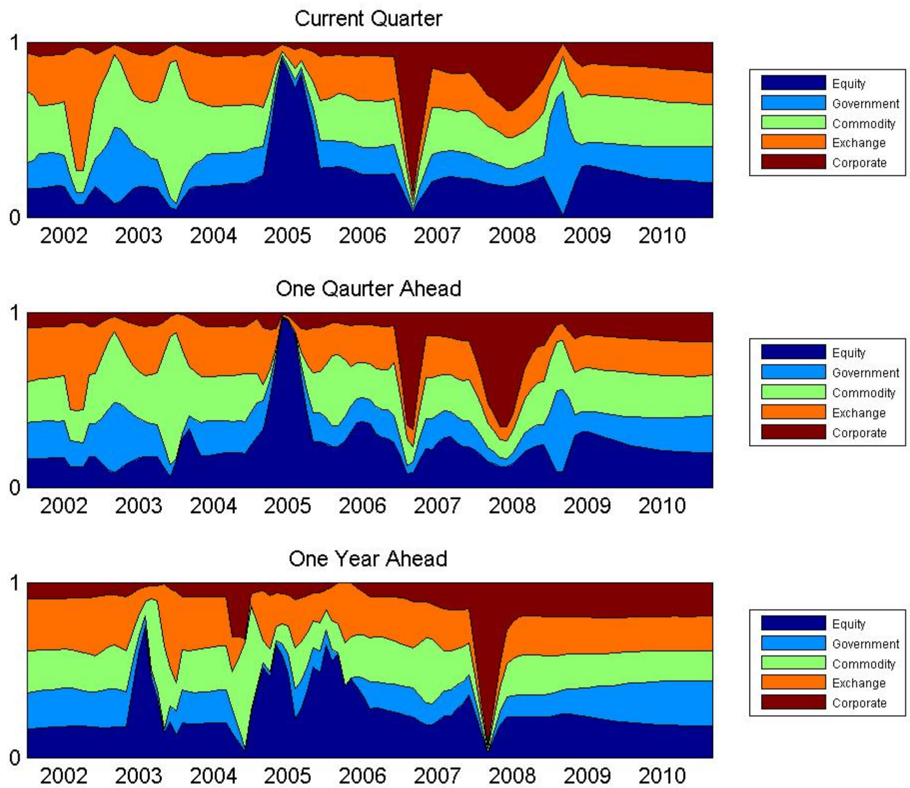


Figure 1.3: Factor Model Weights - Forecasting Real GDP Growth Rate Forecast Errors

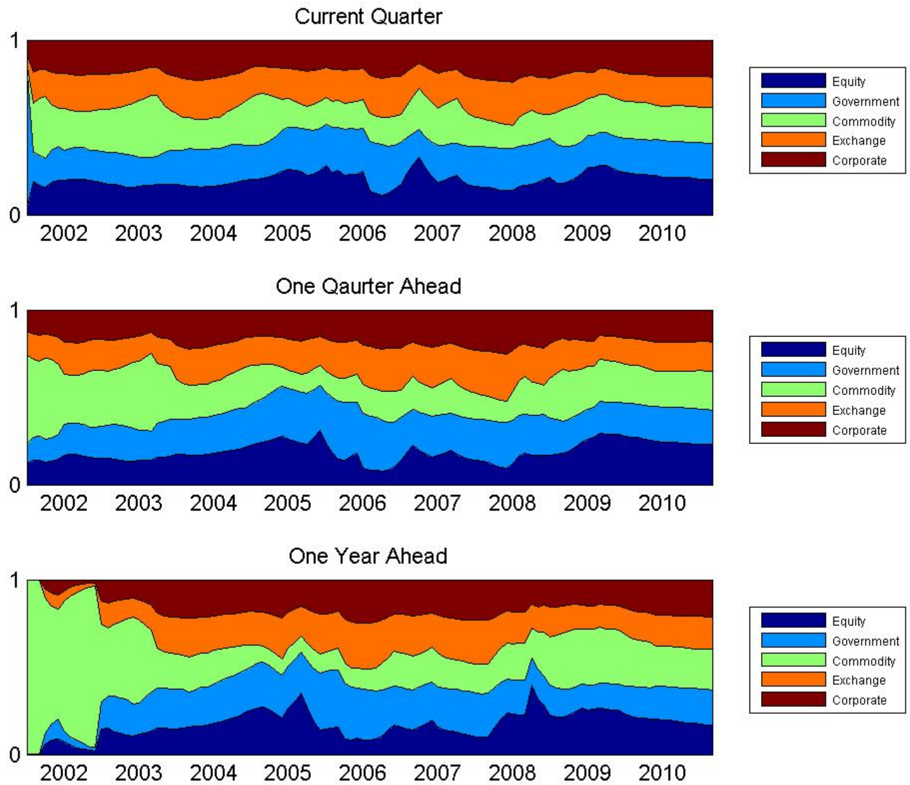
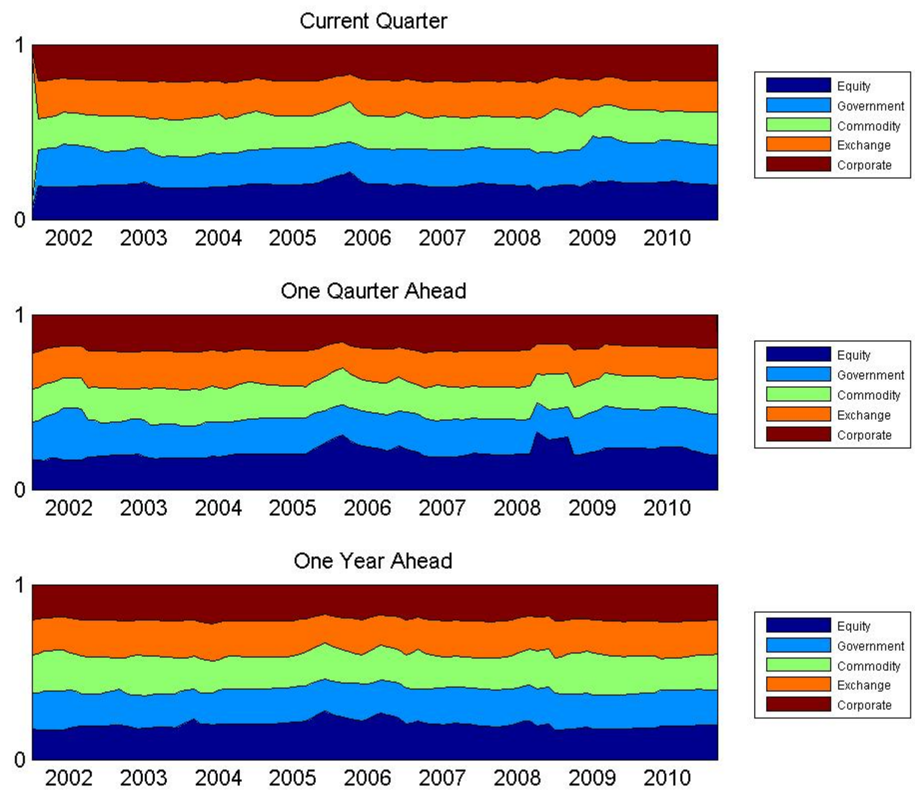


Figure 1.4: Factor Model Weights - Forecasting CPI-based Inflation Rate Forecast Errors



CHAPTER 2

# FORECASTING CORPORATE EARNINGS

## 2.1 Introduction

Earnings Per Share (EPS) is a key input in many asset pricing models, as well as a main indicator of the current and future financial health of listed companies. Not surprisingly, a lot of resources are devoted to produce accurate and timely forecasts of future earnings.

The question whether we can automate the process using econometric models has somewhat the flavor of man versus machine, like a chess player against a computer, or a self-driving car. The main motivation is more practical, however. Analyst coverage is concentrated on large firms. If we succeed in creating reliable EPS forecasts with relatively simple to implement models, we can vastly expand the scope and breath of earnings forecasting. Notably, we can consider relatively smaller firms, and also expand across international markets, provided reliable public domain data is available.

Prior research has examined various forms of univariate extrapolative time series models and concluded that they cannot match the forecast performance of professional analysts.[1] The superiority of analysts' forecasts is partially due to both their informational as well as their timing advantages. Extrapolative time series models, whether a random walk or ARIMA models, generally rely on past earnings or components of earnings (e.g., sales, expenses, cash flows, accruals), which means that forecasts for a given quarter (year) can only be made using information prior to the end of the previous quarter (year). Analysts, however, observe all publicly available (as well as sometimes non-public) information and can update their forecasts well into

[1]Recent studies, such as Bradshaw, Drake, Myers, and Myers (2012), have re-examined this issue and found that a random walk model can outperform analysts at longer time horizons.

the forecast target quarter(year). Past studies support the existence of such information and timing advantages. Fried and Givoly (1982) concludes that analysts' annual earnings forecasts utilize a substantially larger information set, including non-earnings information as well as observations that are not available at the end of the previous year. O'Brien (1988) concurred that analysts' information on firms sales, production, and macroeconomic conditions may have resulted in better quarterly forecasts of firm earnings. Brown, Hagerman, Griffin, and Zmijewski (1987) and subsequent research identified that the superiority of analysts correlated negatively with the forecast horizon.

The empirical challenges of setting up a time series model that can match or outperform analysts are therefore two-fold: (1) include timely data, and (2) potentially use large sources of information. We propose to address both issues taking advantage of recently developed econometric methods. There is indeed a burgeoning literature on mixed frequency regression analysis and related econometric techniques. First, to facilitate real-time updating, we use Mixed Data Sampling (MIDAS) regressions to build forecasting models. The key feature of MIDAS regression models is that they allow regressors to be higher frequency than the dependent variable.[2] Hence, annual/quarterly earnings data can be combined with monthly/weekly/daily data in the same regression model. This implies we can incorporate most up-to-date financial and macroeconomic information in the model's forecasts, just as analysts do. To address the issue of (high frequency) data proliferation, we employ forecast combination methods. This allows us to combine forecasts for a large class of models/variables.

Besides the innovation in forecasting methods, we also utilize a large sample of firms (1474 firms in total) in our paper.[3] Recent studies, such as Bradshaw, Drake, Myers, and Myers (2012), argue that the selection of firms has a significant effect on the conclusions drawn in this field of study. Including a large number of firms enables us to appraise the performance our models against analysts in different industry subgroups and firm size subgroups.

We carried out the study in two main steps: (1) selecting a list of predictors - examining their

[2]For further details, see for example recent surveys on the topic of MIDAS regressions: Andreou, Ghysels, and Kourtellos (2011) and Armesto, Engenmann, and Owyang (2010) - the latter provide a very simple introduction to MIDAS regressions.

[3]A similar study applying forecast combination in firm earnings forecasting only included 30 firms. See Bansal, Strauss, and Nasseh (2012)

in-sample correlation with earnings; and (2) developing a mixed frequency regression model to predict corporate earnings out-of-sample.

Our study yields some surprisingly sharp results. Utilizing the selected list of macroeconomic, financial and accounting predictors in addition to past earnings numbers, we are able to predict a significant portion of the movements in quarterly earnings and consistently outperform analysts at various forecast horizons. In particular, we find that even at very short horizons (the end of the target quarter of the forecast exercise), as far as statistical significance goes, analyst forecasts only outperform our model in a small 4 % of firms and therefore in 96 % of the cases it is either a draw or better (namely for 25 %). Moreover, the superiority of forecasting performance is more evident for cyclical industries.

Our paper relates to many fundamental research papers aiming at finding fundamental signals that can predict earnings. Ou and Penman (1989) carried out a statistical search of 68 financial statement descriptors and identified 17 or 18 to include in a panel logit model predicting earnings movements in-sample. Lev and Thiagarajan (1993) examined 12 most-commonly-cited accounting variables in analysts' earnings pronouncements in-sample, and reported the signs of the parameters estimated on these variables. Abarbanell and Bushee (1997) selected 9 out of those 12 variables and found that although significant, some of the signs of the in-sample estimated parameters are different from Lev and Thiagarajan (1993). Our paper relates to this literature by providing in-sample time series correlation analysis between earnings and a number of accounting variables, which complements the results in the aforementioned studies based on cross-sectional or panel regressions. However, the list of predictors we use is more extensive and includes macroeconomic and financial variables as well.

Another related field is the growing literature of MIDAS-based forecasting. The MIDAS regression framework was first applied to returns and volatility forecasting; see for example Ghysels, Santa-Clara, and Valkanov (2005), among others. A number of studies have also adopted MIDAS regressions in predicting macroeconomic variables, see for example, Clements and Galvão (2008), Armesto, Hernández-Murillo, Owyang, and Piger (2009), Kuzin, Marcellino, and Schumacher (2011), Andreou, Ghysels, and Kourtellos (2013b). Our paper is the first study which applies MIDAS regressions to the prediction of corporate earnings.

The remainder of the paper is organized as follows. Section 2.2 describes the earnings data as well as predictors used in our forecasting model. Section 2.3 introduces the econometric methods employed in this paper, namely stationary bootstrap method, MIDAS regressions, principal component forecast combination, and forecast evaluation methods. Section 2.4 presents the empirical results. Section 2.5 concludes.

## 2.2 Description of the Data

We forecast individual firms' quarterly earnings with real-time macroeconomic series as well as firm-specific financial and accounting variables. Historical vintages of both the earnings and the series used as predictors were collected from multiple databases. The following two subsections describe the sources of the raw data and the transformation carried out on each series.

### 2.2.1 Earnings Actuals and Forecasts

Earnings series are often relatively short and infrequent (quarterly at best). The median firm in the Center for Research in Security Prices (CRSP) database has a listing age of 10 years (see Loderer and Waelchli (2010)), which leaves only 40 quarterly observations for a typical firm. If split evenly to obtain an in-sample and an out-of-sample portion, there are only 20 observations for the in-sample estimation portion. While the available time series data are often limited, ideally one would need to include many predictors in order to approximate the large information set of analysts such as firm-specific financial statement variables, equity market returns and volatility, as well as macroeconomic indicators. The regression-based nature of a time series model therefore imposes some restrictions on the number of variables that can be included. To solve the potential data proliferation problem we will resort to forecast combination techniques, as will be discussed later.

We construct firms' actual and predicted earnings from the unadjusted quarterly earnings detail file retrieved from Institutional Brokers' Estimate System (I/B/E/S). I/B/E/S records firms' Earnings Per Share numbers as well as individual institutional analysts' forecasts for as many as 40,000 firms in 70 markets, together with the dates earnings and their forecasts are released. We restrict our search to listed U.S. firms and adjust the I/B/E/S Earnings Per Share actuals and forecasts by adjustment factors downloaded from the CRSP database to remove the effects of stock splits.

In order to ensure enough observations for model estimation, we exclude firms with less than 15 years of consecutive quarterly earnings actuals. Note this restriction somewhat biases our sample towards larger and more successful firms. Table 2.1 shows a breakdown of our sample by industry affiliations. As indicated at the end of the table, the total number of firms in our sample is 1474 with a large fraction of manufacturing and high tech firms.

We construct consensus forecasts by taking the median of individual analysts' forecasts made for a given forecast horizon. We will refer to the *target* quarter (TQ) as the object of interest in the predictions exercise for both analysts and our models. We consider four forecast scenarios in this paper: (1) one quarter ahead of the target quarter - implying a one-quarter ahead forecast horizon, (2) one month into the target quarter, (3) two months into the quarter and finally (4) at the end of the forecast quarter. Compared to other papers in the literature, we focus on short forecast horizons, as these are forecast horizons where institutional analysts have the most success against time series models.

### 2.2.2 List of Predictors

Predictors used in our paper fall under three categories: macroeconomic variables, firm-specific stock return and volatility, and firm financial statement variables. Macroeconomic variables other than industrial production are retrieved from Federal Reserve Economic Data (FRED) maintained by Federal Reserve Bank of St. Louis. Industrial production uses real-time data vintages provided by Federal Reserve Bank of Philadelphia. Stock returns data are downloaded from the CRSP database. Return is measured as the excess stock return over the corresponding industry portfolio.[4] Volatility is calculated as the 22-day moving average of squared daily stock returns. Financial statement variables are constructed using data from COMPUSTAT. We adjusted each series to remove potential unit roots and seasonality. Table 2.2 provides a list of the variables, their sampling frequencies used in our model and their definitions.

[4] The construction of industry portfolios follow "10 Industry Portfolios" on Kenneth R. French's website. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Macroeconomic variables reflect the state of the economy and aggregate demand conditions. These variables are especially meaningful in capturing the fluctuations in earnings due to business cycle conditions.[5] Financial statement variables are widely cited by industry analysts when making inferences regarding earnings. These fundamental signals are specific to each firm and measure its growth prospects, profit-generating ability and cost and expense management efficiency. Besides accounting variables, excess stock return and volatility are also firm-specific. These equity market variables convey the market's assessment of the value of a firm's equity, often informative of its earnings potential. Compared with accounting variables, equity market variables are more forward-looking and are updated daily, allowing us to incorporate more timely information in our prediction model.

### 2.3 Econometric Methods

This section describes an in-sample bootstrap correlation testing method and an out-of-sample forecasting model. The former can be viewed as a prelude to the selection of a good forecasting model. We begin, however, with two general observations.

First, there is a great degree of heterogeneity in different firms' responsiveness to changes in fundamental factors, the theoretical rationale of which will be discussed in detail in Section 2.4.1.1. Based on this observation, we adopt a strategy of (1) treating each firm individually rather than as a panel in our testing and forecasting models, and (2) then summarizing the results across all firms or subgroups of firms.

Second, the effects of the predictors on earnings can be time-varying due to business cycles or firm life-cycles. For example, macroeconomic factors may have more bearing on earnings during recessions, while firm-specific factors play a bigger role during less tumultuous business conditions. Therefore, we strive to capture a robust relation between earnings and each prediction series by applying a bootstrap method for the in-sample correlation analysis. We also make all forecasts in a rolling fashion, where forecasts are based only on series' values up to the date the forecast is made, and model parameters are re-estimated as the forecast date progresses. In addition, the dynamic instability in the forecasting ability of the predictors favors forecast

[5] The time period of our study includes two recessions: April,2001 to November 2001 and January 2008 to June 2009, as defined by NBER.

combination of multiple models each using one predictor over estimating a single model with the all predictors in one regression.[6]

### 2.3.1 In-sample Correlation Analysis

Correlation analysis aims at examining whether seasonal earnings differentials $\Delta_s EPS_t$, defined as the year-to-year changes $\Delta_s EPS_t \equiv EPS_t - EPS_{t-4}$, correlate significantly with the predictors we proposed in section 2.2. Namely, for each predictor X (X can be the growth rate of GDP, or excess stock returns, for instance), we examine the correlation, and its sign, between $\Delta EPS_t$ and X with different numbers of lags ranging from zero to two quarters.

The statistical method we use to test $H_0 : corr(\Delta_s EPS_t, X_{t-j}) = 0$ ($j = 0, 1, 2, 3$) applies the stationary bootstrap procedure proposed in Politis and Romano (1994a). The advantage of this procedure is that it allows the two tested series to exhibit serial correlation, as long as they are both stationary. The appeal of the procedure is that it does not require the explicit specification of the data generating processes of the two series (apart from some mild regularity conditions). The key inputs include the average block size, and number of bootstrap simulations. Given these inputs, the two series $\Delta_s EPS_t$ and $X_{t-j}$ are re-sampled by blocks of random sizes and the bootstrap generates pseudo-time series $\Delta_s EPS_i^*$ and $X_i^*$ ($i = 1, \ldots, N$ where $N$ is the number of bootstrap replications). Sample correlation can be calculated from the simulated pseudo-time series $\beta_i \equiv corr(\Delta_s EPS_i^*, X_i^*)$. Thus $\beta_i$ ($i = 1, \ldots, N$) form the empirical distribution of $corr(\Delta_s EPS_t, X_{t-j}))$, with which we can test the null hypothesis that the two series are uncorrelated in population, against $H_a : corr(\Delta_s EPS_t, X_{t-j}) < 0$ or $H_a : corr(\Delta_s EPS_t, X_{t-j}) > 0$.

The possible outcomes of the bootstrap test of correlation are positive, negative or insignificant. The test is carried out for each firm. We then calculate percentage of firms where the correlation is positive or negative, respectively. Any percentage that is above 5%, which is the significance level we used in the bootstrap test, is considered significant. If the percentage of firms exhibits positive correlation between their earnings and predictor x dominates the percentage of negative correlations, we consider predictor $X$ to be positively correlated with

[6]See subsection 2.3.2.2 for an overview of the advantages of forecast combination.

earning differentials for an average firm. By examining various lags of $X$, we can also observe whether the correlation changes over time horizons, allowing the predictor to display its effect on earnings with some lags.

### 2.3.2 Out-of-sample Prediction Models

We set up a rolling-window out-of-sample forecasting model utilizing all fourteen predictors in Table 2.2. For a given in-sample estimation window, each predictor is used in the regression model one at the time, generating one forecast per series. The fourteen forecasts are then combined to produce the final model forecast series. The performance of our one-step-ahead forecast is evaluated against the median consensus of analyst forecasts at four forecast horizons: at the end of the forecast quarter, two months into the forecast quarter, one month into the forecast quarter and at the end of the previous quarter.

### 2.3 MIDAS Regressions

The in-sample correlation analysis in subsection 2.3.1 is supposed to be a reality check to see whether the earnings are correlated with different predictors in a way that is consistent with theory. This gives us some comfort that the forecasting regressions we are to discuss are not spurious. The correlation results also complement the accounting literature on earnings' prediction, as previous studies which identified factors were done on panel data, while our analysis is done in a time series setting.

There are two reasons why we take a slightly different approach to measuring earnings growth. First, for the correlation analysis we picked seasonal differences $\Delta_s EPS_t$, as it was a convenient way to deal with the seasonal fluctuations in the data.[7] Second, to make our forecasting models compatible with analyst predictions, we take quarterly growth rates, i.e. $\Delta EPS_t \equiv EPS_t - EPS_{t-1}$ and accommodate for seasonal fluctuations in the formulation of our regressions.

We start with accounting variables as predictors of earnings growth because these predictors

[7] We calculated the correlations between first differences of earnings and each predictor's lagged values. The results were mostly similar but not as strong results as with quarterly differencing, due to the seasonality.

are of quarterly publication frequency, i.e. the same as earnings. The case of high frequency data will be covered later. For each accounting variable, an Augmented Distributed Lag (ADL) model is used to generate the forecasts by this variable.

$$\Delta EPS_{t+1} = c + \sum_{i=1}^{3} \delta_i D_i + \sum_{j=1}^{p_Y^Q} \alpha_j \Delta EPS_{t-j} + \sum_{j=1}^{q_X^Q - 1} \beta_j X_{t-j}^Q + \mu_{t+1} \tag{2.3.1}$$

where $D_i$ (i=1,2,3) are quarter dummies and $X_t^Q$ is a series of quarterly accounting series. The number of lags $p_Y^Q$ and $q_X^Q$ are selected by Bayesian Information Criterion (BIC).

