Autoregressive multifactor APT model for U.S. Equity Markets

Malhotra, Karan

New York University

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Karan Malhotra

New York Universtiy

Abstract

Arbitrage Pricing Theory is a one period asset pricing model used to predict equity returns based on a multivariate linear regression. We choose three sets of factors – Market specific, firm specific, and an autoregressive return term to explain returns on twenty U.S. stocks, using monthly data over the period 2000-2005. Our findings indicate that, apart from the CAPM beta factor, at least five other factors are significant in determining time series and cross sectional variations in returns. The times series regression establishes factor loadings and the cross sectional regression gives the risk premiums associated with these factors.

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I. Introduction

Stock prices change due to a change in supply and demand of the asset. However, this supply and demand is influenced by expected future prices of the stock by investors. Therefore, an increase in stock price generally follows good news. According to the efficient market hypothesis, expected news is already priced into the asset. Therefore it's only the unexpected news that causes a change in the stock price. This, along with mean-reversion, which is explained later, is the basis of this paper, where we regress changes in market specific factors and firm specific factors onto the returns of an asset. Market efficiency is defined by how much asset prices incorporate readily available information. If the markets are efficient, no investor can out-profit the market as all information is already embedded in the asset price. According to the Random Walk Theory, stock prices evolve continuously as a consequence of intelligent investors competing to discover relevant information. However, due to long term economic growth the expected return is generally positive over time. The overall trend is positive and there tend to be random price changes about the trend, which reflect the unsystematic flow of information[1].

Several asset pricing models can be used to explain equity returns. The Capital Asset Pricing Model (CAPM) by Markowitz, Sharpe and Miller[2], and the Arbitrage Pricing Theory (APT) by Ross[3] are the most commonly discussed and tested models. The CAPM has its basis in construction of an efficient 'market portfolio' that maximizes return, given a level of risk. The expected return of an individual security is a function of its risk covariance with the market.

[1] Stephano Bonini, Foundations of Financial Markets, Fall 2009, New York University (April 2010)
[2] J.Burton, Revisiting the CAPM, 1998, http://www.stanford.edu/~wfsharpe/art/djam/djam.htm (April 2010)
[3] Ross, The Arbitrage theory of Capital Asset Pricing, 1973, http://riem.swufe.edu.cn/new/techupload/course/200751013404961128.pdf (April 2010)

The relationship is formally given by:

$$E(R_i) = R_f + \beta_i\big(E(R_m) - R_f\big)$$

Where $E(R_i)$ is the expected return of the security, R_f is the risk free rate of return, R_m is the market rate of return and β_i is the sensitivity of the expected excess asset returns to the expected excess market return. The CAPM is a one factor model with the risk premium,

$\big(E(R_m) - R_f\big)$ being the only factor. Following the empirical failure of the CAPM model, Fama-French extended the CAPM model to include two more factors- Firm Size and Book - Value to Price, to enhance the fit of the model[4].

Arbitrage pricing theory belongs to a different category of models. According to APT, expected return on assets can be modeled as a linear function of various factors. The most prominent APT model was a multi-factor model developed by Stephen Ross in 1976. In this paper we combine the traditional macroeconomic factors of the APT, with firm specific variables and one lagged return term to linearly model equity returns. The factors are selected a priori, and not by using statistical methods such as principal component analysis and factor analysis. We have selected 20 stocks, 10 large cap and 10 mid cap, from the U.S. Equity markets for this study. We then take the monthly logarithmic excess return on each stock for a period of six years, from January 2000 to December 2005. Then, the beta coefficients of each of the factors are estimated by running a linear regression using the OLS approach. It is important to note that according to the APT, the stock price would react only to unanticipated changes in factors. So, the absolute value of the factors is of no use to us. We use the monthly logarithmic return on each factor. Also, we

[4] Eugene F. Fama, Kenneth R. French, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics, February 1993, p 4

do not use advanced methods like GARCH or filters like Kalman or Wiener, to determine the unanticipated change in variables. After running a separate linear regression for each of the twenty stocks, we have twenty sets of beta coefficients. Then, following the traditional approach to test pricing models, we run a cross sectional regression based using these twenty sets of beta coefficients, with the mean of asset returns over the sample period as the dependent variable. Each coefficient resulting from this cross sectional regression gives the estimate of the 'risk premium', that is, the reward the investor gets for bearing that factor's risk. Below is the list of the independent variables used in the regression analysis.

