Expected Stock Returns: A Regression Based Approach

Can Business & Monetary Conditions Predict Variations In Expected Stock Returns?

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Abstract

What moves the stock market? Is it possible to predict expected returns and if so what are the factors that permit this forecast? In this paper, we review the existing literature of time-varying expected returns and conclude that indeed there are certain indicators of business, monetary, and market conditions which are useful in predicting excess stock returns. Furthermore, this predictability is not due to market inefficiencies but to rational variations in expected returns based on changes in these aforementioned conditions. We set forth a methodology to extend the models proposed in previous works by composing a model that incorporates proxies for all three underlying conditions simultaneously. We obtain a model in which all explanatory variables are 1) shown to be significant in predicting variations in expected returns and 2) impact expected returns in a manner consistent with their theoretical rational. Finally we perform sequentially generated out of sample forecasts and evaluate the market-timing ability of the model by subjecting it to the Henrickson-Merton's (1981) test of Merton's requirement for the usefulness of market-timing forecasts. We find that the forecasts generated do indeed outperform a buy and hold strategy. The main conclusion is that variations in expected returns are, after all, partly predictable and sufficiently so as to add value to a buy and hold strategy.

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1. Introduction

Out of clutter find simplicity, from discord find harmony.
Albert Einstein

Ever since gentleman speculators gathered around that buttonwood tree at the corner of Broad and Wall Street, investors have been looking for economic and scientific methods to gage future returns. The experienced speculator knows that apart from love and war, nothing arouses violent human emotions like the stock market. Therefore, we require, a methodology grounded in theory which enables the investor to find simplicity from clutter and harmony from the plethora of negative emotions such as fear hope and greed generated by the stock market. The science of econometrics gives us a means to this end.

For many years, the theory has not been very accommodating to those wishing to understand and gage the components of future returns. The financial literature has, until recently, held that markets are in one form or another " efficient". Broadly speaking, efficient market incorporates all known information at all times, making it all but impossible to forecast future returns. This is known as the random walk theory. This conventional wisdom regarding the predictability of stock prices has shifted dramatically in recent years as accumulating empirical evidence now suggests that stock returns are, in fact, partly predictable. Let us point out that predictor variables can be interpreted as correlated with investors required returns and are not necessarily a sign of an inefficient market. In any case, the first sign of predictability was obtained by examining the univariate time series properties of stock prices (Lo and Mackinley, 1988). The drawback of using only past returns is that they are mostly useful for predicting very short term variations in expected returns:

" we mentioned at the end of chapter 2 that there is its some evidence for predictability of stock returns at long horizons. Based evidence is statistically weak when only past returns are used to forecast future returns, but it becomes considerably stronger when other variables, such as the dividend-price ratio or the level of interest rates are brought into the analysis."(C.L.M The econometrics of financial markets).

Indeed, researchers have found convincing evidence that financial and accounting variables appear to have predictive power for longer term stock returns (Fama and French, 1988, 1989; Campbell and Shiller, 1988; Lakonishok, Shleifer and Vishny, 1994). Following this line of reasoning leads us to the use of multivariate regression analysis as the natural instrument of choice since we are dealing with explanatory variables, wether they be of a macro or micro nature, to predict longer term variations in expected stock returns. Let us quote Lo, Campbell and MacKinley once more:

" economists are exploring a great number of ideas from macro economic models of real business cycles to more heterodox models of investor psychology. At a more practical level, dynamic asset allocation models are becoming increasingly popular. In this context long horizon return regressions may be attractive not only for their potential statistical advantages, but also because investment strategies based on long-horizon return forecasts are likely to incur lower transaction costs".

In this paper, we review the existing literature and extend the research on the determinants of time-varying expected returns. This means that we believe that expected returns vary over time depending on the business and/or monetary environment. We are looking for variables which are proxies of these conditions and hence useful in capturing expected returns. We then group these explanatory variables into a regression based model, testing firstly wether or not these variables are in fact useful in capturing time-varying expected returns. And secondly, if these variables capture sufficiently future returns as to be used in a, real-time, market timing model.

The paper is organized as follows. Section 2 reviews the existing literature. This will not only put us up to date but give us critical insight into the types of variables to be considered as well as the specific econometric techniques used in this field of financial econometrics. We will include a critique of this literature. In section 3, we lay out the methodology to be used. Specifically we detail the model as well as the variables under consideration. Clearly the choice of the types of variables as well as the theoretical reasoning for their inclusion is a major part of time-varying expected returns analysis.

Section 4 is the empirical analysis which essentially estimates the model and deals with the technical econometric difficulties which arise. From the estimation of the model we will be in a position to comment on the power of the model to predict variations in expected stock returns, however, this is not sufficient to claim wether or not the model is useful for forecasting purposes. To this end, we devise a trading rule to implement the model. To assess the market timing ability of this trading rule, we must conduct sequentially generated out-of-sample forecasts. We evaluate the out-of-sample forecast with the Henrikson and Merton (1981) test of Merton's (1981) requirement for the usefulness of market-timing forecasts. Lastly, an alternative estimation technique using a logit model is considered. Final remarks as well as suggestions for future research are provided in Section 5.

2. Review of the literature

Fama and French (1989), Business conditions and expected returns on stocks and bonds:

This is without a doubt the pivotal work in the field of time varying expected returns. The authors and their work are cited in every other article which are in fact very similar with only minor tweaking. For this reason we will focus on it even if it is not the most recent. The main concept of the work is that the predictability of stock returns is a result of rational variation in expected returns and that this variation is related, through time, to the business conditions. They use three variables (dividend yield; default premium; term premium) as proxies of the current business conditions and conclude with the general message that expected returns are lower when economic conditions are strong and higher when conditions are weak. It is interesting to note that every study we have seen on the subject uses the exact same variables as those chosen by Fama&French. The model used is a simple ordinary least squares regression of future excess stock returns on the three explanatory variables related to business conditions.

They conclude that business condition as expressed by the variables are indeed related to future stock returns and also that the regression R^2 tend to increase with the holding period since the variables used are measures of long-term business conditions (the R^2 jumps from 0.06 for one month to 0.42 for the 12 month forecast). Also they use rolling regressions to produce out of sample forecasts and conclude that the out of sample tests support their basic inferences about the variation in expected returns.

Again, as this work is the principal and most widely quoted work in the field, it is difficult to criticize. Rather, we will attempt to extend their work by incorporating variables

related to the monetary environment as well as the technical undertone of the stock market to their proxies of the existing business conditions. We will also attempt to interpret the results as well as offer a slightly different interpretation of the default premium used by Fama&French as well as other researchers. Very minor critiques are that, firstly, the forecasting ability of the model is not tested thoroughly enough to determine if the model has market timing abilities and secondly their choice of forecast variable, the CRSP value weighed index, is more academic than practical. We believe that, although similar, using the S&P 500 would be a better choice as it permits implementation of the results and therefore adds usefulness to this otherwise inherently practical study.

Fuller and Kling (1994)" Can regression based models predict stock and bond returns?":

Fuller and Klings article is cited here as it is very representative of later studies on this theme. They use the same model with the same variables as Fama and French although they use different data. They conclude that the Fama&French model "predicts future excess returns a substantial percentage of the time". They add the common critique that if one includes trading costs it is doubtful that the model can be used for reliable market timing. This paper's main appeal to us is that it introduces a very practical technique to evaluate the model based on the Henrikson and Merton (1981) test of Merton's (1981) requirement for the usefulness of market-timing forecasts. This methodology will be explained fully in section 4.2.

A clear weakness of this work is that only monthly data frequency is considered. As mentioned above, Fama&French found that longer time periods produced much better results due to the nature of the variables. Consequently, it is not surprising that Fuller and Kling find their one month forecast to be unreliable for market timing. We will

consider a longer horizon even if it causes statistical difficulties due to the overlapping data. Another critique is that they do not offer any solutions or even ideas on how one could improve the model. Perhaps they found an improvement, and kept it to themselves, as they have recently started their own hedge fund using proprietary (undisclosed) market timing models! Also it is interesting to note that models that were unusable in the real world due to trading costs must now be reevaluated as these costs have dropped by almost 90% in the past two years.

Jensen Jeffery and Johnson (1996), Business Conditions, Monetary Policy, and Expected Security Returns

This article brings us closer to the content of our paper since the authors extend the work done by Fama&French by adding another dimension to the model by incorporating a proxy of monetary conditions. More precisely, they use an index of the stance of monetary policy based on changes in the discount rate. This index is basically similar to a dummy variable as it remains either in expansive monetary mode or restrictive monetary mode. Their argument is based on Waud's (1970) suggestion that discount rate changes affect market participants expectations about monetary policy because (1) rate changes are made only at substantial intervals , (2) they represent a somewhat discontinuous instrument of monetary policy, and (3) they are established by a public body perceived as being competent in judging the economy's cash and credit needs.