The timing of lags requires some further clarification, because quarterly earnings as well as accounting variables have publication lags. Most firms release their quarterly financial statements within the first month of the subsequent quarter, sometimes in the second month of the subsequent quarter. We retrieve the announcement dates from I/B/E/S database and use real-time observations, i.e. the last available quarter's numbers for both past earnings and past accounting predictors. For example, if a firm regularly releases its quarter $t$ statements on the $15^{th}$ of the first month into quarter $t+1$, then forecasts made at the end of quarter $t$ can not be based on $ESP_t$, but rather $\Delta EPS_{t-j}$ for $j \geq 1$. The same applies to $X_t^Q$ as those numbers are yet to be released as well. Hence, the timing of data on the right hand side of equation (2.3.1) are $t$ - 1 only. However, when we discuss next regressions involving higher frequency data it should be noted that by the end of one month into the forecast quarter, the previous quarter's numbers are available.

Other predictors, whether macroeconomic or equity market performance variables, are available at monthly or even daily frequency. We could include quarterly values of these variables, which are typically the sum or average of the monthly (daily) values. There are two drawbacks of using a predictor's quarterly values when higher frequency values are available: First, it restricts the effects of the predictors to be constant across different months (days) in the same quarter. For example, if $X_t^Q \equiv X_{1,t}^M + X_{2,t}^M + X_{3,t}^M$, only one coefficient $\beta_j$ in equation (2.3.1) for each quarterly lag $j$ is estimated. One may, however, have reasons to believe that changes in the predictor that occur in different months do not have the same effect on $\Delta EPS_{t+1}$.[8] By

[8] One such instance is that stock returns in the month closest to the announcement of earnings may contain

taking the simple average of monthly observations, one loses information. Second, updating can happen only once each quarter in the model, after all the monthly (daily) numbers are released. This means for variables without publication lag (equity market or interest rates), forecasts made with such predictors at the end of the previous quarter are the same as forecasts made two months into the forecast quarter. Hence, one foregoes the real-time flow of information throughout a quarter.

Due to the aforementioned drawbacks of using quarterly predictor values when higher frequency data are available, we use an Augmented Distributed Lag - Mixed Frequency Data Sampling ("ADL-MIDAS") Regression model to generate forecasts made with monthly macroeconomic and equity market variables. There is ample evidence that such regressions - which take advantage of real-time high frequency data - can significantly improve predictions of quarterly macroeconomic variables, using either monthly or daily data, see e.g. Schumacher and Breitung (2008), Clements and Galvão (2008), Armesto, Hernández-Murillo, Owyang, and Piger (2009), Kuzin, Marcellino, and Schumacher (2011), Andreou, Ghysels, and Kourtellos (2013b), among many others.

We will use a double index for monthly data, namely let $X^M_{t,i}$ be the observation of month $i$ in quarter $t$. When forecasts of a given quarter's earnings are made at the end of the previous quarter, the ADL-MIDAS regression model looks like the following:

$$\Delta EPS_{t+1} = c + \sum_{i=1}^{3} \delta_i D_i + \sum_{j=1}^{p_Y^Q} \alpha_j \Delta EPS_{t-j} + \beta \sum_{j=0}^{q_X^M-1} \sum_{i=1}^{3} \omega_{j*3+i} X^M_{t-j,i} + \mu_{t+1} \tag{2.3.2}$$

This regression essentially assigns a slope parameter to each monthly lagged observation of the predictor ($\beta\omega_{j*3+i}$).[9]

When forecasts are made some time into the forecast quarter, information beyond period t becomes available. We integrate this information with an ADL-MIDAS with Leads model that provides the advantage of real-time updating. For example, with one extra month of within

more information regarding earnings.

[9]Regression (2.3.2) is referred to as "U-MIDAS", i.e. Unconstrained MIDAS in the literature, following Foroni, Marcellino, and Schumacher (2013a), as opposed to imposing some structure to the weighting scheme $\omega$ as is typical in MIDAS regressions.

quarter information, we have:

$$\begin{aligned}\Delta EPS_{t+1} &= c+\sum_{i=1}^{3}\delta_i D_i+\sum_{j=1}^{p_Y^Q}\alpha_j\Delta EPS_{t-j} \\ &\quad +\beta\sum_{j=0}^{q_X^M-1}\sum_{i=1}^{3}\omega_{j*3+i}X_{t-j,i}^M+\tilde{\omega}_1 X_{t+1,1}^M+\mu_{t+1} \qquad (2.3.3)\end{aligned}$$

In equation (2.3.3), we can in principle use $k = J_X^M = 1$ (as in the above equation) or 2, 3 number of lead months.[10] When $k$ equals three, the forecasts are made at the end of the forecast quarter, a case often referred to as "nowcasting". Note that we always align analyst forecasts with the real-time specification in equation (2.3.3).

To sum up, each of the fourteen predictors in Table 2.2 is included in a separate forecasting regression, generating a series of rolling-window out-of-sample forecasts. When the predictor X is only available on a quarterly basis, equation 2.3.1 will be used; while for monthly-available series X, either equation (2.3.2) or equation (2.3.3) will be adopted depending on the forecast horizon. When all fourteen forecasts are made, we then apply a principal forecast combination approach outlined in the following subsection to yield a model forecast series.

### 2.3 Principal Component Forecast Combination

Forecast combination has been accepted in the literature as an effective way to summarize information provided by many predictors. Timmermann (2006) points out that compared to estimating a forecast model with all predictors in one regression, carrying out the regression one predictor at a time and using forecast combination methods is more robust to model misspecification and measurement errors. The combined forecast also performs better in the presence of structural breaks and model instability. In addition, as also noted by Timmermann (2006), many studies have shown that forecast combination is superior to the best-performing individual forecasts.

[10] For the variables with a publication lag, i.e. industrial production and inflation, the number of leads equals k minus publication lag measured in months. We retrieved the announcement dates of these two macroeconomic variables and determined that the numbers for a given month are usually released at the middle of the next month, thus we assumed that the publication lag of these two variables is 1.

There are many ways to form a combined forecast from a given number of individual forecasts. Basically, one needs to select a set of dynamic weights assigned to individual forecasts $\omega_{i,t}$ yielding a weighted average forecast combination:

$$cf_{t+h|t} = \sum_{i=1}^{I} \omega_{i,t} f_{i,t+h|t} \tag{2.3.4}$$

where $I = 14$ in our application, the number of individual series used in each of the individual MIDAS regressions. Diebold and Lopez (1996) surveyed the literature on forecast combination methods and categorized them into two groups, "variance-covariance" methods and "regression-based" methods.[11]

In our paper, we follow the principal component forecast combination method proposed by Chan, Stock, and Watson (1999) and Stock and Watson (2004). This method is an extension of the regression-based forecast combination method where one uses a few principal components extracted from the panel of individual forecasts, with the number of principal components determined by the ICp3 criterion proposed in Bai and Ng (2002).

To form a combination forecast($cf_{t+h|t}$) at time point t from individual forecasts ($f_{i,t+h|t}$, $i$ = 1, ..., I), we first extract principal components of the panel of forecasts $f_{i,s+h|s}$ (i=1:I, s=1,...t), then use the history of the principal components and realizations to estimate the following regression:

$$y_{s+h} = \sum_{j=1}^{N} \hat{\lambda}_j PC_{j,s+h|s} + v_{s+h} \tag{2.3.5}$$

where $s = 1, \ldots, t-h$, and finally we use the estimated coefficients to generate $f_{t+h|t}$:

$$cf_{t+h|t} = \sum_{j=1}^{N} \hat{\lambda}_j PC_{j,t+h|t} \tag{2.3.6}$$

We denote the coefficient matrix of the principal component analysis by $C_{I\times I}$. Therefore, the weight assigned to individual forecast series $f_{i,t+h|t}$ can be calculated by equation: $\sum_{j=1}^{N} \hat{\lambda}_j * C_{i,j}$. We include an analysis on the weights in Section 2.4.2.

[11]Granger and Ramanathan (1984) has shown that the optimal variance-covariance combining weight vector has a regression interpretation as the coefficient vector of a linear projection of realizations onto the individual forecasts.

Now that the 14 forecast series have been combined into one, we continue to describe how we evaluate the performance of this combined model forecast series.

### 2.3 Forecast Evaluation Methodology

The out-of-sample forecast performance of the combined model forecasts needs to be appraised against predictions made by other benchmark models and the consensus of analysts and measured in terms of a loss function. Which one to use is an empirical question. Our choice of loss function is in part driven by the observation that there are often outliers in analysts' earnings forecast error series. Various studies have identified and tried to explain the presence such outliers. An important paper on this topic is Abarbanell and Lehavy (2003), where the authors identified that there is a small occurrence of extreme negative values in analysts' earnings forecast error series due to firms' recognition of unexpected accruals. To be robust in the presence of outliers in earnings forecast error series, we apply two criteria in evaluating the forecast performance: the median absolute scaled error ratio (MASER) and a rank-based test using the median scaled error.

Let us denote the forecast error sequence from our model (which is based on a forecast combination scheme) by $e_m$ and the error sequence from the benchmark as $e_b$. Then we define MASER $\equiv median(|\frac{e_m}{\Delta EPS}|)/median(|\frac{e_b}{\Delta EPS}|)$, which is the ratio of relative error medians. A value smaller than one suggests that our model outperforms the benchmark. Since there are slightly less than 1500 firms in the dataset, instead of reporting a MASER value for each firm, we report the summary quantiles of cross-sectional MASER distribution across all firms. The quantiles give an overview of how the model performs against benchmark.

Finally, we use a rank-based test - the Mann-Whitney U Test - which is a non-parametric test for the null hypothesis $H_0 : median(|\frac{e_m}{\Delta EPS}|) = median(|\frac{e_b}{\Delta EPS}|)$.When tested against $H_a : \ median(|\frac{e_m}{y}|) < median(|\frac{e_b}{y}|)$,rejection of the null hypothesis means the model significantly outperforms the benchmark under the chosen significance level. Similarly, rejection of the null when the alternative is $H_a : median(|\frac{e_m}{\Delta EPS}|) > (<) \ median(|\frac{e_b}{\Delta EPS}|)$ implies our model under- (out-)performs against the benchmark. We report the percentages of firms where model outperforms and underperforms analysts, respectively. These test results complement the MASER analysis by examining the statistical significance of the MASER values.

## 2.4 Empirical Results

Since we carried out the study in two steps, we describe the results in two steps as well. Subsection 2.4.1 discusses the empirical correlation between corporate earnings and each of the predictor variables. Subsection 2.4.2 presents the out-of-sample forecasting performance of our models compared to a number of benchmark forecasts at different forecast horizons. A further breakdown by industry and firm size sub-samples is also carried out.

### 2.4.1 In-sample Correlation Analysis

Table 2.3 presents the results for the correlation analysis. The signs of the correlations conform with economic theory and past literature in general. The subsections below are a variable-by-variable interpretation of the results.

#### 2.4 **Macroeconomic Variables**

Industrial production is a monthly business cycle indicator. Rising industrial production signals economic expansion, and consecutive decreases in production are one of the criteria of a recession. The results in Table 2.3 show a uniformly positive correlation between changes in industrial production and earnings.

Inflation is a predictor with complex effects on earnings. On one hand, earnings, being nominal dollar figures, should be positively affected by inflation. However, the accounting practice of depreciating fixed assets based on historic cost means that during high inflation periods, the tax benefits of depreciation are lower, and therefore the de-facto corporate tax rate is higher. The results in Table 2.3 indicate that inflation has a longer term negative effect on earnings, although its contemporaneous quarter's effect is ambiguous.

The default spread is obtained by subtracting ten-year AAA-rated corporate bond yields from a corresponding BAA-rated one. An increase in default spread signals more risk in the overall economy and a deterioration in credit quality. This means that firms face both less favorable macroeconomic conditions and higher borrowing costs. Both channels work to stunt earnings growth. Our results show that for the firms we sampled, default spread is (weakly) negatively correlated with earnings, although there appears to be a gestation lag of a few quarters.

The term spread is the difference between the ten-year Treasury bond and three-month T-bill yields. The market often uses Treasury yields as the benchmark to determine required interest rates on different debt securities. Since firms are, to a greater or lesser extent, net borrowers of long-term funds, an increase of term spread can increase the burden of interest payments and therefore decreasing earnings. The results in Table 2.3 confirm the negative impact of widening term spreads on earnings.

Treasury bill rates represent the cost of short-term borrowing; thus we would expect an increase in T-bill rates to a raise firm's interest payment expense, and therefore decreasing earnings. However, from the business cycle point of view, higher T-bill rates may be the result of growing demand for funds. For example, Rose (1994) noted that T-bill rates typically rise during economic expansions and fall during recessions. Under this assumption, higher T-bill rates should indicate higher future firm earnings. The results of our empirical analysis show that the correlation between T-bill rates and earnings are indeed complex. An increase in T-bill rates on average suppresses earnings growth at near-term, but causes earnings to rise in the longer-term. The reversion in sign of the correlations across time horizons could be the joint effect of the aforementioned two channels.

Oil prices, similar to interest rates, exhibit their effect on earnings through different channels. From the cost point of view, since crude oil and its derivative products are used as raw materials for production in many industries, the cost channel suggests a negative correlation between oil price and firm earnings. At the same time, however, oil price is a strong indicator of economic prosperity. Oil price tends to rise when the economy is strong, thus from the demand channel, an increase in oil price elevates earnings. In Table 2.3, we see a strong positive contemporaneous correlation between oil price and earnings but the sign of the correlation become somewhat ambiguous as lag horizons increase, possibly due to the cost channel.

The VIX is the implied volatility of the S&P 500, sometimes referred to as the "fear index". A sharp increase in the VIX typically coincides with the onset of a recession. As we can see in the results table, firms earnings decrease one quarter after an increase in the VIX.

## 2.4 **Equity Market Variables**

A firm's stock returns and its volatility are two equity market indicators we include in this study. Positive excess returns, as the correlation analysis results suggest, is a very strong signal for good earnings numbers, while an increase in a firm's stock market volatility correlates negatively with earnings across all time horizons.

## 2.4 **Financial Statement variables**

We selected five accounting variables based on the previous literature and the availability of data. These variables are referred to as "fundamental signals", quite often cited by analysts when making earnings-based stock recommendations.

Decreases in capital expenditure are often perceived negatively by analysts. When managers have concerns over the adequacy and liquidity of a firm, they may stop or slow down investing in long-term projects. Our results support this point of view and show that a decrease in capital expenditure bodes poorly for future earnings.

An inventory increase that outruns sales increases may be a negative signal that shows a firm is having difficulty marketing its products. However, since inventory contains unfinished products too, and in some industries, there is a significant build-up of inventories before launching a new product, the correlation of inventory and earnings can vary firm-by-firm due to different inventory-holding motives. Our empirical results suggest that for most firms the correlation between the two are significantly different from zero, and a slight majority of firms show a negative response of earnings to an increase in inventory levels, which may suggest that the first channel prevails for these firms.

Profitability is the ratio of sales minus cost of goods and services over sales, also called "gross margin". A higher gross margin consistently indicates higher future earnings.

Selling, General and Administrative Cost (SG&A Cost) that outruns sales usually means the firm may have performed poorly in cost control. However, a temporary increase in SG&A Cost may be due to profit-generating motives such as a firm's decision to make a sales or advertisement campaign. The results in Table 2.3 show conflicting evidence on the direction of the effect of SG&A cost increases, with the usual negative interpretation true for more firms than the profit generating motives.

Receivables that increase faster than sales also bode poorly for firms' performance, indicating that the firm may have trouble selling its products, and thus have to enter into more credit extensions. Disproportionate increases in receivables may also lead to higher doubtful provisions for receivables, decreasing future earnings. Our correlation analysis shows that excess growth in receivables is more negatively associated with earnings growth.

The results we obtain through time series testing are consistent with economic theory and the conclusions in previous studies. When aggregating across firms, however, we do see a lot of firm-level heterogeneity on how earnings respond to changes in these variables, especially when there is more than one channel for the tested variable to take effect. Such observed heterogeneity is informative on our choice of a time series over a panel forecasting model.

### 2.4.2 Out-of-sample Prediction Performance

For each firm, at each forecast horizon, we estimate the rolling-window out-of-sample forecasting models described in section 2.3.2. The principal components of the individual model/series forecasts are used to generate a combined, i.e. final, forecast. We evaluate the latter against several benchmark model forecasts made at the same forecast horizon.

#### 2.4 **Relative to Various Benchmark**

At each forecast horizon, we evaluate the combined forecasts from the ADL-MIDAS (with Leads) models against three benchmark forecasts and present the results in Tables 2.4 and 2.5.

The first benchmark is a simple extrapolative time series model, namely:

$$\Delta EPS_{t+1} = c + \sum_{i=1}^{3} \delta_i D_i + \sum_{j=1}^{p_Y^Q} \alpha_j \Delta EPS_{t-j} + \epsilon_{t+1} \tag{2.4.1}$$

Compared to the simple extrapolative model, the ADL-MIDAS (with Leads) model, described in equations (2.3.2) and (2.3.3), includes real-time updating using various predictors.

The second benchmark is the quarterly ADL model, where all the predictors are treated as quarterly observations and the model follows the specifications of equation (2.3.1). In this benchmark model, non-earnings information is used, although in a less optimal way, as discussed in the methodology section. Note that use again forecast combinations to obtain a single combined prediction, similar to the ADL-MIDAS modeling approach.

The third benchmark, which is also the hardest-to-beat one, is the consensus analysts' forecasts. For each the ADL-MIDAS (with Leads) models we align properly the most up to date analyst predictions. Hence, the analysts' forecasts are of the same timing as ADL-MIDAS model. More specifically, the consensus analyst forecast was calculated as the median of all the forecasts released on or prior to the forecast date of the ADL-MIDAS models (with leads).

Table 2.4 summarizes the distribution of the median absolute scaled error ratios between the ADL-MIDAS model and each benchmark model for various forecast horizons. A ratio smaller than one suggests that the new proposed model has a smaller forecast error. Furthermore, Table 2.5 summarizes the results of the Mann-Whitney tests. The percentage of firms where the ADL-MIDAS approach outperforms the benchmark is presented in the columns "OPF", while the percentage of firms where the proposed model under-performs the benchmark is presented under "UPF".

Let us start with one quarter ahead of the target quarter (TQ) in Table 2.4. We report the three quartiles of the distribution. We note that the upper $75^{th}$ tail of the distribution is respectively 0.87, 1.01 and 0.99 against the three benchmark models. Hence, for at least three quarters of the firms the real-time ADL-MIDAS forecast combination approach outperforms any of the three benchmarks considered. This observation also is valid for the two middle panels, covering respectively two and one month into the TQ. As the horizon shrinks (one month in the case of two months into TQ) we see that the edge against analysts consensus forecasts deteriorates, while it remains the same for the other two model-based benchmark models. Yet, even against analysts, the real-time ADL-MIDAS forecast combination approach yields MASER ratios below one for well over half of the firms at the end of TQ, the shortest horizon we consider.

In Table 2.5 we report that, as far as statistical significance goes, we see that even at the shortest horizon, 25 % of the firms our proposed ADL-MIDAS model outperforms analysts consensus forecasts. In fact, analyst forecasts only outperform our model in a small 4 % of firms. Hence, for the bulk of firms - 71 % (the compliment of 25 % and 4 %) it is a draw and for 96 % it is either a draw or better.[12]

### 2.4 **Firm Characteristics**

We further investigated the forecast performance of the proposed ADL-MIDAS model within specific subgroups. We focus entirely on one benchmark, namely the consensus forecast of analysts. With this subgroup analysis, we try to examine the relationship between forecast performance and firm characteristics. In the results Tables 2.6 through 2.9, the firm group "All Firms" refers to all of the 1,474 firms in our sample. The results under "All Firms" are the same as the last rows in Table 2.4 and Table 2.5 and are marked in bold to serve as comparison.

In Tables 2.6 and 2.7, we split the firms into five subgroups based on quantiles of firm size measured by average quarterly sales. Forecast performance is summarized within each subgroup, and the results show that our proposed model performs slightly better for smaller firms. For example, in Table 2.7 we see that analysts outperform our real-time ADL-MIDAS forecast combination scheme only between 0 % and 2 % of the small firm cases - depending on the horizon considered. This pattern is consistent with previous studies. Bradshaw, Drake, Myers, and Myers (2012),for example, identified that time series models perform better with smaller or younger firms than with larger and more mature firms. However, the observed disparities in forecast performance among different size percentile groups are small, possibly due to the fact that our sample is biased towards larger firms. More specifically, the firms in our "small"-size groups may still be relatively large in the universe of COMPUSTAT firms due to the constraints we imposed on the availability of historical data.

Other than size subgroups, we also categorized the firms by their industry affiliations and summarized the results within different industry subgroups.[13] Tables 2.8 and 2.9 present the forecast performance stratified by industry subgroups. We ranked the industries in the table by our model's performance at the end of the target quarter. We achieve better forecast performance with energy, high-tech, manufacturing and consumer durable goods firms than wholesale retail, health, consumer non-durable, utility and telecommunication firms. Our conjecture is

[12]The significance level of the Mann-Whitney test is 5%.

[13]We use the industry classification of the Famma-French 10 industry portfolios.

that such a pattern emerges because of the varying degrees of sensitivity to business cycles. Cyclical industries are affected more by macroeconomic conditions, which we seem to better exploit in our model as it includes many macroeconomic indicators.

### 2.4 Forecast Combination Weights

The success of our models relative to various benchmarks can be attributed to the application of newly-developed econometrics techniques, namely mixed frequency regressions and forecast combination methods. The models not only use large sources of information, but also synthesize and update, just like analysts. To illustrate the workings of the forecast combination process and therefore shed some light on the dynamics of the model, we examine the weights assigned to each category of predictors in this subsection.

The forecast combination procedure estimates weights in a rolling fashion, giving more consideration to the variables that performed better in the preceding periods. Since weights are estimated separately for each firm and every time period a forecast was made, we opt to show the general dynamics, i.e. the average weights across all firms. Figure 2.1, 2.2, and 2.3 display such weights plotted against the dates on which they were estimated to yield the out-of-sample model forecasts. We use the red dashed lines to show the scenario of equal-weighting. For example, since there are in total 14 predictors, with 7 of them being macroeconomic variables, the weights assigned to this category should be 0.5 (7 over 14) under an equal weighting scheme. The figures show that around the most recent financial crisis, there can be seen a surge in weights assigned to the macroeconomic variables, and a drop in those on the firm-specific accounting indicators. The weights gradually recover towards their pre-crisis levels after 2010. This pattern suggests that our models correctly pick up the economy-wide factors during tumultuous business conditions.

