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Evaluating *Wall Street Journal* Survey Forecasters: A Multivariate Approach

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Abstract: This paper proposes a methodology for assessing the joint performance of multivariate forecasts of economic variables. The methodology is illustrated by comparing the rankings of forecasters by the *Wall Street Journal* with the authors' alternative rankings. The results show that the methodology can provide useful insights as to the certainty of forecasts as well as the extent to which various forecasts are similar or different.

JEL classification: C53

Key words: *Wall Street Journal*, joint forecast, probability, ranking, correlation, variance, multivariate assessment

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I. Introduction

Economic forecasting usually involves making simultaneous predications of key financial and real macro economic variables at intervals of months, quarters or even years into the future. Yet even when models are estimated simultaneously, forecasters typically focus on the out-of-sample accuracy of individual variables or dimensions of economic performance and not on the overall accuracy of their description of the economy. Bluechip Economic Indicators collects forecasts from a panel of experts monthly, and the forecasted values of many series are presented, but no summary measures of joint accuracy are provided. In contrast, twice a year at the beginning of January and July, the *Wall Street Journal* (WSJ) surveys a group of forecasters for their forecasts of several key macroeconomic variables designed to characterize what the performance of the economy will be. The *Journal* publishes the individual forecasts and does provide a ranking of a few of the top forecasters, based on how close the forecasts of the variables are to their realized values. The actual methodology used to provide these rankings has changed over time, but at present it simply ranks the forecasters on the sum of the weighted absolute percentage deviation from the actual realized value of each series, where the weight for each series is simply the inverse of the actual realized value of the series. This performance assessment method may become distorted, and even undefined, when the realized value is close to or equal to zero. Moreover, it does not consider the correlations in the data among the variables being forecast. This latter consideration is important because accuracy should reflect internally consistency in predicting the performance of the economy and not merely good luck on one particular dimension.

In this paper we propose a methodology, which not only yields a measure of joint forecast performance, but also provides a single measure of how similar a joint forecast is to those of other forecasters. The method also allows us to assess the collective forecast accuracy of all the forecasters and the accuracy of individual forecasters over time. The procedure is not even dependent upon having all forecasters represented in each forecast period. Finally, it provides some indication of how tightly the forecasts are clustered around the realized values, and can be used to compare judgmental forecasts as well as those of formal econometric models. The next section describes the proposed methodology and subsequent sections illustrate its use with data from the *Wall Street Journal.*

II. Methodology

Two considerations are important in evaluating the accuracy of a joint forecast of several economic variables. First, some variables are inherently less stable than others and thus are harder to forecast than others. For instance, the unemployment rate is both persistent and does not vary significantly from quarter to quarter. Hence, it is easier to predict on average than a highly volatile variable like GDP growth. Whatever measure used to compare forecasts should take into account this difference in variability by penalizing forecast errors in easy-to-forecast variables more than similar size errors in hard-to-forecast variables.

Second, because many important economic variables are correlated; certain combinations of these variables are more or less likely to occur together than others. For instance, because the CPI and short-term interest rates tend to be positively correlated, any model that reflects this underlying structure in the data should generate forecast errors in these two variables that would also likely be positively correlated. A forecast that over-estimated CPI inflation while under estimating interest rates should be penalized more than a forecast that over estimated both. That is, going out on a limb and missing on a key dimension that did not reflect the underlying data structure should be penalized more because such errors are less likely, on average.

The most common measure of variability is variance and the corresponding measure of correlation between two variables is covariance. In a multivariate setting the variance-covariance matrix can be formed with the variance of each variable along the diagonal and the covariances of the variables in the off diagonal entries. This variance-covariance matrix Ω can be used to form a multivariate distance chi-squared statistic commonly used in statistical inference, if we are willing to assume that the forecast errors are multivariate normally distributed with mean zero. The statistic is of the form:

$$\hat{c}^2 = \left(\hat{\mathbf{y}}_t - \mathbf{y}_t\right)' \Omega_t^{-1} \left(\hat{\mathbf{y}}_t - \mathbf{y}_t\right) \sim \mathrm{chi}^2\left(n\right),$$

where $\hat{\mathbf{y}}_t$ is the time t forecast of a vector of economic variables, $\mathbf{y}_t$ is the realized value of the forecast vector, and Ω_t^{-1} is the inverse of the variance-covariance matrix, and n is the number of variables in $\mathbf{y}_t$. is distributed as chi^2(n).

The remaining problem is to devise an estimate of the variance matrix, which we approach by decomposing it into more tractable components. The exact details are described in Appendix 1.

Given a vector of forecast errors associated with a particular forecast, we can compute the *p*-value for its associated chi^2 and call it an "accuracy score." The summary measure provided by the computed accuracy score has several useful properties. First, it is a probability that is invariant to the underlying scale of the errors. Second, it can be interpreted as a measure of how similar, or close, the joint forecast is to the realized values in the economy. Third, we can go even further and interpret the *p-value, expressed as a percentage,* associated with a particular forecast as indicating that it is closer to the true value than *p* % of all possible forecasts. Fourth, it can be used to compare and rank forecasts. And finally, the distribution of forecasts across forecasters can be compared both within a forecast period and across periods. The next section illustrates how the methodology can be used in a simple two-variable case, and then it is extended in **Section IV** to the entire set of *Wall Street Journal* forecast variables.

III. Empirical Illustration – Two variable case

To illustrate what the methodology is doing, we first present a two dimensional forecast example in Chart 1. The *Wall Street Journal* publishes semiannually the forecasts of between 30 and 50 economic forecasters, who submit their projections for many key economic variables. Chart 1 plots just the forecasts of two variables from the July 1999 *Journal* survey: the 3 month T-bill for December 31, 1999 and the dollar/yen exchange rate for December 31, 1999.

Several features of this chart are noteworthy. First, the ellipse, centered around the true, realized values being forecast, represents the two-third probability surface showing how similar forecasts lie. Any forecast lying on this ellipse can be said to be closer to the true value (the gray square) than two thirds of all possible forecasts. Forecasts on an inner concentric ellipse (not drawn) outperform those lying on the two-third ellipse, and forecasts outside the ellipse under-perform those on the ellipse.