This measure, which we initially found attractive, was later revealed as theoretically inadequate as it would weigh the impact of a change in monetary policy at time t on expected returns, similarly to the impact on expected returns at time t+x, irrespective of wether the central bank had acted several times in the same direction, or had taken no action whatsoever.

In any case, they add this measure of the monetary policy to the same business conditions variables discussed above and find essentially that the impact of the various business conditions proxies vary across monetary environment. Their work however was later picked up by Booth and Booth (1997) in an attempt to reproduce the results.

Booth and Booth (1997) concluded that the slope parameters of the business conditions proxies were stable across the monetary regimes and also that monetary conditions have unique explanatory powers in the variations of expected returns not captured by the business conditions proxies. They claim that the findings of Jensen et al. may not be robust to slightly different measures of portfolios and/or measures of the business conditions variables. In their work they syllogize that monetary policy contains significant information that may be used to forecast expected stock returns. Thus the criticism of Jensen et al. is simply that their results are not robust. At any rate, we pick up on their idea of using a proxy of monetary policy in extending the classic Fama&French model.

Brock Lakonishok and Lebaron (1992), Simple Technical Trading rules and the Stochastic Properties of Stock Returns

This is the main literature on technical analysis. Any calculation using only price and/or volume is in the realm of technical analysis. This article is particularly interesting not only for it's content but also because it is a clear signal of the recent shift taking place in the academic community. Until recently, technical analysis was considered by academics to be completely useless and even slightly ridiculous. However this article shows the willingness of academics to at least examine this field which has been adopted by wall street for over 100 years. In any case, this article is an inspiration to us as it marries the practical world of the trader with the knowledge and tools of the scientist.

In this pathbreaking research, the authors investigated two of the simplest and most popular trading rules, the moving average and trading-range breakout. They found strong support in favor of these technical rules. They also compared their results to simulated comparison series generated by a fitted model from the null hypothesis class being tested. The null models tested were : random walk with a drift, AR(1), GARCH-M and E-GARCH. They found that the signals generated by their rules were not likely to be generated by the four null models. They conclude the paper by saying that they do not know why the technicals seem to work.

The main critique is that the work does little in terms of explanation and offers little theoretical insight on expected returns. Also, a trader would respond that the profitable results realized by their technical trading rule is in large part due to the fact that they have a clear entry strategy that has the advantage of permitted profits to run while having a strict exit strategy that cuts losses very quickly. Hence the results are likely largely due to this strict money management rather than to the actual system that generates the signal. Whether it is simply investor psychology or a self fulfilling prophecy or a derivative of basic money management, does not change the fact that a technical indicator should be included in our model as it is an important component in the decision making process of investors.

At this juncture we would like to briefly review the use of specific variables, which serve as proxies for the business conditions as well as the monetary environment, in the literature.

Business Conditions and Security Returns

As we have discussed, most of the recent research on the relation between stock returns and business conditions have focused on three measures of the business environment: dividend yield, the default spread, and the term spread.

The **dividend yield**, as a business conditions proxy, is perhaps the oldest of the measures believed to affect expected stock returns (Dow 1920). The intuition for this relation, provided by Fama (1990), is that stock prices are low relative to dividends when expected returns are high, and vice versa, so D(t)/P(t) varies with expected returns. Another way of looking at it is simply that dividend yields and expected returns are high when prices are temporarily low and Vice-versa. Rozeff (1984), Shiller (1984), Campbell and Shiller (1988), Fama and French (1988, 1989), Fama (1990), and Jensen, et al. (1996) document that dividend yields are significant in capturing expected stock returns.

Evidence that the **default spread** is important in explaining stock and/or bond returns is more recent. Chen, Roll, and Ross (1986) argue that the spread of lower-to higher-grade bonds is a proxy for business conditions. They argue that when business conditions are poor, spreads are likely to be high, and when business conditions are strong, spreads are likely to be low. Studies by Fama and French (1989), Fama (1990), and to a lesser degree Jensen, et al. (1996), find that the default spread captures variations in expected returns in response to business conditions.

The third measure of business conditions that has been used in previous studies is the **term spread**. The motivation for this is that the term spread is shown to decrease near peaks of economic activity and increase near economic troughs. Consistent with this motivation, Campbell (1987), Fama and French (1989), Fama (1990), Schwert (19 9 0) , Shiller (1984), Campbell and Shiller (1987), and Jensen, et al. (1996) find that the term spread explains variations in expected returns of portfolios containing securities of

different maturities, ie bond portfolios but are not statistically useful in terms of long term stock returns. In fact, Fama&French drop this variable altogether when estimating the longer-horizon expected stock returns.

Monetary Policy and Security Returns

It has long been contended that monetary policy affects not only economic activity, but also security returns. An early examination of the link between stock returns and monetary policy by, Geske and Roll (1983), and Kaul (1987) present evidence linking the monetary environment to stock returns. More recently, Jensen et al. (1996) examine changes in the Federal Reserve discount rate. Their motivation for using the **discount rate** as a proxy for the stance of monetary policy follows from the view that the discount rate is routinely regarded as a signal of monetary and possibly economic developments.

Finally, Thorbecke (1998) presents evidence that expansive monetary policy does increase ex-post stock returns using various measures of monetary policy such as the federal funds rate, policy changes and nonborrowed reserves.

Having reviewed the existing literature we have a clear idea of the types of variables to be included in our analysis. We start with the dividend yield and default spread as proxies for the business conditions. This is the foundation since we wish to extend the Fama&French (1989) model. As mentioned we believe there is sufficient evidence that any model of expected returns should have a component related to the monetary environment. The candidates are the discount rate changes, the federal funds rate, various interest rates, and the free reserves which are a variation of the nonborrowed reserves used in the recent study by Thorbecke (1998). Finally we want to include some kind of technical measure of the market ie past prices or a variation thereof.

Knowing the types of variables to be included, we proceed to establish the best model using model selection criteria such as the adjusted R^2, Akaike's information criterion [AIC:Akaike(1974)] as well as Schwartz's criterion [a Bayesian information criterion, BIC:Schwartz (1978)]. We are now ready to examine the model and methodology used in capturing expected stock returns.

3.Methodology

As discussed we want variables that are proxies for business, monetary, and technical conditions. To this end we considered numerous potential variables, however, due to limitations in terms of cost of data as well as length of time series available we were forced to limit our analysis to the variables in appendix page 34. The explanatory variables that were used, based on our model selection criteria, are detailed below and are presented graphically in appendix pp.28-33.

Our goal is to combine the fewest significant variables into the best usable model that will forecast the returns of our chosen benchmark, the S&P 500. As many researchers have already demonstrated, the type of variables we have chosen are much more relevant to a longer term forecast as they attempt to capture the determinants of macro factors rather than the noise. Wherefore we will use monthly data and our forecast variable will be the 6 month excess return of stocks over risk free treasuries of similar maturity.

The idea of excess returns as the forecast variable rather than purely the expected return is quite logical. Let us suppose that an investor has forecast the 6 month return of equities to be 15% which is several percentage points above the historical average. This expected return takes on much different implications if risk-free treasuries are yielding 5% or 15%. Clearly a rational risk-averse investor will choose the risk free asset if it is yielding the same expected return. Therefore by modeling the excess return we automatically consider the risk-free alternative.

It is important to specify that our forecast variable is slightly different than the one used by most other studies, as mentioned above. They use the CRSP value weighed aggregate. The difference is only minor, nevertheless, we feel that ours is a more logical choice simply because there exists several cash instruments by which one can implement the forecasts on the index (the Amex Spyder index as well as index funds) however there exists no tradeable instrument for the CRSP average.

Following the lead of the previous studies, we use an ordinary least squared regression technique. Due to the amount of variables used (the bare minimum were used in this final version) a VAR model would contain too many parameters and be impractical to implement. Also the added benefit of being able to make one month forecasts would likely be of little use du to the nature of our variables. We verified that $E(x_t u_{t,k})=0$ as this is the key requirement for the ordinary least square β estimators to be consistent (Table 3.1). The matter of the errors being serially uncorrelated will be discussed in section 4.1. Suffice it to say that we will be using the same formulation as all the other studies in the field:

$$Y_{t+k} = X_t \beta + u_{t,k}$$

TABLE 3.1

INDEPENDENT VARIABLES AND RESIDUAL CORRELATION

$E(x_t u_{t,k})$	X1	X2	X3	X4	X5
RES	0.012	0.014	0.055	-0.001	0.0145
T-Stats	0.185	0.219	0.85	-0.02	0.22

3.1 The Model

The model presented here, takes into account proxies of the business conditions (dividend yield), the monetary environment (CPI and free reserves), the technical undertone (trend) of the market as well as the prevailing sentiment (we interpret the default spread as a sentiment indicator rather than a business conditions proxy).

$$Yt+6= Cst + B1(DIVt) + B2(CPIt) + B3(DEFt) + B4(Trendt) + B5(FREEt) + et+6$$

Where

- **Y t+6**= Excess return of the S&P 500 over the next 6 month relative to 6 month risk- free treasuries

- **DIV**= Dividend yield obtained by dividing the dividends of all the components of the index weighed by market cap by the price of the index. The dividend yield is likely one of the oldest variables recognized as having explanatory powers in predicting stock returns. It is the quintessential measure of value. We expect to confirm that when yields are high, investors are getting good value which means higher returns. On the contrary when yields are low investors are paying dearly for the stocks and can expect low returns.