To further understand the advantages of the ADL-MIDAS models with cyclical firms, we report the average weights (across time) given to macroeconomic variables in each industry subgroup. The results in Table 2.10 are ranked by the weights used in the "End of Target Quarter" forecast scenario, but the rankings are roughly the same in the other three cases. We observe that for firms in cyclical industries, higher weights are applied towards the forecasts based on macroeconomic predictors. This is consistent with our conjecture that our models exploit the effects of economy-wide factors on earnings well.

## 2.5 Conclusions

Our paper examines the time series correlation between earnings and various macroeconomic, equity market, and financial statement variables. We analyzed the signs of the correlation and ensured that they are consistent with theory and economic intuition. Utilizing these variables as predictors, we use recently developed advances in the econometric analysis of mixed frequency data to formulate real-time forecasting models in a data-rich environment. In particular, ADL-MIDAS regressions are used to obtain forecasts of each firm's earnings at various short term horizons. We evaluated our model against a number of benchmark models including the consensus of analysts' forecasts, and show that we are able to achieve superior performance with a substantial portion of the firms, and match analysts performance with the rest of the firms.

The forecasting framework devised in this study could also be utilized in the future to predict other components on the corporate balance sheet, such as sales; or be extended to perform forecasts on private firms.

Table 2.1: Industry Composition of the Sampled Firms

| Industry Subgroup | Number of Firms |
|---|---|
| Consumer NonDurables | 72 |
| Consumer Durables | 43 |
| Manufacturing | 226 |
| Energy | 63 |
| High Tec | 260 |
| Telecom | 16 |
| Wholesale Retail | 181 |
| Health | 138 |
| Utilities | 76 |
| Other | 399 |
| Total | 1474 |

Table 2.2: List of Predictors

| Frequency | Category | Predictor | Definition and Transformation |
|---|---|---|---|
| Monthly & Quarterly | Macro Variables | Industrial Production | Year-over-year Growth Rate |
| | | CPI | Year-over-year Growth Rate |
| | | Default Spread | First Differenced Yield Spread between BAA Corporate Bonds and AAA Corporate Bonds |
| | | Term Spread | First Differenced Yield Spread between 10-year Treasury Bonds and 3-month Treasury Bills |
| | | Tbill Rate | First Differenced 3-month Treasury Bills Yield |
| | | Oil Price | Year-over-year Growth Rate |
| | | VIX | First Differenced |
| | Stock Returns & Volatility | Excess Stock Returns | Firm's Stock Returns Minus Industry Portfolio Returns |
| | | Stock Volatility | 22-day Moving Average of Firm's Squared Daily Stock Returns |
| Quarterly Only | Firm Accounting Variables | Capital Expenditure | Year-over-year Growth Rate |
| | | Inventory | Year-over-year Growth Rate of Inventory Minus Year-over-year Growth Rate of Sales |
| | | Profitability | Year-over-year Growth Rate of (Revenue-Cost of Goods and Services)/Revenue |
| | | SG&A Cost | Year-over-year Growth Rate of Selling,General and Administrative Cost Minus Year-over-year Growth Rate of Sales |
| | | Receivable | Year-over-year Growth Rate of Receivable Minus Year-over-year Growth Rate of Sales |

Table 2.3: In-sample Correlation Results

| | | Same Quarter | | Lag One Quarter | | Lag Two Quarters | | Lag Three Quarters | |
|---|---|---|---|---|---|---|---|---|---|
| | | Negative | Positive | Negative | Positive | Negative | Positive | Negative | Positive |
| Macro Variables | Industrial Production | 0% | 100% | 0% | 100% | 0% | 100% | 0% | 100% |
| | CPI | 12% | 16% | 16% | 10% | 24% | 8% | 27% | 7% |
| | Default Spread | 8% | 9% | 10% | 7% | 14% | 6% | 16% | 7% |
| | Term Spread | 28% | 5% | 22% | 5% | 17% | 5% | 17% | 7% |
| | Tbill | 11% | 5% | 8% | 6% | 7% | 8% | 5% | 8% |
| | Oil Monthly | 6% | 32% | 9% | 28% | 12% | 19% | 17% | 11% |
| | VIX | 9% | 11% | 13% | 5% | 19% | 4% | 22% | 3% |
| Firm Equity Variables | Excess Stock Return | 2% | 39% | 2% | 42% | 2% | 45% | 5% | 29% |
| | Stock Volatility | 27% | 4% | 29% | 4% | 26% | 6% | 20% | 8% |
| Firm Accounting Variables | Capital Expenditure | 9% | 47% | 13% | 41% | 18% | 37% | 21% | 35% |
| | Inventory | 41% | 29% | 39% | 31% | 34% | 32% | 27% | 34% |
| | Profitability | 1% | 79% | 3% | 65% | 4% | 55% | 10% | 40% |
| | SG&A Cost | 54% | 26% | 43% | 29% | 35% | 30% | 21% | 34% |
| | Receivable | 34% | 17% | 31% | 19% | 29% | 20% | 26% | 21% |

Note: The entries of the table are percentages of firms where earning changes ($\Delta_s EPS_t$) are positively or negatively correlated with each predictor's contemporaneous or lagged changes ($X_{t-j}$ with $j = 0$ for "Same Quarter", $j = 1$ for "Lag One Quarter", $j = 2$ for "Lag Two Quarters", and $j = 3$ for "Lag Three Quarters"). For given predictor X and selected lag j, the percentage of firms where $H_0 \quad : corr(\Delta_s EPS_t, X_{t-j}) = 0$ can be rejected against $H_a \quad : corr(\Delta_s EPS_t, X_{t-j}) < 0$ ($> 0$) is reported under column "Negative"("Positive"). The average block size used for the stationary bootstrap test is 12 observations, and the number of bootstrap simulations is 5000. The significance level is set at 5%.

Table 2.4: Out-of-Sample Predictive Performance Test MASER Distribution

| | End of TQ | | | Two Months into TQ | | | One Month into TQ | | | Quarter ahead of TQ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Benchmark Models | 25th | Median | 75th | 25th | Median | 75th | 25th | Median | 75th | 25th | Median | 75th |
| Extrapolative Model | 0.62 | 0.74 | 0.86 | 0.64 | 0.75 | 0.87 | 0.64 | 0.76 | 0.88 | 0.65 | 0.76 | 0.87 |
| Quarterly ADL Model | 0.66 | 0.79 | 0.92 | 0.71 | 0.83 | 0.97 | 0.71 | 0.85 | 0.99 | 0.74 | 0.88 | 1.01 |
| Analysts' Consensus | 0.63 | 0.84 | 1.08 | 0.62 | 0.81 | 1.06 | 0.58 | 0.78 | 1.03 | 0.54 | 0.72 | 0.99 |

Note: For each firm, forecasts of quarterly earnings made at various horizons (marked by the column groups of the table) by applying the MIDAS model are evaluated against forecasts from the benchmark models at the same horizon. Dividing the median scaled forecast error of the former with that of a later yields a ratio, indicating which model forecasts better. A ratio smaller than 1 favors the MIDAS model against the benchmark model. For example, a value of 0.8 means the former reduces the median forecast error of the later by 20%. To assess whether or how much MIDAS outperforms its counterpart in general, such ratio is calculated for each firm in our sample, and the results form an empirical distribution. The numbers reported in the table are various percentile measurements of this distribution for the given forecast horizons. The benchmark models are described in Section 2.4.2.1. We will refer to the *target* quarter (TQ) as the object of interest in the predictions exercise for both analysts and our models and consider (1) end of the target quarter, (2) two months into the target quarter, (3) one month into target quarter and (4) a quarter ahead of the target quarter.

Table 2.5: Out-of-Sample Predictive Performance Mann-Whitney U Test Results

| | End of TQ | | Two Months into TQ | | One Month into TQ | | Quarter ahead of TQ | |
|---|---|---|---|---|---|---|---|---|
| Benchmark Models | OPF | UPF | OPF | UPF | OPF | UPF | OPF | UPF |
| Extrapolative Model | 38% | 0% | 36% | 0% | 35% | 0% | 34% | 0% |
| Quarterly ADL Model | 27% | 0% | 23% | 0% | 20% | 0% | 18% | 0% |
| Analysts' Consensus | 25% | 4% | 26% | 4% | 30% | 4% | 35% | 3% |

Note: The entries of the table are percentages of firms where the MIDAS model outperforms or under-performs each benchmark model when forecasting at different horizons, according to the Mann-Whitney U Test. "OPF"stands for outperform while "UPF" stands for under-perform. The significance level of the Mann-Whitney U Test is set at 5%. The benchmark models are described in Section 2.4.2.1. We will refer to the *target* quarter (TQ) as the object of interest in the predictions exercise for both analysts and our models and consider (1) end of the target quarter, (2) two months into the target quarter, (3) one month into target quarter and (4) a quarter ahead of the target quarter.

Table 2.6: Out-of-Sample Predictive Performance Test MASER Distribution by Firm Size

| | End of TQ | | | Two Months into TQ | | | One Month into TQ | | | Quarter Ahead of TQ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 25th | Median | 75th | 25th | Median | 75th | 25th | Median | 75th | 25th | Median | 75th |
| **All Firms** | **0.63** | **0.84** | **1.08** | **0.62** | **0.81** | **1.06** | **0.58** | **0.78** | **1.03** | **0.54** | **0.72** | **0.99** |
| Smallest (0-20th percentile) | 0.63 | 0.82 | 0.99 | 0.63 | 0.79 | 1.01 | 0.57 | 0.75 | 0.97 | 0.54 | 0.71 | 0.93 |
| Small (20-40th percentile) | 0.61 | 0.81 | 1.08 | 0.61 | 0.78 | 1.01 | 0.55 | 0.74 | 0.96 | 0.52 | 0.72 | 0.93 |
| Medium (40-60th percentile) | 0.62 | 0.79 | 1.04 | 0.60 | 0.80 | 1.02 | 0.58 | 0.76 | 1.04 | 0.54 | 0.70 | 0.97 |
| Large (60-80th percentile) | 0.64 | 0.84 | 1.08 | 0.62 | 0.84 | 1.11 | 0.58 | 0.78 | 1.08 | 0.54 | 0.74 | 1.03 |
| Largest (80-100th percentile) | 0.67 | 0.93 | 1.26 | 0.65 | 0.87 | 1.20 | 0.65 | 0.82 | 1.14 | 0.56 | 0.76 | 1.06 |

Note: The firms in our sample are divided into five equal-sized subgroups based on sales. The median scaled forecast error ratios between the MIDAS model and consensus analysts' forecasts made at various horizons are calculated for each firm in each subgroup. Summary percentile numbers of these ratios are reported in the table for each subgroup. We will refer to the *target* quarter (TQ) as the object of interest in the predictions exercise for both analysts and our models and consider (1) end of the target quarter, (2) two months into the target quarter, (3) one month into target quarter and (4) a quarter ahead of the target quarter.

Table 2.7: Out-of-Sample Predictive Performance Mann-Whitney U Test Results by Firm Size

| | End of TQ | | Two Months into TQ | | One Month into TQ | | Quarter ahead of TQ | |
|---|---|---|---|---|---|---|---|---|
| | OPF | UPF | OPF | UPF | OPF | UPF | OPF | UPF |
| **All Firms** | **25%** | **4%** | **26%** | **4%** | **30%** | **4%** | **35%** | **3%** |
| Smallest (0-20th percentile) | 25% | 1% | 28% | 2% | 30% | 0% | 37% | 1% |
| Small (20-40th percentile) | 28% | 2% | 28% | 3% | 31% | 2% | 38% | 2% |
| Medium (40-60th percentile) | 27% | 4% | 28% | 4% | 32% | 5% | 35% | 2% |
| Large (60-80th percentile) | 22% | 5% | 24% | 4% | 29% | 5% | 33% | 3% |
| Largest (80-100th percentile) | 20% | 7% | 23% | 6% | 26% | 6% | 33% | 5% |

Note: The firms in our sample are divided into five equal-sized subgroups based on sales. The percentages of firms in each subgroup where the MIDAS model outperforms or under-performs consensus analysts' forecasts at various horizons according to the Mann-Whitney U Test are reported in the table. "OPF"stands for outperform while "UPF" stands for under-perform. The significance level of the Mann-Whitney U Test is set at 5%. We will refer to the *target* quarter (TQ) as the object of interest in the predictions exercise for both analysts and our models and consider (1) end of the target quarter, (2) two months into the target quarter, (3) one month into target quarter and (4) a quarter ahead of the target quarter.

Table 2.8: Out-of-Sample Predictive Performance Test MASER Distribution by Industry

| | End of TQ | | | Two Months into TQ | | | One Month into TQ | | | Quarter Ahead of TQ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 25th | Median | 75th | 25th | Median | 75th | 25th | Median | 75th | 25th | Median | 75th |
| **All Firms** | **0.63** | **0.84** | **1.08** | **0.62** | **0.81** | **1.06** | **0.58** | **0.78** | **1.03** | **0.54** | **0.72** | **0.99** |
| High Tech | 0.60 | 0.75 | 0.98 | 0.59 | 0.74 | 0.98 | 0.54 | 0.72 | 0.93 | 0.52 | 0.68 | 0.91 |
| Energy | 0.58 | 0.76 | 1.02 | 0.55 | 0.73 | 0.92 | 0.50 | 0.62 | 0.81 | 0.48 | 0.57 | 0.76 |
| Manufacturing | 0.60 | 0.78 | 0.99 | 0.60 | 0.77 | 1.00 | 0.54 | 0.73 | 0.98 | 0.49 | 0.65 | 0.87 |
| Other | 0.61 | 0.80 | 1.00 | 0.60 | 0.78 | 0.97 | 0.58 | 0.75 | 0.95 | 0.55 | 0.71 | 0.90 |
| Consumer Durables | 0.65 | 0.81 | 0.92 | 0.65 | 0.74 | 0.96 | 0.52 | 0.68 | 0.96 | 0.53 | 0.65 | 0.78 |
| Wholesale Retail | 0.63 | 0.89 | 1.17 | 0.62 | 0.80 | 1.17 | 0.61 | 0.83 | 1.16 | 0.55 | 0.80 | 1.07 |
| Health | 0.71 | 0.94 | 1.16 | 0.71 | 0.93 | 1.18 | 0.66 | 0.90 | 1.15 | 0.60 | 0.83 | 1.08 |
| Consumer NonDurables | 0.74 | 1.00 | 1.27 | 0.73 | 0.95 | 1.28 | 0.73 | 0.95 | 1.29 | 0.59 | 0.88 | 1.21 |
| Utilities | 0.87 | 1.12 | 1.44 | 0.93 | 1.16 | 1.40 | 0.85 | 1.09 | 1.36 | 0.84 | 1.05 | 1.34 |
| Telecom | 0.76 | 1.22 | 1.42 | 0.82 | 1.00 | 1.32 | 0.70 | 1.02 | 1.41 | 0.67 | 0.93 | 1.28 |

Note: The firms in our sample are divided into ten subgroups based on industry affiliations. The median scaled forecast error ratios between the MIDAS model and consensus analysts' forecasts made at various horizons are calculated for each firm in each subgroup. Summary percentile numbers of these ratios are reported in the table for each subgroup. We will refer to the *target* quarter (TQ) as the object of interest in the predictions exercise for both analysts and our models and consider (1) end of the target quarter, (2) two months into the target quarter, (3) one month into target quarter and (4) a quarter ahead of the target quarter.

Table 2.9: Out-of-Sample Predictive Performance
Mann-Whitney U Test Results by Industry

| | End of TQ | | Two Months into TQ | | One Month into TQ | | Quarter ahead of TQ | |
|---|---|---|---|---|---|---|---|---|
| | OPF | UPF | OPF | UPF | OPF | UPF | OPF | UPF |
| **All Firms** | **25%** | **4%** | **26%** | **4%** | **30%** | **4%** | **35%** | **3%** |
| Energy | 40% | 0% | 48% | 0% | 59% | 0% | 65% | 0% |
| High Tech | 34% | 3% | 37% | 3% | 40% | 2% | 43% | 2% |
| Manufacturing | 30% | 3% | 30% | 2% | 35% | 3% | 41% | 2% |
| Consumer Durables | 27% | 0% | 29% | 0% | 38% | 0% | 50% | 0% |
| Other | 24% | 4% | 26% | 4% | 30% | 4% | 36% | 2% |
| Wholesale Retail | 20% | 4% | 18% | 4% | 24% | 6% | 27% | 4% |
| Consumer NonDurables | 17% | 10% | 16% | 10% | 14% | 10% | 25% | 6% |
| Health | 15% | 6% | 19% | 7% | 18% | 4% | 25% | 5% |
| Telecom | 7% | 20% | 13% | 13% | 7% | 13% | 7% | 7% |
| Utilities | 3% | 8% | 3% | 4% | 7% | 8% | 8% | 7% |

Note: The firms in our sample are divided into ten subgroups based on industry affiliations. The percentages of firms in each subgroup where the MIDAS model outperforms or under-performs consensus analysts' forecasts at various horizons according to the Mann-Whitney U Test are reported in the table. "OPF"stands for outperform while "UPF" stands for under-perform. The significance level of the Mann-Whitney U Test is set at 5%. We will refer to the *target* quarter (TQ) as the object of interest in the predictions exercise for both analysts and our models and consider (1) end of the target quarter, (2) two months into the target quarter, (3) one month into target quarter and (4) a quarter ahead of the target quarter.