It will also be noticed that the probability surface is not a circle, indicating that dispersions (variances) are not equal. Furthermore, because the ellipse is tilted upward, there is a positive correlation between the two variables, which is 0.48 according to the bottom panel of Table 2. The methodology considers these correlations in its calculation of the measure of joint forecast accuracy. Finally, it is clear that while the forecasts are generally fairly tightly grouped, most are outside the two-third ellipse and only two are reasonably close to the joint realization. Several forecasts are reasonably close on the 3-month T-bill rate, but most of the forecasts show significant errors on the dollar/yen exchange rate. Because the T-bill rate had a smaller variance than the exchange rate, errors on that dimension will be less severe than errors on the exchange rate. But the best forecasters did a substantially better job on both dimensions and stand out above the rest of the pack. The distributions of individual forecasters' joint forecast accuracy scores for this two variable example are shown in Chart 2. It can be clearly seen that three of the forecasters had a much higher score than did the other forecasters. Moreover the distribution of the forecasts is quite spread out. As will be shown in the next section, the pattern of these probabilities varies significantly from forecast period to forecast period.

III. Empirical Results – Multivariate

As indicated earlier, forecasters usually predict many economic variables, and the proposed methodology for assessing accuracy is robust enough to handle a large number of variables. We explore the properties of the *Wall Street Journal* forecasts using the proposed methods. The variables included in the forecast survey collected by the *Wall Street Journal* have changed over time, and again, the proposed methodology can take this into account by simply dropping the appropriate row and column from the variance-covariance matrix for each variable not in the sample. Because of the sheer volume of data, only the results for a few of top forecasters in one *Wall Street Journal* survey will be discussed (Chart 3), but we will provide some summary information of the key features of the forecasts over time (Charts 4 and 5 and Table 3).

Chart 3 presents the joint forecast accuracy scores and each forecaster's rank for a selected few of the top forecasters according to our method (labeled EWZ rank) together with the rankings according to the WSJ's selection criteria for July 1999. Except for the two best forecasters, Fosler and Sinai, the EWZ ranking is different from the *Wall Street Journal* ranking. The *Journal*'s placement of Ramirez third compares with our placement of only 19th, and Orr ranks sixth compared with our placement of 44th. This raises some interesting questions concerning the differences in the forecasts on the different variables and how these differences are weighted.

Table 1 displays relevant forecasts and their realized values at the time the rankings were done.[1] For this survey, the *Journal* evaluation first computes the absolute value of the difference between forecast and actual value for each variable and then weights the error by the inverse of the actual value. The smaller the weighted sum is, the higher a forecaster is ranked. The weights vary over time as the values of the variable change. However, if the actual value of a variable is close to zero (which is not uncommon for a

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[1] In some instances, data are revised. The tables here include the real-time data available to the *Journal* at the time the evaluations were made.

variable like GDP growth rate), the weight assigned to the GDP error becomes arbitrarily large, and can be misleading.

In the absence of correlations between forecast variables, our methodology is similar to the *Journal* method except that the weights applied to the errors are equal to the inverse of the forecast variance for each variable rather than the value of the variable itself. According to the covariance matrix reported in top panel of Table 2, the weights assigned to the squared differences between forecast and actual values would be, ignoring the correlations for the time being, 5.39 for the 3-month Treasure bill rate, 8.90 GDP growth, 21.00 CPI inflation, 45.12 the unemployment rate, 19.46 the 30-year Treasure bond yield, and 0.13 the exchange rate. The weight assigned to forecast errors of the unemployment rate is large because this series does not vary as much, and the forecast variability is relatively low. The weight given to errors in the exchange rate is small because this series is more volatile and hard to forecast.

The following examples illustrate the importance of using the variance as a weight as well as taking account of the correlations in the variables being forecast. Consider first that Ramirez (Table 1) is ranked 19th by our method because the errors in her forecasts of both 30-year Treasury bond yield (7%) and the exchange rate for yen (125) compared with the realized values (6.48% and 102) are large relative to the variances of these variables. Similarly, Orr is placed at 44th by our ranking largely because of the large error in his exchange rate forecast of (135) relative to the actual value (102). Reynolds is ranked Number 5 by our method as compared to 20th by the *Journal* method, mainly because of the negative correlation, -0.34, between GDP and unemployment (see the bottom panel of Table 2). He under-forecast the average annual rate of GDP growth in the 3rd quarter of 1999 and over-forecast the unemployment rate in November 1999. The negative correlation implies that this kind of forecast error is expected, and thus should not punished as much. The case of Thayer, ranked sixth by our method and 37th by the *Journal* method is more complicated. He over-forecast the exchange rate and under-forecast the 30-year Treasury bond rate, which is contrary to the positive correlation of forecast errors of these two variables. But his under-forecast of the 3-month Treasury bill rate, GDP growth, the 30-year Treasure bond rate, combined with his over-forecast of the unemployment rate, are consistent with the pair wise negative correlations reported in the top panel of Table 2. Furthermore, his under-forecast of both interest rates is consistent with the positive correlation of forecast errors in both interest rates.

The methods we are proposing can also be used to explore the forecast performance of individual forecasters over time. Charts 4 and 5 compare the forecasts and model rankings for two particular forecasters: Ramirez and Yardeni. Ramirez (Chart 4) had a mean EWZ rank of 27.3 and a mean accuracy score of 58.8%, meaning that on average she would be expected to out-perform about 59% of the forecasters.

Yardeni (Chart 5) had a mean EWZ rank of 27.6 and a mean accuracy score of 57.4%. Both these forecasters had similar performance, and like Rameriz, Yardeni was also recognized for his forecasting performance, but on two rather than only one occasion. For the July 1998 survey he was ranked 6th by the *Wall Street Journal*, whereas our method would have ranked him 23rd, and for the July 1999 survey he was ranked 1st by the *Journal* whereas we would have ranked him 8th.

Table 3 presents the mean EWZ rank and average accuracy scores, together with their respective standard deviations, for those forecasters that appeared in the *Wall Street*

Journal forecast for at least 4 periods between July of 1986 and January of 2002. The scores and ranks for January 2002 are also provided. The data are sorted, so that those active forecasters who provided a survey for January of 2002 appear first. Among the active forecasters, several performed quite well. Soss and Kudlow both have low mean ranks, but these were largely accumulated in the late 1980's and early 1990's, and may not reflect their current expected performance. In fact, for the January 2002 survey, Kudlow dropped to 53 rd; again this illustrates the difficulty of maintaining performance over time. Hoffman not only had the fifth lowest mean rank over a very long period of time, but also had a high mean accuracy score with relatively lower standard deviations on both, and especially on his mean rank. Considering the entire table, the people with the superior performance record tend to be those whose forecasts covered a short period of time in the early to mid-1980s. Interestingly, this was a relatively more volatile period than the 1990's, but also it is worth noting that the variables forecast were different and the number of variables was smaller.

