The Forecasting Value of Dividend Yields within Industry Data

by

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Abstract

The economic and statistical significance of using dividend yields to forecast future returns has been examined in numerous manners. This paper examines the topic through a time series analysis of dis-aggregated industry returns regressed onto aggregated equity-market dividend yields. In addition, a trading model is employed to further examine if any statistical significance of the proposed relationships between dividend yields and future returns can be translated into economic significance. Economic significance is measured as both absolute dollar return, as well as return per unit risk over that of industry benchmarks.

Dedication

To my fiancé, Jessie K, who provided me
with encouragement throughout my studies.

To my parents, Romesh & Swarn Bhangu,
who provided me with the foundation to undertake my studies.

And to my best friends, Ajbinder & Naveen,
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Introduction

There has been extensive discussion regarding the value of dividend yields in forecasting future equity returns. The final conclusion as to whether or not dividend yields do indeed possess return forecasting value is debatable. However, further examination of this topic within disaggregated sector data may identify the market sectors, if any, where dividend yields provide significant forecasting value. A review of the literature concerning the value of using dividend yields in forecasting returns, as well as other topics related to dividend yields which are relevant to the general context of the proposed study, follow.

When examining dividend yields as a predictive indicator, an initial concern is that dividends can be subject to relatively ad-hoc changes in dividend policy by corporate management. Although the statistical impact of such changes is dampened when examining aggregated data, it still warrants investigation. One of the earlier and more relevant papers examining the impact of dividend policy on stock prices, Black and Scholes [1974], found that corporations that increase dividends do not see a definitive affect on stock price. Specifically, Black and Scholes [1974] found that any temporary change in stock price resulting from an increase in dividends would diminish if the initial change in dividend does not correspond to a real change in expected future earnings. Black and Scholes [1974] thereby alleviate concerns that ad-hoc changes in dividend policies may hinder the accuracy of equity return forecasts.

Keim [1985] further addressed several topics related to dividend yields such as taxation, firm size, stock returns, and seasonality; through his examination of NYSE data over the period of 1931 to 1978. Among other findings, Keim [1985] confirmed earlier results of Blume [1980] who found that there existed a non-linear relation between long-run yields and returns. However, Keim [1985] reported that the findings were dominated by the effects of January data and that when January data was removed from the examined data set, the relationship was no longer significant. Furthermore, Keim [1985] hypothesized that the January yield effect may be the result of the significant relationship between January stock returns and market value of equity. It is also notable to mention that Keim [1985] examined the marginal explanatory power of dividend yields in January data while controlling for firm size. Keim's [1985] findings on this analysis suggested that dividend yields and size are related to the same asset pricing factor. Furthermore, Keim [1985] noted a few important observations between dividend yields and firm size such as the tendency of dividend yields and firm size to be inversely related, and that the largest firms on the NYSE are not the largest dividend yield firms, which instead tend to be firms of "mid-size".

Fama and French [1987a] further demonstrated the importance of firm size through their examination of autocorrelations and return predictability. Specifically, Fama and French [1987a] found that returns are more predictable for portfolios consisting of smaller firms. These findings resulted from an examination of first-order autocorrelations of returns for industry portfolios and portfolios formed on the basis of size. In addition to their findings, Fama and French [1987a] cited the works of King [1966], Banz [1981], and Huberman and Kandel [1985] to support their assertion that firm size and industry type are dimensions which are known to impact return behaviour.

This direct examination of the effectiveness of using dividend yield in forecasting future returns begins by reviewing the findings of Fama and French [1988]. This particular study examined the use of dividend yields to forecast returns over one month to four year periods using continuously compounded rates of return. Fama and French [1988] found that regressions of returns on dividend yields often explain more than 25% of the variance of two to four year returns. In general, their finding suggested that the forecasting ability of future returns based on dividend yields increased in relation to increases with return horizon. However, they went on to note that dividend yield is, in general, a noisy proxy for expected returns because it also reflects expected dividend growth. Later studies of return predictability based on dividend yields often either support Fama and French's findings or challenge both their findings and their methodologies, as examined later.

Campbell and Shiller [1989] examined the time variation in corporate stock prices relative to their dividends. Their approach utilized a log dividend yield as the measure for expectation of the present value of future dividend growth and discount rates. Campbell and Shiller's [1989] study consisted of three main findings: first, log dividend-price ratio moves in relation to rationally expected future growth in dividends; second, Campbell and Shiller [1989] found that measures of short term discount rates, consumption growth, and stock returns are insignificant when explaining stock-price movements; and finally, the authors found that there are large unexplained variations in the log dividend yield ratios examined. In summary, further evidence regarding the strength of the relationship between dividends and earnings is supported by the findings of Campbell and Shiller [1989].

Kothari and Shanken [1991] examined further the relationship between dividends and stock returns by examining the extent to which aggregate stock return variation can be explained by variables which are used as proxies for intra-period revisions in expectations of future dividends. To examine this, Kothari and Shanken [1991] used both cross sectional, as well as time series data analysis approaches. Kothari and

Shanken's [1991] time series analysis revealed that even their simple model accounted for 72% of annual return variation, and found that returns were significantly related to future changes in dividends, as far as three years into the future. Their cross sectional analysis also found that 90% of the variation in aggregate returns could be explained by dividend and expected return variables. Thus, Kothari and Shanken [1991] provided evidence that suggests a strong relationship between stock variations and intra-period revisions to expected future dividends. Notably, this did not examine the relationship between current dividend yields and future returns, instead, it was suggested that current returns reflect future changes to dividends. However, Kothari and Shanken [1996] went on to examine the relationship between book-to-market ratio, dividend yields, and expected market returns through a time series analysis over a period of 1926-1991. By employing a vector auto-regressive framework they found evidence that dividend yield and book-to-market ratio track time-series variation in one-year expected real returns over the examined period, as well as over a sub period from 1941-1991. Specifically, the authors found changes in expected return movements from three to eight percentage points resulting from a corresponding change in dividend yield. In addition, Kothari and Shanken [1996] found that over the examined 1926-1991 sub period, dividend yield explained more variation in expected one-year stock returns than book-to-market ratio. Thus, the authors recognized the forecasting ability of dividend yields on future stock returns.