Figure 2.1: Weights Assigned to Macroeconomic Variables

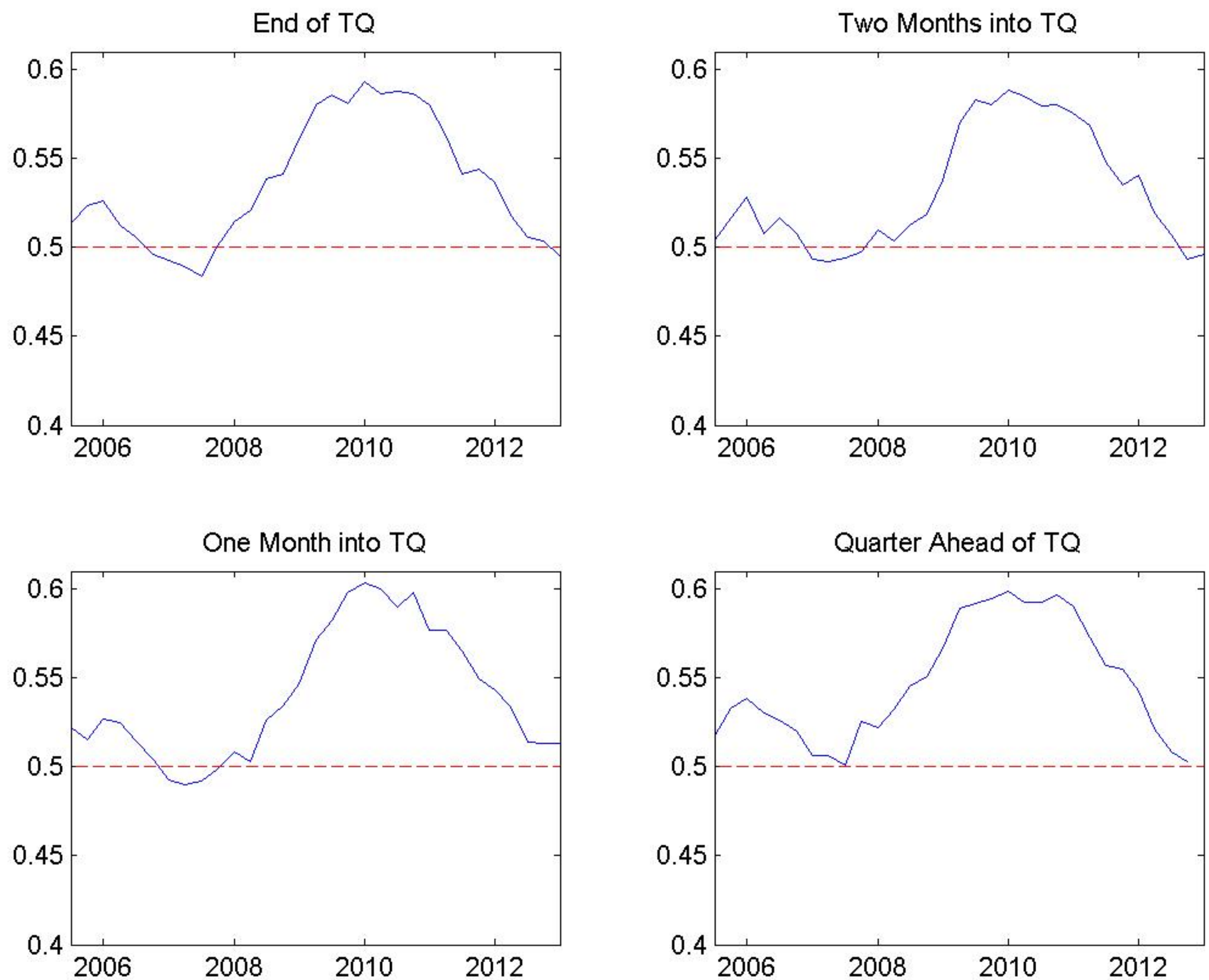


Figure 2.2: Weights Assigned to Firm-Specific Equity Variables

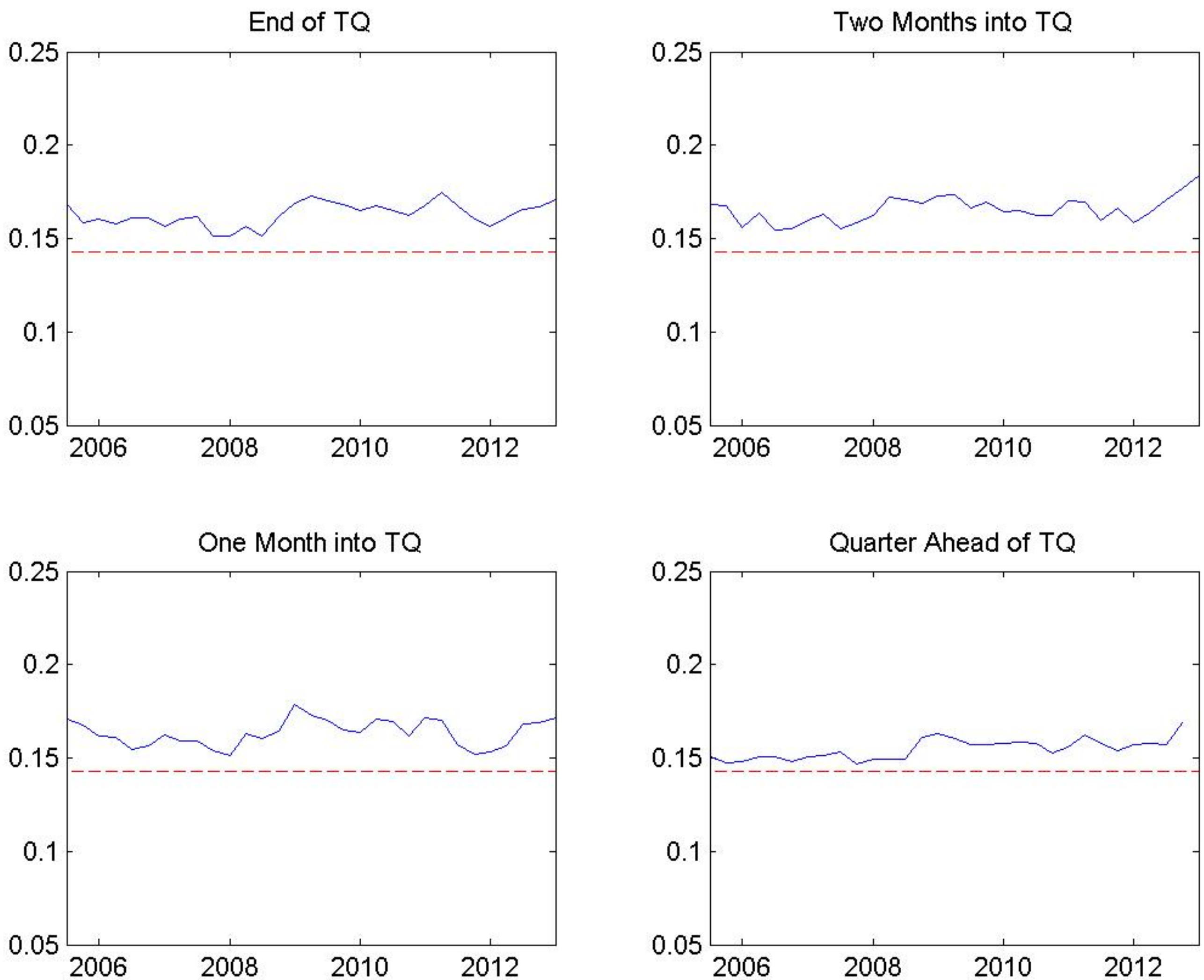


Figure 2.3: Weights Assigned to Firm-Specific Accounting Variables

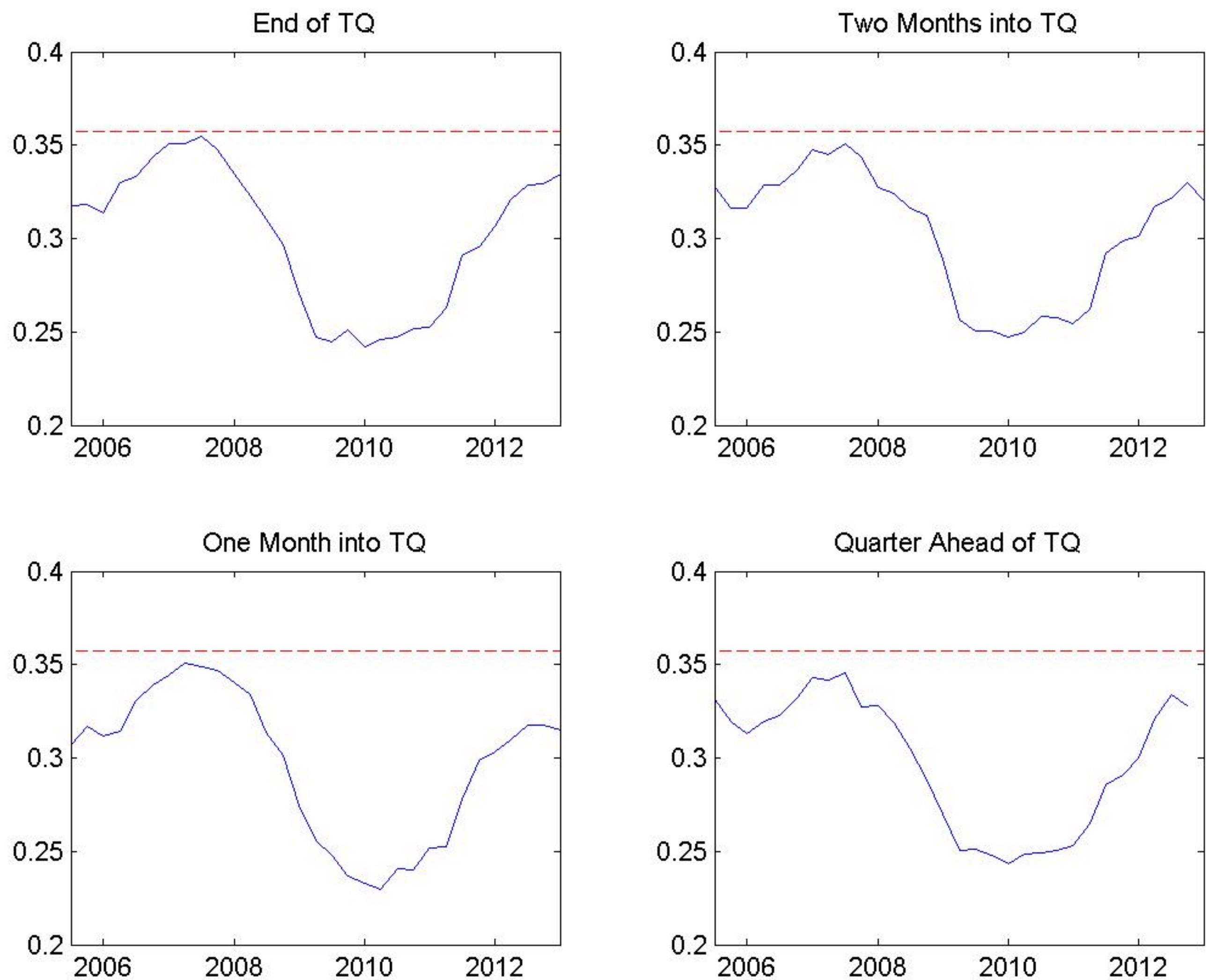


Table 2.10: Average Weights Assigned to Macroeconomic Variables by Industry

| | End of TQ | Two Months into TQ | One Month into TQ | Quarter ahead of TQ |
|---|---|---|---|---|
| **All Firms** | **0.551** | **0.544** | **0.555** | **0.561** |
| Energy | 0.607 | 0.591 | 0.574 | 0.604 |
| High Tech | 0.560 | 0.554 | 0.567 | 0.581 |
| Consumer Durables | 0.559 | 0.559 | 0.557 | 0.571 |
| Manufacturing | 0.555 | 0.549 | 0.547 | 0.563 |
| Telecom | 0.554 | 0.526 | 0.557 | 0.546 |
| Wholesale Retail | 0.553 | 0.540 | 0.553 | 0.553 |
| Health | 0.547 | 0.546 | 0.558 | 0.574 |
| Consumer NonDurables | 0.546 | 0.534 | 0.546 | 0.561 |
| Other | 0.533 | 0.530 | 0.548 | 0.545 |
| Utilities | 0.524 | 0.508 | 0.525 | 0.505 |

Note: The entries in this table are the average weights assigned to the seven macroeconomic variables in ADL-MIDAS models. Such averaging is first done across all the firms in a given subgroup, and then the entire out-of-sample period. Industry subgroups are ranked by the column "End of TQ".

CHAPTER 3

# HYPER-PARAMETERIZED AR MODEL

## 3.1 Introduction

When making direct multi-step-ahead forecasts with an autoregressive (AR) model, the number of coefficients estimated equals the number of lags plus one (for the constant term). When the number of lags is large, the AR structure requires a large number of coefficients to be estimated, which hurts the forecast accuracy due to loss of efficiency.

In order to have a more parsimonious direct forecasting model, especially in the case that the best-performing AR model contains long lags, we propose applying hyper-parameterization, namely imposing structure on the coefficients of an AR model. Under this alternative specification, we only estimate a few hyper-parameters, rather than all the lags coefficients.

When the true data-generating process (DGP) is autoregressive, limiting the lag coefficients to have a certain structure obviously introduces mis-specification. However, given a finite sample, the gain in estimation efficiency may overcome such mis-specification and yield a better set of out-of-sample forecasts. We evaluate such trade off with a Monte Carlo experiment, and results suggest that the hyper-parameterized models, although mis-specified perform at least as well as, and in many cases, better than the AR model out-of-sample with simulated data.

The trade-off is more ambiguous when taking the forecasting practice to real-world data, since the true DGP is unknown. Thus the issue becomes empirical. We use a dataset of monthly macroeconomic series, provided by Marcellino, Stock, and Watson (2006) to assess the performance of the hyper-parameterized AR models, against their AR counterpart. The results suggest as much as a 5% improvement for an average macro series, when forecast horizon is long.

Our paper is related to the literature in direct multiperiod forecasting. Cox (1961) and following papers suggested that direct multiperiod estimation of dynamic forecasting models can be advantageous to their iterative counterpart, given that the one-step-ahead lower order autoregressive models tend to be mis-specified. However, Marcellino, Stock, and Watson (2006) examined this issue in an empirical setting and concluded that although being more robust to model misspecification, direct forecasting suffer from having larger estimation variance and does not perform as well as the iterative method in a dataset of monthly macroeconomic variables. We contribute to this literature by providing a class of direct forecasting models that have better estimation efficiency than the standard direct autoregressive models.

Another related field is the growing literature of Mixed Frequency Data Sampling (MIDAS) models. These models apply hyper-parameterization to address the issue of high-frequency data proliferation. Although our models do not use high frequency data, the underlying logic is similar to that of the MIDAS models. The comparison made in this paper is an example of the trade-off between misspecification and estimation efficiency, which is present in the MIDAS models as well.[1]

Section 3.2 outlines the specification of the hyper-parameterized AR models. Section 3.3 presents the out-of-sample forecasting experiment using Monte Carlo simulations. Section 3.4 discusses an empirical study with 170 monthly macroeconomic series. Section 3.5 concludes.

### 3.2 Hyper-parameterized AR Models

In this paper, we hyper-parametrization the AR model by grouping the lags by either two or three, and restrict the coefficients to be the same within a group. More complex structure could be used here such as the Almon or Beta polynomial, but we opt for this step function approach as (1) it can be easily estimated by Ordinary Least Squares (OLS) (2) it allows the estimated coefficient groups to differ in signs.[2]

Suppose we have monthly observations of an I(0) or I(1) macroeconomic series. We convert this series into a stationary $y_t$ by taking first difference when the series contains a unit root.

[1]See Foroni, Marcellino, and Schumacher (2013b), for example, for a comparison between unrestricted models vs functional distributed lags models.

[2]See Andreou, Ghysels, and Kourtellos (2010) for the setup of Almon and Beta polynomial.

To illustrate the grouping scheme, below are models under comparison (for the I(0) scenario, $z_{t+h} = y_{t+h}$; for the I(1) scenario, $z_{t+h} = \sum_{i=1}^{h} y_{t+i}$ ):

- Tri-monthly Hyper-parameterized AR: $z_{t+h} = c_0 + \alpha\,(y_t + y_{t-1} + y_{t-2}) + ... + \epsilon_{t+h}^{TH}$
- Bi-monthly Hyper-parameterized AR: $z_{t+h} = c_0 + \alpha\,(y_t + y_{t-1}) + ... + \epsilon_{t+h}^{BH}$
- Benchmark AR: $z_{t+h} = c_0 + \alpha y_t + \beta y_{t-1} + \gamma y_{t-2} + ... + \epsilon_{t+h}^{AR}$

When the true DGP is in the form of the benchmark, the two hyper-parameterized models will be mis-specified. We evaluate the mis-specification against gains in estimation efficiency with a Monte Carlo experiment described in the next section.

## 3.3 Monte Carlo Simulations

We simulate monthly[3] time series y containing different levels of persistence and lag structure with the following data generating process:

$$y_t = \rho * \sum_{j=1}^{J} \omega_j(\theta_1, \theta_2) y_{t-j} + \epsilon_t$$

The lag coefficients follow an exponential Almon scheme determined by two parameters $\theta_1$ and $\theta_2$: $\omega_j(\theta_1, \theta_2) \equiv \frac{exp(\theta_1 * j + \theta_2 * j^2)}{\sum_{j=1}^{J} exp(\theta_1 * j + \theta_2 * j^2)}$. Different theta values lead to different shapes of the lag structure and we select four combinations of theta values to simulate four shapes of the lag structure: fast decaying, slow decaying, near flat and hump shape. The theta combinations are described in Figure 3.1. The total number of lags J equals 40, assuming a memory of roughly four years, although the coefficients can be very close to zero for some of these lags.

The other parameters of the simulation are described in Table 3.1. We consider two order of integration, namely I(0) and I(1), for the reason that when the series is integrated of the order one, it is the sum of the simulated y (changes) that we forecast in a h-step ahead forecasting practice. Because the lag coefficients $\omega_j$ sum up to one, by definition, we use $\rho$ to control the persistence in the DGP.

[3]On a high frequency, such as monthly, macroeconomic series tend to have more persistence and the coefficients of the estimated AR model will not differ in signs.

To replicate typical macroeconomic series, the simulated samples have 360 observations, representing 30 years' monthly data. Rolling-window out-of-sample forecasts were generated under each of the three models described in Section 1.1. The in-sample estimation window size is 120. In the in-sample estimation, two lag selection criteria (AIC, BIC) were separately used to determine the optimal number of lags included (which need to be a multiple of 2 for the bi-monthly hyper-parameterized AR model, and 3 for the tri-monthly hyper-parameterized AR model). The maximum number of lags allowed is 24 months.

We use the root mean squared error(RMSE)[4] to measure forecast performance. When the RMSE of a hyper-parameterized AR model divided by RMSE of the benchmark AR model is less than 1, the former outperforms the latter. Given that there are three persistence levels ($\rho$=0.1,0.5, 0.9) for each order of integration (y is I(0) or I(1)), there are six sets of forecast results. We discuss the best performing scenario (I(1) high persistence series) and worst performing scenario(I(0) low persistence series) for the hyper-parameterized AR models.

Table 3.2 presents the forecasting results assuming y is a highly persistent ($\rho = 0.9$) I(1) series. Each cell in table 3.2 reports the median of RMSE ratios across the 200 Monte Carlo simulations, with the p-value of such ratio being greater than 1 in the parentheses. The results suggest that the hyper-parameterized AR models outperform the benchmark AR model when forecast horizon increases. Among the four sets of lag structures, the largest forecast improvement is achieved when the lag polynomial is "fast decaying" or "hump shape". The forecast improvement varies between 1% to 5% in terms of RMSE, depending on the lags shape and forecast horizon.

Table 3.3, on the other hand, presents the forecasting results assuming y is an I(0) series with low persistence ($\rho = 0.9$). In this scenario, hyper-parameterized AR models do not improve upon the benchmark AR model, as all RMSE ratios are essentially 1. Such results, however, still suggest that the hyper-parameterized model perform as well as the correctly specified AR models.

To summarize, hyper-parameterized AR models tend to outperform the benchmark AR model in our Monte Carlo simulations under the following conditions:

[4] $RMSE = \sqrt{\frac{\sum_{t=W+h}^{T} \epsilon_t^2}{T-W-h+1}}$

- when y is an I(1) series
- when the DGP assumes a high persistence parameter
- when forecasting at a longer horizon
- when the lag polynomial is “fast decaying” or “hump shape”

To further analyze why the above conditions are favorable to hyper-parameterized AR models, we look into the average number of lags selected in the in-sample estimation under each scenario. Theoretically, grouping the AR lag coefficients would only provide efficiency gains when the benchmark AR model would select to include a large number of lags. The numbers of lags selected under the best-performing scenario and under the worst-performing scenario are thus separately reported in Table 3.4 and Table 3.5.

We can see that both AIC and BIC select more lags when y is a persistent I(1) series. Within Table 3.5, “fast decaying” and “hump shape” lag polynomial structures lead to more lags being selected in the in-sample estimation, while longer forecast horizons also require more lags. Overall, the pattern of forecast improvement is consistent with that of the numbers of lags selected, confirming that the forecast improvement derives from having to estimate fewer parameters.

## 3.4 Empirical Application

To assess whether the more parsimonious hyper-parameterized AR models forecast better with real-world data, we apply methods similar to those in the Monte Carlo experiment to a panel of 170 monthly macroeconomic series used in Marcellino, Stock, and Watson (2006). The data span more than 40 years (1959-2002) and include production series, prices, unemployment, interest rates, as well as stock indices and exchange rates.

We estimate under a rolling-window scheme, with the window size being 120 monthly observations. Since we aim at showing whether the hyper-parameterized AR models forecast better than the benchmark AR model *on average*, rather than for a specific series, we report the median MSFE ratio across these series. Based on the pattern identified in the Monte Carlo simulated data, we expect the number of lags selected to play a central role in the forecast improvement, so the macroeconomic series are partitioned into five subgroups based on the average number of lags selected in the in-sample estimation with a given forecast horizon.

The models under comparison are the tri-monthly hyper-parameterized AR and the benchmark AR, as described in section 1.1.[5] For each series, we calculate the root mean squared forecast errors (RMFE) for each model and divide the RMFE of the tri-monthly hyper-parameterized AR with that of the benchmark AR. A RMSE ratio smaller than 1 suggests the former outperform the latter.

For a given forecast horizon h, the benchmark AR model was estimated on a macroeconomic series, and the numbers of lags selected in the rolling-window in-sample estimation steps are averaged into one number, which was used as the partitioning criterion. At each forecast horizon, series are categorized into five equal-sized percentile subgroups based on their average number of lags calculated.[6] The cut-off average numbers of lags for each subgroup are reported in table 3.6 (using AIC as criterion) and table 3.7 (using BIC as criterion). In general, AIC tends to select more lags to be included in the benchmark model than BIC. The average numbers of lags range widely across the different subgroups, with as few as 1 lag selected for the lest persistent subgroup, and as many as more than 10 lags for the most persistent series.

Table 3.8 and table 3.9 report the median of RMSE ratio within each subgroup. Tri-monthly hyper-parameterized AR model forecasts better than the benchmark AR for the subgroups that have more lags and when the forecast horizon is longer. The improvement can be as large as 5 % for the subgroups with the most lags.

The clear pattern emerging from subsetting the series by lag numbers, as well as the fact that the forecast improvement is more evident when AIC is used as the lag selection criterion, show that with some series, the parameter proliferation issue of estimating a direct AR forecast model can be alleviated by grouping the AR coefficients.

[5] Results of the bi-monthly hyper-parameterized AR are calculated too. The results are similar to those of the tri-monthly model, although the forecast improvement is smaller.

[6] Although a series should consistently fall into the same percentile subgroup in theory, the noise in lag selection may change the composition of the percentile subgroups somewhat across different forecast horizons.

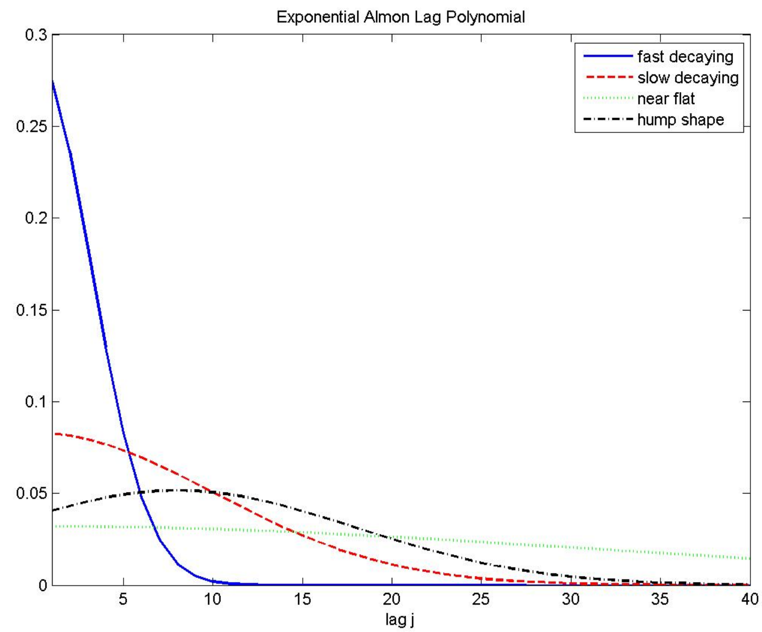
## 3.5 Conclusion

The analysis we've carried out so far confirms that when the autoregressive process picks up more lags, the efficiency gain of imposing a structure on the lag coefficients may improve the out of sample forecast performance.

Introducing a trade-off between model mis-specification and estimation efficiency, imposing a structure like the ones we use in this paper on the lag coefficients was shown to improve upon the (sometimes correctly-specified) autoregressive models, in both a Monte Carlo simulated setting and a panel dataset of 170 monthly macroeconomic series.

The framework devised in this paper can be used in the future to 1) include iterative AR forecasts as benchmark, and 2) to use a more complex structure such as almon polynomials, thus further reducing the number of coefficients estimated.

Figure 3.1: Alternative lag schemes of the exponential Almon polynomial




Note: This figure shows various shapes of the exponential Almon polynomial. The solid, dashed, dotted and dash-dot lines correspond to fast decaying weights ($\theta_1 = 0$ and $\theta_2 = -5 \times 10^{-2}$), slow decaying weights ($\theta_1 = 0$ and $\theta_2 = -5 \times 10^{-3}$), near flat weights ($\theta_1 = 0$ and $\theta_2 = -5 \times 10^{-4}$), and hump shaped weights ($\theta_1 = 8 \times 10^{-2}$ and $\theta_2 = -5 \times 10^{-3}$).