- **CPI**= This is the one year change in the consumer price index.{ (CPI t-1 - CPI t-13) / CPI t-13} The reason we leave a one month lag is that the consumer price index is released with a one month lag and we want our model to be usable in real-time. Obviously, inflation erodes the value of financial assets. As inflation

picks up, bond holders require additional yield as compensation. These higher bond yields make bonds more attractive than stocks (opportunity cost) limiting stock market returns. Also rising inflation usually leads to a tightening of monetary conditions leading to a slowdown of economic activity. As a rule of thumb disinflation is positive for stock returns while inflation leads to poor returns. Here we depart a bit from the conventional wisdom by using the inflation rate rather then a measure of interest rates. This is for two reasons, firstly it seems that investors, for the most part, are concerned with the inflation component of interest rates and secondly, our results are considerably better with the inflation rate than with the various measures of interest rates.

- **DEF**=Stands for Default spread, a term which refers to the spread of high and low quality bonds. We use the difference on the yield of the Baa-Aaa corporate bond yields as published by Moodies Investors Services as a proxy for the default spread. The variable DEF is in fact the one year change in this credit spread. Our interpretation of this variable is slightly different than the one espoused by most researchers. Although clearly related to prevailing business conditions, as this variables truly represents a perception of risk, it is really a sentiment indicator. As it is related to sentiment, it is naturally a contrarian indicator. The expected sign is thus counterintuitive since a high spread (high perceived risk) usually represents the bottom of an economic slowdown and therefore higher returns while a tight spread (low perceived risk) usually represents the top of an economic expansion and is therefore followed by lower expected returns

- **Trend**= natural logarithm of the previous 24 month holding period return of the S&P500. The theoretical reason for a 24 month holding period is simply that it represents roughly half a business cycle and was confirmed empirically (Keim

and Stambaugh,1986). This variable represents our technical factor. This variable is theoretically not as easy to predict since there are two opposing viewpoints. We do not know if we are dealing with a price persistency situation usually associated with short term returns or rather if we will find a reversion to the mean process usually associated with longer term returns. In any case the previous returns are evidently part of the investors' decision making process and thus useful in capturing expected returns.

- **FREE=** This is the free reserves of the Federal reserve. This variable is the difference between two monetary aggregates published by the Federal Reserve Board: Excess reserves and Borrowing of Depositary Institutions from the Fed. This variable is a proxy for the liquidity in the banking system. Again, we depart from the standard variables of the discount rate and the federal funds rate used to measure monetary policy. The discount rate is mostly symbolic and the target federal funds rate often differs from the effective federal funds rate. Rather than attempt to measure changes in these variables, we examine directly the availability of liquidity to the banking sector through the free reserves. Obviously, we expect to find that increases in liquidity lead to higher returns and vice-versa.

3.2 Sampling period

Fama suggests researchers choose periods free of *unusual* effects such as the great depression; World Wars; Korean War; pegging of Treasury Bill interest rates prior to the accord between the Treasury and the Fed; periods of fixed exchange rates. Also the quality of data reliability, for example the reliability of inflation rates prior to the mid 1950's (Fama 1975) is known to be questionable. Of course we do not want to avoid

situations which do not fit with our model, simply we want to avoid conditions which are so unusual as to create outliers which are misleading. We have chosen the thirty year period of 1964-1994. This sampling period gives us sufficient observations as well as a variety of bull and bear markets, periods of prosperity, recessions, high inflation and disinflation. As a bonus it also includes a crash (1987). Therefore this sample period truly represents a myriad of business, monetary and financial conditions.

4. Regression Results

$$Y_{t+6} = -13.144 + 6.93(DIV_t) - 2.08(CPI_t) + 9.3(DEF_t) - 15.78(TREND_t) + 4.93(FREE_t) + e_{t+6}$$

$$R^2 = 0.4043 \quad R^{2adj} = 0.3959$$

We notice firstly, from the preceding equation, that the signs of the coefficients are as we anticipated thereby confirming our theoretical reasoning. The dividend yield has a positive sign implying that higher dividend yields (better value) are indeed associated with higher expected returns and vice-versa. Our inflation measure has a negative sign implying that high levels of inflation are associated with lower expected returns. Whether this is due to higher interest rates, erosion of financial assets or because higher inflation leads to tighter monetary policy is unknown however it clearly is negatively correlated with expected returns.

Our sentiment indicator, the default spread, representing the perception of risk in the economy, has a positive sign. When the perception of risk is high, investors are unsure of the ability of the lower quality companies to meet their interest expenses let alone the principal and therefore require higher rates of returns. This leads to a higher default spread which is associated with higher expected returns over the following 6 months. As expected, this is a contrary indicator since the high perception of risk is associated with a bottom (vice-versa). The technical indicator has a negative sign expressing a mean reverting process. Remember that we were unsure if this would be the case as little has been done on intermediary analysis. Theory holds that long term (more than 5 years) returns are mean reverting, and in the short term (less than 1 year), they are persistent. We conclude here that intermediary returns of 2 years are closer to

longer term processes i.e. mean reverting. Let us note that this technical measure produced superior results than the moving average indicator. Perhaps this is due to the fact that we are working with intermediary returns. Finally proxy for the monetary environment, free reserves, has a positive sign implying that higher liquidity in the banking sector is associated with higher expected returns and vice-versa.

TABLE 4.1
T-STATS OF VARIABLES

Variable	T-STAT	T-STAT (White)
dividend yield	9.843	10.030
CPI 1 year change	-8.403	-8.283
default spread	6.927	7.182
Trend	-5.568	-4.213
free reserves	6.365	6.386

Table 4.1 shows that the indicators chosen are statistically significant. We also display the t-stats corrected for heteroskedasticity using the White correction. Notice that applying the correction yielded almost exactly the same results as the uncorrected t-stats. This is not so surprising since low frequency stock returns by and large exhibit much less heteroskedasticity than high frequency data.

Next we must consider wether there is any excessive correlation between the explanatory variables. The pairwise correlations observed directly from the correlation matrix shows the highest correlation to be between the dividend yield and the 12 month change in CPI at 0.71. However this correlation is not excessively high. Also, checking the pairwise correlation alone is not sufficient as a variable may be correlated with 2 or more other variables. One simple way of checking for this type of correlation is simply to regress each of the explanatory variables against the other four. The results appear in table 4.2.

TABLE 4.2

MULTICOLLINEARITY

div vs cpi def trend free	0.52
cpi vs div def trend free	0.66
def vs div cpi trend free	0.32
trend vs div cpi def free	0.26
free vs div cpi def trend	0.35

Again we notice that the multiple correlations are not dangerously high.

Finally, we found a problem of positive serial correlation as exhibited by the Durbin-Watson statistic of 0.54. However, we will show, in the following section, that the serial correlation is not due to a misspecified model but rather due to the fact that the data is sampled more finely than the forecast interval. Specifically,

$$\text{Forecast error: } u_{t,k} = y_{t+,k} - E(y_{t+,k} / \Phi_t)$$
$$E(u_{t,k} u_{t+h,k}) = 0 \text{ for } h \geq k.$$

However only in the case in which the sampling interval equals the forecast interval, that is, k=1, will the forecast errors be serially uncorrelated. Since we are using a six month forecast with monthly data, serial correlation is expected and must be corrected.

4.1 Adjustments

There is a problem of overlapping monthly observations with our analysis thus far since our specification of the forecast variable is the 6 month excess return over thirty years. We have 360 monthly observations but those observations are not independent. For example the 6 month jan'64-june'64 is correlated to the Feb '64 to july'64. This overlapping data obviously creates an autocorrelation in the forecasts and also increases the T-Stats found above.