Although the review of the literature thus far seems to suggest an almost unquestionable significance of dividend yields to forecast stock returns, Goetzmann and Jorion [1995] found mixed results through their examination of US and UK data over the period of 1871-1992. Specifically, Goetzmann and Jorion [1995] examined the impact of survivorship bias on dividend yield regressions. The authors went on to suggest that mean reversion tendencies of dividend yields create the false appearance of return predictability. After attempting to correct for the effects of survivorship bias through the employment of a boot-strapping model, Goetzmann and Jorion [1995] concluded weak forecasting ability existed over only some sub-periods within both the US and UK data sets.

Wilkie [1992] continued the discussion in a similar manner as Fama and French [1988] but added an examination of optimal return horizon in relation to dividend forecasting ability. Wilkie's [1992] findings suggested that correlation between stock returns and dividend yields continue to heighten as return horizons increase up to a maximum appearing between 70 and 80 months. This study is significant because it serves to recognize the relationship between current dividend yields and its importance on future returns over a defined horizon.

Hodrick [1992] utilized three alternative measures for long return-horizon forecasting by using Monte Carlo experiments intended to address small sample bias believed to be present in preceding studies. The three alternative measures Hodrick [1992] utilized are as follows: first, Hodrick [1992] examined forecasting future stock returns based on an OLS regression as presented by Richardson and Smith [1991]; second, Hodrick [1992] examined forecasting future stock returns based on an OLS regression reformulation as introduced by Jegdeesh [1990]; and finally, the author examined forecasting future stock returns based on a vector auto-regressive method as performed by Campbell and Shiller [1988]. Hodrick [1992] concluded that the vector auto-regressive method of Cambell and Shiller [1988] is the most effective method for studying long return-horizon forecasting. Notably, this methodology was not inline with the methodology employed by Fama and French [1988].

Harris and Sanchez-Vale [1999] briefly examined a series of five multivariable lag regression models, utilizing historical dividend yield, as well as dividend yield transformations, in order to forecast future returns. Their analysis used UK equity returns while investigating the gain from allowing equity and bond yields and lagged yields to freely enter the proposed regression equations. The authors found little statistical difference between the five models tested. However, when testing the models with an out-of-sample trading strategy, Harris and Sanchez-Vale [1999] discovered greater profitability arising from the regression model that utilized a series of "reverse yield gaps", defined as the difference between the consol yield and the equity dividend yield. Thus, Harris and Sanchez-Vale [1999] provided further support for the value of return forecasting through dividend yields, as well as through dividend yield transformations.

Wolf [2000] presented a very rich summary and critical examination of findings from the literature examining return forecasting from dividend yields. Specifically, Wolf [2000] commented that the models proposed by Rozeff [1984], Campbell and Shiller [1988a], Fama and French [1988], Nelson and Kim [1993] and Hodrick [1992]; contained numerous statistical problems. In particular, Wolf [2000] noted that stock return regressions contain strong dependency structures which result in biases within the coefficient estimations. In fact, Wolf [2000] stated that such statistical methodologies tend to over support the no-predictability hypothesis. Furthermore, Wolf [2000] described Jorion's [1993] boot-strapping methodology as not being supported by theoretical properties. To avoid the problems of preceding studies, Wolf [2000] employed a sub sampling methodology. However, he concluded that there was no significant evidence to suggest future stock returns can be forecasted by dividend yields.

Schwert [2003] also conducted an investigation of dividend yields and their forecasting ability. Schwert [2003] began his study through an examination of Fama and French's [1988] study which found a statistically significant relationship between dividend yields and future returns. The data set used by Fama and French [1988] covered the period from 1927 through to 1986, however Schwert [1988] expanded on this to include data from 1872-2000. Schwert [2003] suggested that by examining this larger data set, the findings of Fama and French [1988] are diminished as a result of a much weaker relation. To further examine his findings, Schwert [2003] employed an "out of sample" trading strategy which invests in either a completely short-term bond portfolio or entirely in an equity portfolio. Notably, Schwert [2003] only used regression parameters derived from the original 1927-1986 Fama French [1988] data set to test his trading model over a period of 1872-2000. Thus, Schwert's [2003] criticism of the use of dividend yields to forecast returns may not be as justifiable as it initially appeared.

In summary, this brief review of the literature demonstrates the differing opinions and research findings with regards to the predictive ability of dividend yields in forecasting future rates of return. This paper continues the discussion by utilizing a similar methodology to that of Fama and French [1988] by examining aggregated dividend yields in the US market place and their ability to forecast disaggregated industry returns for 12 US sub-industries.

The innovation of the methods proposed here, arise from some of the above findings with respect to the correlation of firm size and dividends by examining both equally weighted and value weighted industry returns and market dividend yields. In addition, the use of a risk free rate of return, 30 day US treasury bills, is used to enhance the statistical and economic explanatory power of dividend yields in forecasting disaggregated industry returns. Finally, this paper examines the economic explanatory power of the aforementioned indicators through a series of decade long trading model tests spanning each decade from the 1940's to the 1990's, as well as the aggregated period from December 1930 to January 2005.

The remainder of this paper is organized as follows:

The section entitled "Data" summarizes the details of the examined data set, including data sources and data manipulations used to derive market dividend yields. The section entitled "Testing Methods" outlines the proposed testing methodologies including the trading model and regression model to be examined. Likewise, the section entitled "Results" contains a discussion of the findings from both the regression and trading model analysis. Finally, a summary of this paper along with conclusions and recommendations for future testing are presented under the section entitled "Summary & Conclusions".

Data

The data used in this study has been compiled from two sources: the Kenneth French online data library[1] and the University of Toronto's "Computing in the Humanities and Social Sciences" (CHASS) data centre[2].

The Kenneth French online data library was used for obtaining 30 day US treasury bill rates, as well as the aggregated monthly industry returns for 12 specified industry portfolios. The returns of 12 industry portfolios were examined on both a value-weighted and equal weighted basis. Further detail regarding the methodology of the portfolio construction is outlined within the Kenneth French online data library. However, the specific industry groupings are presented here as follows:

1. **NoDur:** Consumer NonDurables; *eg. Food, Tobacco, Textiles, Apparel, Leather, Toys.*
2. **Durbl:** Consumer Durables; *eg. Cars, TV's, Furniture, Household Appliances.*
3. **Manuf**: Manufacturing; *eg. Machinery, Trucks, Planes, Paper, Commercial Printing.*
4. **Enrgy:** Oil, Gas, and Coal Extraction and Products.
5. **Chems:** Chemicals and Allied Products.
6. **BusEq:** Business Equipment *eg. Computers, Software, and Electronic Equipment.*
7. **Telcm:** Telephone and Television Transmission.
8. **Utils:** Utilities.
9. **Shops:** Wholesale, Retail, and Some Services (Laundries, Repair Shops).
10. **Hlth:** Healthcare, Medical Equipment, and Drugs.
11. **Money:** Finance.
12. **Other:** Other; *eg. Mines, Construction, Transportation, Hotels, Entertainment.*