The charts on individual performance can also be used to highlight those instances when forecasters take extreme positions. Yardeni made a big point about his concern for Y2K and the consequences if the US and the rest of the world didn't make the necessary preparations. His concerns were reflected in his forecasts in Chart 5 for the July 1999 and January 2000 *Journal* surveys: the accuracy scores are extremely low when compared with both those of other forecasters and how the economy actually performed. But not all forecasting accuracy problems are due to taking extreme positions. This is illustrated by the lower performance in terms of accuracy scores for all forecasters in January 1995 and in July 1990 . This highlights the difficulty in predicting turning points. All forecasters had trouble with turning points, which is shown in Chart 6. containing the mean accuracy scores for all the forecasters, as well as the top and bottom-ranked 5 forecasters. All forecasters made large errors in their January 1995and July 1990 forecasts. More recently, forecasters made big errors in their forecasts for January 2001, and clearly also had some difficulty with their January 2002 forecasts, as the strength of the economy was under-estimated. In addition, while there was a lot of agreement among the forecasters January 2001 as the distribution of the forecasts was reasonably tight, all were also systematically off the mark.

This chart also illustrates that at times there is more unanimity among forecasters than at others. For example the bottom 5 and top 5 forecasters were closer to each other in some periods than in others, suggesting that the variation in the forecasts may serve as an indication of how much uncertainty there may be about where the economy is going. The dispersions, for example, widened considerably during the Asian crisis in the summer of 1997.

IV. Conclusion

In this paper we have offered a systematic approach to evaluating a forecaster's performance relative to others, and illustrated the methodology in the context of specific examples. Our approach formalizes a way of assessing forecast accuracy, but could be applied to a number of different multivariate performance assessment problems. One may differ on how to estimate the variance-covariance matrix but once it is reasonably approximated, our approach provides not only the ranking results but also the probability of how close to the actual data a particular forecast is in comparison with all other potential forecasts.

Appendix 1

When we make a forecast today of the values of a set of economic variables at some points in the future, we would not expect our forecasts to be perfect even if we had perfect knowledge of the inner workings of the economy. There are always events, such as political or natural disasters, that are impossible to predict and effect the economy. More formally, we could not give perfect forecasts even if we knew the "correct" model of the economy. We will use the notation $\boldsymbol{\Omega}_t^E$ to denote the variance-covariance matrix of the forecast errors inherent in the economy and $\boldsymbol{\Omega}_t^F$ to denote the variance-covariance matrix of the forecast errors made by individual forecasters. If $\mathbf{y}_t$ is the *n*-vector of variables to be forecast and $\hat{\mathbf{y}}_t$ is the forecast of $\mathbf{y}_t$, we assume that both $\mathbf{y}_t$ and $\hat{\mathbf{y}}_t$ have the same mean $\overline{\mathbf{y}}_t$, the variance-covariance matrix of $\mathbf{y}_t$ is $\boldsymbol{\Omega}_t^E$, and the variance-covariance matrix of $\hat{\mathbf{y}}_t$ is $\boldsymbol{\Omega}_t^F$.

If we make a rather mild assumption that forecast errors inherent in the economy ($\mathbf{y}_t - \overline{\mathbf{y}}_t$) are uncorrelated with those made by forecasters ($\hat{\mathbf{y}}_t - \overline{\mathbf{y}}_t$), then the total variance matrix of the forecast errors ($\hat{\mathbf{y}}_t - \mathbf{y}_t = (\hat{\mathbf{y}}_t - \overline{\mathbf{y}}_t) - (\mathbf{y}_t - \overline{\mathbf{y}}_t)$) will be $\boldsymbol{\Omega}_t = \boldsymbol{\Omega}_t^E + \boldsymbol{\Omega}_t^F$.

The advantage of having forecasts from many different forecasters is that the cross-sectional variance-covariance matrix gives us an estimate of $\boldsymbol{\Omega}_t^F$. Note that this does not depend on having a time series of the individual forecasters. Forming an estimate of $\boldsymbol{\Omega}_t^E$ is more delicate. For the exercises in this paper, we use the variance-covariance matrix estimated from the reduced-form Bayesian dynamic, multiple-equation model described in Robertson and Tallman (1999). The covariance matrix $\boldsymbol{\Omega}_t^E$ is simulated with ten thousand simulations whose computing time takes about 95 minutes for each survey on a Pentium III 800 PC. Intuitively, this model incorporates the features of random walk, unit root, and cointegration inherent in the data, and thus it offers a good benchmark. The sample used by the model begins at January 1959. From January 1961 to February 1977, the 30-yr Treasury bond yield is replaced by the 20-yr bond yield; from January 1959 to December 1960, it is replaced by the 10-yr bond yield. As for the exchange rate between Euro and US$ from January 1959 to September 1979, it is extrapolated from the January 1980-September 2001 regression of the synthetic Euro exchange rate with US$ on the Mark exchange rate with US$. We take account of both parameter (model) uncertainty and randomness in future shocks in simulating the variance-covariance matrix Ω_t^E at each forecast date (Waggoner and Zha, 1999). Take the July 1999 *Journal* survey as an example. When the survey was published, forecasters had only the data released in June 1999. That means that they had some data (such as financial data) up to June 1999 and some data (such as CPI) up to May 1999 while GDP was available only up to the first quarter of 1999. To be comparable with the information set used by all forecasters, the model uses the data set as though it was available at the end of June 1999.