To make sure that our variables are indeed useful in capturing expected returns we can bypass the overlapping observation difficulty by simply dividing the model into 6 subregressions as shown in table 4.3. We make two six month forecasts, for example, a forecast in January and one in July (JanJul) for the following six month period:

TABLE 4.3
SUBREGRESSION T-STATS

period	div	cpi	def	trend	free	R^2
janjuly	4.17	-4.07	3.82	-2.16	3.23	0.4949
febaug	3.87	-3.26	2.03	-2.4	3.27	0.4241
marsep	3.99	-3.67	1.84	-2.27	0.78	0.3419
aproct	3.64	-3.302	3.768	-2.186	2.10	0.4350
maynov	3.78	-3.127	2.939	-1.98	2.66	0.4295
jundec	3.89	-2.772	2.435	-2.612	3.39	0.4358

We see that our variables are still significant, as shown by the T-stats obtained through this subregression technique which is free from the overlapping data complication. Also the signs remain consistent with our theoretical interpretations. In fact there seems to be a seasonal effect in the subregressions as the model for march-

September considerably underperforms. It is a well known fact that September is the weakest month of the year as it is the only month with historically negative average returns. Aside from this anomaly, our previous results hold up very well in the subregression analysis.

As mentioned above, our model exhibits a Durbin-Watson statistic of 0.5452; as we know, this statistic lies between 0 and 4 where values around 2 mean there is no first order autocorrelation, values smaller then 2 mean there is positive serial autocorrelation ie positive errors tend to be followed by positive errors. Here we run into the same problem as with the T-stat due to the fact that our observations are not independent. Therefore we again break up the regression into 6 subregressions incorporating only independent observations and recalculate the Durbin-Watson statistic. See table 4.4

TABLE 4.4
DURBIN-WATSON OF SUBREGRESSIONS

Period	Durbin-Watson
January&July	1.8315
February&August	1.6549
march&September	1.9754
April&October	1.9215
may&November	1.6548
June&December	1.7646
Average	*1.80*

We notice that the average is 1.80 indicating that no positive autocorrelation exists. Also, none of the subregression Durbin-Watson statistics falls below 1.57, the level which would demonstrate conclusive evidence of positive autocorrelation.

Thankfully, we find that our results in terms of estimating the expected returns equation still holds once we surcomvent the overlapping data difficulty. Also we see that the serial correlation was indeed caused by the overlapping data and not due to a misspecified model since the subregressions show that the Durbin-Watson statistic is in fact very close to 2. Again, the point of these subregressions is simply to show that the model is meaningful and that positive serial correlation in the full regression is due to the overlapping data.

Convinced that our model is adequate, we now present a superior technique for estimating the expected return equation as it does not sacrifice observations in the process (as was done in the subregression analysis). To accomplish this goal, we make use of the Newey-West technique in making the appropriate modifications in the estimation of the covariance matrix. In this manner, we are able to dramatically increase our sample size of the data used in the estimation. Also the resulting t-stats will be much more representative of the real statistical significance of the variables.

As mentioned, we have chosen to follow the lead of the other papers discussed above and adjust the covariance matrix using the Newey-West technique rather than use a generalized least squares estimate model. There are two reasons for this, firstly because of concerns related to the use of time series versions of GLS which requires the strict econometric exogeneity of the X_t process. The strict exogeneity is a claim that knowledge of futures X_t's would be useless in determining the optimal forecast of T_{t+k}. Usually, this is not the case in financial market series. Secondly, and more to the point, to enable easy comparison of our model and the ones elaborated in previous studies. Remembering that we are simply repeating, with slight modifications, previous research. In any case, let us proceed with the application of the Newey-west covariance matrix to our model.

The standard covariance matrix presumes that the residuals of the estimated equation are serially uncorrelated. Newey and West (Newey-West,1987) have proposed an alternative that gives consistent estimates of the covariance matrix in the presence of both heteroskedasticity and autocorrelation. We present the results using the Newey-West covariance matrix:

$$(X'X)^{-1}\Omega\,(X'X)^{-1}$$

Where:

$$\Omega = \Sigma^T_{t=1}\ u_t\,x_t\,x'_t + \Sigma^q_{v=1}\,[1-(v/(q+1))]\ \Sigma^T_{T=v+1}\,(x_t\,u_t\,u_{t-v}\,x'_{t-v} + x_{t-v}\,u_{t-v}\,u_t\,x'_t)$$

and q, the truncated lag is a parameter representing the number of autocorrelations used to approximate the dynamics of u_t. Following the suggestion of Newey-West, we set q as:

$$q = 4(T/100)^{2/9} = 5.317$$

TABLE 4.5
NEWEY-WEST ADJUSTED T-STATS

Variable	T-STAT (Newey-West adjusted)
dividend yield	5.748
CPI 1 year change	-4.654
default spread	4.645
trend	-2.526
free reserves	4.693

Although the T-Stats we obtain are much lower, they are theoretically more valid and still leave us with statistically valid variables which prove empirically the theory established behind each of them.

Finally, remember that our choice of variables was meant to capture the

intermediate to longer term expected returns. This is why we used regression analysis with macro type explanatory variables rather than univariate time series which has been shown by Lo and MacKinley to be more suitable to short term high frequency data. As anticipated, and similar to previous studies, the results improve with the length of the expected return forecast up to one year as shown in table 4.6.

TABLE 4.6
FORECAST IMPROVES WITH LENGTH

Forecast length	R^2	Fama & French
1 month	0.0785	0.06
3 month	0.2611	0.11
6 month	0.4043	na
12 month	0.5315	0.45

Thus we conclude this section on a good note as we have been able to successfully extend the research of Fama&French by incorporating to their model of business conditions, proxies for monetary environment as well as the technical undertone of the market. Although our results, in terms of capturing 40% of time varying expected returns, are very interesting from a theoretical standpoint, these results do not imply that the model is adequate for market timing purposes. This is the subject of the next section.

4.2 Market timing

There is an important distinction between the ability of a model to give statistically reliable predictions of variations in expected returns and that same model's ability to actually forecast periods of negative excess returns allowing investors to earn abnormal profits. In order to test the model for market timing ability we sequentially generate out-of sample forecasts using our model. We initially estimate the model with a 9 year sample from 1964 to 1973 and then sequentially reestimate the model each month. For each month, a forecast of the excess return for the upcoming six month period is generated (see appendix, p.40), and a trading rule is applied to create a market timing return series. We use an ultra simple trading rule, if the forecast is larger than 0 we are fully invested in the S&P 500. If the forecast is smaller or equal to 0 we are fully invested in cash or other risk free assets.

When examining the forecast versus actual excess return chart we notice that the sequentially generated out of sample forecast does indeed track the direction of excess return quite closely, with the exception of the major divergence in early 1980. When examining the data for that period we notice the dividend yield and default spread both indicated that we were approaching a bottom in terms of business conditions. On the other hand, inflation was very high and free reserves were low, indicating that monetary conditions were still unfavorable. Hence, the model was indicating that conditions were not yet fully conducive to a sustainable rally. As we can see, after the sharp run up, excess return turned sharply negative, thereupon our forecast realigned with the actual excess returns. Also we note that the model did give advance warning of Black Monday 1987, a requirement most researchers and practitioners insist upon. We now proceed with the analysis of the market timing usefulness of the trading signal generated by our model.

Let us firstly examine the average rate of return obtained when our model indicates we should be long stocks versus the average rate of return realized when our model indicates that we should be in cash (T-bills):

TABLE 4.7
TRADING RULE AVERAGE EXCESS RETURN

	Full Sample	Forecast>0	Forecast<0
Average Excess Return	0.61%	5.42%	-5.07
# of Observations	240	130	110

This is interesting as it shows that our model, which was shown to be useful theoretically, does produce impressive realtime, out of sample, results. We now proceed to a more rigorous examination of the usefulness of our market-timing forecasts through the Henrickson and Merton (1981) technique designed to determine if a model is a valid market-timing tool:

$$R_{m,t}-R_{f,t}= b0 + b1X(T)_t +e_t$$

Where:

$R_{m,t}$ = return of the S&P500 over the forecast period

$R_{f,t}$ = Return of the risk free T-bills over the forecast period

$X(T)_t$ = 1 if the market timer forecasts excess return is positive; 0 or else

Our results are:

$$R_{m,t}-R_{f,t}= -5.07 + 10.49X_t +e_t$$
$$(-2.97) \quad (4.82)$$

(T-stats are Newey-West corrected)

Although this is a fairly straight forward analysis, it is quite powerful in terms of the information it contains. Firstly, If the market timer is able to forecast periods where $R_{m,t}-R_{f,t}$ is different from its unconditional sample average, then we will find that b1 is larger than 0. As we can see, our b1=10.49 implies therefore that we are at least making a forecast which is different than the unconditional sample average.

Secondly, according to our trading rule, the only time we will have returns different from the market is when we have forecasted a negative excess return since we are fully invested when the model is forecasting positive excess returns. In other words the b0 estimator can be interpreted as the average return on T-bills minus the average return on the market, when invested in T-bills, which according to our trading rule, occurs only when the model is forecasting negative excess returns (table 4.7). Therefore we can conclude that if the returns from our trading rule devised from our model are superior to a buy and hold strategy then, on average, the return on T-bills will be higher than the return on stocks when negative excess returns are predicted. This is illustrated through the estimate b0, which measures the average difference in returns from a buy and hold strategy and returns from our trading rule strategy when the forecast of excess returns is negative or null. Thus if the estimated b0 is negative and statistically significant, the model gives statistically reliable forecasts of negative excess returns.