Market Specific Variables

■ *Inflation (CPI)* ■ *Money Supply (MS)* ■ *Industrial Production (IND)* ■ *Oil Prices (OIL)*

■ *Risk Premium (RPREM)* ■ *A broad market index (SP500)* ■ *Size Factor (SMB)*

■ *Exchange rate (EXR)* ■ *Yield Spread (YSP)*

Firm Specific Variables

■ *Number of shares traded (TRAD)* ■ *Price to Earnings ratio (PE)* ■ *Market Capitalization (CAP)*

Autoregressive term: ■ *One month lagged return (LAG)*

These are the independent variables in the model, with the monthly return on equity being the dependent variable. The next chapter discusses the theoretical background of the APT and choice of factors whilst reviewing previous literature and research on the arbitrage pricing theory. Then, in Chapter 3, we discuss the linear regression model in greater detail, the problems associated with choosing such a model to test APT and explaining the importance of each variable in our regression. Chapter 4 provides an empirical analysis of the data. In Chapter 5, we explore the results of the regression, analyzing the significance of the model factors.

II. Theory and literature

The arbitrage pricing theory was developed by Ross in 1976. It states that the return on equity is governed by a factor structure. According to Ross, if equilibrium prices of assets offer no opportunities for arbitrage over static portfolios of these assets, then the expected return can be modeled as a linear function of the factors[5]. Any well diversified portfolio is exposed only to factor risks. If the portfolio is well diversified then the error term of the portfolio return is given by: $\tilde{u}_P = \sum_{i=1}^{n} w_i \, \tilde{u}_i$

where w_i is the weight of each asset in the portfolio. Assuming $\tilde{u}_1, \tilde{u}_2, \tilde{u}_3, \dots, \tilde{u}_n$ are uncorrelated, then $\tilde{u}_P$ is equal to zero. This implies that the idiosyncratic risk is diversified away and the portfolio is only exposed to factor risk. This is the basis of the APT model. APT also assumes that in an efficient market, arbitrage profit opportunities are swiftly eliminated by market participants and an investor cannot make an additional profit without taking on additional risk. This is in accordance with the law of one price.

A formal statement of the APT is given below:

$$(R_{it}) = a_i + \beta_{i1} F_{1t} + \cdots + \beta_{iJ} F_{Jt} + \varepsilon_{it}$$

Or in matrix notation:

$$r = \mu + \beta F + \varepsilon$$

[5] Huberman, Wang, Arbitrage Pricing Theory, 2005. http://www.ny.frb.org/research/economists/wang/APT-Huberman-Wang.pdf p1 (April 2010)

Where r is an (n x 1) matrix containing the asset returns, F is a (k x 1) matrix of the factors in the model, β is a (n x k) matrix of the factor loadings(beta coefficients), and ε is a (n x 1) matrix containing the error terms.

Factor Selection

The theory explicitly does not list any factors. Therefore it is up to the researcher to identify the factors appropriate to the end goal. For example, a country might have specific risk factors that are exclusive to that market. According to Berry et al., the factors structure should be chosen in guidance with following properties[6]

■ *Only the unexpected changes in the factors should influence the asset prices*

■ *The factors should be justifiable on economic grounds*

■ *The times series movements of factors explain a significant portion of the times series movements of the return on assets.*

■ *The residual terms that are not explained by the factors should be more or less uncorrelated.*

There are primarily three methods to determine the factor structure[7]. First method consists of an algorithmic analysis of the estimated covariance matrix with purely statistical methods like factor analysis and principal component analysis. In the second approach, the researcher is guided by factor and or principal component analysis but chooses factors based on his subjective judgment. This method has been widely used in the past, mostly famously by Fama and French in 1993.