Data used to derive monthly dividend yields, namely ex-dividend and dividend-inclusive market rates of return, has been provided through the CHASS data centre. The methodology for deriving monthly dividend yields from ex-dividend and dividend-

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[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html

[2] http://datacentre.epas.utoronto.ca.proxy.lib.sfu.ca/crsp/index.html

inclusive rates of return is consistent with that of Fama and French [1998]. As with the industry portfolio returns mentioned above, dividend yields have been derived for both equally weighted and value weighted US market portfolios. However, unlike the industry portfolio returns mentioned above, the dividend yield data examined is aggregated over all security listings on the NASDAQ, AMEX, and NYSE stock exchanges and is not partitioned into dividend yields for various sectors.

Data for all examined indicators span from January 1930 to December 2005, inclusive.

Testing Methods

This examination consists of initially performing an Ordinary Least Squares (OLS) regression to determine the statistical significance of both US 30 day treasury bills and aggregated monthly dividend yields in forecasting future monthly rates of return in 12 specified industries. The industries under examination are: Consumer Durables, Manufacturing, Energy, Chemicals, Business Equipment, Telecommunications, Utilities, Shops, Healthcare, Financial, and Other. This model is examined with both equally-weighted and market-weighted industry returns and dividend yields in order to identify the statistical advantages of both groupings. The model is represented mathematically by equation [1] below:

$$R_{i,t+1} = \beta_0 + \beta_1 D_t + \beta_2 r_{f,t} + \varepsilon_{t+1} \qquad [1]$$

Where:

$i \in \{1, 2, \ldots, 12\}$ and represents any one of the 12 unique industry portfolios.

$R_{i,t+1}$: The portfolio return for the i^{th} industry in the $t+1^{st}$ period.

$r_{f,t}$: The risk free (treasury bill) rate of return for the t^{th} period.

D_t: The dividend yield for t^{th} period, defined as the: Annualized dividend in the th period divided by the underlying security Price in the th-1 period.

β_0: The regression intercept coefficient.

β_1: The regression dividend yield coefficient.

β_2: The regression risk free rate of return coefficient.

ε_{t+1}: Random error term for the forecasted value in the $t+1^{st}$ period.

In addition, an OLS regression model excluding the 30 day treasury bill rate is also imposed on the data set in order to isolate the added explanatory power of this variable. This model is represented mathematically by equation [2] below:

$$R_{i,t+1} = \beta_0 + \beta_1 D_t + \varepsilon_{t+1} \qquad [2]$$

Note, variable definitions are consistent with those listed with equation [1] above.

Both regression model [1] and [2] are run over the complete data set spanning a period of January 1930 to December 2005, for all 12 industry portfolios. Note, unlike Fama and French [1988] and Schwert [2003] who both utilized continuously compounded rates of return in their analyses, this paper examines monthly compounded returns. The impact on the outcomes as a result of using a different method of return compounding should be minimal. If this study were to be conducted with less frequent rates of return it would be recommended to utilize a continuously compounded rate of return.

Once completing the aforementioned regression analyses, the model is tested to examine its potential economic significance through a trading model. The trading model begins by using 96 months, 8 years, of historical data to forecast industry returns one month into the future for each of the 12 examined industries. If the forecasted result in this first period is greater than the current period's 30 day treasury bill return, then one dollar is invested into the industry portfolio, otherwise the one dollar of initial investment is invested into 30 day treasury bills. An iterative process is employed for each month in order to generate the regression parameters. This is achieved by using a moving window of 86 months of data. In other words, for each month the oldest data point used in the previous month's regression is replaced by the most current available monthly data.

The trading model is tested over a 65 year period ranging form January 1940 to December 2004. The results are reported as both dollar returns and return per unit risk. Dollar return is defined as the accumulated value at the end of a given examined period of one dollar invested through the proposed trading model at the beginning of the same period. Likewise, return per unit risk is measured through Sharpe Ratios calculated from the monthly returns generated by the trading model over an examined time period. Each of these two measures are reported over the aggregated 65 year examination period, and per decade; ranging from the 1940's through to the 1990's, as well as over the five year period of January 2000 to December 2004. This reporting methodology allows us to isolate and examine economic sub periods where the trading model may have provided significantly superior or inferior results in comparison to the industry portfolio. Furthermore, all trading model results are reported along with the corresponding results generated by the industry portfolio for each examined period of time.

Results

Regression Analysis

The regression analysis on equally weighted industry returns, as well as equally weighted market dividend yields was conducted as per the following regression model, introduced earlier.

$$R_{i,t+1} = \beta_0 + \beta_1 D_t + \beta_2 r_{f,t} + \varepsilon_{t+1} \qquad [1]$$

The results of the regression are highlighted in **Table 1** below.

Table 1: Regression of Equal Weighted Industry Return on Dividend-Yield and Risk-Free-Return

912 observations from Jan 1930 to Dec 2005 were used for each of the 12 industry portfolios in accordance to regression model: $R_{i,t+1} = \beta_0 + \beta_1 D_t + \beta_2 r_{f,t} + \varepsilon_{t+1}$

Industry	β_0	t-stat	β_1	t-stat	β_2	t-stat	Adj R^2
NoDur	0.0034	0.4947	0.2792	1.8171 *	0.1127	0.1188	0.21%
Durbl	0.0076	0.8260	0.2651	1.3065	-0.8438	-0.6736	0.18%
Manuf	0.0104	1.2430	0.1924	1.0396	-0.8326	-0.7287	0.09%
Enrgy	0.0172	2.0023 *	0.0833	0.4384	-1.5312	-1.3052	0.11%
Chems	0.0081	1.1455	0.1641	1.0431	-0.2452	-0.2525	-0.03%
BusEq	0.0101	1.0506	0.2047	0.9577	-0.5173	-0.3919	-0.03%
Telcm	0.0012	0.1680	0.2471	1.5274	1.1167	1.1178	0.06%
Utils	-0.0036	-0.5088	0.3435	2.2185 *	1.2266	1.2830	0.33%
Shops	0.0099	1.2959	0.1571	0.9271	-0.6851	-0.6549	0.03%
Hlth	0.0029	0.3978	0.2380	1.4588	1.1389	1.1305	0.05%
Money	0.0034	0.4385	0.3190	1.8766 *	0.0483	0.0460	0.25%
Other	0.0054	0.6027	0.3270	1.6600 *	-0.6574	-0.5406	0.30%

** Significant at alpha = 0.1 level*

The findings noted in **Table 1** show relatively little industry return forecasting significance by dividend yields and 30 day treasury bill returns. This is evident when examining the t-test statistics at the α = 0.1 significance level. By doing so, it is found that none of the treasury bill return coefficients, β_2, are significant. In addition, the only industries with dividend yield coefficients, β_1, found to be significant at the α = 0.1 level, include: Non-

Durables, Utilities, Money, and Other. Even in these four industries, the regression adjusted R^2 statistic is less than 0.5%, suggesting little statistical significance of the model.