Table 3.1: Monte Carlo Simulation Parameters

| Parameter | Interpretation | Values |
|---|---|---|
| $T_{mc}$ | length of the simulated samples | 360 |
| $N_{mc}$ | number of monte carlo simulation | 200 |
| $y_0$ | initial value of y | 1 |
| $T_0$ | length of the burn in period | 100 |
| $\sigma$ | variance of $\epsilon$ | 1 |
| $\rho$ | persistence | 0.1/0.5/0.9 |

Table 3.2: Hyper-parameterized AR against Benchmark AR: I(1) Series with $\rho = 0.9$

| Model(Lag Selection) | Lags Scheme | H=1 | H=3 | H=6 | H=12 | H=24 |
|---|---|---|---|---|---|---|
| Bi-monthly HP-AR(AIC) | fast decaying | 0.996 (0.4) | 0.968 (0.19) | 0.96 (0.16) | 0.961 (0.13) | 0.958 (**) |
| | slow decaying | 1 (0.53) | 1 (0.5) | 0.992 (0.4) | 0.99 (0.31) | 0.975 (0.22) |
| | near flat | 0.997 (0.46) | 0.999 (0.48) | 0.986 (0.32) | 0.98 (0.32) | 0.974 (0.23) |
| | hump shape | 0.993 (0.31) | 0.988 (0.27) | 0.972 (0.2) | 0.971 (0.13) | 0.971 (0.18) |
| Bi-monthly HP-AR(BIC) | fast decaying | 0.999 (0.44) | 0.991 (0.4) | 0.969 (0.29) | 0.961 (0.25) | 0.963 (0.15) |
| | slow decaying | 1 (0.54) | 1 (0.56) | 1 (0.55) | 1 (0.51) | 0.989 (0.29) |
| | near flat | 0.998 (0.39) | 1 (0.55) | 0.996 (0.4) | 0.994 (0.42) | 0.982 (0.28) |
| | hump shape | 0.994 (0.28) | 0.983 (0.22) | 0.971 (0.12) | 0.964 (*) | 0.961 (*) |
| Tri-monthly HP-AR(AIC) | fast decaying | 0.99 (0.31) | 0.962 (0.13) | 0.943 (0.11) | 0.948 (*) | 0.942 (**) |
| | slow decaying | 0.997 (0.4) | 0.992 (0.43) | 0.986 (0.3) | 0.98 (0.29) | 0.961 (0.16) |
| | near flat | 0.995 (0.37) | 0.994 (0.38) | 0.977 (0.23) | 0.972 (0.25) | 0.964 (0.22) |
| | hump shape | 0.99 (0.25) | 0.979 (0.21) | 0.964 (0.15) | 0.956 (0.12) | 0.962 (0.18) |
| Tri-monthly HP-AR(BIC) | fast decaying | 1 (0.48) | 0.977 (0.23) | 0.951 (0.23) | 0.95 (0.22) | 0.945 (*) |
| | slow decaying | 1 (0.57) | 1 (0.57) | 1 (0.52) | 0.997 (0.48) | 0.975 (0.27) |
| | near flat | 0.998 (0.35) | 0.998 (0.46) | 0.987 (0.38) | 0.985 (0.37) | 0.962 (0.22) |
| | hump shape | 0.991 (0.19) | 0.974 (0.16) | 0.958 (0.14) | 0.945 (*) | 0.936 (*) |

Note: Each cell reports the median of RMSE ratios across the 200 Monte Carlo simulations, with the p-value of such ratio being greater than 1 in the parentheses.

Table 3.3: Hyper-parameterized AR against Benchmark AR: I(0) Series with $\rho = 0.1$

| Model(Lag Selection) | Lags Scheme | H=1 | H=3 | H=6 | H=12 | H=24 |
|---|---|---|---|---|---|---|
| Bi-monthly HP-AR(AIC) | fast decaying | 0.994 (0.32) | 0.996 (0.41) | 0.999 (0.48) | 1 (0.48) | 0.997 (0.4) |
| | slow decaying | 0.999 (0.48) | 1 (0.58) | 0.999 (0.46) | 0.998 (0.42) | 0.999 (0.46) |
| | near flat | 0.997 (0.36) | 0.999 (0.45) | 0.996 (0.38) | 1 (0.5) | 1 (0.67) |
| | hump shape | 0.998 (0.45) | 0.998 (0.46) | 1 (0.54) | 0.999 (0.42) | 0.997 (0.35) |
| Bi-monthly HP-AR(BIC) | fast decaying | 1 (0.52) | 0.999 (0.47) | 0.999 (0.44) | 1 (0.44) | 1 (0.44) |
| | slow decaying | 1 (0.54) | 1 (0.61) | 1 (0.57) | 1 (0.47) | 1 (0.46) |
| | near flat | 1 (0.52) | 0.999 (0.46) | 1 (0.48) | 1 (0.5) | 1 (0.58) |
| | hump shape | 1 (0.52) | 0.999 (0.45) | 0.999 (0.45) | 0.999 (0.42) | 1 (0.49) |
| Tri-monthly HP-AR(AIC) | fast decaying | 0.994 (0.34) | 0.998 (0.42) | 0.999 (0.42) | 0.998 (0.45) | 0.995 (0.36) |
| | slow decaying | 0.998 (0.45) | 0.998 (0.44) | 0.998 (0.42) | 0.999 (0.46) | 0.997 (0.43) |
| | near flat | 0.997 (0.41) | 0.997 (0.41) | 0.999 (0.47) | 1 (0.5) | 1 (0.5) |
| | hump shape | 0.997 (0.43) | 0.999 (0.43) | 1 (0.51) | 1 (0.49) | 0.996 (0.38) |
| Tri-monthly HP-AR(BIC) | fast decaying | 1 (0.48) | 1 (0.53) | 0.998 (0.39) | 1 (0.5) | 0.999 (0.42) |
| | slow decaying | 1 (0.55) | 0.999 (0.48) | 1 (0.53) | 1 (0.53) | 0.999 (0.45) |
| | near flat | 0.999 (0.44) | 1 (0.49) | 0.999 (0.46) | 1 (0.48) | 1 (0.63) |
| | hump shape | 1 (0.54) | 0.999 (0.46) | 1 (0.54) | 1 (0.5) | 1 (0.49) |

Note: Each cell reports the median of RMSE ratios across the 200 Monte Carlo simulations, with the p-value of such ratio being greater than 1 in the parentheses.

Table 3.4: Optimal Number of Lags Selected by Benchmark AR: I(1) Series with $\rho = 0.9$

| Lag Selection | Lags Scheme | H=1 | H=3 | H=6 | H=12 | H=24 |
|---|---|---|---|---|---|---|
| AIC | fast decaying | 5.6 | 12 | 15 | 16 | 13 |
| | slow decaying | 2.4 | 5.3 | 7.7 | 9 | 8.2 |
| | near flat | 2 | 3.4 | 4.6 | 5.8 | 7.3 |
| | hump shape | 2.8 | 4.4 | 5.3 | 6.3 | 6.8 |
| BIC | fast decaying | 1.2 | 2.4 | 4.9 | 9.8 | 7.7 |
| | slow decaying | 1 | 1.2 | 1.7 | 3.3 | 3.2 |
| | near flat | 1.1 | 1.1 | 1.4 | 1.8 | 2.6 |
| | hump shape | 1.2 | 1.7 | 2.1 | 2.6 | 2.7 |

Table 3.5: Optimal Number of Lags Selected by Benchmark AR: I(0) Series with $\rho = 0.1$

| Lag Selection | Lags Scheme | H=1 | H=3 | H=6 | H=12 | H=24 |
|---|---|---|---|---|---|---|
| AIC | fast decaying | 2.2 | 2.1 | 2.1 | 2 | 2 |
| | slow decaying | 2 | 1.9 | 1.9 | 1.8 | 1.9 |
| | near flat | 2.1 | 2.1 | 2 | 1.9 | 1.8 |
| | hump shape | 1.9 | 1.9 | 1.9 | 1.9 | 2.1 |
| BIC | fast decaying | 1 | 1 | 1.1 | 1.1 | 1.1 |
| | slow decaying | 1 | 1 | 1 | 1 | 1 |
| | near flat | 1 | 1 | 1 | 1.1 | 1 |
| | hump shape | 1 | 1 | 1 | 1 | 1.1 |

Table 3.6: Range of Optimal Lags Selected by the Benchmark AR Model using AIC

| Pctl Subgroups | H=1 | H=3 | H=6 | H=12 | H=24 |
|---|---|---|---|---|---|
| Fewest Lags | 1-2 | 1-1 | 1-1 | 1-1 | 1-1 |
| Fewer Lags | 2-3 | 1-3 | 1-3 | 1-2 | 1-2 |
| Mid Lags | 3-4 | 3-5 | 3-5 | 2-5.5 | 2-6 |
| More Lags | 4-6.8 | 5-8 | 5-8 | 5.5-9 | 6-11 |
| Most Lags | 6.8-22 | 8-20 | 8-18 | 9-19 | 11-24 |

Table 3.7: Range of Optimal Lags Selected by the Benchmark AR Model using BIC

| Pctl Subgroups | H=1 | H=3 | H=6 | H=12 | H=24 |
|---|---|---|---|---|---|
| Fewest Lags | 1-1 | 1-1 | 1-1 | 1-1 | 1-1 |
| Fewer Lags | 1-1 | 1-1 | 1-1 | 1-1 | 1-1 |
| Mid Lags | 1-2 | 1-2 | 1-2 | 1-2 | 1-1 |
| More Lags | 2-3 | 2-4 | 2-5 | 2-5 | 1-5 |
| Most Lags | 3-7 | 4-8 | 5-9 | 5-11 | 5-12 |

Table 3.8: Median RMSE Ratio using AIC

| Pctl Subgroups | H=1 | H=3 | H=6 | H=12 | H=24 |
|---|---|---|---|---|---|
| Fewest Lags | 0.996 | 0.999 | 0.986 | 0.975 | 1 |
| Fewer Lags | 1 | 1.01 | 0.992 | 0.981 | 0.99 |
| Mid Lags | 0.997 | 0.991 | 0.991 | 0.989 | 0.962 |
| More Lags | 0.975 | 0.976 | 0.981 | 0.973 | 0.964 |
| Most Lags | 0.964 | 0.962 | 0.953 | 0.94 | 0.932 |

Table 3.9: Median RMSE Ratio using BIC

| Pctl Subgroups | H=1 | H=3 | H=6 | H=12 | H=24 |
|---|---|---|---|---|---|
| Fewest Lags | 1 | 1 | 1 | 1 | 0.994 |
| Fewer Lags | 1 | 1 | 1 | 1 | 0.994 |
| Mid Lags | 1 | 1 | 1 | 0.999 | 0.994 |
| More Lags | 0.992 | 0.992 | 0.986 | 0.984 | 0.987 |
| Most Lags | 0.964 | 0.955 | 0.945 | 0.941 | 0.943 |

APPENDIX A

TECHNICAL APPENDICES TO CHAPTER 1

## A.1 In-sample Correlation Test Results on SPF One Quarter Ahead Forecast Errors

Table A.1: Summary Results on Individual Assets in Each Assets Class

| Asset Class | No. of Assets | Percentage | Max Corr. | Min Corr. |
|---|---|---|---|---|
| Real GDP Growth Rate Forecasts | | | | |
| Equity | 268 | 57.95% | -0.43 | 0.52 |
| Government Securities | 239 | 15.06% | -0.23 | 0.30 |
| Commodity | 269 | 29.37% | -0.44 | 0.63 |
| Exchange Rates | 88 | 17.24% | -0.26 | 0.15 |
| Corporate Securities | 119 | 14.29% | -0.23 | 0.31 |
| CPI-based Inflation Rate Forecasts | | | | |
| Equity | 268 | 6.15% | -0.35 | 0.27 |
| Government Securities | 239 | 7.11% | -0.17 | 0.19 |
| Commodity | 269 | 26.77% | -0.37 | 0.36 |
| Exchange Rates | 88 | 8.05% | -0.32 | 0.27 |
| Corporate Securities | 119 | 13.45% | -0.22 | 0.23 |

Table A.2: Testing Factors of Each Asset Class

Real GDP Growth Rate Forecasts

| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
|---|---|---|---|
| Equity | 0.31 ** | -0.09 | 0.14 |
| Government Securities | 0.10 | -0.16 * | -0.06 |
| Commodity | 0.57 *** | -0.03 | -0.08 |
| Exchange Rates | 0.06 | -0.10 ** | 0.03 |
| Corporate Securities | -0.12 | 0.19 ** | -0.04 |

CPI-based Inflation Rate Forecasts

| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
|---|---|---|---|
| Equity | -0.15 * | -0.05 | 0.16 |
| Government Securities | -0.01 | 0.07 | 0.14 ** |
| Commodity | 0.08 | -0.15 | 0.15 * |
| Exchange Rates | -0.02 | -0.03 | 0.03 |
| Corporate Securities | 0.06 | 0.03 | -0.01 |

## A.2 In-sample Correlation Test Results on SPF One Year Ahead Forecast Errors

Table A.3: Summary Results on Individual Assets in Each Assets Class

| Real GDP Growth Rate Forecasts | | | | |
|---|---|---|---|---|
| Asset Class | No. of Assets | Percentage | Max Corr. | Min Corr. |
| Equity | 268 | 28.72% | -0.47 | 0.64 |
| Government Securities | 239 | 24.69% | -0.20 | 0.27 |
| Commodity | 269 | 29.74% | -0.52 | 0.53 |
| Exchange Rates | 88 | 11.49% | -0.36 | 0.17 |
| Corporate Securities | 119 | 39.50% | -0.30 | 0.24 |
| CPI-based Inflation Rate Forecasts | | | | |
| Equity | 268 | 23.59% | -0.19 | 0.24 |
| Government Securities | 239 | 11.30% | -0.20 | 0.19 |
| Commodity | 269 | 13.01% | -0.31 | 0.27 |
| Exchange Rates | 88 | 10.34% | -0.18 | 0.11 |
| Corporate Securities | 119 | 9.24% | -0.34 | 0.07 |

Table A.4: Testing Factors of Each Asset Class

Real GDP Growth Rate Forecasts

| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
|---|---|---|---|
| Equity | 0.48 *** | 0.14 * | 0.13 |
| Government Securities | 0.15 * | -0.06 | -0.27 * |
| Commodity | 0.46 *** | 0.05 | -0.15 |
| Exchange Rates | 0.04 | 0.02 | -0.01 |
| Corporate Securities | -0.04 | -0.09 | 0.21 *** |

CPI-based Inflation Rate Forecasts

| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
|---|---|---|---|
| Equity | -0.17 | 0.06 | 0.06 |
| Government Securities | -0.00 | 0.11 | 0.03 |
| Commodity | -0.04 | -0.08 | 0.23 ** |
| Exchange Rates | -0.09 * | -0.08 | 0.05 |
| Corporate Securities | 0.05 | 0.02 | -0.20 *** |

## A.3 In-sample Correlation Test Results on Blue Chip One Quarter Ahead Forecast Errors

Table A.5: Summary Results on Individual Assets in Each Assets Class: Full Sample

| Real GDP Growth Rate Forecasts | | | | |
|---|---|---|---|---|
| Asset Class | No. of Assets | Percentage | Max Corr. | Min Corr. |
| Equity | 268 | 75.38% | -0.50 | 0.52 |
| Government Securities | 239 | 37.66% | -0.34 | 0.19 |
| Commodity | 269 | 30.48% | -0.52 | 0.53 |
| Exchange Rates | 88 | 6.90% | -0.15 | 0.18 |
| Corporate Securities | 119 | 6.72% | -0.19 | 0.18 |
| **CPI-based Inflation Rate Forecasts** | | | | |
| Asset Class | No. of Assets | Percentage | Max Corr. | Min Corr. |
| Equity | 268 | 34.36% | -0.40 | 0.21 |
| Government Securities | 239 | 49.79% | -0.28 | 0.20 |
| Commodity | 269 | 46.47% | -0.48 | 0.43 |
| Exchange Rates | 88 | 41.38% | -0.34 | 0.34 |
| Corporate Securities | 119 | 15.97% | -0.17 | 0.26 |

Table A.6: Testing Factors of Each Asset Class: Full Sample

| | | | |
|---|---|---|---|
| Real GDP Growth Rate Forecasts | | | |
| Equity | 0.46 ** | 0.01 | 0.32 ** |
| Government Securities | -0.31 ** | 0.07 | -0.20 * |
| Commodity | 0.45 *** | -0.19 ** | -0.17 |
| Exchange Rates | -0.03 | -0.04 | -0.01 |
| Corporate Securities | -0.02 | 0.07 | 0.06 |
| CPI-based Inflation Rate Forecasts | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | -0.25 ** | -0.02 | -0.02 |
| Government Securities | -0.02 | 0.15 *** | 0.09 |
| Commodity | -0.06 | 0.05 | 0.02 |
| Exchange Rates | 0.05 * | -0.10 | -0.04 |
| Corporate Securities | -0.03 | 0.05 | 0.10 ** |

Table A.7: Summary Results on Individual Assets in Each Assets Class: Sub-samples

| Real GDP Growth Rate Forecast | | | | |
|---|---|---|---|---|
| Pre-crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 53.85% | -0.53 | 0.46 |
| Government Securities | 239 | 12.55% | -0.25 | 0.23 |
| Commodity | 269 | 30.11% | -0.51 | 0.46 |
| Exchange Rates | 88 | 10.34% | -0.31 | 0.21 |
| Corporate Securities | 119 | 5.88% | -0.16 | 0.10 |
| Crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 55.90% | -1.00 | 1.00 |
| Government Securities | 239 | 11.72% | -0.41 | 0.52 |
| Commodity | 269 | 49.81% | -0.62 | 0.72 |
| Exchange Rates | 88 | 50.57% | -0.56 | 0.58 |
| Corporate Securities | 119 | 19.33% | -0.42 | 0.56 |
| CPI-based Inflation Rate Forecast | | | | |
| Pre-crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 30.26% | -0.30 | 0.23 |
| Government Securities | 239 | 53.97% | -0.24 | 0.19 |
| Commodity | 269 | 51.30% | -0.40 | 0.36 |
| Exchange Rates | 88 | 16.09% | -0.10 | 0.15 |
| Corporate Securities | 119 | 46.22% | -0.21 | 0.06 |
| Crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 18.97% | -1.00 | 1.00 |
| Government Securities | 239 | 17.57% | -0.47 | 0.37 |
| Commodity | 269 | 39.03% | -0.63 | 0.67 |
| Exchange Rates | 88 | 67.82% | -0.61 | 0.65 |
| Corporate Securities | 119 | 1.68% | -0.19 | 0.48 |

Table A.8: Testing Factors of Each Asset Class: Sub-samples

| Real GDP Growth Rate Forecast | | | |
|---|---|---|---|
| Pre-crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | 0.44 *** | 0.01 | -0.37 *** |
| Government Securities | -0.24 ** | 0.10 * | -0.15 |
| Commodity | 0.33 *** | -0.26 ** | 0.13 |
| Exchange Rates | -0.05 | 0.06 | -0.01 |
| Corporate Securities | 0.00 | -0.03 | -0.07 |
| Crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | 0.44 ** | -0.34 * | -0.23 * |
| Government Securities | 0.12 | -0.01 | 0.59 *** |
| Commodity | 0.51 ** | -0.46 ** | -0.32 |
| Exchange Rates | 0.15 | -0.10 | -0.17 ** |
| Corporate Securities | 0.31 ** | 0.30 | -0.19 |
| CPI-based Inflation Rate Forecast | | | |
| Pre-crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | -0.22 ** | -0.01 | 0.05 |
| Government Securities | 0.11 | 0.18 *** | 0.16 * |
| Commodity | -0.17 * | 0.17 * | -0.05 |
| Exchange Rates | 0.07 *** | -0.02 | 0.03 |
| Corporate Securities | -0.01 | -0.00 | -0.19 *** |
| Crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | 0.53 *** | -0.30 | 0.16 |
| Government Securities | 0.22 *** | -0.19 | 0.08 |
| Commodity | -0.02 | -0.21 | -0.50 *** |
| Exchange Rates | 0.04 | -0.11 | -0.06 |
| Corporate Securities | 0.28 ** | 0.29 | -0.07 |

## A.4 In-sample Correlation Test Results on Blue Chip One Year Ahead Forecast Errors

Table A.9: Summary Results on Individual Assets in Each Assets Class: Full Sample

| Real GDP Growth Rate Forecasts | | | | |
|---|---|---|---|---|
| Asset Class | No. of Assets | Percentage | Max Corr. | Min Corr. |
| Equity | 268 | 70.77% | -0.53 | 0.56 |
| Government Securities | 239 | 17.15% | -0.36 | 0.25 |
| Commodity | 269 | 29.00% | -0.53 | 0.61 |
| Exchange Rates | 88 | 11.49% | -0.14 | 0.16 |
| Corporate Securities | 119 | 19.33% | -0.26 | 0.22 |
| CPI-based Inflation Rate Forecasts | | | | |
| Equity | 268 | 18.97% | -0.35 | 0.22 |
| Government Securities | 239 | 0.84% | -0.14 | 0.19 |
| Commodity | 269 | 22.30% | -0.23 | 0.27 |
| Exchange Rates | 88 | 27.59% | -0.11 | 0.25 |
| Corporate Securities | 119 | 0.84% | -0.01 | 0.15 |

Table A.10: Testing Factors of Each Asset Class: Full Sample

| | | | |
|---|---|---|---|
| Real GDP Growth Rate Forecasts | | | |
| Equity | 0.48 *** | 0.12 | 0.28 * |
| Government Securities | -0.33 ** | 0.07 * | -0.25 ** |
| Commodity | 0.58 *** | -0.09 | -0.16 |
| Exchange Rates | 0.05 | -0.05 | -0.04 |
| Corporate Securities | -0.02 | 0.04 | 0.07 |
| CPI-based Inflation Rate Forecasts | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | -0.38 *** | -0.01 | -0.04 |
| Government Securities | 0.00 | -0.08 | 0.19 ** |
| Commodity | 0.10 | 0.04 | 0.07 |
| Exchange Rates | -0.00 | -0.03 | 0.01 |
| Corporate Securities | 0.03 | -0.09 | -0.07 |

Table A.11: Summary Results on Individual Assets in Each Assets Class: Sub-samples

| Real GDP Growth Rate Forecast | | | | |
|---|---|---|---|---|
| Pre-crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 45.64% | -0.57 | 0.51 |
| Government Securities | 239 | 18.83% | -0.24 | 0.17 |
| Commodity | 269 | 30.86% | -0.55 | 0.41 |
| Exchange Rates | 88 | 11.49% | -0.14 | 0.10 |
| Corporate Securities | 119 | 35.29% | -0.21 | 0.08 |
| Crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 72.31% | -1.00 | 1.00 |
| Government Securities | 239 | 7.53% | -0.33 | 0.65 |
| Commodity | 269 | 36.43% | -0.48 | 0.91 |
| Exchange Rates | 88 | 28.74% | -0.35 | 0.48 |
| Corporate Securities | 119 | 38.66% | -0.22 | 0.55 |
| CPI-based Inflation Rate Forecast | | | | |
| Pre-crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 36.92% | -0.36 | 0.25 |
| Government Securities | 239 | 1.67% | -0.21 | 0.26 |
| Commodity | 269 | 29.37% | -0.33 | 0.36 |
| Exchange Rates | 88 | 18.39% | -0.18 | 0.19 |
| Corporate Securities | 119 | 3.36% | -0.16 | 0.08 |
| Crisis | | | | |
| Asset Class | No. of Assets | Percentage | Min Corr. | Max Corr. |
| Equity | 268 | 6.67% | -1.00 | 1.00 |
| Government Securities | 239 | 30.13% | -0.20 | 0.43 |
| Commodity | 269 | 3.72% | -0.35 | 0.59 |
| Exchange Rates | 88 | 16.09% | -0.16 | 0.42 |
| Corporate Securities | 119 | 52.94% | 0.04 | 0.41 |