[6] Berry M. A., Burmeister E., McElroy M. 1988. "Sorting out risks using known APT factors". Financial Analyst Journal, Vol. 44, No. 2, 29–41.
[7] Huberman, Wang p11

The third approach is purely subjective in nature and the researcher relies on intuition to pick factors and then estimate their coefficients and see if they are statistically significant. This approach has been implemented by Chen, Roll and Ross in 1986. Most empirical work on APT is based on factor analysis and principal component analysis. However, Upton finds that the conventional factor analysis method used to determine factors has its limitations as it does not allow for economic significance of the factors derived[8].

Literature review

In 1978, Gehr conducted the first test of the APT using factor analysis on 41 individual companies from the U.S. equity markets using 30 years of monthly data[9]. Only one factor was found to be significant over the 30 years. Roll and Ross used maximum likelihood factor analysis for 1260 firms to test five macroeconomic factors. They found 4 of the five to have significant risk premiums. Trzinka(1986) also finds that there are five macroeconomic factors that are dominant in explaining U.S. equity returns[10]. Greenwood and Fraser (1997) found three factors for Australian markets[11]. According to Cheng, who tested the APT for the UK market, most information about equity returns is embedded in the market beta factor[12]. Cagnetti tested both the CAPM and the APT model (using factor analysis) on Italian equity markets and found that APT

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[8] David E. Upton, Cross-validation of the economic significance of factors in security returns, Journal of Business Research, Volume 31, Issue 1, September 1994, Pages 33-38

[9] Connor, Korajczyk, The Arbitrage Pricing Theory and Multifactor Models of Asset Returns, 1992, http://www.kellogg.northwestern.edu/faculty/korajczy/ftp/wp139.pdf p28

[10] Trzinka, C. 1986. "On the number of the factors in the Arbitrage Pricing model". The Journal of Finance, Vol. 41, No. 2, June, 327–338

[11] Greenwood, N. & Fraser, P. 1997. "Share prices and macroeconomic factors". Journal of business finance and accounting, Vol. 24, No. 9, 1367-1381

[12] Cheng, A. C. S. 1996. "The UK stock market and economic factors: A new approach", Journal of Business Finance & Accounting, Vol. 22, No. 1, 129–142.

had better explanatory power in all cases[13]. Chen used daily return data from 1963-1978, dividing the study into 4 sub-periods, also found that APT performs better than the CAPM. He however found that the firm size does not contribute additional explanatory power[14].

Korajczyk and Viallet performed time series tests of the CAPM and APT[15]. They used monthly stock returns from France, Japan, United States and the UK for a period from 1969 to 1983. The number of firms with return data varied from 4211 to 6692. Over the sample, the statistical tests provided at least some evidence against both APT and CAPM. The APT, however, seemed to perform better than CAPM.

It is also important to note that market efficiency may vary across countries. For example, most developing countries do not have efficient markets and flow of information is significantly slower. Pricing models would not be as successful in a relatively inefficient market.

Strengths and weaknesses of the APT

The basis for the CAPM model is a mean variance efficient market portfolio. Following Roll's critique[16], which states that such a market portfolio is unobservable and the proxies used in the testing the model are insufficient, CAPM cannot be truly tested. The arbitrage pricing theory relaxes this assumption of this market portfolio. Therefore CAPM can be considered as a special case of the Arbitrage pricing theory where the only factor influencing asset returns is the market portfolio.