The second treatment of our regression analysis examines model [1], indicated earlier, by generating coefficients using value weighted industry return and dividend yields instead of corresponding equally weighted figures.

The results of the regression are highlighted in **Table 2** below.

Table 2: Regression of Value Weighted Industry Return on Dividend-Yield and Risk-Free-Return

912 observations from Jan 1930 to Dec 2005 were used for each of the 12 industry portfolios in accordance to regression model: $R_{i,t+1} = \beta_0 + \beta_1 D_t + \beta_2 r_{f,t} + \varepsilon_{t+1}$

Industry	β_0	t-stat	β_1	t-stat	β_2	t-stat	Adj R^2
NoDur	-0.0049	-0.9477	0.2729	2.6140 *	1.3444	2.1283 *	0.79%
Durbl	-0.0023	-0.2974	0.3990	2.5373 *	-0.8424	-0.8852	0.74%
Manuf	-0.0040	-0.5520	0.3745	2.5500 *	-0.2059	-0.2317	0.57%
Enrgy	0.0033	0.5122	0.2025	1.5660	-0.0636	-0.0813	0.07%
Chems	-0.0009	-0.1461	0.2716	2.1749 *	0.0096	0.0127	0.33%
BusEq	-0.0008	-0.0929	0.3309	1.9790 *	-0.4346	-0.4296	0.30%
Telcm	-0.0022	-0.4502	0.1776	1.8059 *	1.0861	1.8251 *	0.36%
Utils	-0.0057	-0.9598	0.2592	2.1498 *	1.1966	1.6399	0.43%
Shops	-0.0019	-0.3061	0.2675	2.1072 *	0.4943	0.6436	0.27%
Hlth	-0.0032	-0.5231	0.2757	2.1948 *	1.0350	1.3616	0.39%
Money	-0.0095	-1.3176	0.4584	3.1345 *	0.7498	0.8471	0.85%
Other	-0.0078	-1.0813	0.3980	2.7321 *	0.5051	0.5730	0.60%

** Significant at alpha = 0.1 level*

The findings noted in **Table 2** show significantly greater forecasting ability by value weighted dividend yields and 30 day treasury bill returns. Again, this is examined through t-test statistics at the $\alpha = 0.1$ significance level. The dividend yield coefficients, β_1, were found to be significant for most industries, with the exception of the Energy industry. In addition, the adjusted R^2 statistic, for all but the Energy industry, has increased over those that were generated with the previous equally weighted data set.

However, the treasury bill return coefficients, β_2, are again insignificant for most industries, with the exception of Non-Durables and Telecommunications.

The lack of significance of the treasury bill return coefficients, β_2, prompt a further examination of the value weighted data set through the use of regression model [2] listed below.

$$R_{i,t+1} = \beta_0 + \beta_1 D_t + \varepsilon_{t+1} \qquad [2]$$

Notably, this regression model does not contain the treasury bill independent variable contained in model [1]. The results of the regression are highlighted in **Table 3** below.

Table 3: Regression of Value Weighted Industry Return on Dividend-Yield

912 observations from 1930 to 2005 were used for each of the 12 industry portfolios in accordance to regression model: $R_{i,t+1} = \beta_0 + \beta_1 D_t + \varepsilon_{t+1}$

Industry	β_0	t-stat	β_1	t-stat	Adj R^2
NoDur	0.0013	0.3030	0.2196	2.1624 *	0.40%
Durbl	-0.0062	-0.9633	0.4324	2.8328 *	0.77%
Manuf	-0.0049	-0.8263	0.3826	2.6854 *	0.68%
Enrgy	0.0030	0.5648	0.2051	1.6341	0.18%
Chems	-0.0009	-0.1682	0.2713	2.2385 *	0.44%
BusEq	-0.0028	-0.4053	0.3481	2.1457 *	0.39%
Telcm	0.0028	0.6981	0.1345	1.4073	0.11%
Utils	-0.0002	-0.0438	0.2118	1.8075 *	0.25%
Shops	0.0004	0.0681	0.2479	2.0122 *	0.33%
Hlth	0.0015	0.2948	0.2347	1.9234 *	0.30%
Money	-0.0061	-1.0173	0.4287	3.0199 *	0.88%
Other	-0.0054	-0.9184	0.3780	2.6737 *	0.67%

** Significant at alpha = 0.1 level*

The results reported in **Table 3** suggest a series of interesting relationships. It is clear that the Energy sector shows no statistical significance by either regression model [1] or [2]. The remaining eleven industries can thus be sorted into two groups. The first such group consists of those industries for which regression model [1] demonstrates greater ability over regression model [2] in forecasting industry returns. Included in this grouping are; Non-durables, Telecommunications, Utilities, and the Health industry. The second industry grouping consists of those industries for which regression model [2] demonstrates greater forecasting ability than regression model [1] and includes; Durables, Manufacturing, Chemicals, Business Equipment, Shops, Money, and Other industries.

As a result of the industry specific sensitivities to each regression model, it is prudent to examine the proposed trading model over all industries by utilizing both regression models [1] and [2]. Hypothetically, one would expect to see those industries demonstrating statistically significant relationships to also generate earnings over and above those of the industry portfolio by employing the corresponding trading rule.

Trading Rule - Dollar Return Analysis

The results of the trading rule analysis are reported under two categories. Firstly, this paper examines the findings of a trading rule strategy based on the earlier described regression model [1] (Trading model [1]), inclusive of both the dividend yield, as well as the monthly treasury bill rate as dependent variables. Secondly, this paper examines the findings of a trading rule strategy based on regression model [2] (Trading model [2]), inclusive of the dividend yield, yet excluding the monthly treasury bill rate as a dependent variable. The trading rule analysis for both underlying regression models are evaluated exclusively over the value weighted data set.