Table A.12: Testing Factors of Each Asset Class: Sub-samples

| Real GDP Growth Rate Forecast | | | |
|---|---|---|---|
| Pre-crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | 0.48 *** | 0.13 | -0.33 *** |
| Government Securities | -0.23 ** | 0.15 ** | -0.21 * |
| Commodity | 0.36 *** | -0.22 * | 0.25 * |
| Exchange Rates | 0.07 | -0.03 | -0.01 |
| Corporate Securities | -0.02 | -0.02 | -0.14 * |
| Crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | 0.21 | 0.08 | -0.31 * |
| Government Securities | -0.10 | 0.27 * | 0.56 *** |
| Commodity | 0.86 ** | -0.22 | -0.25 |
| Exchange Rates | 0.14 | -0.09 | -0.06 |
| Corporate Securities | 0.27 ** | 0.37 ** | -0.20 ** |
| CPI-based Inflation Rate Forecast | | | |
| Pre-crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | -0.33 *** | -0.00 | 0.07 |
| Government Securities | 0.14 * | -0.02 | 0.25 ** |
| Commodity | -0.23 * | 0.06 | -0.08 |
| Exchange Rates | 0.02 | -0.03 | -0.06 * |
| Corporate Securities | -0.01 | -0.02 | -0.03 |
| Crisis | | | |
| Asset Class | corr(1st PC,errors) | corr(2nd PC,errors) | corr(3rd PC,errors) |
| Equity | 0.16 | 0.28 *** | 0.02 |
| Government Securities | -0.25 ** | 0.16 | 0.00 |
| Commodity | 0.48 | 0.03 | -0.76 *** |
| Exchange Rates | -0.02 | -0.07 | 0.02 |
| Corporate Securities | 0.09 | 0.34 *** | 0.00 |

## A.5 Out-of-Sample Forecast Ability Test Results with Alternative Benchmark Model

Benchmark: Forecast Error $e_t^h$ = c + $\alpha$*forecast + $\epsilon_b$

Model: Forecast Error $e_t^h$ = c + $\alpha$*forecast + $\beta$*financial series+ $\epsilon_m$

Table A.13: Can Financial Series Predict Forecast Errors

| Real GDP Growth Rate Forecast Errors | | | | | | |
|---|---|---|---|---|---|---|
| Forecast Horizon | Uncond. | P Value | Cond. | P Value | b0 | b1 |
| Current Quarter | +10.92 | 0.00 | +14.42 | 0.00 | 0.29 | 0.69 |
| One Quarter Ahead | +10.09 | 0.00 | +9.07 | 0.01 | 0.25 | 1.19 |
| One Year Ahead | +7.65 | 0.01 | +8.14 | 0.02 | 0.38 | 2.02 |
| **CPI-based Inflation Rate Forecast Errors** | | | | | | |
| Forecast Horizon | Uncond. | P Value | Cond. | P Value | b0 | b1 |
| Current Quarter | +4.87 | 0.03 | +6.90 | 0.03 | 0.14 | 3.28 |
| One Quarter Ahead | +2.67 | 0.10 | +6.82 | 0.03 | 0.18 | 4.70 |
| One Year Ahead | +0.83 | 0.36 | +1.21 | 0.55 | 0.05 | 0.35 |

Benchmark: Forecast Error $e_t^h$ = c + $\alpha$*forecast + $\epsilon_b$

Model: Forecast Error $e_t^h$ = c + $\alpha$*forecast + $\beta$*financial factors+ $\epsilon_m$

Table A.14: Can Financial Factors Predict Forecast Errors

| Real GDP Growth Rate Forecast Errors | | | | | | |
|---|---|---|---|---|---|---|
| Forecast Horizon | Uncond. | P Value | Cond. | P Value | b0 | b1 |
| Current Quarter | +9.42 | 0.00 | +7.86 | 0.02 | 0.31 | -0.06 |
| One Quarter Ahead | +9.95 | 0.00 | +8.72 | 0.01 | 0.22 | 1.36 |
| One Year Ahead | +5.34 | 0.02 | +10.03 | 0.01 | 0.47 | 2.87 |
| **CPI-based Inflation Rate Forecast Errors** | | | | | | |
| Forecast Horizon | Uncond. | P Value | Cond. | P Value | b0 | b1 |
| Current Quarter | +1.35 | 0.25 | +2.65 | 0.27 | -0.00 | 0.56 |
| One Quarter Ahead | +1.15 | 0.28 | +1.18 | 0.55 | 0.02 | 0.60 |
| One Year Ahead | +1.33 | 0.25 | +1.54 | 0.46 | 0.05 | 0.76 |

## A.6 List of Financial Variables

Table A.15: Commodity

Average Spot Price: Kerosene-Type Jet Fuel f.o.b. (Cents/Gallon)
Cash Price: London Gold Bullion, PM Fix (US Dollar/Troy oz)
Cocoa Futures Price: 1st Expiring Contract Open (Dollar/ton)
Cocoa Futures Price: 1st Expiring Contract Settlement (Dollar/ton)
Cocoa Futures Price: 2nd Expiring Contract Open (Dollar/ton)
Cocoa Futures Price: 2nd Expiring Contract Settlement (Dollar/ton)
Coffee Futures Price: 1st Expiring Contract Open (Cents/lb)
Coffee Futures Price: 1st Expiring Contract Settlement (Cents/lb)
Coffee Futures Price: 2nd Expiring Contract Open (Cents/lb)
Coffee Futures Price: 2nd Expiring Contract Settlement (Cents/lb)
Commodity Prices: Aluminum, LME Spot (Dollar/Metric Ton)
Commodity Prices: Benzene (Dollar/Gal)
Commodity Prices: Burlap, NY 10 Oz, 40” (Cents/Yard)
Commodity Prices: Copper Scrap, NY No. 2 (Cents/Lb)
Commodity Prices: Cotton, 1 1/16”, Avg Seven Markets (Cents/Lb)
Commodity Prices: Crude Oil, West Texas Intermediate (Dollar/Barrel)
Commodity Prices: Hides, Chicago, Heavy Native Steers (Cents/Lb)
Commodity Prices: Lead, Pig: Common Corroding (Cents/Lb)
Commodity Prices: Natural Rubber, New York TSR20 (Cents/Lb)
Commodity Prices: Random Lengths’ Framing Lumber Composite (Dollar/1000 Bd Ft)

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| |
|---|
| Commodity Prices: Random Lengths' Structural Panel Composite (Dollar/1000 Sq Ft) |
| Commodity Prices: Steel Scrap, No. 1 Heavy Melting (Dollar/gross Ton) |
| Commodity Prices: Tallow, Chicago Inedible Prime (Cents/Lb) |
| Commodity Prices: Zinc, Special High Grade (Cents/Lb) |
| Corn Futures Price: 1st Expiring Contract Settlement (Cents/bu) |
| Cotton Futures Price: 1st Expiring Contract Settlement (Cents/lb) |
| CRB Spot Commodity Price Index: All Commodities (1967=100) |
| CRB Spot Commodity Price Index: Fats and Oils (1967=100) |
| CRB Spot Commodity Price Index: Foodstuffs (1967=100) |
| CRB Spot Commodity Price Index: Livestock and Products (1967=100) |
| CRB Spot Commodity Price Index: Metals (1967=100) |
| CRB Spot Commodity Price Index: Raw Industrials (1967=100) |
| CRB Spot Commodity Price Index: Textiles and Fibers (1967=100) |
| Cushing OK Crude Oil Futures Price: 2-Month Contract Settlement (Dollar/barrel) |
| Cushing OK Crude Oil Futures Price: 2-Month Contract Settlement (Dollar/barrel) |
| Cushing OK WTI Spot Price FOB (Dollars per Barrel) |
| Domestic Spot Market Price: Crude Louisiana Sweet, St James (Dollar/Barrel) |
| Domestic Spot Market Price: Crude West Texas Sour, Midland (Dollar/Barrel) |
| Domestic Spot Market Price: West Texas Intermediate, Cushing (Dollar/Barrel) |
| Domestic Spot Mkt Price: Alaskan North Slope Oil Delivered Pacific (Dollar/Barrel) |
| Dow Jones-AIG Futures Price Index (1/2/91=100) |
| Europe Brent Spot Price FOB (Dollars per Barrel) |
| European Free Market Price: Brent Crude Oil (Dollar/Barrel) |
| FIBER Industrial Materials Price Index: All Items (1990=100) |
| FIBER Industrial Materials Price Index: Crude Oil and Benzene (1990=100) |
| FIBER Industrial Materials Price Index: Metals (1990=100) |
| FIBER Industrial Materials Price Index: Textiles (1990=100) |
| Gas Oil Futures Price: 1st Expiring Contract Settlement (Dollar/metric ton) |
| Gas Oil Futures Price: 1st Expiring Contract Settlement (Dollar/metric ton) |
| Gold Futures Price: 1st Expiring Contract Settlement (Dollar/troy oz) |
| Gold Futures Price: 6-Month Contract Settlement (Dollar/troy oz) |
| Gold Lending Rate: Local London Market Mean: One-Month (vs US Dollar) |
| Gold Lending Rate: Local London Market Mean: Three-Months (vs US Dollar) |
| Gulf Coast Residual Fuel Oil 1.0% Sulfur LP Spot Price CIF (Cents per Gallon) |
| High Grade Copper Futures Price: 1st Expiring Contract Settlement (Cents/lb) |
| Light Sweet Crude Oil Futures Price: 1st Expiring Contract Settlement (Dollar/bbl) |
| Light Sweet Crude Oil Futures Price: 1st Expiring Contract Settlement (Dollar/bbl) |
| Light Sweet Crude Oil Futures Price: 3-Month Contract Settlement (Dollar/bbl) |
| Light Sweet Crude Oil Futures Price: 3-Month Contract Settlement (Dollar/bbl) |
| Live Cattle Futures Price: 1st Expiring Contract Settlement (Cents/lb) |

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| |
|---|
| LME Aluminum Alloy: Closing 3-Month Forward Price (Dollar/Metric Tonne) |
| LME Aluminum Alloy: Closing Cash Price (Dollar/Metric Tonne) |
| LME Aluminum, 99.7% Purity: Closing 3-Month Forward Price (Dollar Metric/Tonne) |
| LME Aluminum, 99.7% Purity: Closing Cash Price (Dollar/Metric Tonne) |
| LME Copper, Grade A: Closing 3-Month Forward Price (Dollar/Metric Tonne) |
| LME Copper, Grade A: Closing Cash Price (Dollar/Metric Tonne) |
| LME Lead: Closing 3-Month Forward Price (Dollar/Metric Tonne) |
| LME Nickel: Closing 3-Month Forward Price (Dollar/Metric Tonne) |
| LME Nickel: Closing Cash Price (Dollar/Metric Tonne) |
| LME Tin: Closing 3-Month Forward Price (Dollar/Metric Tonne) |
| LME Tin: Closing Cash Price (Dollar/Metric Tonne) |
| LME Zinc: Closing Cash Price (Dollar/Metric Tonne) |
| LME: Aluminum Alloy Warehouse Stocks (Metric Tons) |
| LME: Aluminum Warehouse Stocks (Metric Tons) |
| LME: Copper Warehouse Stocks (Metric Tons) |
| LME: Copper Warehouse Stocks (Metric Tons) |
| LME: Lead Warehouse Stocks (Metric Tons) |
| LME: Lead Warehouse Stocks (Metric Tons) |
| LME: Nickel Warehouse Stocks (Metric Tons) |
| LME: Nickel Warehouse Stocks (Metric Tons) |
| LME: Tin Warehouse Stocks (Metric Tons) |
| LME: Tin Warehouse Stocks (Metric Tons) |
| LME: Zinc Warehouse Stocks (Metric Tons) |
| LME: Zinc Warehouse Stocks (Metric Tons) |
| Los Angeles CA Conventional Gasoline Regular Spot Price FOB (Cents per Gallon) |
| Los Angeles CA No 2 Diesel Spot Price FOB (Cents per Gallon) |
| Los Angeles CA Residual Fuel Oil 180 Spot Price FOB (Cents per Gallon) |
| Mont Belvieu TX Propane Fut Price: 1st Expiring Contract Settlement (Cts/gal) |
| Mont Belvieu TX Propane Fut Price: 1st Expiring Contract Settlement (Cts/gal) |
| Mont Belvieu TX Propane Futures Price: 2-Month Contract Settlement (Cts/gallon) |
| Mont Belvieu TX Propane Futures Price: 2-Month Contract Settlement (Cts/gallon) |
| Mont Belvieu TX Propane Futures Price: 3-Month Contract Settlement (Cts/gallon) |
| Mont Belvieu TX Propane Futures Price: 3-Month Contract Settlement (Cts/gallon) |
| Mont Belvieu TX Propane Spot Price FOB (Cents per Gallon) |
| Natural Gas Futures Price: 1st Expiring Contract Settlement (Dollar/MMBtu) |
| Natural Gas Futures Price: 1st Expiring Contract Settlement (Dollar/MMBtu) |
| Natural Gas Futures Price: 2-Month Contract Settlement (Dollar/MMBtu) |
| Natural Gas Futures Price: 2-Month Contract Settlement (Dollar/MMBtu) |
| New York Harbor Conventional Gasoline Regular Spot Price FOB (Cents per Gallon) |
| New York Harbor No 2 Diesel Low Sulfur Spot Price FOB (Cents per Gallon) |

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| |
|---|
| New York Harbor No 2 Heating Oil Spot Price FOB (Cents per Gallon) |
| New York Harbor Residual Fuel Oil 1.0% Sulfur LP Spot Price CIF (Cents/Gallon) |
| No 2 Heating Oil Futures Price: 1st Expiring Contract Settlement (Dollar/gal) |
| No 2 Heating Oil Futures Price: 1st Expiring Contract Settlement (Dollar/gal) |
| No 2 Heating Oil Futures Price: 3-Month Contract Settlement (Dollar/gal) |
| No 2 Heating Oil Futures Price: 3-Month Contract Settlement (Dollar/gal) |
| NY Harbor #2 Heating Oil Futures Price: 2-Month Contract Settlement(Dollar/gallon) |
| NY Harbor #2 Heating Oil Futures Price: 2-Month Contract Settlement(Dollar/gallon) |
| Oats Futures Price: 1st Expiring Contract Settlement (Cents/bu) |
| Oil Price: Fuel Oil No 2, NY (Dollar/Gallon) |
| Orange Juice Futures Price: 1st Expiring Contract Settlement (Cents/lb) |
| Palladium: Engelhard fabricated products (Dollar/troy oz) |
| Palladium: Engelhard Industrial bullion (Dollar/troy oz) |
| Philadelphia Exchange: Gold & Silver Index (Close, 6/7/89=90) |
| Philadelphia Semiconductor Index (12/01/93=100) |
| Platinum Futures Price: 1st Expiring Contract Settlement (Dollar/troy oz) |
| Pork Bellies Futures Price: 1st Expiring Contract Settlement (Cents/lb) |
| Propane Price, Mont Belvieu (Dollar/gal) |
| Random Length Lumber Futures: 1st Expiring Contract Settlement(Dollar/1000 board ft) |
| Reuters/Jefferies CRB Futures Price Index: All Commodities (1967=100) |
| Rotterdam [ARA] Gasoil Spot Price FOB (Cents per Gallon) |
| Rotterdam [ARA] Residual Fuel Oil Sulfur: 1.0 Spot Price FOB (Cents per Gallon) |
| Rough Rice Futures Price: 1st Expiring Contract Settlement (Cents/Cwt) |
| S&P GSCI 1 Month Forward Total Excess Return Index (Jan-16-95=100) |
| S&P GSCI 2 Month Forward Total Excess Return Index (Jan-16-95=100) |
| S&P GSCI 3 Month Forward Total Excess Return Index (Jan-16-95=100) |
| S&P GSCI 4 Month Forward Total Excess Return Index (Jan-16-95=100) |
| S&P GSCI 5 Month Forward Total Excess Return Index (Jan-16-95=100) |
| S&P GSCI Agricultural & LiveStock Excess Return Index (Jan-2-70=100) |
| S&P GSCI Agriculture Total Excess Return Index (Jan-2-70=100) |
| S&P GSCI Biofuel Total Excess Return Index (Jan-16-95=100) |
| S&P GSCI Brent Crude Total Excess Return Index (Jan-6-99=100) |
| S&P GSCI Cocoa Total Excess Return Index (Dec-30-83=100) |
| S&P GSCI 1 Month Forward Index (Jan-16-95=100) |
| S&P GSCI 1 Month Forward Total Return Index (Jan-16-95=100) |
| S&P GSCI 2 Month Forward Index (Jan-16-95=100) |
| S&P GSCI 2 Month Forward Total Return Index (Jan-16-95=100) |
| S&P GSCI 3 Month Forward Index (Jan-16-95=100) |
| S&P GSCI 3 Month Forward Total Return Index (Jan-16-95=100) |
| S&P GSCI 4 Month Forward Index (Jan-16-95=100) |

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S&P GSCI 4 Month Forward Total Return Index (Jan-16-95=100)

S&P GSCI 5 Month Forward Index (Jan-16-95=100)

S&P GSCI 5 Month Forward Total Return Index (Jan-16-95=100)

S&P GSCI Agricultural & LiveStock Index (Jan-2-70=100)

S&P GSCI Agricultural & LiveStock Total Return Index (Jan-2-70=100)

S&P GSCI Agricultural Commodities Nearby Index (Jan-2-70=100)

S&P GSCI Agricultural Commodities Total Return Index (Jan-2-70=100)

S&P GSCI All Crude Index (Dec-31-86=100)

S&P GSCI All Crude Total Excess Return Index (Dec-31-86=100)

S&P GSCI All Crude Total Return Index (Dec-31-86=100)

S&P GSCI All Wheat Index

S&P GSCI All Wheat Total Excess Return Index

S&P GSCI All Wheat Total Return Index

S&P GSCI Aluminum Index (Dec-31-90=100)

S&P GSCI Aluminum Total Excess Return Index (Dec-31-90=100)

S&P GSCI Aluminum Total Return Index (Dec-31-90=100)

S&P GSCI Biofuel Index (Jan-16-95=100)

S&P GSCI Biofuel Total Return Index (Jan-16-95=100)

S&P GSCI Brent Crude Total Return Index (Jan-6-99=100)

S&P GSCI Cocoa Index (Dec-30-83=100)

S&P GSCI Cocoa Total Return Index (Dec-30-83=100)

S&P GSCI Coffee Index (Dec-31-80=100)

S&P GSCI Coffee Total Excess Return Index (Dec-31-80=100)

S&P GSCI Coffee Total Return Index (Dec-31-80=100)

S&P GSCI Copper Index (Dec-30-76=100)

S&P GSCI Copper Total Excess Return Index (Dec-30-76=100)

S&P GSCI Copper Total Return Index (Dec-30-76=100)

S&P GSCI Corn Excess Returns Index (Dec-31-69=100)

S&P GSCI Corn Total Return Index (Dec-31-69=100)

S&P GSCI Cotton Index

S&P GSCI Cotton Total Excess Return Index

S&P GSCI Cotton Total Return Index

S&P GSCI Crude Oil Index

S&P GSCI Crude Oil Total Excess Return Index

S&P GSCI Crude Oil Total Return Index

S&P GSCI Energy and Metals Index (Jan-6-95=100)

S&P GSCI Energy and Metals Total Excess Return Index (Jan-6-95=100)

S&P GSCI Energy and Metals Total Return Index (Jan-6-95=100)

S&P GSCI Energy Commodities Nearby Index (12/31/82=100)

S&P GSCI Energy Commodities Total Return Index (12/31/82=100)

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| |
|---|
| S&P GSCI Four Energy Commodities Excess Return Index (Jan-16-95=100) |
| S&P GSCI Four Energy Commodities Index (Jan-16-95=100) |
| S&P GSCI Four Energy Commodities Total Return Index (Jan-16-95=100) |
| S&P GSCI GasOil Index |
| S&P GSCI GasOil Total Excess Return Index |
| S&P GSCI GasOil Total Return Index |
| S&P GSCI Gold Index |
| S&P GSCI Gold Total Excess Return Index |
| S&P GSCI Gold Total Return Index |
| S&P GSCI Grains Index (Jan-5-70=100) |
| S&P GSCI Grains Total Excess Return Index (Jan-5-70-100) |
| S&P GSCI Grains Total Return Index (Jan-5-70-100) |
| S&P GSCI Heating Oil Index (Dec-31-82=100) |
| S&P GSCI Heating Oil Total Excess Return Index (Dec-31-82=100) |
| S&P GSCI Heating Oil Total Return Index (Dec-31-82=100) |
| S&P GSCI Industrial Metals Nearby Index (Dec-31-76) |
| S&P GSCI Industrial Metals Total Excess Return Index (Dec-31-76) |
| S&P GSCI Industrial Metals Total Return Index (Dec-31-76) |
| S&P GSCI Lead Index (Dec-30-94=100) |
| S&P GSCI Lead Total Excess Return Index (Dec-30-94=100) |
| S&P GSCI Lead Total Return Index (Dec-30-94=100) |
| S&P GSCI Lean Hogs Index (Dec-31-75=100) |
| S&P GSCI Lean Hogs Total Excess Return Index (Dec-31-75=100) |
| S&P GSCI Lean Hogs Total Return Index (Dec-31-75=100) |
| S&P GSCI Light Energy CPW 4 Total Excess Return Index (Jan-02-70=100) |
| S&P GSCI Light Energy CPW 4 Total Return Index (Jan-02-70=100) |
| S&P GSCI Light Energy Index -CPW 4 (Jan-02-70=100) |
| S&P GSCI Live Cattle Excess Returns Index (Dec-31-69=100) |
| S&P GSCI Live Cattle Index (Dec-31-69=100) |
| S&P GSCI Live Cattle Total Return Index (Dec-31-69=100) |
| S&P GSCI Livestock Nearby Index (Jan-2-70=100) |
| S&P GSCI Livestock Total Excess Return Index (Jan-2-70=100) |
| S&P GSCI Livestock Total Return Index (Jan-2-70=100) |
| S&P GSCI Natural Gas Index (Dec-31-93=100) |
| S&P GSCI Natural Gas Total Excess Return Index (Dec-31-93=100) |
| S&P GSCI Natural Gas Total Return Index (Dec-31-93=100) |
| S&P GSCI Nickel Index (Dec-31-92=100) |
| S&P GSCI Nickel Total Return Index (Dec-31-92=100) |
| S&P GSCI Non-Energy Nearby Index (Jan-2-70=100) |
| S&P GSCI Non-Energy Total Excess Return Index (Jan-2-70=100) |