Appendix 2

We have spent a lot of time describing the estimation of the variance-covariance matrix of forecast errors Ω_t^E using simulation methods, which ideally should be re-estimated each time a forecast is made for a new period. It turns out, however, that experiments with re-estimation of the matrix is not really necessary. The rank correlations for the forecast rankings with and without re-estimation are so high that the rankings are reasonably robust to changes in this matrix over time. For example, comparing rankings one year apart the Spearman rank correlation is .99, and even 5 years apart is .98. Hence we have supplied the current estimate that could be used by any interested party for some time into the future, when combined with the variance-covariance matrix Ω_t^F estimated from the *Wall Street Journal* published forecast data. These two matrices can be combined as shown in Appendix 1, so that any interested party could replicate our rankings for the forthcoming survey. Below is the estimated Ω_t^E matrix

Variance-Covariance Matrix							
	T-Bill	**DGP**	**CPI**	**CUR**	**T-Bond**	**Yen/US$**	**US$/Euro**
T-Bill	3.2324	0.79906	-0.3147	-0.32571	1.1581	9.6655	-0.0525
DGP	0.79906	8.3368	0.068871	-0.61587	0.31782	-2.0202	-0.004986
CPI	-0.3147	0.068871	0.7801	0.02141	-0.11968	-3.0315	0.021998
CUR	-0.32571	-0.61587	0.02141	0.29975	-0.12797	-0.067084	0.0075195
T-Bond	1.1581	0.31782	-0.11968	-0.12797	0.96538	5.0814	-0.024588
Yen/US$	9.6655	-2.0202	-3.0315	-0.067084	5.0814	94.593	-0.29445
US$/Euro	-0.0525	-0.004986	0.021998	0.0075195	-0.024588	-0.29445	0.0038811

The variables in the above table are defined as follows:

T-Bill 3 = 6-month-ahead forecast of 3-Month Treasury Bills, Secondary Market (% p.a.)

DGP = One-quarter ahead forecast of quarterly Real GDP growth

CPI = 5-month-ahead forecast of annual CPI inflation rate (prior to 12 months ago)

CUR = 5-month-ahead forecast of Civilian Unemployment Rate (SA, %)

T-Bond = 6-month-ahead forecast of 10-Year Treasury Bond Yield at Constant Maturity (% p.a.)

Yen/US$ = 6-month-ahead forecast of Yen/US$ exchange rate

US$/Euro = 6-month-ahead forecast of US$/Euro exchange rate

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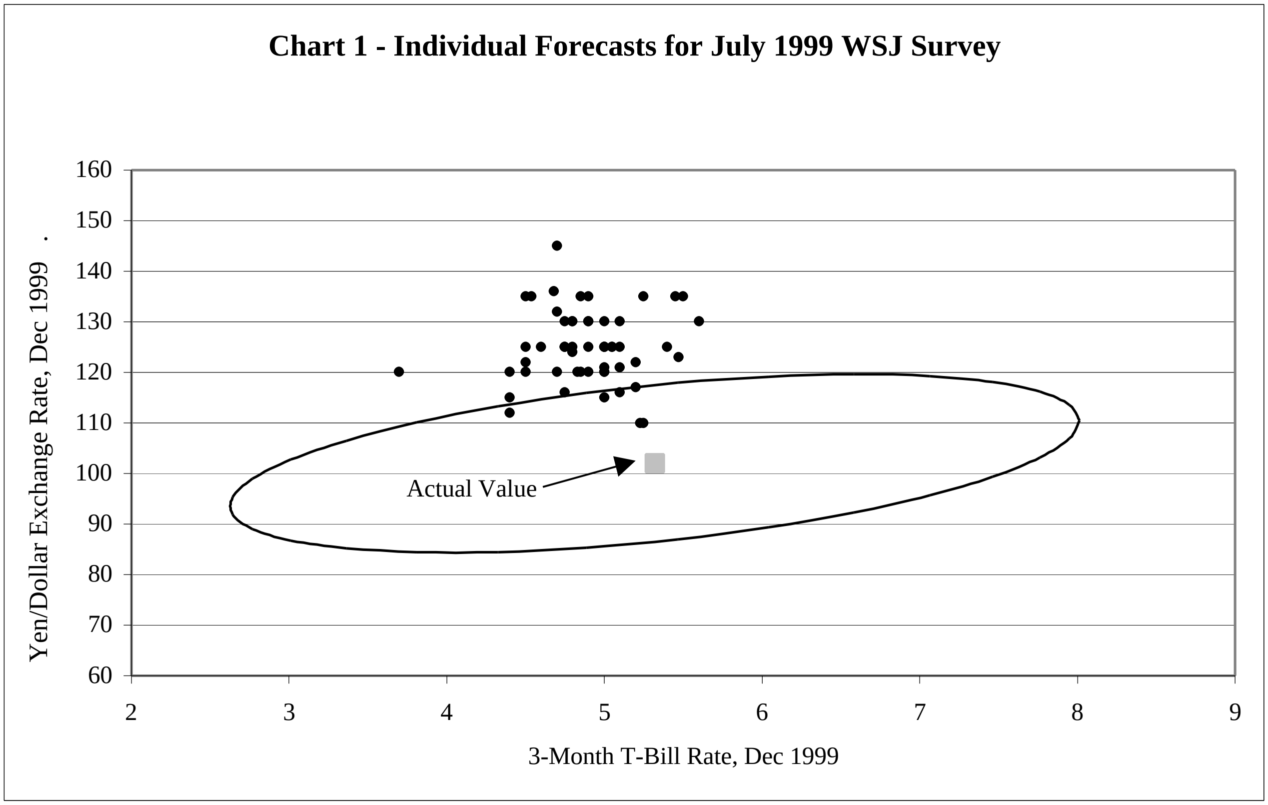


Chart 1 - Individual Forecasts for July 1999 WSJ Survey
Yen/Dollar Exchange Rate, Dec 1999
3-Month T-Bill Rate, Dec 1999
Actual Value
160
150
140
130
120
110
100
90
80
70
60
2
3
4
5
6
7
8
9