As we can see our b0 is indeed significant and the constant does have a negative sign. From this we can conclude that our model would outperform a buy and hold strategy in a real-time situation. Therefore the model, previously shown to partially predict variations in expected returns, is also useful as a market timing tool. We now briefly consider an alternative estimation method which seems perticularly well suited to the trading rule described above.

4.4 Alternative Estimation Method:

Logit Model

As we are trying to model the excess returns, market returns in excess of treasury bill returns, it is quite natural to express this binary choice between assets as the probability that the market return will exceed treasury bill returns. This type of probabilistic formulation is well suited for a qualitative model of the type probit or logit. Due to an extreme choice situation, where the range can fall outside the normal 0 to 1 probability range, the logit model is a better representation than a linear probability model since it does not provide predicted probabilities outside the 0 to 1 range. We focus here on the use of a logit model because the logistic function has slightly fatter tails than the probit model and therefore, better describes the extreme choice situation. The logit model specification takes the form:

$$\text{Log } (P/(1-P)) = a + BL(Xt)$$

P=Probability that the S&P 500 outperforms T-bills

1-P=Probability that T-bills outperform the S&P500

L(Xt)=Characteristic vector, using the same variables as in section 3

The dependent variable in a logit model will always take a value of zero or one.

$$Yt=1 \text{ if excess return} > 0$$

$$Yt=0 \text{ if not}$$

The logit specification then provides a model of the probability of observing Yt=1. Probabilities always lie between zero and one, so the specification for the probability needs to embody this restriction by using a functional form based upon the cumulative distribution function for a logistic random variable,

$$\Pr(Yt=1 \mid Xt) = (e^{xt\beta}) / (1+e^{xt\beta})$$

Thus we model the probability of the event as depending on a linear combination of the observed variables, xt with weights given by the coefficients. The task of estimation is to find the best values for these coefficients.

Estimation of the logit model is performed by maximizing the likelihood function with respect to all of the coefficients. The maximization requires an iterative method, however, the algorithm operates smoothly since the logit likelihood functions is very well behaved.

$$Pr[Y_{t+6}=1]=-1.84 +1.21(DIV_t)-0.43(CPI_t)+2.32(DEF_t)-2.42(TREND)+1.1(FREE_t)$$

| | (5.06) | (-5.31) | (5.17) | (-2.94) | (4.55) |

Interpretation of the output of logit is similar to interpretation of regression output, but analysis of the magnitudes of the coefficients must be made with the logit functional form in mind. Since the dependent variable is a binary indicator, the expected values of the dependent variable equal the probabilities given above

$$E(Yt|Xt) = Pr(Yt=1 \mid Xt) = (e^{xt\beta}) / (1+e^{xt\beta})$$

Differentiating with respect to the jth explanatory variable X_{tj} yields

$$[\partial E(Y_t|X_t) / \partial X_{tj}] = [\{(e^{xt\beta}) / (1+e^{xt\beta})^2\} \beta_j]$$

When weighed by the appropriate nonlinear factors, the β_j coefficient measures the change in the expected value (probability) in response to changes in X_{tj}. Positive values for β_j imply that increasing X_{tj} will increase the probability of the response; negative values imply the opposite. Therefore we can observe that the values obtained with the logistic model are consistent with the values found in the OLS regression model in terms of expected directional impact of changes.

TABLE 4.8

LOGIT TRADING RULE AVERAGE EXCESS RETURN

	Full Sample	Probability>50%	Probability<50%
Average Excess Return	0.61%	2.13%	-2.73%
# of Observations	240	165	75

The first thing we notice through this approach is that the signs of the coefficients are indeed as we expected and similar to those obtained in section 3. Clearly the magnitudes are different since we are now forecasting probabilities rather than excess returns. Next, we produced out of sample sequentially generated forecasts. The table shows the average excess return when the model has a probability in excess of 50%, suggesting we should invest in stocks, and vice versa. Although the forecast seems useful, these results appear less promising than those obtained using the linear forecasting model and shown in Table 4.7. We can determine if this is in fact the case by applying the Henrickson-Merton test for market timing usefulness:

$$R_{m,t}-R_{f,t}= -2.73 + 4.86X_t +e_t$$

$$(-0.97) \quad (1.67)$$

(T-stats are Newey-West corrected)

We see that the logit specification of the model does not pass the Henrickson-Merton test for market timing since the coefficients are not statistically significant. We can easily detect the superiority of our linear forecasting model described in section 3 over this logit model by examining the observations when the forecasts are different.

TABLE 4.9

LOGIT VERSUS OLS

240 total observations	ols>0 and logit<0.5	ols<0 and logit>0.5	*ols>0 and logit>0.5*	*ols>0 and logit>0.5*
Mean Excess Return	7.18%	-4.23%	*5.14%*	*-5.86%*
# observations	18	53	*112*	*57*

In other words the mistakes that the model makes tend to be very expensive.

Thus it would seem that the simpler linear excess return forecasting using ordinary least squares is the preferred methodology. Likely this is the reason most researchers have adopted it in the use of time-varying expected return analysis at the exclusion of more elaborate statistical techniques such as the logit model presented in this section.

5.Conclusion

The theoretical literature reviewed in Section 2 provided us with a great deal of information both on the types of variables which should be considered as well as the methodology to be used. We learned firstly, that stock returns are in fact partly predictable. Secondly, that this predictability is a result of a rational variation in expected returns and thirdly, that this variation is related to business and monetary conditions as well as to the technical condition of the market. Armed with this invaluable knowledge, we proceeded to extend and improve the previous studies by essentially combining the various components of expected returns. In other words, we knew that a complete model would incorporate not only business conditions or monetary conditions or technical analysis, but rather all three drivers of expected returns. The next step was to select the actual variables which would serve as proxies for these components of expected returns. There are not only the choice of variables to consider, but also the specific form to use as there are many ways to measure the default spread as well as various measures of inflation, excess returns, liquidity etc. This behind the scenes work yielded the model exhibited in Section 3.

We started with the key variables found in this field of finance; dividend yield and the default spread. Although we gave a different interpretation to the default spread, changing somewhat it's theoretical basis in the model, thus far our work was simply a reproduction of other studies. We started to innovate by combining proxies of the monetary conditions to the previous business or economic cycle representatives. Here again, after experimenting with various measures and keeping in mind the most theoretically justifiable variables, we chose the inflation rate (key component to interest rates) rather than a particular measure of interest rates. We also made an unusual choice with the free reserves as component of monetary conditions rather than a more traditional measure such as the discount rate or changes therein. The combination of changes in

the inflation rate as well as the liquidity in the banking system seems to better capture the monetary aspect of expected returns. Finally we added a trend measure of past returns knowing that it is an intrinsic component of the investors decision making process.,

The result was a model that explains 40% of the variations in expected returns. The estimated equation also proves the validity of our chosen variables which were shown to be statistically significant and conformed to our beliefs in terms of the direction of impact on expected returns. This, ergo, is very interesting from a theoretical standpoint and also, very encouraging from a practical outlook. However, we did not fall into the trap of claiming that these results meant that the model could be used for market-timing. Hence we discussed, firstly, the necessity of conducting sequentially generated out-of-sample forecasts and secondly the trading rule used to implement the forecast as well as a rigorous method of evaluating and comparing the market-timing ability of our model. The Henrickson and Merton's (1981) test of Merton's requirement for the usefulness of market-timing forecasts is extemely appealing as it not only tells us if the forecaster is able to forecast periods when the excess return is different from it's unconditional mean but also if he is outperforming a buy and hold strategy. In short it is a powerful and relatively simple way of testing the real-life usefulness of the model which we have already shown to be quite interesting from a theoretical standpoint. We found, happily, that our model was in fact useful as a real-time market-timing tool. In fact, the results were not only significant but quite impressive.,

The possibilities for future research are endless and limited only by the availability of often expensive and sometimes unreliable data. Aside from the obvious tweaking of existing variables or the inclusion of perhaps better proxies, there could be the inclusion of a new type of variable representing the global conditions. Another worthy continuation would be to incorporate more advanced econometric techniques to the research. For example, one could envision the training of a neural network to learn and adapt to the patterns exhibited by the proxies of underlying conditions. This is a fairly

new branch of active research open to new techniques as well as new ideas where the opportunity for advancement is massive. It is an easy prediction to make that this field will see an explosion of research in coming years.