It would be expected that those industry portfolios demonstrating statistical significance over the entire 1930 to 2005 examination period, would also demonstrate economic significance in most examined sub-periods. Economic significance is defined as the ability to produce excess returns over and above those generated by buying and holding the industry portfolio for the duration of the examined period. **Table 4** reports both the dollar return generated by trading model [1], as well as the dollar return generated by the industry portfolio. Specifically, reported in **Table 4** is the accumulated value at the end of each examined period of one dollar invested at the beginning of the period through both the proposed trading rule and through investing solely in the industry portfolio.

Table 4: Dollar Return Generated by Trading Model using Dividend-Yield and Risk-Free-Return Based Forecasting vs. Dollar Return of Industry Portfolios – value weighted data

Trading Model Strategy

	1940's	1950's	1960's	1970's	1980's	1990's	2000-2004	**Jan '40 - Dec '04**
NoDur **	2.02	2.08	2.62	3.30	5.92	3.52	1.41	1,063.24
Durbl	0.91	6.45	2.66	2.85	4.71	3.52	1.11	819.16
Manuf	1.07	5.96	1.90	3.03	3.57	2.17	1.25	356.67
Enrgy	2.09	6.30	1.72	3.62	2.50	2.67	1.36	742.79
Chems	1.32	5.40	1.62	2.28	3.04	3.90	1.09	341.36
BusEq	1.46	5.90	2.51	1.66	4.30	7.87	0.45	551.11
Telcm **	1.48	3.00	1.89	2.55	6.51	3.20	0.63	281.86
Utils **	1.75	2.11	2.03	2.81	5.02	1.56	1.56	255.91
Shops	2.82	2.32	1.97	3.17	6.58	4.70	0.93	1,172.25
Hlth **	1.69	3.10	1.91	1.85	4.34	4.22	1.18	401.67
Money	2.08	2.65	2.08	3.07	5.04	4.44	1.49	1,173.78
Other	1.11	3.13	1.81	3.73	4.15	4.60	1.23	553.09
Equal Weighted Portfolio	1.65	4.03	2.06	2.83	4.64	3.86	1.14	642.74

Industry Portfolio - Buy and Hold Strategy

	1940's	1950's	1960's	1970's	1980's	1990's	2000-2004	**Jan '40 - Dec '04**
NoDur	2.43	3.24	3.06	1.61	9.89	3.18	1.53	1,863.41
Durbl	2.66	7.00	2.07	1.62	4.35	3.31	1.19	1,069.27
Manuf	2.40	7.02	2.08	1.71	3.89	3.31	1.39	1,073.67
Enrgy	3.50	5.96	2.12	3.64	4.10	2.90	1.79	3,429.01
Chems	2.12	5.58	1.53	1.82	5.16	4.11	1.21	845.64
BusEq	2.15	9.88	4.10	1.30	2.19	13.74	0.46	1,580.31
Telcm	1.59	3.46	1.80	2.01	8.65	4.92	0.47	399.07
Utils	2.32	3.56	1.93	1.87	5.35	2.26	1.68	601.99
Shops	3.29	3.54	2.78	1.38	6.24	4.65	1.09	1,413.78
Hlth	2.36	5.86	3.13	1.56	5.52	5.57	1.13	2,359.23
Money	3.55	4.35	2.46	1.65	5.06	5.59	1.59	2,816.02
Other	2.61	5.35	2.06	2.03	4.73	4.55	0.93	1,168.99
Equal Weighted Portfolio	2.58	5.40	2.43	1.85	5.43	4.84	1.21	1,551.70

** Industry portfolios found to be most significant under regression model [1][3]

The above table contains the accumulated value at the end of each indicated period of one dollar invested at the beginning of the given period through either trading model [1], as described below, or through the industry portfolio.

A moving window of 96 historical months was used to forecast the industry return one month into the future. This process was continued every month from the first January to the last December of the following decades: 1940's, 1950's, 1960's, 1970's, 1980's, 1990's, as well as for the half decade of 2000-2004, and finally for the entire period of 1940 to 2004. The forecasting model utilizes the relationship of regression model [1]: $R_{i,t+1} = \beta_0 + \beta_1 D_t + \beta_2 r_{f,t} + \varepsilon_{t+1}$.

In the first month of each period the trading model invests one dollar into the portfolio indicated by the greater of the forecasted industry return or the current monthly treasury bill rate. This process is continued each subsequent month using the accumulated investment total to-date.

[3] See Table 2: Regressions using Value Weighted data, model [1].

By examining the above table we find that over the entire period ranging from January 1940 to December 2004, the trading strategy did not produce dollar returns greater than those of the industry portfolios even in industries that were statistically significant under regression model [1]. Notably, the 1970's proved to be the only decade in which the trading model produced dollar returns greater than those of most industry portfolios, as well as for an equally weighted portfolio of the 12 examined industries.[4] This outcome can be explained by two economic factors prevalent in the 1970's. Firstly, the 1970's were witness to historically high short term interest rates, as measured by US 30 day treasury bill returns, averaging roughly six percent per annum for the decade.[5] Secondly, as indicated in **Table 4** industry returns during the 1970's were at an historical low, also averaging roughly six percent per annum. Due to the similar returns during this time period for both of the investment options assessed by the trading model, the trading model portfolio return was not penalized as significantly as in other decades if it incorrectly invested in the lower yielding portfolio for a given month.

The Telecommunications industry performed the best relative to its benchmark under the examined trading model, with $1 invested on January 1, 1930, accumulating to almost $282 on December 31, 2004, $117 less than investing in the corresponding industry portfolio for the same period. Notably, the economic performance of the trading model on the Telecommunications industry surpassed the economic performance of the trading model on seven other industry portfolios which possessed higher adjusted R^2 statistics from the corresponding regression analysis.[6] Likewise, the Non-Durables industry which possessed the highest adjusted R^2 statistic and the highest significance

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[4] The equally weighted portfolio return (EW Portfolio) is calculated as the average return over the 12 of the examined value-weighted industry portfolios.

[5] See Appendix, Table A, for the Absolute Dollar Value Return of Investing in US 30 day Treasury Bills.