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[13] Arduino Cagnetti, CAPM and APT in the Italian Stock Market: An empirical Study http://www.era.lib.ed.ac.uk/bitstream/1842/1821/1/CFMR_021.pdf (April 2010)

[14] Chen, N. 1983. "Some empirical tests of the theory of arbitrage pricing". The Journal of Finance, Vol. 38, No. 5, 1393–1414

[15] Korajczyk, Robert A. and Claude J. Viallet, 1989, An empirical investigation of international asset pricing, Review of Financial Studies 2, 553-585.

[16] Shanken, Jay, 1987a, Multivariate proxies and asset pricing relations: Living with Roll critique, Journal of Financial Economics 18, 91-110.

Strengths

1. The model gives a reasonable description of risk and risk characteristics of assets 2. Unlike the CAPM model, there is no need to measure the market portfolio correctly. This evades Roll's critique. 3. It may be very useful in hedging as it identifies particular risk factors as opposed to a market portfolio.

Weaknesses

1. The APT does not specify the factors and therefore, unlike the CAPM, there is no uniformity across various APT models 2. Factors can change over time rendering the model less useful 3. Factors may vary across firms therefore a different model might have to be constructed for each firm 4. Estimation requires more data. This can especially be the case when there are several significant factors explaining returns.

Another criticism of the APT model from a statistical point of view is that, since APT can be considered an extension of the CAPM model and includes the CAPM beta, its r-squared value cannot be less than the CAPM model. And as you add more regressors to the APT model, the r-squared will be either remain the same or increase, but never decrease.

Applications of the APT

The linear factor structure model of the APT is widely used by investment professionals for risk management purposes[17]. If the stock price significantly differs from what is predicted by the model, it might imply that the security is either undervalued or overpriced. Therefore, the

[17] Sungard, http://www.sungard.com/apt/learnmore (April 2010)

investment manager can profit by going long or short on the security respectively. These models also give asset manager the ability to decompose the sources of risk in the fund and identify which set of factors are most powerful for the fund. Securities and instruments covered by the risk models include equities, fixed income, ETF's, derivative securities and currencies.

The APT has been used to calculate the cost of capital[18]. Elton, Gruber and Mei (1994) used the APT to find the cost of capital for electrical utilities for the NY State Utility commission. Bower and Schink (1994) also used a multifactor model to propose a cost of capital for the commission. However, the commission decided to use the CAPM. APT has also been used to evaluate money managers (Jensen 1968), where the managed fund's returns are regressed on the various factors[19].

[18] Huberman, Wang, p13
[19] Huberman, Wang, p14

III. The Model

Guidelines proposed by Gujarati and Porter[20], have been kept in mind while selecting an econometric model for empirical analysis of the APT theory. The model is consistent with the APT theory which proposed a multifactor linear model. The parameters are expected to be consistent over the sample period. Therefore unless we experience a 'breakpoint', such as a strong economic or political event that disrupts parameter constancy, we can make predictions using the model. The model is also encompassing of almost all the previous models. This model is capable of explaining results of the CAPM model as well as the general macroeconomic APT model. To our knowledge, no other model has combined macroeconomic factors with firm specific factors and an autoregressive term to help explain equity returns. This model, in a sense, integrates the CAPM model, the multifactor APT model and autoregressive equity models.

This study uses the methodology proposed by Fama-Macbeth(1973)[21]. First we choose 10 large cap stocks and 10 medium cap stocks and take their monthly logarithmic returns over the period of the study. Then, for each of the equity the following algorithm was applied:

- *Derivation of descriptive statistics for the variables Return(RET), Number of shares traded(TRAD), P/E Ratio(PE) and market capitalization(CAP).*
- *Multicollinearity was tested for using auxiliary regressions for each variable in the model*
- *Presence of heteroscedasticity was checked using White's test*

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[20] Gujarati, Dawn, Basic Econometrics, 5th edition (Mc-Graw Hill/Irwin, 2008), p 507
[21] Fama, E. F. & Macbeth, J. 1973. "Risk, return, and equilibrium: Empirical tests". Journal of Political Economy, Vol. 81, No. 3, 607–636.