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S&P GSCI Non-Energy Total Return Index (Jan-2-70=100)

S&P GSCI Non-Livestock Index (Jan-5-96=100)

S&P GSCI Petroleum ex-GasOil Total Excess Return Index (Dec-30-82=100)

S&P GSCI Precious Metal Nearby Index (Jan-2-73=100)

S&P GSCI Precious Metals Total Excess Return Index (Dec-29-72=100)

S&P GSCI Precious Metals Total Return Indx (Dec-29-72=100)

S&P GSCI Silver Index (Dec-29-72=100)

S&P GSCI Silver Total Excess Return Index (Dec-29-72=100)

S&P GSCI Silver Total Return Index (Dec-29-72=100)

S&P GSCI Softs Index (Jan-16-95=100)

S&P GSCI Softs Total Excess Return Index (Jan-16-95=100)

S&P GSCI Softs Total Return Index (Jan-16-95=100)

S&P GSCI Soybeans Excess Returns Index (Dec-31-69=100)

S&P GSCI Soybeans Index (Dec-31-69=100)

S&P GSCI Soybeans Total Return Index (Dec-31-69=100)

S&P GSCI Sugar Index (Dec-29-72=100)

S&P GSCI Sugar Total Excess Return Index (Dec-29-72=100)

S&P GSCI Total Excess Return Index (Jan-2-70=100)

S&P GSCI Total Return Index (Jan-2-70=100)

S&P GSCI Ultra-Light Energy CPW 8 Excess Return Index (Jan=2-70=100)

S&P GSCI Ultra-Light Energy CPW 8 Total Return Index (Jan=2-70=100)

S&P GSCI Ultra-Light Energy Index CPW 8 (Jan=2-70=100)

S&P GSCI Unleaded Gasoline Index (Dec-31-87=100)

S&P GSCI Unleaded Gasoline Total Excess Return Index (Dec-31-87=100)

S&P GSCI Unleaded Gasoline Total Return Index (Dec-31-87=100)

S&P GSCI Wheat Excess Returns Index (Dec-31-69=100)

S&P GSCI Wheat Index (Dec-31-69=100)

S&P GSCI Wheat Total Return Index (Dec-31-69=100)

S&P GSCI Zinc Index (Dec-31=90=100)

S&P GSCI Zinc Total Excess Return Index (Dec-31=90=100)

S&P GSCI Zinc Total Return Index (Dec-31=90=100)

Singapore Gasoil Spot Price FOB (Cents per Gallon)

Singapore Leaded Regular Gasoline Spot Price FOB (Cents per Gallon)

Singapore Residual Fuel Oil 180 Spot Price FOB (Cents per Gallon)

Soybean Oil Futures Price: 1st Expiring Contract Settlement (Cents/lb)

Soybeans Futures Price: 1st Expiring Contract Settlement (Cents/bu)

Spot Price: Los Angeles CA Kerosene-Type Jet Fuel f.o.b. (Cents/Gallon)

Spot Price: New York Harbor Kerosene-Type Jet Fuel f.o.b. (Cents/Gallon)

Spot Price: Rotterdam [ARA] Kerosene-Type Jet Fuel f.o.b. (Cents/Gallon)

Spot Price: Singapore Kerosene-Type Jet Fuel f.o.b. (Cents/Gallon)

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Spot Price: U.S. Gulf Coast Kerosene-Type Jet Fuel f.o.b. (Cents/Gallon)

Unleaded Gas Price, Premium Non-Oxygenated, NY (Dollar/gal)

Unleaded Gas Price, Regular, Non-Oxygenated, NY (Dollar/gal)

US Gulf Coast Conventional Gasoline Regular Spot Price FOB (Cents per Gallon)

US Gulf Coast No 2 Diesel Low Sulfur Spot Price FOB (Cents per Gallon)

US Gulf Coast No 2 Heating Oil Spot Price FOB (Cents per Gallon)

US Midcontinent Propane Spot Price FOB (Cents per Gallon)

Wheat Futures Price: 1st Expiring Contract Settlement (Cents/bu)

World Sugar Futures Price: 1st Expiring Contract Settlement (Cents/lb)

## Table A.16: Foreign Exchange

Argentina: Spot Exchange Middle Rate, NY Close (Pesos/US Dollar)

Australia: Spot Exchange Middle Rate, NY Close (Australian Dollar/US Dollar)

Brazil: Spot Exchange Middle Rate, NY Close (Reais/US Dollar)

Canada: Spot Exchange Middle Rate, NY Close (Canadian Dollar/US Dollar)

Chile: Spot Exchange Middle Rate, NY Close (Pesos/US Dollar)

China: Spot Exchange Middle Rate, NY Close(Yuan/US Dollar)

Colombia: Spot Exchange Middle Rate, NY Close (Pesos/US Dollar)

Euro 1-Month Forward Rate: U.S. (US Dollar/Euro)

Euro 3-Month Forward Rate: U.S. (US Dollar/Euro)

Europe: Spot Exchange Middle Rate, NY Close (Euro/US Dollar)

Foreign Exchange Rate: Australia (US Dollar/Australian Dollar)

Foreign Exchange Rate: Australia (US Dollar/Australian Dollar)

Foreign Exchange Rate: Austria (Schilling/US Dollar)

Foreign Exchange Rate: Belgium (Franc/US Dollar)

Foreign Exchange Rate: Brazil (Real/US Dollar)

Foreign Exchange Rate: Brazil (Real/US Dollar)

Foreign Exchange Rate: Canada (C Dollar/US Dollar)

Foreign Exchange Rate: Canada (C Dollar/US Dollar)

Foreign Exchange Rate: European Monetary Union (US Dollar/Euro)

Foreign Exchange Rate: Finland (Markka/US Dollar)

Foreign Exchange Rate: France (Franc/US Dollar)

Foreign Exchange Rate: Germany (D. Mark/US Dollar)

Foreign Exchange Rate: Hong Kong (Dollar/US Dollar)

Foreign Exchange Rate: Hong Kong (Dollar/US Dollar)

Foreign Exchange Rate: India (Rupee/US Dollar)

Foreign Exchange Rate: India (Rupee/US Dollar)

Foreign Exchange Rate: Ireland (US Dollar/Pound)

Foreign Exchange Rate: Italy (Lira/US Dollar)

Foreign Exchange Rate: Japan (Yen/US Dollar)

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| |
|---|
| Foreign Exchange Rate: Japan (Yen/US Dollar) |
| Foreign Exchange Rate: Malaysia (Ringgit/US Dollar) |
| Foreign Exchange Rate: Malaysia (Ringgit/US Dollar) |
| Foreign Exchange Rate: Mexico (Peso/US Dollar) |
| Foreign Exchange Rate: Mexico (Peso/US Dollar) |
| Foreign Exchange Rate: Netherlands (Guilder/US Dollar) |
| Foreign Exchange Rate: People's Republic of China (Yuan/US Dollar) |
| Foreign Exchange Rate: People's Republic of China (Yuan/US Dollar) |
| Foreign Exchange Rate: Portugal (Escudo/US Dollar) |
| Foreign Exchange Rate: Singapore (Singapore Dollar/US Dollar) |
| Foreign Exchange Rate: Singapore (Singapore Dollar/US Dollar) |
| Foreign Exchange Rate: South Korea (Won/US Dollar) |
| Foreign Exchange Rate: South Korea (Won/US Dollar) |
| Foreign Exchange Rate: Spain (Peseta/US Dollar) |
| Foreign Exchange Rate: Sri Lanka (Rupee/US Dollar) |
| Foreign Exchange Rate: Sri Lanka (Rupee/US Dollar) |
| Foreign Exchange Rate: Sweden (Krona/US Dollar) |
| Foreign Exchange Rate: Sweden (Krona/US Dollar) |
| Foreign Exchange Rate: Switzerland (Swiss Franc/US Dollar) |
| Foreign Exchange Rate: Switzerland (Swiss Franc/US Dollar) |
| Foreign Exchange Rate: Taiwan (Taiwan Dollar/US Dollar) |
| Foreign Exchange Rate: Taiwan (Taiwan Dollar/US Dollar) |
| Foreign Exchange Rate: Thailand (Baht/US Dollar) |
| Foreign Exchange Rate: Thailand (Baht/US Dollar) |
| Foreign Exchange Rate: United Kingdom (US Dollar/Pound) |
| Foreign Exchange Rate: United Kingdom (US Dollar/Pound) |
| Foreign Exchange Rate: Venezuela (Bolivar Fuerte/US Dollar) |
| FRB Exchange Rate: Australia/Brazil (A Dollar/Real) |
| FRB Exchange Rate: United Kingdom/United States (Pound/US Dollar) |
| FRB Exchange Rate: United States/European Monetary Union (Euro/US Dollar) |
| Hong Kong: Spot Exchange Middle Rate, NY Close (Hong Kong Dollar/US Dollar) |
| India: Spot Exchange Middle Rate, NY Close (Rupees/US Dollar) |
| Indonesia: Spot Exchange Middle Rate, NY Close (Rupiah/US Dollar) |
| International Currency Rate: Canadian Dollar: Short-term (%) |
| International Currency Rate: Euro: Short-Term (%) |
| International Currency Rate: Japanese Yen: Short-term (%) |
| International Currency Rate: Singapore Dollar: Short-term (%) |
| International Currency Rate: Swiss Franc: Short-term (%) |
| International Currency Rate: U.K. Pound: Short-term (%) |
| International Currency Rate: U.S. Dollar: Short-term (%) |

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|---|
| Israel: Spot Exchange Middle Rate, NY Close (New.Sheqalim/US Dollar) |
| Japan: Spot Exchange Middle Rate, NY Close (Yen/US Dollar) |
| JP Morgan Trade-Weighted Exchange Rate Index: U.S. (2000=100) |
| Malaysia: Spot Exchange Middle Rate, NY Close (Ringgit/US Dollar) |
| Mexico: Spot Exchange Middle Rate, NY Close (New.Pesos/US Dollar) |
| New Zealand: Spot Exchange Middle Rate, NY Close (New Zealand Dollar/US Dollar) |
| Nominal Broad Trade-Weighted Exchange Value of the US Dollar (1/97=100) |
| Nominal Trade-Weighted Exch Value of US Dollar vs Major Currencies (3/73=100) |
| Nominal Trade-Weighted Exchange Value of US Dollar vs OITP (1/97=100) |
| Philippines: Spot Exchange Middle Rate, NY Close (Pesos/US Dollar) |
| Russia: Spot Exchange Middle Rate, NY close (Rubles/US Dollar) |
| S. Korea: Spot Exchange Middle Rate, NY Close (Won/US Dollar) |
| Singapore: Spot Exchange Middle Rate, NY Close (Singapore Dollar/US Dollar) |
| Sweden: Spot Exchange Middle Rate, NY Close (Kronor/US Dollar) |
| Switzerland: Spot Exchange Middle Rate, NY Close (Francs/US Dollar) |
| Taiwan: Spot Exchange Middle Rate, NY Close (Taiwan Dollar/US Dollar) |
| Thailand: Spot Exchange Middle Rate, NY Close (Baht/US Dollar) |
| United Kingdom: Spot Exchange Middle Rate, NY Close (Pounds/US Dollar) |
| Venezuela: Spot Exchange Middle Rate, NY Close (Bolivar Fuerte/US Dollar) |

## Table A.17: Corporate Securities

| |
|---|
| 15-Day A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 15-Day A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 15-Day AA Financial Commercial Paper (% per annum) |
| 15-Day AA Financial Commercial Paper (% per annum) |
| 15-Day AA Nonfinancial Commercial Paper (% per annum) |
| 15-Day AA Nonfinancial Commercial Paper (% per annum) |
| 1-Day A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 1-Day A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 1-Day AA Financial Commercial Paper (% per annum) |
| 1-Day AA Financial Commercial Paper (% per annum) |
| 1-Day AA Nonfinancial Commercial Paper (% per annum) |
| 1-Day AA Nonfinancial Commercial Paper (% per annum) |
| 1-Month A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 1-Month A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 1-Month AA Financial Commercial Paper (% per annum) |
| 1-Month AA Financial Commercial Paper (% per annum) |
| 1-Month AA Nonfinancial Commercial Paper (% per annum) |
| 1-Month AA Nonfinancial Commercial Paper (% per annum) |
| 1-Month Certificates of Deposit, Secondary Market (% p.a.) |

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|---|
| 1-Month Eurodollar Deposits (London Bid) (% p.a.) |
| 1-Month Financial Commercial Paper (% per annum) |
| 1-Month London Interbank Bid Rate (%) |
| 1-Month London Interbank Offered Rate (%) |
| 1-Month Nonfinancial Commercial Paper (% per annum) |
| 1-Year London Interbank Offered Rate: Based on US Dollar (%) |
| 2-Month A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 2-Month A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 3-Month Certificates of Deposit, Secondary Market (% p.a.) |
| 3-Month Eurodollar Deposits (London Bid) (% p.a.) |
| 3-Month London Interbank Bid Rate (%) |
| 3-Month London Interbank Offered Rate (%) |
| 6-Month Certificates of Deposit, Secondary Market (% p.a.) |
| 6-Month Eurodollar Deposits (London Bid) (% p.a.) |
| 6-Month London Interbank Bid Rate (%) |
| 6-Month London Interbank Offered Rate (%) |
| 6-Month London Interbank Offered Rate: Based on US Dollar (%) |
| 7-Day A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 7-Day A2/P2/F2 Nonfinancial Commercial Paper (% per annum) |
| 7-Day AA Financial Commercial Paper (% per annum) |
| 7-Day AA Financial Commercial Paper (% per annum) |
| 7-Day AA Nonfinancial Commercial Paper (% per annum) |
| 7-Day AA Nonfinancial Commercial Paper (% per annum) |
| 7-Day London Interbank Bid Rate (%) |
| 7-Day London Interbank Offered Rate (%) |
| Merrill Lynch Agency Master: AAA Rated: Effective Yield (%) |
| Merrill Lynch Agency Master: AAA Rated: Yield to Maturity (%) |
| Merrill Lynch Agency Master: AAA Rated: Yield to Worst (%) |
| Merrill Lynch Asset-Backeds: Automobiles Fixed Rate: Effective Yld(%) |
| Merrill Lynch Asset-Backeds: Home Equity: Fixed Rate: Effective Yield (%) |
| Merrill Lynch Broad Market: Effective Yield (%) |
| Merrill Lynch Broad Market: Yield to Maturity (%) |
| Merrill Lynch Broad Market: Yield to Worst (%) |
| Merrill Lynch Corporate & Government Master: Effective Yield (%) |
| Merrill Lynch Corporate & Government Master: Yield to Maturity (%) |
| Merrill Lynch Corporate & Government Master: Yield to Worst (%) |
| Merrill Lynch Corporate Bonds: 1 to 3 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: 3 to 5 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: 5 to 7 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: A Rated: Effective Yield (%) |

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|---|
| Merrill Lynch Corporate Bonds: AA Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: AAA Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: BBB Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Financials: 1 to 3 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Financials: 3 to 5 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Financials: 5 to 7 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Financials: 7 to 10 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Financials: A Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Financials: AA Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Financials: AAA Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Financials: BBB Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Financials: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Industrials: 1 to 3 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Industrials: 3 to 5 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Industrials: 5 to 7 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Industrials: 7 to 10 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Industrials: A Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Industrials: AA Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Industrials: AAA Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Industrials: BBB Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Industrials: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Utilities: 1 to 3 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Utilities: 3 to 5 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Utilities: 5 to 7 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Utilities: 7 to 10 Years: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Utilities: A Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Utilities: AA Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Utilities: BBB Rated: Effective Yield (%) |
| Merrill Lynch Corporate Bonds: Utilities: Effective Yield (%) |
| Merrill Lynch Corporate Master: Effective Yield (%) |
| Merrill Lynch Domestic Master: Effective Yield (%) |
| Merrill Lynch Domestic Master: Yield to Maturity (%) |
| Merrill Lynch Domestic Master: Yield to Worst (%) |
| Merrill Lynch High Yield Corporate Master II: Effective Yield (%) |
| Merrill Lynch High Yield Corporates: B Rated: Effective Yield (%) |
| Merrill Lynch High Yield Corporates: BB Rated: Effective Yield (%) |
| Merrill Lynch High Yield Corporates: Cash Pay: B Rated: Effective Yield (%) |
| Merrill Lynch High Yield Corporates: Cash Pay: BB Rated: Effective Yield (%) |
| Merrill Lynch High Yield Corporates: Cash Pay: Effective Yield (%) |
| Merrill Lynch High Yield Corporates: Rated: CCC & Lower: Effective Yield (%) |

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Merrill Lynch High Yield: Cash Pay: Rated CCC & Lower: Effective Yield (%)

Merrill Lynch Mortgage Master: Effective Yield (%)

Merrill Lynch Mortgage Master: Effective Yield (%)

Merrill Lynch Mortgages: All FHLMC & FNMA 30 Year: Effective Yield (%)

Merrill Lynch Mortgages: FNMA 30 Year Current Coupon: Effective Yield (%)

Merrill Lynch Mortgages: GNMA 30 Year Current Coupon: Effective Yield (%)

Merrill Lynch Treasuries: Current 10 Year: Yield to Maturity (%)

Merrill Lynch Treasuries: Current 10 Year: Yield to Worst (%)

Merrill Lynch Treasury Master: Effective Yield (%)

Merrill Lynch Treasury Master: Yield to Maturity (%)

Merrill Lynch Treasury Master: Yield to Worst (%)

Merrill Lynch Treasury/Agency Master: AAA Rated: Effective Yield (%)

Merrill Lynch Treasury/Agency Master: AAA Rated: Yield to Maturity (%)

Merrill Lynch Treasury/Agency Master: AAA Rated: Yield to Worst (%)

Moody's Seasoned Aaa Corporate Bond Yield (% p.a.)

Moody's Seasoned Baa Corporate Bond Yield (% p.a.)

One-Year London Interbank Bid Rate (%)

One-Year London Interbank Offered Rate (%)

Overnight London Interbank Bid Rate (%)

Overnight London Interbank Offered Rate (%)

## Table A.18: Equity

Alternext Interactive Week Internet Index

Alternext Major Markets Index (Close, 1/27/89=229)

CBOE Market Stats: Dow Jones Industrial Avg [DJX]: Call Open Interest

CBOE Market Stats: Dow Jones Industrial Avg [DJX]: Call Volume

CBOE Market Stats: Dow Jones Industrial Avg [DJX]: Put Open Interest

CBOE Market Stats: Dow Jones Industrial Avg [DJX]: Put Volume

CBOE Market Stats: Index Option: Total Index Call Volume

CBOE Market Stats: Index Option: Total Index Put Volume

CBOE Market Stats: Nasdaq 100 Index [NDX]: Call Open Interest

CBOE Market Stats: Nasdaq 100 Index [NDX]: Call Volume

CBOE Market Stats: Nasdaq 100 Index [NDX]: Put Open Interest

CBOE Market Stats: Nasdaq 100 Index [NDX]: Put Volume

CBOE Market Stats: Put/Call Ratio

CBOE Market Stats: Russell 2000 Index [RUT]: Call Open Interest

CBOE Market Stats: Russell 2000 Index [RUT]: Call Volume

CBOE Market Stats: Russell 2000 Index [RUT]: Put Open Interest

CBOE Market Stats: Russell 2000 Index [RUT]: Put Volume

CBOE Market Stats: S&P 100 Index [OEX]: Call Open Interest

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CBOE Market Stats: S&P 100 Index [OEX]: Call Volume

CBOE Market Stats: S&P 100 Index [OEX]: Put Open Interest

CBOE Market Stats: S&P 100 Index [OEX]: Put Volume

CBOE Market Stats: S&P 500 Index [SPX]: Call Open Interest

CBOE Market Stats: S&P 500 Index [SPX]: Call Volume

CBOE Market Stats: S&P 500 Index [SPX]: Put Open Interest

CBOE Market Stats: S&P 500 Index [SPX]: Put Volume

CBOE Market Stats: Sum of All Products: Total Call Open Interest

CBOE Market Stats: Sum of All Products: Total Call Volume

CBOE Market Stats: Sum of All Products: Total Put Open Interest

CBOE Market Stats: Sum of All Products: Total Put Volume

CBOE Market Volatility Index, VIX

CBOE Market Volatility Index, VXO

CBOE NASDAQ Volatility Index

CBOE NASDAQ Volatility Index, VXN

Daily Bond Volume: New York Stock Exchange (Thous.Dollar)

Dow Jones Global Index: World (Avg, 12/31/91=100)

Dow Jones Global Index: World excl U.S. (12/31/91=100)

Dow Jones Internet Commerce Index (6/30/98=100)

Dow Jones Internet Composite Index (6/30/98=100)

Dow Jones Internet Services (6/30/98=100)

Dow Jones U.S Index (12/31/91=100)

Dow Jones U.S. Completion Total Stock Market Total Return Index(Jan-30-87=1.11)

Dow Jones U.S. Total Stock Market Total Return Index (Dec-31-70=830.27)

Dow Jones-AIG Spot Price Index (1/7/91=100)

Eurofirst 300 Eurozone: FTSE Share Price Index (7/25/97=1000)

Eurofirst 300: FTSE Share Price Index (7/25/97=1000)

Europe: DJ STOXX 50 Price Index: Based in US Dollar (EOP, 12/31/91=1000)

Europe: DJ STOXX Broad Price Index: Based in Euro (EOP, 12/31/91=100)

Europe: DJ STOXX Broad Price Index: Based in US Dollar (EOP, 12/31/91=100)

Euro-zone: DJ EURO STOXX 50 Price Index: Based in Euro (EOP, 12/31/91=1000)

Euro-zone: DJ EURO STOXX 50 Price Index: Based in US Dollar (EOP, 12/31/91=1000)

Euro-zone: DJ EURO STOXX Broad Price Index: Based in Euro (EOP, 12/31/91=100)

Euro-zone: DJ EURO STOXX Broad Price Index: Based in US Dollar (EOP, 12/31/91=100)