[6] See Table 2: Regressions using Value Weighted data, model [1].

of both independent variables for the corresponding regression analysis, produced lower trading model dollar returns relative to its benchmark than that of seven other industries. Thus, it does not appear that the level of statistical significance of the underlying regression model corresponds directly with the level of economic significance of the trading model. A similar examination of the industries based on the regression model [2] trading model is outlined on the following page in **Table 5**.

Table 5: Dollar Return Generated by Trading-Model using Dividend-Yield Based Forecasting vs. Dollar Return of Industry Portfolios – value weighted data

Trading Model Strategy

	1940's	1950's	1960's	1970's	1980's	1990's	2000-2004	Jan '40 - Dec '04
NoDur	2.45	2.54	3.46	2.13	7.20	1.57	1.39	721.56
Durbl **	2.18	5.76	2.48	2.02	3.85	2.76	1.18	788.15
Manuf **	1.85	6.27	2.17	1.76	3.25	1.82	1.24	327.09
Enrgy	2.14	5.96	2.04	2.93	3.29	2.02	1.79	906.45
Chems **	1.64	5.22	2.00	1.76	3.94	2.37	1.36	382.54
BusEq **	1.86	8.82	4.28	1.28	4.09	9.44	0.46	1,607.53
Telcm	1.50	3.32	2.13	2.01	5.02	2.71	0.61	175.19
Utils	2.43	2.50	2.31	2.39	4.78	1.45	1.59	371.18
Shops **	2.86	2.85	2.77	1.68	5.49	3.28	1.09	740.01
Hlth	1.96	4.02	3.20	1.49	4.14	4.19	1.13	740.09
Money **	2.37	3.83	2.66	1.40	6.54	3.87	1.59	1,352.94
Other **	2.09	4.42	2.25	2.36	4.29	4.13	0.93	810.62
Equal Weighted Portfolio	2.11	4.63	2.65	1.93	4.66	3.30	1.20	743.61

Industry Portfolio - Buy and Hold Strategy

	1940's	1950's	1960's	1970's	1980's	1990's	2000-2004	Jan '40 - Dec '04
NoDur	2.43	3.24	3.06	1.61	9.89	3.18	1.53	1,863.41
Durbl	2.66	7.00	2.07	1.62	4.35	3.31	1.19	1,069.27
Manuf	2.40	7.02	2.08	1.71	3.89	3.31	1.39	1,073.67
Enrgy	3.50	5.96	2.12	3.64	4.10	2.90	1.79	3,429.01
Chems	2.12	5.58	1.53	1.82	5.16	4.11	1.21	845.64
BusEq	2.15	9.88	4.10	1.30	2.19	13.74	0.46	1,580.31
Telcm	1.59	3.46	1.80	2.01	8.65	4.92	0.47	399.07
Utils	2.32	3.56	1.93	1.87	5.35	2.26	1.68	601.99
Shops	3.29	3.54	2.78	1.38	6.24	4.65	1.09	1,413.78
Hlth	2.36	5.86	3.13	1.56	5.52	5.57	1.13	2,359.23
Money	3.55	4.35	2.46	1.65	5.06	5.59	1.59	2,816.02
Other	2.61	5.35	2.06	2.03	4.73	4.55	0.93	1,168.99
Equal Weighted Portfolio	2.58	5.40	2.43	1.85	5.43	4.84	1.21	1,551.70

** Industry portfolios found to be most significant under regression model [2][7]

The above table contains the accumulated value at the end of each indicated period of one dollar invested at the beginning of the given period through either trading model [2], as described below, or through the industry portfolio.

A moving window of 96 historical months was used to forecast the industry return one month into the future. This process was continued every month from the first January to the last December of the following decades: 1940's, 1950's, 1960's, 1970's, 1980's, 1990's, as well as for the half decade of 2000-2004, and finally for the entire period of 1940 to 2004. The forecasting model utilizes the relationship of regression model [1]: $R_{i,t+1} = \beta_0 + \beta_1 D_t + \varepsilon_{t+1}$.

In the first month of each period the trading model invests one dollar into the portfolio indicated by the greater of the forecasted industry return or the current monthly treasury bill rate. This process is continued each subsequent month using the accumulated investment total to-date.

By examining **Table 5**, we find that the trading model produced dollar returns in excess of the industry portfolio return for the Business Equipment industry. Specifically, one dollar invested through the trading model on January 1, 1940 through to December 31,

[7] See Table 3: Regressions using Value Weighted data, model [2].

2004 accumulated to $27 more than if invested solely into the Business Equipment industry portfolio over the same period. However, none of the other industries examined produced dollar returns in excess of the corresponding industry portfolios over the 1940 to 2004 period. For this same period however, the return for an equally weighted portfolio of all industries produced larger dollar returns through trading model [2] than through trading model [1]. This finding in turn suggests that on average US 30 day treasury bills provide little added economic significance to the underlying regression relationship.

As with the results of trading model [1] indicated in **Table 4**, trading model [2] produced dollar returns in excess of the equally weighted portfolio during the 1970's. However unlike trading model [1], trading model [2] also produced dollar returns in excess of the equally weighted portfolio during the 1960's. Again, this result is likely due to the fact that as in the 1970's, the 1960's experienced a narrowing between the difference of industry portfolio returns and US 30 day treasury bill returns over historical norms[8].

It is important to note that those industries which were found to have the greatest statistical significance through regression model [2]: Money, Durables, Manufacturing, and Other; were found in **Table 5** to have the 10th, 4th, 8th, and 5th greatest excess returns in comparison to the industry portfolio respectively. This observation again suggests that the economic and statistical significance of the underlying regression relationships do not coincide with one another.

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[8] See Appendix, Table A, for the Absolute Dollar Value Return of Investing in US 30 day Treasury Bills.

Trading Rule – Sharpe Ratio Analysis

Returns in excess of those generated from investing in the industry portfolio were not generated by either trading model [1] or [2] when examined on a risk un-adjusted basis. However, it is possible that each trading model possesses higher return per unit of risk exposure than that of simply investing in the industry portfolio. To examine if this is indeed true, a series of Sharpe Ratios have been calculated over both the trading model returns and the industry portfolio returns for each examined industry and time period.[9] The Sharpe Ratios can be interpreted for each portfolio over an examined period as its return per unit of risk exposure.

Our analysis of return per unit risk begins by examining the Sharpe Ratios generated through trading model [1]. The results of this examination are indicated in **Table 6** on the following page along with the Sharpe Ratios generated by the industry portfolios.