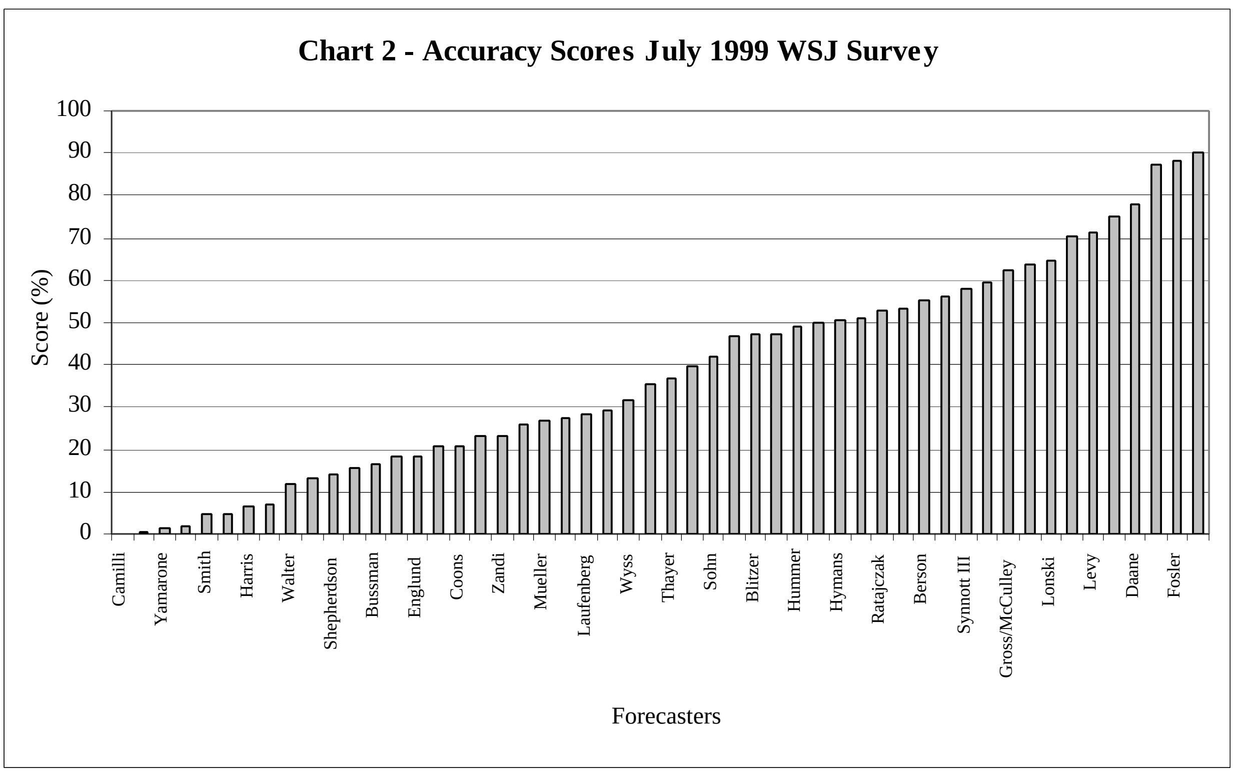


Chart 2 - Accuracy Scores July 1999 WSJ Survey
Score (%)
Forecasters
100
90
80
70
60
50
40
30
20
10
0
Camilli
Yamarone
Smith
Harris
Walter
Shepherdson
Bussman
Englund
Coons
Zandi
Mueller
Laufenberg
Wyss
Thayer
Sohn
Blitzer
Hummer
Hymans
Ratajczak
Berson
Synnott III
Gross/McCulley
Lonski
Levy
Daane
Fosler

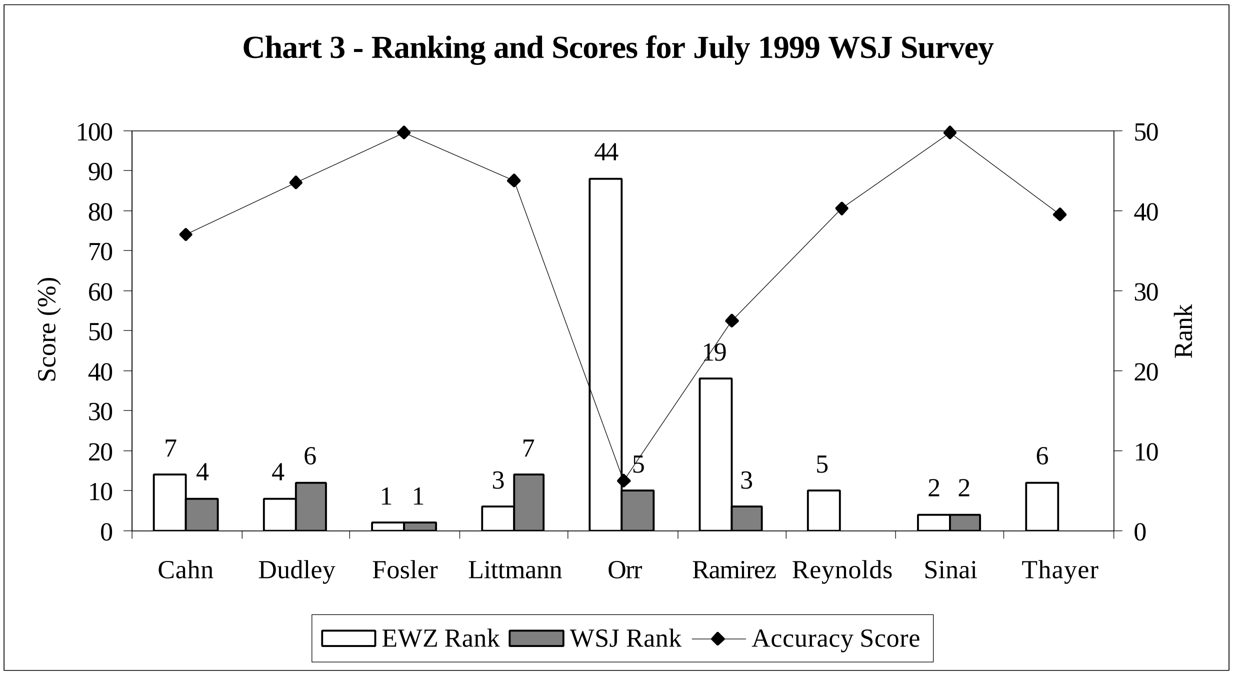
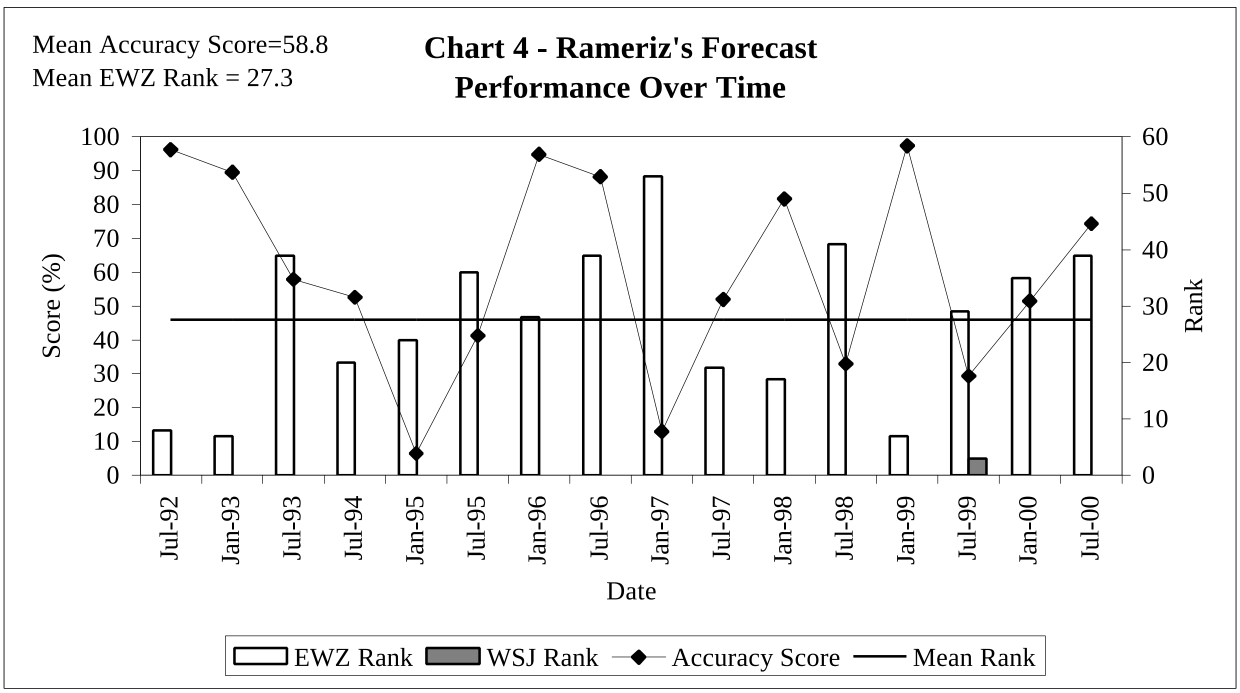