We agree with other researchers that the predictability of market returns, is not due to an inefficient market, but rather to a rational variation of expected returns based on prevailing conditions in the economy. Thus returns are not completely random, they vary depending on the state of the business, monetary and financial environment. More than that, these variations in expected returns are significantly predictable through a handful of variables which serve as indicators of the aforementioned underlying conditions. We also find that the model is useful for market timing purposes Thus we have positively answered the question set forth at the beginning of this paper: "Can business & monetary conditions predict variations in expected stock returns?". Suffice it to say, the next time we are perplexed about the stock market, we will evaluate the business, monetary and financial conditions prevailing in the economy, consider an intermediate to long term forecast and arrive at a well informed conclusion. As opposed to listening to those talking heads who are continuously trying to make sense of the noise!

Generally, our results indicate that when economic conditions are very strong, inflation starts to "rear it's ugly head", when past returns have been phenomenal, and liquidity is starting to tighten, expected excess returns are low or negative. Alternatively, when economic conditions are poor, inflation is slowing, past returns are lackluster, and liquidity is loosening, we can expect high excess returns. Or as a well known M.Sc. in economics says it:
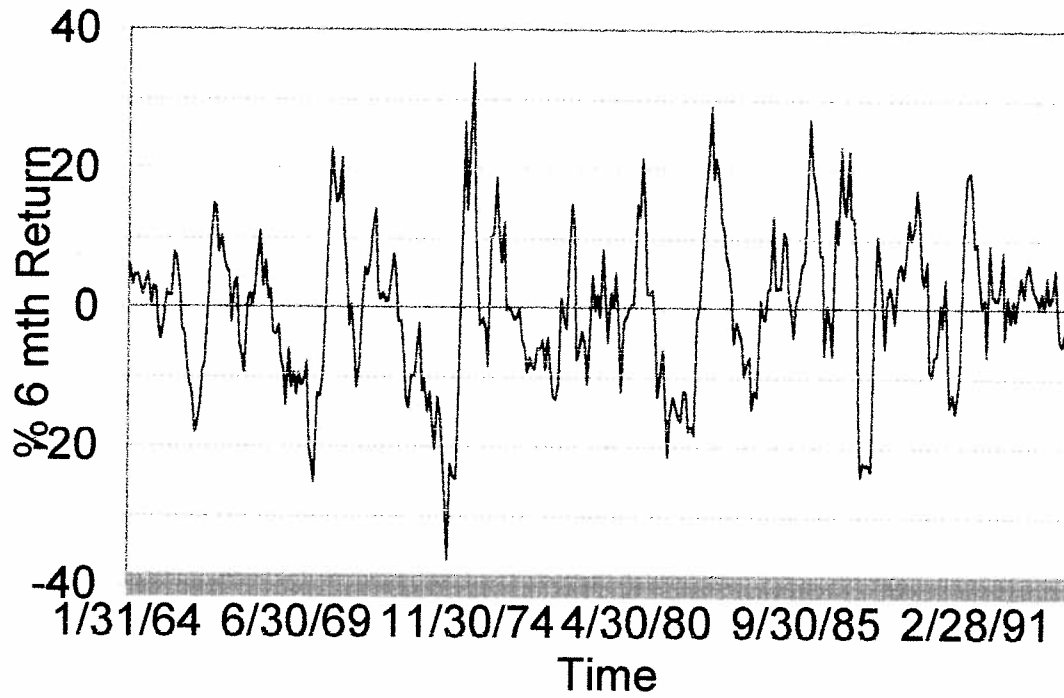
Get Greedy when everyone is fearful and fearful when everyone is greedy!
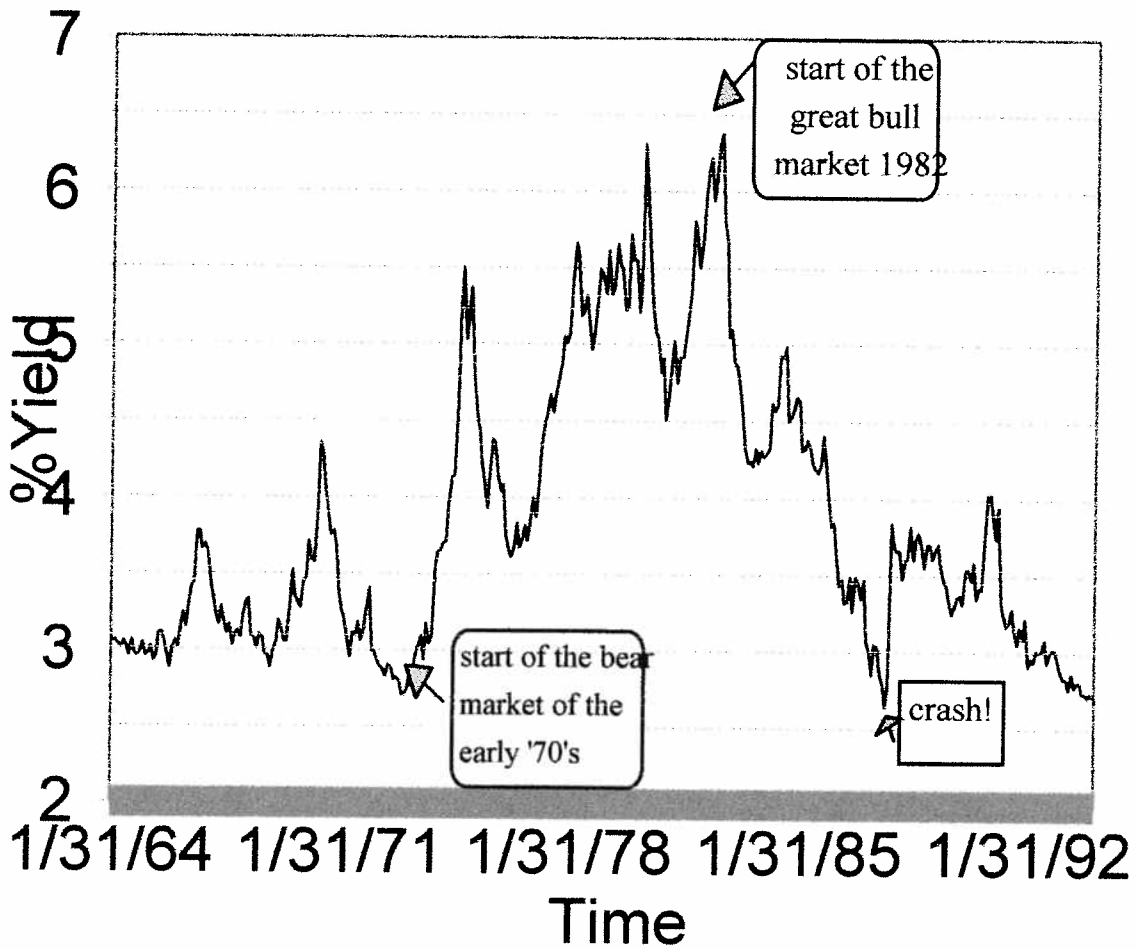*Warren Buffet*

APPENDIX

CHART 1

Excess Returns

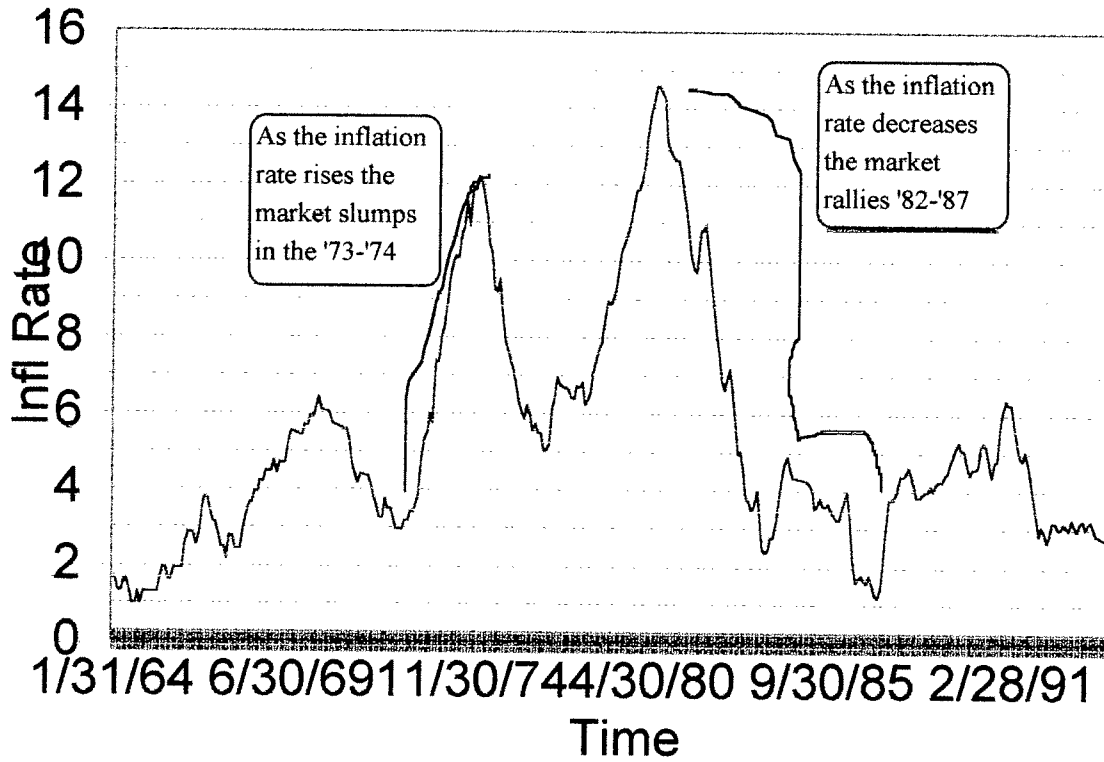Source: Global Financial Data Corporation