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[9] Sharpe Ratio = (portfolio return – risk free return)/(portfolio standard deviation)

Table 6: Sharpe Ratios Generated by Trading Model using Dividend-Yield and Risk-Free-Return Based Forecasting vs. Sharpe Ratios of Industry Portfolios – value weighted data

Trading Model Strategy

	1940's	1950's	1960's	1970's	1980's	1990's	2000-2004	**Jan '40 - Dec '04**
NoDur **	0.14	0.29	0.13	0.11	0.18	0.18	0.09	**0.15**
Durbl	(0.02)	0.35	0.18	0.09	0.13	0.15	(0.00)	**0.12**
Manuf	0.01	0.38	0.07	0.09	0.08	0.08	0.02	**0.10**
Enrgy	0.12	0.34	0.06	0.16	0.01	0.10	0.03	**0.12**
Chems	0.05	0.35	0.03	0.04	0.05	0.19	(0.01)	**0.11**
BusEq	0.06	0.34	0.09	(0.02)	0.13	0.24	(0.08)	**0.09**
Telcm **	0.11	0.37	0.07	0.08	0.21	0.14	(0.11)	**0.11**
Utils **	0.10	0.22	0.09	0.09	0.20	(0.01)	0.08	**0.11**
Shops	0.18	0.27	0.07	0.09	0.23	0.26	(0.04)	**0.14**
Hlth **	0.09	0.23	0.05	0.00	0.13	0.19	0.01	**0.10**
Money	0.12	0.26	0.08	0.09	0.16	0.20	0.06	**0.14**
Other	0.01	0.25	0.05	0.12	0.10	0.23	0.02	**0.11**
Equal Weighted portfolio	0.10	0.47	0.11	0.10	0.17	0.26	(0.00)	**0.16**

Industry Portfolio - Buy and Hold Strategy

	1940's	1950's	1960's	1970's	1980's	1990's	2000-2004	**Jan '40 - Dec '04**
NoDur	0.17	0.35	0.16	(0.02)	0.25	0.13	0.06	**0.15**
Durbl	0.14	0.31	0.06	(0.02)	0.09	0.11	0.00	**0.10**
Manuf	0.14	0.37	0.07	(0.01)	0.08	0.14	0.03	**0.11**
Enrgy	0.19	0.30	0.08	0.11	0.07	0.11	0.07	**0.14**
Chems	0.14	0.31	0.01	(0.00)	0.12	0.17	0.01	**0.11**
BusEq	0.11	0.39	0.16	(0.05)	(0.01)	0.28	(0.07)	**0.10**
Telcm	0.11	0.41	0.05	0.02	0.25	0.21	(0.11)	**0.10**
Utils	0.12	0.36	0.07	0.00	0.19	0.08	0.06	**0.12**
Shops	0.20	0.34	0.13	(0.04)	0.14	0.19	(0.01)	**0.12**
Hlth	0.14	0.30	0.14	(0.02)	0.14	0.21	(0.00)	**0.13**
Money	0.19	0.33	0.09	(0.02)	0.13	0.20	0.05	**0.14**
Other	0.15	0.31	0.06	0.01	0.10	0.18	(0.03)	**0.11**
Equal Weighted portfolio	0.17	0.43	0.11	0.00	0.15	0.25	0.01	**0.15**

** Industry portfolios found to be most significant under regression model [1].[10]

The above table contains Sharpe Ratios calculated for both the returns of trading model [1] and for the returns of each industry portfolio. US 30 day treasury bills have been used to approximate the risk free rate of return, as well; standard deviations of monthly data were used when calculating the Sharpe Ratios. Note, trading model [1] utilizes the relationship of regression model [1]: $R_{i,t+1} = \beta_0 + \beta_1 D_t + \beta_2 r_{f,t} + \varepsilon_{t+1}$

Table 6 reveals that trading model [1] produces Sharpe Ratios in excess of those produced by the industry portfolio for the industries of Durables, Telecommunications, and Shops; when examined over the period ranging from January 1940 to December 2004. In addition, four of the industries have portfolio and trading model Sharpe Ratios which are equal to one another over this same time period. When examining the results per decade we find that trading model [1] produces Sharpe Ratios in excess of those of

[10] See Table 2: Regressions using Value Weighted data, model [1].

the industry portfolio in the 1950's, 1970's, 1980's, and 1990's. Therefore, it appears that trading model [1] adds economic value over holding the industry portfolio by increasing return per unit of risk exposure. However, industries which appear to demonstrate greater return per unit of risk exposure through trading model [1] are not necessarily those industries that had the highest statistical significance through the same underlying regression model.[11] Therefore, the risk reduction benefits of employing trading model [1] may be the result of chance and are not necessarily due to any enhanced predictive ability resulting from the regression relationship.

As with trading model [1], trading model [2] has also been examined in a similar manner on a return per unit of risk basis. The results of this examination are indicated in **Table 7** on the following page.

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[11] See Table 2: Regressions using Value Weighted data, model [1].

Table 7: Sharpe Ratios Generated by Trading Model using Dividend-Yield Based Forecasting vs. Sharpe Ratios of Industry Portfolios – value weighted data

Trading Model Strategy

	1940's	1950's	1960's	1970's	1980's	1990's	2000-2004	**Jan '40 - Dec '04**
NoDur	0.18	0.28	0.20	0.03	0.21	(0.01)	0.05	**0.13**
Durbl **	0.11	0.29	0.10	0.02	0.09	0.11	0.00	**0.11**
Manuf **	0.10	0.35	0.09	(0.01)	0.06	0.03	0.01	**0.09**
Enrgy	0.12	0.30	0.10	0.09	0.05	0.05	0.07	**0.12**
Chems **	0.09	0.30	0.09	(0.01)	0.09	0.09	0.04	**0.11**
BusEq **	0.10	0.37	0.17	(0.05)	0.14	0.27	(0.07)	**0.11**
Telcm	0.11	0.40	0.09	0.02	0.16	0.11	(0.08)	**0.09**
Utils	0.15	0.26	0.13	0.05	0.18	(0.03)	0.05	**0.11**
Shops **	0.18	0.29	0.14	(0.02)	0.20	0.18	(0.01)	**0.13**
Hlth	0.11	0.25	0.15	(0.04)	0.12	0.18	(0.00)	**0.11**
Money **	0.14	0.31	0.15	(0.05)	0.23	0.17	0.05	**0.14**
Other **	0.12	0.28	0.10	0.04	0.11	0.21	(0.03)	**0.11**
Equal Weighted portfolio	0.15	0.40	0.17	0.01	0.18	0.21	0.01	**0.15**