Chart 3 - Ranking and Scores for July 1999 WSJ Survey
Score (%)
Rank
100
90
80
70
60
50
40
30
20
10
0
50
40
30
20
10
0
44
19
7
4
4
6
1
1
3
7
5
3
5
2
2
6
Cahn
Dudley
Fosler
Littmann
Orr
Ramirez
Reynolds
Sinai
Thayer
EWZ Rank
WSJ Rank
Accuracy Score


Mean Accuracy Score=58.8
Mean EWZ Rank = 27.3
Chart 4 - Rameriz's Forecast Performance Over Time
Score (%)
Rank
100
90
80
70
60
50
40
30
20
10
0
60
50
40
30
20
10
0
Jul-92
Jan-93
Jul-93
Jul-94
Jan-95
Jul-95
Jan-96
Jul-96
Jan-97
Jul-97
Jan-98
Jul-98
Jan-99
Jul-99
Jan-00
Jul-00
Date
EWZ Rank
WSJ Rank
Accuracy Score
Mean Rank

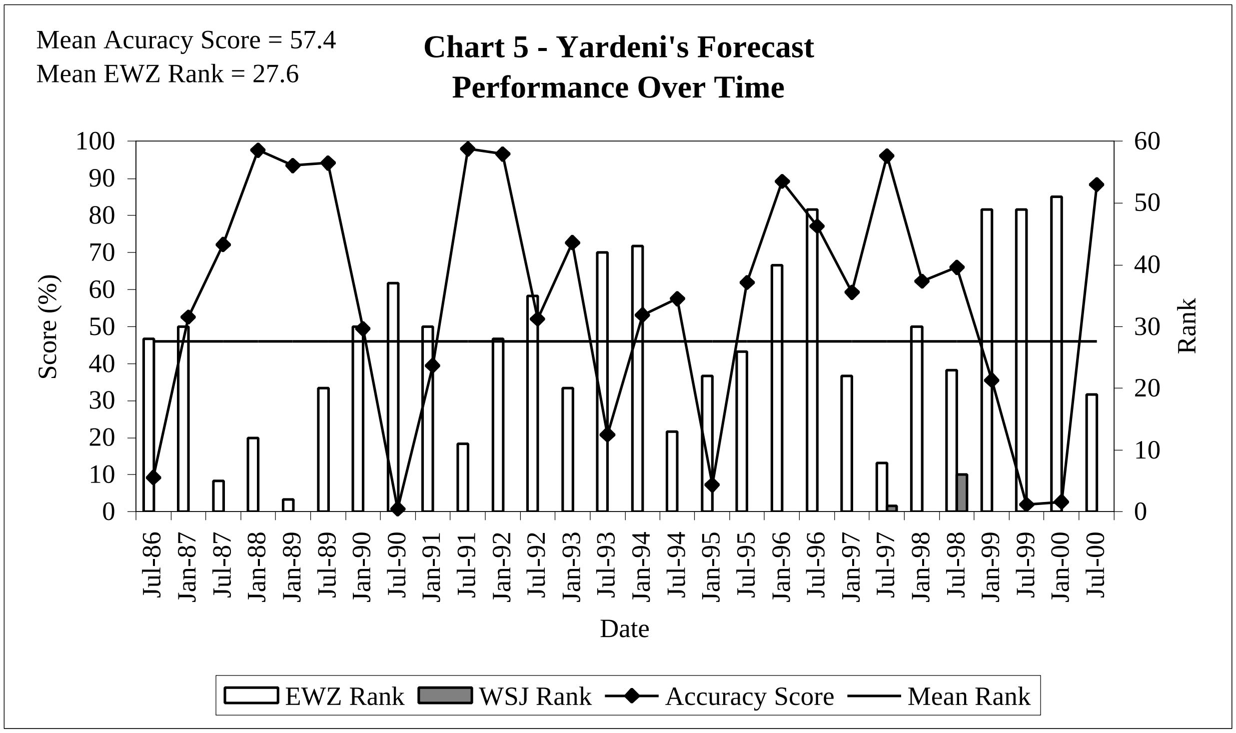

Mean Acuracy Score = 57.4
Mean EWZ Rank = 27.6
Chart 5 - Yardeni's Forecast Performance Over Time
Score (%)
Rank
Date
EWZ Rank
WSJ Rank
Accuracy Score
Mean Rank
Jul-86
Jan-87
Jul-87
Jan-88
Jan-89
Jul-89
Jan-90
Jul-90
Jan-91
Jul-91
Jan-92
Jul-92
Jan-93
Jul-93
Jan-94
Jul-94
Jan-95
Jul-95
Jan-96
Jul-96
Jan-97
Jul-97
Jan-98
Jul-98
Jan-99
Jul-99
Jan-00
Jul-00