CHART 2

Dividend Yield

Source: Global financial data corporation

CHART 3

Inflation

As the inflation rate rises the market slumps in the '73-'74
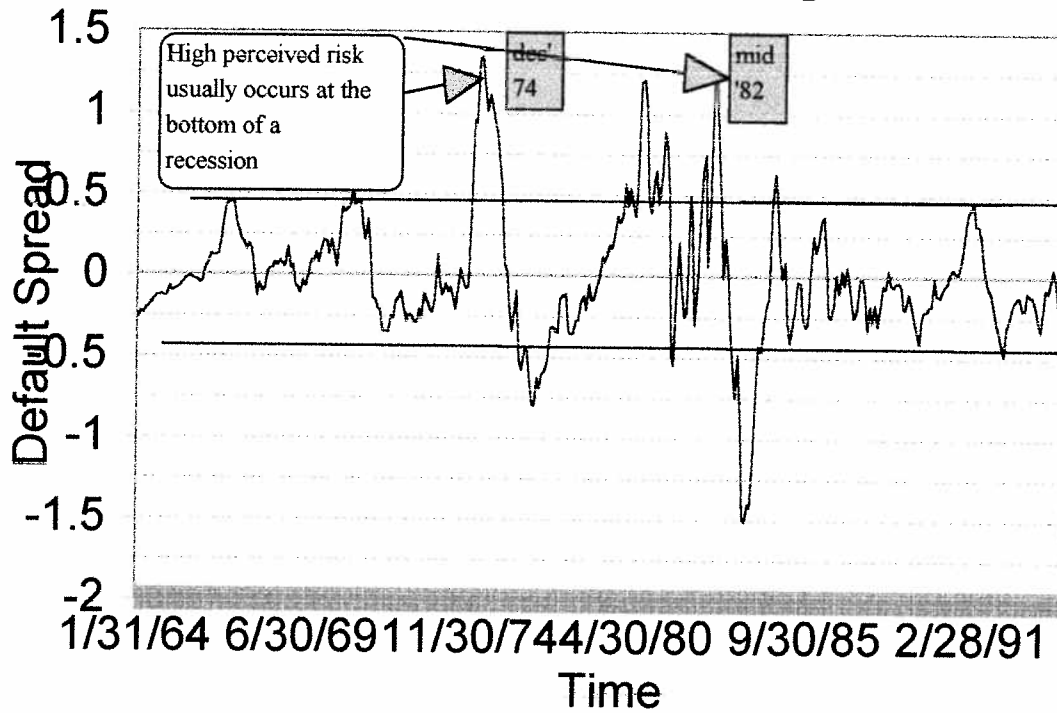
As the inflation rate decreases the market rallies '82-'87