Industry Portfolio - Buy and Hold Strategy

	1940's	1950's	1960's	1970's	1980's	1990's	2000-2004	**Jan '40 - Dec '04**
NoDur	0.17	0.35	0.16	(0.02)	0.25	0.13	0.06	**0.15**
Durbl	0.14	0.31	0.06	(0.02)	0.09	0.11	0.00	**0.10**
Manuf	0.14	0.37	0.07	(0.01)	0.08	0.14	0.03	**0.11**
Enrgy	0.19	0.30	0.08	0.11	0.07	0.11	0.07	**0.14**
Chems	0.14	0.31	0.01	(0.00)	0.12	0.17	0.01	**0.11**
BusEq	0.11	0.39	0.16	(0.05)	(0.01)	0.28	(0.07)	**0.10**
Telcm	0.11	0.41	0.05	0.02	0.25	0.21	(0.11)	**0.10**
Utils	0.12	0.36	0.07	0.00	0.19	0.08	0.06	**0.12**
Shops	0.20	0.34	0.13	(0.04)	0.14	0.19	(0.01)	**0.12**
Hlth	0.14	0.30	0.14	(0.02)	0.14	0.21	(0.00)	**0.13**
Money	0.19	0.33	0.09	(0.02)	0.13	0.20	0.05	**0.14**
Other	0.15	0.31	0.06	0.01	0.10	0.18	(0.03)	**0.11**
Equal Weighted portfolio	0.17	0.43	0.11	0.00	0.15	0.25	0.01	**0.15**

** Industry portfolios found to be most significant under regression model [2][12]

The above table contains Sharpe Ratios calculated for both the returns of trading model [2] and for the returns of each industry portfolio. US 30 day treasury bills have been used to approximate the risk free rate of return, as well; standard deviations of monthly data were used when calculating the Sharpe Ratios. Note, trading model [2] utilizes the relationship of regression model [2]: $R_{i,t+1} = \beta_0 + \beta_1 D_t + \varepsilon_{t+1}$

The findings contained within **Table 7** demonstrate that over the period ranging from January 1940 to December 2004, trading model [2] produces Sharpe Ratios in excess of those of the industry portfolio for the industries of Durables, Business Equipment, and Shops. In addition, three of the industries have portfolio and trading model Sharpe Ratios which are equal to one another. When examining the results per decade we find that trading model [2] produces greater Sharpe Ratios than the industry portfolio from the 1960's through to the 1980's. Despite this, the benefits on a risk adjusted basis of

[12] See Table 3: Regressions using Value Weighted data, model [2].

employing trading model [2] do not appear to be as significant as those indicated in **Table 6,** when employing trading model [1].

Again it appears that the industries which demonstrated enhanced risk adjusted returns through the employment of trading model [2] were not necessarily those industries which had the highest statistical significance from the underlying regression model.[13] Thus, little compelling evidence exists to suggest that the benefits of either trading model, as examined on a risk adjusted basis, has resulted from the significance of the underlying regression model.

[13] See Table 3: Regressions using Value Weighted data, model [2].

Summary and Conclusions

Numerous studies have been conducted for the purpose of examining the return forecasting ability of dividend yields. Such studies have employed a variety of statistical methodologies, yet, there has been no decisive conclusion as to whether or not any forecasting ability of dividend yields exists. In addition, there has not been any decisive conclusion as to which testing methodology is most appropriate to examine such a relationship.

The analysis of Fama and French [1988] is frequently cited by literature examining dividend-yield based forecasting. Although the conclusions from the aforementioned paper were not always supported by the body of literature that followed, there is also a lack of significant evidence to completely dismiss the paper's findings or the methodology that Fama and French [1988] proposed. Thus, the analysis presented here borrows from the Fama and French examination by employing a similar ordinary-least-squares (OLS) regression model to forecast future returns from historical dividend yields. Unique to this paper are the following: first, an independent variable consisting of a risk free rate of return, 30 day US treasury bills, is added to the regression model in an attempt to enhance the forecasting ability of the dividend yields; second, the statistical significance of the regression model is tested over both value and equally weighted return and dividend yield data; third, the regression model is analyzed over 12 unique dis-aggregated industry portfolio returns, however, the dividend yield independent variable remains aggregated at the market level; and finally, an economic significance test in the form of a trading model is tested against the returns of the industry portfolios on both an absolute and risk adjusted basis.

The findings here suggest that US 30 day treasury bills do little to enhance the predictive ability of dividend yields in forecasting future industry returns. However, the returns for the industries of Telecommunications, Non-Durables, Utilities, and Health were better forecasted by the regression model containing US 30 day treasury bills. Likewise, dividend yields were found to be far more significant when used to forecast value weighted returns over that of equally weighted returns. The statistical significance of all employed regressions remained weak, however, with the regression models in any given industry explaining less than 0.9% of the observed variability in industry returns, as measured by the adjusted-R^2 statistic.

The regression relationships that were found to be statistically significant were then used to formulate trading strategies in order to test their economic significance. A series of time periods were used to examine if a dividend yield based trading strategy could consistently produce excess returns on an absolute and risk adjusted basis over that of the corresponding industry portfolio. Although the findings of our examination on a risk-adjusted basis were promising, no conclusive evidence was found to suggest that the underlying regression relationships was the cause of any observed economic significance.

The analysis presented here did not find any outstanding statistical or economic significance from employing dividend yields to forecast disaggregated industry returns, however, further examination is encouraged. The following adjustments may prove to enhance the explanatory power of dividend yields within industry data: first, consistent with much of the prevailing literature, the ability of dividend yields to forecast returns increases with an increase in return horizon, therefore, examining the relationships presented in this paper by substituting monthly data with either quarterly, semi-annual, or annual data may uncover more significant results; likewise, utilizing multiple lagged dividend yield variables may enhance the robustness of the regression models; and finally, it would be prudent for future examinations to test and, if necessary, control for the presence of heteroscedasticity and autocorrelation which may be present.

Appendix

Table A: Absolute Dollar Value Return of Investing in US 30 day Treasury Bills.

	1940's	1950's	1960's	1970's	1980's	1990's	2000-2004	**Jan '40 - Dec '04**
Risk free rate	1.04	1.20	1.46	1.84	2.34	1.62	1.14	14.65

At the beginning of each period one dollar is invested into the US 30 day Treasury Bill rate of return (risk free rate) and accumulated to the end of the last month in the given period. The final accumulated value of the initial investment is displayed above.

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