Table 1 - Forecast Performance for Top Forecasters July 1999 WSJ Survey

	3-Month T-Bill Rate	GDP Growth Rate	CPI Inflation	Civilian Unemployment Rate	30-Year T-Bond Rate	Yen/Dollar Exchange Rate	EWZ Rank	Accuracy Score	WSJ Rank
Cahn	4.90	3.63	2.4	4.0	6.50	120	7	73.84	4
Dudley	5.00	3.27	2.5	4.0	5.80	115	4	86.85	6
Fosler	5.25	3.73	2.3	4.0	6.40	110	1	99.64	1
Littmann	4.75	3.27	2.7	4.2	6.15	116	3	87.43	7
Orr	5.45	3.80	2.5	4.2	6.35	135	44	12.73	5
Ramirez	5.40	3.67	2.5	4.0	7.00	125	19	52.31	3
Reynolds	5.20	2.57	2.8	4.7	6.40	117	5	80.29	20
Sinai	5.23	3.13	2.5	4.1	6.55	110	2	99.40	2
Thayer	4.40	2.80	2.2	4.4	5.20	112	6	79.08	37
Actual data	5.32	3.70	2.6	4.1	6.48	102			

Table 2 - July 1999 WSJ Survey

Variance-Covariance Matrix

	3-Month T-Bill Rate	GDP Growth Rate	CPI Inflation	Civilian Unemployment Rate	30-Year T-Bond Rate	Yen/Dollar Exchange Rate
3-Month T-Bill	3.27	0.35	-0.18	-0.36	0.87	10.26
GDP Growth	0.35	1.98	0.03	-0.29	0.12	-0.04
CPI	-0.18	0.03	0.84	0.02	0.13	-2.44
Unemployment	-0.36	-0.29	0.02	0.39	-0.11	0.06
30-Year T Bond	0.87	0.12	0.13	-0.11	0.91	3.09
Yen/Dollar	10.26	-0.04	-2.44	0.06	3.09	140.16

Correlation

	3-Month T-Bill Rate	GDP Growth Rate	CPI Inflation	Civilian Unemployment Rate	30-Year T-Bond Rate	Yen/Dollar Exchange Rate
3-Month T-Bill	1.00	0.14	-0.11	-0.32	0.51	0.48
GDP Growth	0.14	1.00	0.02	-0.34	0.09	0.00
CPI	-0.11	0.02	1.00	0.03	0.14	-0.22
Unemployment	-0.32	-0.34	0.03	1.00	-0.18	0.01
30-Year T Bond	0.51	0.09	0.14	-0.18	1.00	0.27
Yen/Dollar	0.48	0.00	-0.22	0.01	0.27	1.00

Table 3

Overall Forecast Performance For Those Forecasters With Four or More Available Forecasts

Forecasters	Periods Covered	Average Score	Standard Deviation of Scores	Average Rank	Standard Deviation of Ranks	Number of Forecast Surveys	Jan 2002 Survey Score	Jan 2002 Survey Rank
Kudlow**	July 88 - Jan 92, Jan 94, Jan 01 - Jan 02	69.6	38.78	19.75	16.42	12	11.4	53
Resler	Jan 86 - Jan 02	68.3	28.28	18.15	12.17	33	86.9	3
Soss*	Jan 88 - Jan 94, July 01 - Jan 02	68.2	26.74	23.21	15.20	14	66.1	15
DiClemente	July 00 - Jan 02	67.4	44.60	14.25	19.81	4	76.3	9
Hoffman	Jan 88 - Jan 02	66.5	26.72	19.89	9.44	28	33.5	38
Levy	Jan 86- Jan 02	63.7	29.38	22.18	10.79	33	33.5	37
Wyss	Jan 89 - July 99, July 01 - Jan 02	63.6	27.86	25.48	12.95	29	60.3	20
Harris	July 86 - Jan 02	62.8	31.35	21.68	12.59	31	42.7	30
Hymans	July 86 - Jan 02	62.3	32.81	21.34	14.20	29	80.8	6
Swonk	July 98 - Jan 02	61.7	29.30	19.57	16.97	7	71.9	12
Littmann	Jan 93- Jan 02	61.5	32.34	22.72	14.83	18	82.8	5
Perna	July 94 - Jan 02	61.4	31.33	21.25	14.48	16	37.4	34
Sinai	Jan 86 - Jan 02	61.0	32.15	25.29	15.52	31	1.9	55
Berson	Jan 90-Jan 02	60.7	28.88	22.52	13.24	25	26.1	43
Rippe	Jan 90 - Jan 02	60.7	31.22	24.28	11.23	25	76.8	8
Daane	July 88 - Jan 02	60.5	30.32	24.33	14.33	27	20.6	49
Karl	Jan 94 - Jan 02	60.5	31.63	24.25	13.74	16	46.6	26
Hyman/Lazar	Jan 86 - Jan 02	59.7	28.46	25.68	12.13	31	72.4	11
Cosgrove	Jan 94 - Jan 02	59.7	32.99	25.65	16.48	17	62.9	19
Ramirez	July 92 - Jan 02	59.4	28.85	26.58	16.48	19	68.8	14
Synnott	July 94 - Jan 02	59.4	31.34	22.13	16.80	16	69.8	13
Berner/Greenlaw	Jan 94-Jan 02	59.2	31.59	28.09	18.23	17	65.6	16
Wilson	Jan 86, Jan 01 - Jan 02	58.4	30.67	16.25	14.29	4	29.6	41
Sterne	July 94, July 99 - Jan 02	57.4	29.93	22.00	13.35	9	89.0	2
Mueller	July 91- Jan 02	56.3	31.30	26.68	14.94	19	49.1	25
McCulley	July 94- Jan 02	55.0	30.93	25.87	13.23	15	49.4	24
Coons	Jan 94 - Jan 02	54.9	31.12	26.65	15.45	17	40.5	32
Hummer	Jan 93 - Jan 02	54.7	28.61	28.37	12.12	19	65.5	17
Thayer	July 99 - Jan 02	54.3	21.83	21.17	15.05	6	21.5	47
Lonski	Jan 94- Jan 02	53.9	31.81	27.82	15.40	17	56.2	22
Zandi	July 95 - Jan 02	52.9	26.06	30.10	11.83	13	52.7	23
Dudley	Jan 96 - Jan 02	51.7	37.99	32.38	19.16	13	65.5	18
Sohn	Jan 98 - Jan 02	51.4	32.25	24.89	17.25	9	12.6	52
Smith	Jan 87 - Jan 02	49.0	35.65	32.72	17.38	29	26.0	44
Herrick	July 94 - Jan 02	48.4	30.74	32.94	15.19	16	39.3	33
Shepherdson	July 99 - Jan 02	47.4	28.87	25.50	19.17	6	25.5	45
Laufenberg	July 95 - Jan 02	47.0	35.45	29.57	20.68	14	92.3	1
Fosler	Jan 91 - Jan 02	45.6	34.17	32.57	19.64	23	32.7	39
Steinberg	July 97 - Jan 02	45.6	29.66	29.40	14.99	10	45.7	27
Evans	Jan 94 - July 96	45.5	32.88	33.71	17.50	7	18.3	50
Gallagher	Jan 99 - Jan 02	45.1	28.92	33.43	12.50	7	15.1	51
Allyn	July 93-Jan 02	44.3	31.77	34.24	12.53	17	36.7	35
Orr	July 99 - Jan 02	40.0	36.90	31.00	15.85	6	40.8	31
Camilli	July 99 - Jan 02	39.9	37.80	29.17	16.94	6	44.5	29
Yamarone	July 99 - Jan 02	39.8	33.62	29.33	18.82	6	21.5	48
Shilling	Jan 86 - Jan 02	39.7	33.71	32.90	16.94	31	3.7	54
Wesbury	July 98 - Jan 02	35.9	33.35	33.02	20.18	7	30.2	40