Merrill Lynch Option Volatility Estimate Index: 1-month

Merrill Lynch Option Volatility Estimate Index: 3-month

Merrill Lynch Swaption Volatility Estimate Index: 3-month

Merrill Lynch Swaption Volatility Estimate Index: 6-month

Morgan Stanley Consumer Index (911231=200)

Morgan Stanley Cyclical Index (911231=200)

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Morgan Stanley High Tech 35 Index (12/16/94=100)

NASDAQ: Number of Advancing Stocks (Units)

NASDAQ: Number of Declining Stocks (Units)

NASDAQ: Stock Volume (Thousand Shares)

NYSE Volume Traded: Preliminary and Final Figures (Thousand Shares)

NYSE Volume Traded: WSJ Preliminary Estimates (Thousands Shares)

NYSE: Number of Advancing Stocks (Units)

NYSE: Number of Declining Stocks (Units)

PSE Technology 100 Index (5/18/93=100.1)

Russell 1000 Growth Share Price Index (12/31/90=100)

Russell 1000 Share Price Index (12/29/78=100)

Russell 1000 Share Price Index (12/31/86=130)

Russell 1000 Value Share Price Index (12/31/90=100)

Russell 2000 Growth Share Price Index (5/31/93=1000)

Russell 2000 Share Price Index (12/29/78=100)

Russell 2000 Share Price Index (12/31/86=135)

Russell 2000 Value Share Price Index (5/31/93=1000)

Russell 3000 Growth Share Price Index (5/31/95=1000)

Russell 3000 Share Price Index (12/29/78=100)

Russell 3000 Share Price Index (12/31/86=140)

Russell 3000 Value Share Price Index (5/31/93=1000)

S&P 400 Midcap Futures Price: 1st Expiring Contract Open (Index)

S&P 400 Midcap Futures Price: 1st Expiring Contract Open (Index)

S&P 400 Midcap Futures Price: 1st Expiring Contract Settlement (Index)

S&P 400 Midcap Futures Price: 1st Expiring Contract Settlement (Index)

S&P 500 Futures Price: 1st Expiring Contract Settlement (Index)

S&P 500: Financials - GICS (12/30/94=100)

Standard & Poor's 500 Industrial Stock Price Index (1941-43=10)

Standard & Poor's 500 Stock Price Index (1941-43=10)

Standard & Poors' Smallcap 600 Stock Price Index (12/31/93=100)

Stock Price Averages: Dow Jones 10 Industrials, NYSE

Stock Price Averages: Dow Jones 15 Utilities, NYSE (Close)

Stock Price Averages: Dow Jones 20 Transportation, NYSE (Close)

Stock Price Averages: Dow Jones 30 Industrials, NYSE (Close)

Stock Price Averages: Dow Jones 5 Industrials, NYSE

Stock Price Averages: Dow Jones 65 Composite, NYSE (Close)

Stock Price Index: Alternext Average (8/31/73=100)

Stock Price Index: France: Paris CAC 40 (12/31/87=1000)

Stock Price Index: Germany: Frankfurt Xetra Dax (12/30/87=1000)

Stock Price Index: Italy: Milan Mib30 (12/31/92=10000)

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Stock Price Index: Italy: Milan Mibtel General

Stock Price Index: Japan: Nikkei 225 Average (5/16/49=100)

Stock Price Index: NASDAQ 100

Stock Price Index: NASDAQ Composite (2/5/71=100)

Stock Price Index: NASDAQ Industrials (2/5/71=100)

Stock Price Index: NYSE Composite (Dec. 31, 2002=5000)

Stock Price Index: S&P/TSX Composite Index (1975=1000)

Stock Price Index: Spain: Madrid General Index (12/30/85=100)

Stock Price Index: Standard & Poor's 100 (Close, 1/2/76=100)

Stock Price Index: UK: London Financial Times 100 (1/2/84=1000)

Value Line Arithmetic Index

Value Line Geometric Index

Eurofirst 100: FTSE Share Price Index (12/31/2002=3000)

Eurofirst 80: FTSE Share Price Index (12/31/2002=3000)

AMEX: Sock Volume Decline (Thousand Shares)

Stock Price Index: Netherlands AEX (1983=100)

Stock Price Index: Sweden: Stockholm Affarsvarlden (12/29/95=100)

Stock Price Index: Jordan: Amman Financial Market Stock Index DISC

Stock Price Index: Jordan: Amman Stock Index weighted by Market Cap (1991=1000)

Alternext: Issues Traded: New Highs (Units)

Alternext: Issues Traded: New Lows (Units)

Alternext: Issues Traded (Units)

Alternext: Stock Volume (Thousand Shares)

Stock Price Index: Greece: Athens, SE (12/31/80=100)

Alternext: Number of Unchanged Stocks (Units)

Stock Price Index: Australia: All Ordinaries (1/1/80=500)

NYSE: Stock Volume Advance (Thousand Shares)

Stock Price Index: Thailand: Bangkok SET (4/30/75=100)

Stock Price Index: Brussels: Bel-20 Index (1/1/91=1000)

Stock Price Index: Brazil: Bovespa (12/29/83=100)

Stock Price Index: India: Bombay Sensex (1979=100)

Stock Price Index: Hungary: BUX (1/2/91=1000)

S&P Commodity Index Arithmetic Series Price Index

Alternext: Number of Advancing Stocks (Units)

Alternext: Stock Volume Advance (Thousand Shares)

Alternext: Number of Declining Stocks (Units)

S&P Commodity Index Arithmetic Series Continuous Contract

NYSE Common Stock: Number of Advancing Stocks (Units)

Stock Price Index: New Zealand: NZSE 40 Capital DISC (7/1/86=100)

Stock Price Index: New Zealand: NZX 50 (3/3/2003=1880.86)

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S&P Commodity Index Arithmetic Series Total Return

Stock Price Index: Amsterdam ANP-CBS General (1983=100)

NYSE Common Stock: Number of Declining Stocks (Units)

Stock Price Index: Egypt: Cairo SE General

NYSE Common Stock: Number of Unchanged Stocks (Units)

Stock Price Index: Czech Republic: PX50 (3/1/95=100)

Stock Price Index: China: Dow Jones China 88 (12/31/93=100)

Dow Jones 5 Industrials, NYSE: Total Return

Dow Jones 10 Industrials, NYSE: Total Return

Dow Jones 65 Composite, NYSE: Total Return

Stock Price Averages: Dow Jones 30 Industrials, NYSE (High)

Stock Price Averages: Dow Jones 30 Industrials, NYSE (Low)

Dow Jones 30 Industrials, NYSE: Total Return

Dow Jones 20 Transportation, NYSE: Total Return

Dow Jones 15 Utilities, NYSE: Total Return

Stock Price Index: China: Dow Jones Shanghai (12/31/93=100)

Stock Price Index: China: Dow Jones Shenzhen (12/31/93=100)

NYSE: Stock Volume Decline (Thousand Shares)

Stock Price Index: UK: London Financial Times 30 (1/9/84=800)

Stock Price Index: UK: London Financial Times All Share (4/10/62=100)

Stock Price Index: Argentina: Buenos Aires General (6/30/2000=19570.98)

Stock Price Index: Finland: OMX Helsinki General (12/28/90=100)

Stock Price Index: Hong Kong: Hang Seng (7/31/64=100)

Stock Price Index: Colombia: IGBC (7/3/01=1001.99)

Stock Price Index: Chile: IGPA General (12/31/80=100)

Stock Price Index: Turkey: IMKB Nat 100 (1986=100)

Stock Price Index: Mexico IPC (11/78=0.78)

Stock Price Index: Ireland: ISEQ Overall (1/4/88=1000)

Stock Price Index: Indonesia: Jakarta Composite (8/10/82=100)

Stock Price Index: South Africa: FTSE/JSE All Share Index

Stock Price Index: South Africa: FTSE/JSE Top 40 Index

Stock Price Index: Pakistan: Karachi Stock Exchange 100

Stock Price Index: Denmark: OMX Copenhagen Benchmark (12/31/95=100)

Stock Price Index: Denmark: OMX Copenhagen 20 (7/3/89=100)

Stock Price Index: Malaysia: KLSE Composite (4/4/86=100)

Stock Price Index: South Korea: Korea Composite EX (1/4/80=100)

Stock Price Index: Peru: Lima General IGBVL (12/30/91=100)

Stock Price Index: Casablanca Most Active Share Price Index (12/31/91=1000)

Stock Price Index: Philippines: Manila Composite (1/2/85=100)

Stock Price Index: Casablanca All Share Stock Price Index

*Continued on next page*

Stock Price Index: Argentina: Merval (6/30/86=.01 US Dollar)

Standard & Poors' Midcap 400 Stock Price Index (12/31/90=100)

Merrill Lynch Early Cyclical Index

Merrill Lynch Late Cyclicals Index

Merrill Lynch Stable Growth Index

Merrill Lynch Swaption Volatility Estimate Index: 1-month

Merrill Lynch Option Volatility Estimate Index: 6-month

NASDAQ: Issues Traded: New Highs (Units)

NASDAQ: Issues Traded: New Lows (Units)

NASDAQ: Issues Traded (Units)

NASDAQ: Stock Volume Advance (Thousand Shares)

NASDAQ: Stock Volume Decline (Thousand Shares)

Stock Price Index: Nigeria SE All Share

Stock Price Index: Japan: Nikkei 300 Index (10/1/82=100)

NASDAQ: Number of Unchanged Stocks (Units)

NYSE Energy Stock Price Index (Dec 31, 2002=5000)

NYSE Health Care Stock Price Index (Dec 31, 2002=5000)

NYSE Financial Stock Price Index (Dec 31, 2002=5000)

NYSE: Issues Traded: New Highs (Units)

NYSE: Issues Traded: New Lows (Units)

NYSE: Number of Issues Traded (Units)

Stock Price Index: Norway: Oslo OBX Index

Stock Price Index: Norway: Oslo OSE All Share Index (12/29/95=100)

Stock Price Index: Norway: Oslo Benchmark Index (12/29/95=100)

Ocean Tomo 300 Patent Index (12/31/2004=5000)

Stock Price Index: Portugal: PSI-20 (921231=3000)

Stock Price Index: Russia: RTS (09/01/95=100)

Total Return: Russell 1000 Growth Share Price Index (12/31/90=100)

Total Return: Russell 1000 Share Price Index (12/31/78=100)

Total Return: Russell 1000 Value Share Price Index (12/31/90=100)

Total Return: Russell 2000 Growth Share Price Index (5/31/93=1000)

Total Return: Russell 2000 Share Price Index (Dec 29, 1978=100)

Total Return: Russell 2000 Value Share Price Index (5/31/93=1000)

Total Return: Russell 3000 Growth Share Price Index (5/31/95=1000)

Total Return: Russell 3000 Share Price Index (12/29/78=100)

Total Return: Russell 3000 Value Share Price Index (5/31/95=1000)

Total Return: Russell 2500 Growth Share Price Index (5/31/95=1000)

Total Return: Russell 2500 Share Price Index (12/31/90=100)

Total Return: Russell 2500 Value Share Price Index (5/31/95=1000)

Total Return: Russell MicroCap Share Price Index (6/24/05=1000)

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Table A.18 – *Continued from previous page*

Total Return: Russell Microcap Growth Share Price Index (6/30/06=1000)

Total Return: Russell Microcap Value Share Price Index (6/30/06=1000)

Total Return: Russell Midcap Growth Share Price Index (12/31/85=100)

Total Return: Russell Midcap Share Price Index (12/31/78=100)

Total Return: Russell Midcap Value Share Price Index (12/31/85=100)

Total Return: Russell Smallcap Growth Share Price Index (3/31/99=1000)

Total Return: Russell Smallcap Share Price Index (3/31/99=1000)

Total Return: Russell Smallcap Value Share Price Index (3/31/99=1000)

Total Return: Russell Top 200 Growth Share Price Index (12/31/85=100)

Total Return: Russell Top 200 Share Price Index (12/31/78=100)

Total Return: Russell Top 200 Value Share Price Index (12/31/85=100)

Russell 2500 Growth Share Price Index (5/31/95=1000)

Russell 2500 Share Price Index (12/31/90=100)

Russell 2500 Value Share Price Index (5/31/95=1000)

Russell MicroCap Share Price Index (6/24/05=100)

Russell Microcap Growth Share Price Index 6/30/06=1000)

Russell Microcap Value Share Price Index 6/30/06=1000)

Russell Midcap Growth Share Price Index (12/31/85=100)

Russell Midcap Share Price Index (12/29/78=100)

Russell Midcap Value Share Price Index (12/31/85=100)

Russell Smallcap Growth Share Price Index (3/31/99=1000)

Russell Smallcap Share Price Index (3/31/99=1000)

Russell Smallcap Value Share Price Index (3/31/99=1000)

Russell Top 200 Growth Share Price Index (12/31/85=100)

Russell Top 200 Share Price Index (12/29/78=100)

Russell Top 200 Value Share Price Index (5/31/95=300)

Stock Price Index: Slovakia: SAX

Stock Price Index: France: Paris SBF 250 (12/28/90=1000)

Stock Price Index: Sri Lanka: CSE All Share

Stock Price Index: Singapore Straits Times (8/31/89=1356)

Stock Price Index: Switzerland: Swiss Market Index SMI (Jun-30-88=1500)

Stock Price Index: Israel: Tel Aviv 100 (12/91=100)

Stock Price Index: Japan: Topix Cash Index (01/04/68=100)

Stock Price Index: Austria: Traded Index (1/2/91=1000)

Stock Price Index: Taiwan: Weighted Price (6/30/66=100)

NYSE: Number of Unchanged Stocks (Units)

Stock Price Index: Venezuela: Bursatil Index (12/31/93=100)

Dow Jones U.S. Completion Total Stock Market Index [Float Adj](Jan-30-87=111.14)

Dow Jones U.S. Total Stock Market Index [Float Adj] (Dec-31-70=830.27)

Dow Jones U.S. Total Stock Market Index [Full Cap] (Dec-31-70=830.27)

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Dow Jones U.S. Total Stock Market Total Return [Full Cap] (Dec-31-70=830.27)

Europe: DJ STOXX 50 Price Index: Based in Euro (EOP, 12/31/91=1000)

Europe: DJ STOXX 50 Total Return Index: Based in Euro (EOP, 12/31/91=1000)

Europe: DJ STOXX 50 Total Return Index: Based in US Dollar (EOP, 12/31/91=1000)

Euro-zone:DJ EURO STOXX 50 Total Return Index: Based in Euro (EOP,12/31/91=1000)

Euro-zone: DJ EURO STOXX 50 Total Return Index: Based in US Dollar(EOP, 12/31/91=1000)

Europe: DJ STOXX Broad Total Return Index: Based in Euro (EOP, 12/31/91=100)

Europe: DJ STOXX Broad Total Return Index: Based in US Dollar (EOP, 12/31/91=100)

Euro-zone: DJ EURO STOXX Broad Tot Return Index: Based in Euro(EOP,12/31/91=100)

Euro-zone: DJ EURO STOXX Broad Tot Return Index: Based in US Dollar(EOP,12/31/91=100)

## Table A.19: Government Securities

10-Year Treasury Bond Yield at Constant Maturity (%)

10-Yr Treasury Note Constant Maturity Total Return (%)

10-Yr Treasury Note Constant Maturity Total Return Index (Jan-01-62=100)

1-Month London Interbank Offered Rate: Based on US Dollar (%)

1-Year Treasury Bill Yield at Constant Maturity (% p.a.)

20-Year Treasury Bond Yield at Constant Maturity (% p.a.)

2-Year Treasury Note Yield at Constant Maturity (% p.a.)

2-Yr Treasury Note Constant Maturity Total Return (%)

2-Yr Treasury Note Constant Maturity Total Return Index (Jun-01-76=100)

30-Day Fed Funds Futures: 3-Month Rolling Contract Settlement (100-daily avg)

30-Day Fed Funds Futures: 3-Month Rolling Contract Settlement (100-daily avg)

30-Day Fed Funds Futures: Next Settlement by FOMC Meeting (100-daily avg)

30-Day Fed Funds Futures: Next Settlement by FOMC Meeting (100-daily avg)

30-Year Treasury Bond Futures Price: 1st Expiring Contract Settlement(Pts/100%)

30-Year Treasury Bond Futures Price: 1st Expiring Contract Settlement(Pts/100%)

30-Year Treasury Bond Futures Price: 2nd Expiring Contract Settlement(Pts/100%)

30-Year Treasury Bond Futures Price: 2nd Expiring Contract Settlement(Pts/100%)

30-Year Treasury Bond Yield at Constant Maturity (% p.a.)

3-Month London Interbank Offered Rate: Based on US Dollar (%)

3-Month Treasury Bill Constant Maturity Total Return (%)

3-Month Treasury Bill Constant Maturity Total Return (%)

3-Month Treasury Bill Constant Maturity Total Return Index (Aug-31-81=100)

3-Month Treasury Bill Market Bid Yield at Constant Maturity (%)

3-Month Treasury Bill Market Bid Yield at Constant Maturity (%)

3-Month Treasury Bill Secondary Market Total Return (%)

3-Month Treasury Bill Secondary Market Total Return Index (Jan-01-54=100)

3-Month Treasury Bills, Secondary Market (% p.a.)

3-Year Treasury Note Yield at Constant Maturity (% p.a.)

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| |
|---|
| 5-Year Treasury Note Yield at Constant Maturity (% p.a.) |
| 5-Yr Treasury Note Constant Maturity Total Return (%) |
| 5-Yr Treasury Note Constant Maturity Total Return Index (Jan-01-62=100) |
| 6-Month Treasury Bill Constant Maturity Total Return (%) |
| 6-Month Treasury Bill Constant Maturity Total Return (%) |
| 6-Month Treasury Bill Constant Maturity Total Return Index (Aug-31-81=100) |
| 6-Month Treasury Bill Market Bid Yield at Constant Maturity (%) |
| 6-Month Treasury Bill Market Bid Yield at Constant Maturity (%) |
| 6-Month Treasury Bill Secondary Market Total Return (%) |
| 6-Month Treasury Bill Secondary Market Total Return Index (Jan-01-59=100) |
| 6-Month Treasury Bills, Secondary Market (% p.a.) |
| 7-Year Treasury Bond Yield at Constant Maturity (%) |
| Fed Funds Rate Implied by 1 or 2 Mo Futures Price Based on FOMC Meeting(% p.a.) |
| Fed Funds Rate Implied by 1 or 2 Mo Futures Price Based on FOMC Meeting(% p.a.) |
| Federal Funds [Effective] Rate (% p.a.) |
| Federal Funds [effective] Rate (% p.a.) |
| Federal Funds Rate Implied by the 1-Month Futures Price (% p.a.) |
| Treasury Bond, Long-Term Composite: Over 10 Years (% p.a.) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 10-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 11-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 12-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 13-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 14-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 15-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 16-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 17-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 18-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 19-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 20-Yr (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 5-Year (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 6-Year (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 7-Year (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 8-Year (%) |
| US Inflation Compen: Continuously Compounded Instantaneous Fwd Rate: 9-Year (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 10-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 11-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 12-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 13-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 14-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 15-Yr (%) |

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| |
|---|
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 16-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 17-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 18-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 19-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 20-Yr (%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 5-Year(%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 6-Year(%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 7-Year(%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 8-Year(%) |
| US Inflation Compensation: Continuously Compounded Zero-Coupon Yield: 9-Year(%) |
| US Inflation Compensation: Coupon Equivalent Forward Rate: 5-10 Years (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 10-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 11-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 12-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 13-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 14-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 15-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 16-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 17-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 18-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 19-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 20-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 5-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 6-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 7-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 8-Year (%) |
| US Inflation Compensation: Coupon-Equivalent Par Yield: 9-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 10-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 11-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 12-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 13-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 14-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 15-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 16-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 17-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 18-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 19-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 20-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 5-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 6-Year (%) |

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| |
|---|
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 7-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 8-Year (%) |
| US TIPS Yields: Continuously Compounded Instantaneous Forward Rate: 9-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 10-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 11-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 12-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 13-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 14-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 15-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 16-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 17-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 18-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 19-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 20-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 5-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 6-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 7-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 8-Year (%) |
| US TIPS Yields: Continuously Compounded Zero-Coupon Yield: 9-Year (%) |
| US TIPS Yields: Coupon Equivalent Forward Rate Beginning 4 Yrs Hence: 1-Year (%) |
| US TIPS Yields: Coupon Equivalent Forward Rate Beginning 9 Yrs Hence: 1-Year (%) |
| US TIPS Yields: Coupon Equivalent Forward Rate: 5-10 Years (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 10-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 11-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 12-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 13-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 14-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 15-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 16-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 17-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 18-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 19-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 20-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 5-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 6-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 7-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 8-Year (%) |
| US TIPS Yields: Coupon-Equivalent Par Yield: 9-Year (%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 10-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 11-Yrs(%) |

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Table A.19 – *Continued from previous page*

| |
|---|
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 12-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 13-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 14-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 15-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 16-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 17-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 18-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 19-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 1-Yr(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 20-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 21-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 22-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 23-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 24-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 25-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 26-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 27-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 28-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 29-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 2-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 30-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 3-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 4-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 5-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 6-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 7-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 8-Yrs(%) |
| US Treasury Yield: Continuously Compounded Instantaneous Fwd Rate: 9-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 10-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 11-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 12-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 13-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 14-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 15-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 16-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 17-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 18-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 19-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 1-Yr(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 20-Yrs(%) |

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Table A.19 – *Continued from previous page*

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|---|
| US Treasury Yield: Continuously Compounded Zero-Coupon: 21-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 22-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 23-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 24-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 25-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 26-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 27-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 28-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 29-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 2-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 30-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 3-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 4-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 5-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 6-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 7-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 8-Yrs(%) |
| US Treasury Yield: Continuously Compounded Zero-Coupon: 9-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Fwd Rate Beginning 1 Yr Hence: 1-Yr(%) |
| US Treasury Yield: Coupon Equivalent Fwd Rate Beginning 4 Yrs Hence: 1-Yr(%) |
| US Treasury Yield: Coupon Equivalent Fwd Rate Beginning 9 Yrs Hence: 1-Yr(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 10-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 11-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 12-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 13-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 14-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 15-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 16-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 17-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 18-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 19-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 1-Yr(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 20-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 21-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 22-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 23-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 24-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 25-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 26-Yrs(%) |
| US Treasury Yield: Coupon Equivalent Par Yield: 27-Yrs(%) |

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US Treasury Yield: Coupon Equivalent Par Yield: 28-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 29-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 2-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 30-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 3-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 4-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 5-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 6-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 7-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 8-Yrs(%)

US Treasury Yield: Coupon Equivalent Par Yield: 9-Yrs(%)

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