Source: Federal Reserve of the United-States of America

CHART 4

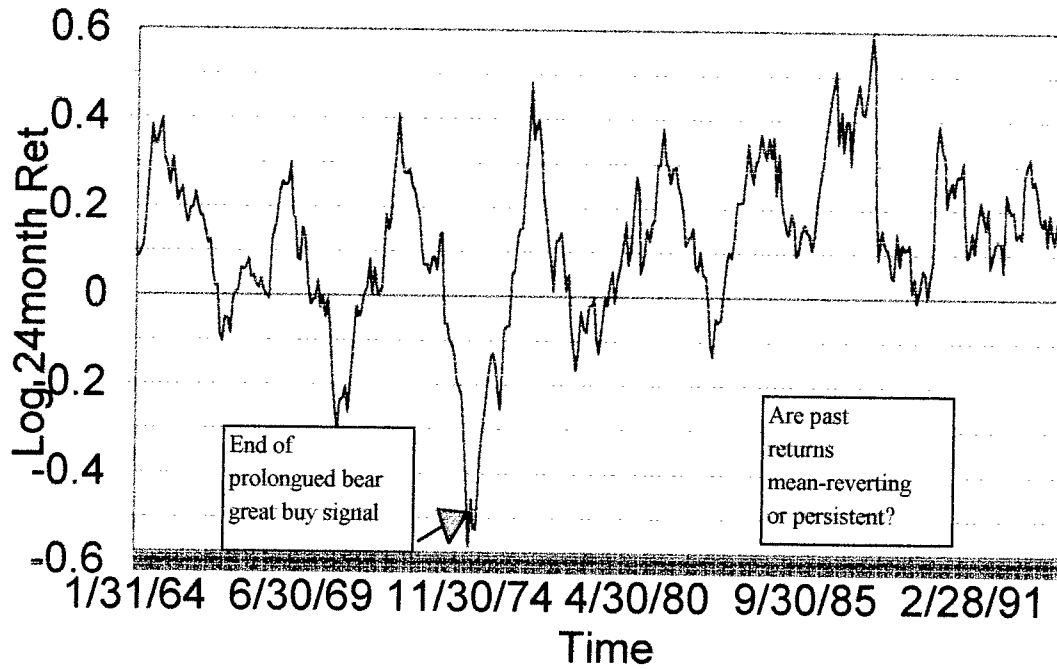# Risk Perception

Source: Federal Reserve of the United-States of America

CHART 5
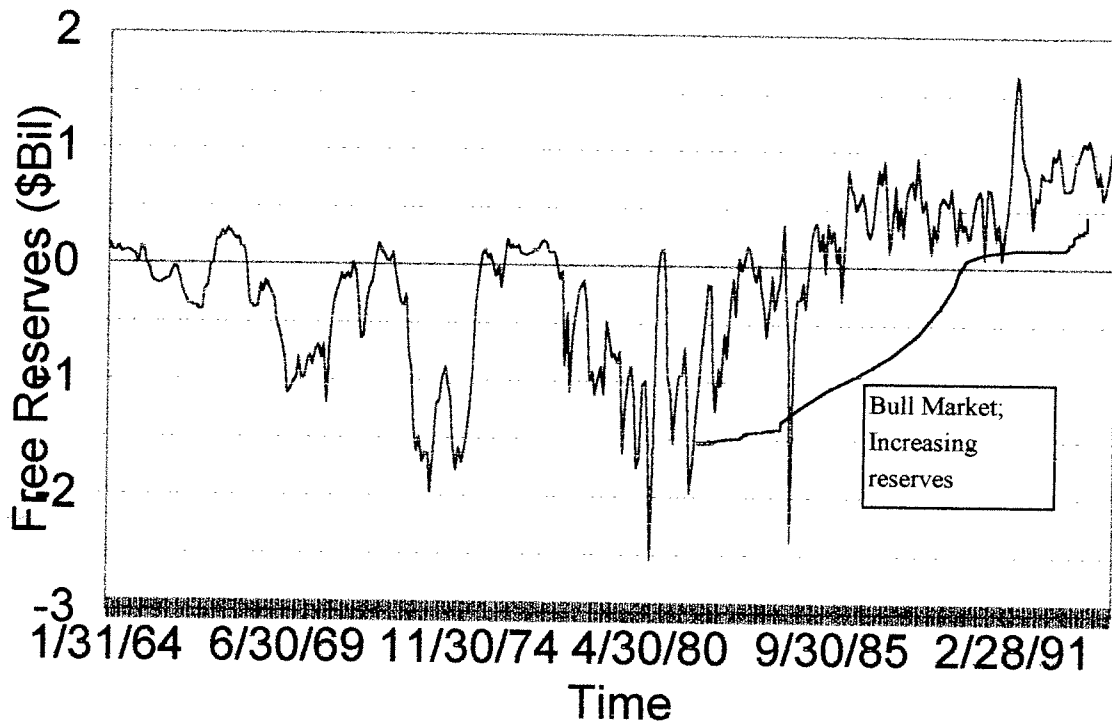
Past Returns
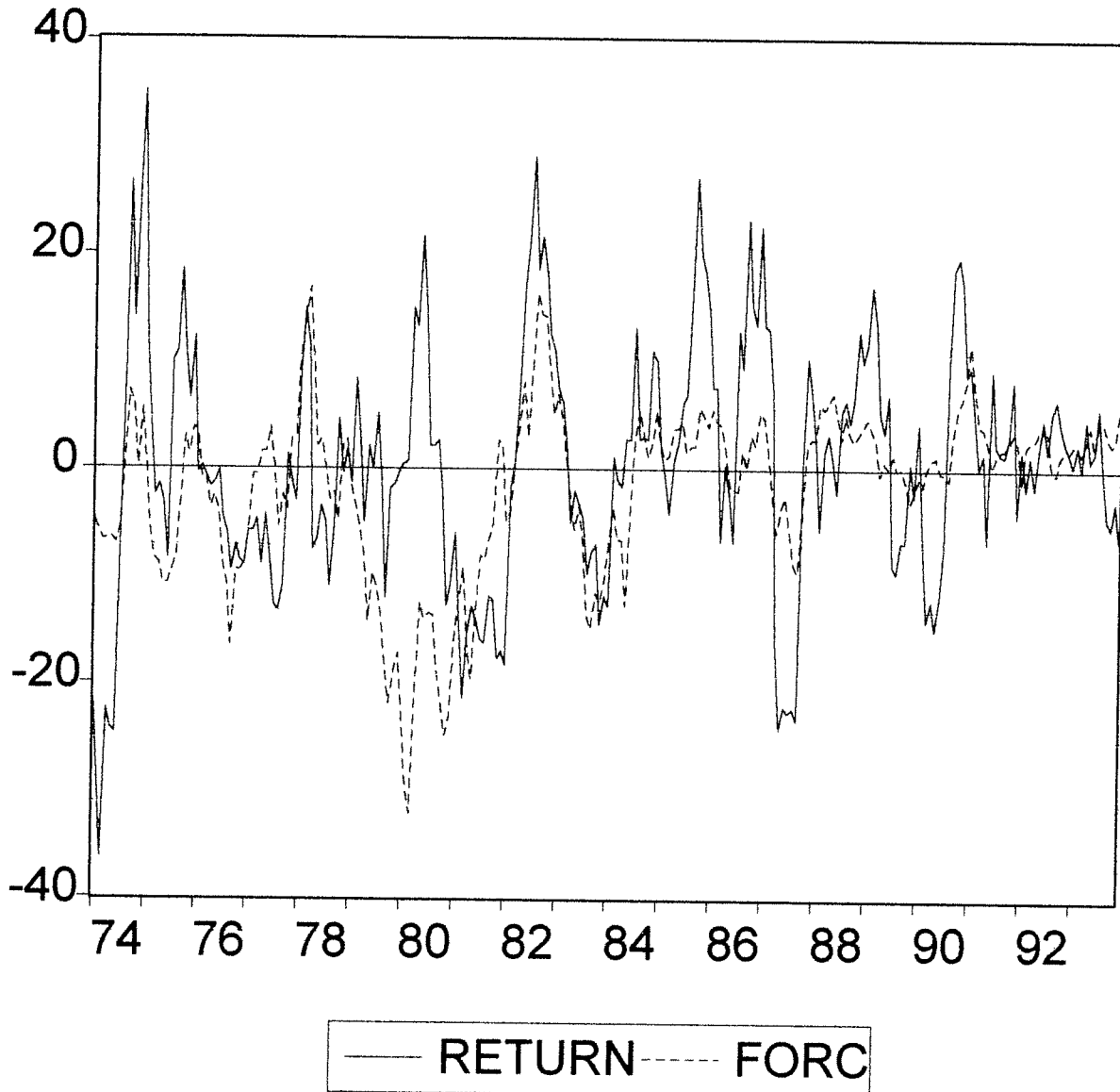

Source: Global Financial Data Corporation

CHART 6

Banking Liquidity

Source: Federal Reserve of the United-States of America

CHART 7

Out of Sample Forecast V.S. Actual Excess Return

Variables Considered

Monetary indicators

Treasury Bonds: Longer term, interest-bearing debt of the U.S. Treasury. Treasuries are backed by the U.S. government and are the benchmark against which all other debt securities are measured. The U.S. is considered risk free.

3 month Treasury Bill: Short term debt security of the U.S. government

CPI: consumer price index is a measure of the relative cost of living compared to a base year (currently 1982). The CPI is the most widely used indicator of inflation.

Yield Curve: The relationship between bond yields and maturity length. For example the difference between 30 year and the 3 month yield. This is a critical indicator for the bond markets.

Money Supply: The amount of money in the economy is a key element in determining economic activity. Where large increases usually bring fears of inflation.

Free Reserves: This variable is the difference between two monetary aggregates published by the Fed. It is the difference of excess reserves and borrowings of depositary institutions from the fed. This is an excellent, though little known, indicator of banking system liquidity.

Federal Funds Rate: The interest rate banks charge on overnight loans to banks that need more cash to meet bank reserve requirements. The federal reserve sets this rate.

Data source: Each of these time series are available from the federal reserve board.

Business conditions

Credit Quality Spread: This is the difference in yield, at a given time, between two different segments of the bond market. For example, difference between BAA and AAA (quality) bonds of similar maturity. This is an indicator of perceived risk in the economy and is extremely useful in modeling expected returns. It is a sentiment contrarian indicator.

Dividend Yield: Historically dividend/price has been a critical part of the valuation process of the market. It is a proxy of business conditions and is the foundation of any and every model in the field of time-varying expected returns.

Leading economic indicator: Maintained by the Conference Board, this indicator attempts to indicate the future direction of economic activity. Traders rightfully claim that this number does not move markets. However the reason they don't is that this indicator is never a surprise as it is a composite of known information. This does not mean that it's level or change in level is not useful for determining the value of the index we are attempting to forecast.

Data source:; *Dividend yield's* are available from Global Financial Data; *Leading economic indicators* are available from the conference board

Technical indicators

Technical indicators: Any calculation using only price and/or volume is in the realm of technical analysis. "Don't fight the tape" is a commandment on wall street, where the tape represents prices and volume as displayed on the "tape".

Advance-Decline: A cumulative total of the daily number of stocks advancing in price minus the daily number of stocks declining in price. Technicians use this indicator as a measure of breadth of the market in order to determine the strength and validity of market movement. We want a movement in the same direction as the index in order to confirm the move. Reversal signals are generated by divergences.

New Highs - New lows: A cumulative tabulation of the number of stocks hitting new highs minus the number of stocks hitting new lows (52 week period). Technicians use this indicator to measure the strength of the markets movement. The interpretation is similar to the advance-decline.

Upvolume-Downvolume: A cumulative tabulation of the volume of stocks rising minus the volume of stocks going down. The interpretation is the same as the two previous indicators.

Moving Average: When an index is above its simple moving average it is considered positive, when it falls under its moving average it is considered to be in a negative mode. Usually the 200 day moving average is used when examining intermediate to long term trends.

Past values or Trend: It is not clear if high past returns lead to future high returns (persisting) or conversely if above average returns are followed by lower than normal returns (reversion to the mean). However it seems this is a relevant indicator as in any market , the participants take into consideration previous prices, in formulating current prices.

Data source: This data is available from dial/data corporation; For a hefty fee!.Moving averages as well as lagged value of the forecast can obviously be derived from the S&P 500 data.

STATIONARITY

Augmented Dickey-Fuller Unit Root test on Excess Returns

ADF Test Statistic	-6.803045	1% Critical Value*	-3.4539
		5% Critical Value	-2.8713
		10% Critical Value	-2.5719

Augmented Dickey-Fuller Unit Root test on Dividend Yield

ADF Test Statistic	-2.65906	1% Critical Value*	-3.447
		5% Critical Value	-2.8682
		10% Critical Value	-2.5703

Augmented Dickey-Fuller Unit Root test on Change in CPI

ADF Test Statistic	-2.637329	1% Critical Value*	-3.4465
		5% Critical Value	-2.868
		10% Critical Value	-2.5702

Augmented Dickey-Fuller Unit Root test on Default Spread

ADF Test Statistic	-4.71585	1% Critical Value*	-3.4505
		5% Critical Value	-2.8698
		10% Critical Value	-2.5711

.*MacKinnon critical values for rejection of hypothesis of a unit root.
Augmented Dickey-Fuller Unit Root test on Trend variable

ADF Test Statistic	-3.803259	1% Critical Value*	-3.4505
		5% Critical Value	-2.8698
		10% Critical Value	-2.5711

Augmented Dickey-Fuller Unit Root test on Free Reserves

ADF Test Statistic	-2.816021	1% Critical Value*	-3.4539
		5% Critical Value	-2.8713
		10% Critical Value	-2.5719

MacKinnon critical values for rejection of hypothesis of a unit root.

Each series used in our model is stationary over long samples, such as in our 30 year sample. Although there may be short term trends on occasion, none of the series are inherently trending series and therefore we can, as other researchers in this field, use them without transformation, in our econometric model.

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