** Kudlow's record was accumulated over largely the late 1980s and early 1990s. His ranks in Jan. and July of 2001 were 41st and 5th, res

* Soss's record was accumulated over largely the late1980s and early 1990's. His rank in July 2001 was 51st.

Table 3 (cont.)

Overall Forecast Performance For Those Forecasters With Four or More Available Forecasts

Forecasters	Periods Covered	Average Score	Standard Deviation of Scores	Average Rank	Standard Deviation of Ranks	Number of Forecast Surveys
McDevitt	July 96- July 01	59.0	29.93	26.89	13.99	9
Angell	July 94-July 01	58.8	34.99	23.67	16.25	15
Englund	Jan 94 - July 01	46.2	26.24	33.27	13.87	15
Cahn	July 95 - Jan 01	59.2	29.12	27.40	14.01	10
Blitzer	July 94-Jan 01	55.8	30.05	27.64	17.82	14
Bussman	July 97 - Jan 01	44.7	29.83	32.83	8.47	6
Moskowitz	Jan 86- July 99, July 00	65.2	29.45	19.79	10.53	28
Brown	Jan 92 - July 00	59.6	33.12	27.39	17.80	18
Yardeni	July 87 - July 00	57.0	30.35	27.25	15.05	28
Walter	Jan 97 - July 00	54.9	35.58	27.75	22.77	8
Platt	July 88 - Jan 00	68.7	28.00	21.26	13.20	23
Reynolds	July 86 - Jan 00	65.0	29.56	24.59	14.42	27
Braverman	Jan 86 -Jan 99	71.6	27.31	20.00	13.88	28
Worseck	Jan 89 - Jan 99	62.6	36.24	24.11	18.64	19
Williams	Jan 94 - Jan 99	56.4	31.40	28.09	12.77	10
Karczmar	July 93 - July 98	47.7	32.38	36.00	14.82	10
Boltz	Jan 86 -Jan 98	62.0	30.27	25.24	15.59	25
Leisenring	July 87- July 97	73.7	22.95	19.52	11.69	21
Bostian	Jan 94 -July 97	64.4	29.24	23.63	17.11	8
Palash	July 95 - July 97	60.5	20.52	34.80	19.06	5
Straszheim	July 86 - Jan 97	70.7	26.55	16.05	10.30	21
Kellner	Jan 86 - Jan 97	62.7	33.24	24.14	13.55	22
Dederick	July 86 - July 96	72.1	29.66	18.62	12.13	21
Laughlin	July 94- July 96	58.6	28.05	24.20	15.94	5
Evans	Jan 94 - July 96	50.0	33.43	31.00	17.48	6
Reaser	July 92 - Jan 96	72.8	25.62	15.50	8.42	8
Robertson	Jan 86 - Jan 96	69.4	30.73	17.45	10.36	20
Wahed	July 89 - Jan 96	65.4	34.91	22.42	12.92	12
Kahan	Jan 87 - Jan 96	62.0	35.20	22.24	15.11	17
Keran	Jan 94- Jan 96	51.3	21.19	27.40	17.99	5
Ciminero	Jan 94, Jan 95 - Jan 96	48.2	37.25	25.50	14.71	4
Gramley	Jan 87-Jan 95	72.5	31.33	16.00	11.29	17
Vignola	July 92 - July 94	66.9	32.02	24.20	15.61	5
Barbera	Jan 90-Jan 94	56.2	32.56	29.11	8.65	9
Hoey	Jan 86 - Jan 94	54.0	33.66	25.00	11.58	16
Eickhoff	July 91 - July 93	93.2	10.73	10.20	11.65	5
Lerner	July 86- July 93	62.5	26.52	23.73	13.12	15
Jones	July 86 - Jan 93	71.1	28.72	17.47	9.01	15
Melton	Jan 86- Jan 93	64.7	33.49	20.87	10.64	15
Michaelis	July 87- Jan 92	78.4	28.54	11.50	7.44	10
Jordan	Jan 89 - Jan 92	56.6	39.35	21.00	12.37	7
Schott	Jan 86 - Jan 91	76.6	26.49	10.00	5.55	11
Cooper	Jan 86 - July 90	69.2	32.01	12.10	9.30	10
Pate	Jan 87 - July 89	82.3	25.67	11.33	9.42	6
Nathan	July 96- Jan 89	64.6	30.55	19.50	6.72	6
Hunt	Jan 86 - Jan 89	41.5	31.12	26.43	6.70	7
Maude	July 86- July 88	65.5	26.48	22.00	8.34	5
Howard	Jan 86 - July 87	40.7	35.96	21.25	8.46	4