- *Autocorrelation was investigated using the Breusch-Godfrey Serial LM test*
- *Both Autocorrelation and Heteroscedasticity were corrected using Newey West HAC consistent covariances method.*
- *Linear regression using the OLS methodology was run*
- *A histogram for the residual was produced for analysis*

We have 4 firm specific variables and 9 market specific variables. The regression equation is:

$$R_{it} = \beta_{0i} + \beta_{1i}TRAD_t + \beta_{2i}PE_t + \beta_{3i}CAP_t + \beta_{4i}LAG_t + \beta_{5i}CPI_t + \beta_{6i}MS_t + \beta_{7i}IND_t + \beta_{8i}OIL_t + \beta_{9i}RPREM_t + \beta_{10i}YSP_t + \beta_{11i}SP500_t + \beta_{12i}SMB_t + \beta_{13i}EXR_t + \varepsilon_t$$

Where TRAD is the number of shares traded, PE is the P/E ratio, LAG is the security's return lagged by one month, CPI, MS, IND, OIL refer to the log return on Consumer Price Index, M3 money supply, Industrial Production and Oil prices respectively. RPREM, YSP, SP500, SMB, EXR are the returns on risk premium, yield spread, Standard and Poor's 500 index, return on small cap index minus large cap index and return on exchange rate respectively. After running this regression, we obtain 20 sets of beta coefficients.

In the last stage, the coefficients found in the previous regression are used as independent variables and are regressed against the mean of stock returns to estimate the risk premium associated with each factor. This is a cross sectional regression. The regression equation is:

$$\bar{R}_i = \gamma_o + \gamma_1\beta_{1i} + \gamma_2\beta_{2i} + \gamma_3\beta_{3i} + \gamma_4\beta_{4i} + \gamma_5\beta_{5i} + \gamma_6\beta_{6i} + \gamma_7\beta_{7i} + \gamma_8\beta_{8i} + \gamma_9\beta_{9i} + \gamma_{10}\beta_{10i} + \gamma_{11}\beta_{11i} + \gamma_{12}\beta_{12i} + \gamma_{13}\beta_{13i} + \varepsilon_i$$

where $\bar{R}_i$ is the mean logarithmic return on the asset I over the sample period. β_{1i} to β_{13i} are the security's sensitivity to the factors in the regression and γ_1 to γ_{13} are the reward for bearing these risks. The coefficients of regression, γ_{ij} ,are same for all securities as they are estimated using a cross sectional regression.

Problems with regression

A linear regression makes the following assumptions about the stochastic disturbance term:

I. *The residual terms have a zero mean*
II. *The variance of the errors in constant and finite*
III. *The errors are independent of each other*
IV. *The error terms are normally distributed*
V. *There is no relationship between an error term and the corresponding X value*

If the error terms are uncorrelated and homoscedastic, then the coefficients of regressions are BLUE, that is, best linear unbiased estimators- their average value $E(\hat{\beta}_i)$, is equal to the true value of β_i and they have minimum variance in the class of all such linear unbiased estimators.

If these assumptions are violated we face the problem of methodology. If the first assumption, that the mean of error terms is equal to zero, is violated then we obtain a biased estimate of the intercept term. However, the intercept term is not of much importance to us in this study. Also the slope coefficients remain unaffected.

If the variance of the error term is not constant, then it is said to be heteroscedastic. The estimators are no longer BLUE. As we expect some outliers in our data and some of the regressors might be skewed, presence of heteroscedasticity is expected. If the bias is negative, then the estimated standard errors would be smaller than they actually are, and the t-statistic would be overestimated. White's test has been done to ensure accuracy of conclusions. However, since some of the X variables are ratios of the dependent term, we may also suffer from the problem of 'spurious correlation', as proposed by Karl Pearson[22].

The third assumption, that there is no autocorrelation, can also have significant impact on the accuracy of estimators. If autocorrelation exists, then the regression coefficients will have underestimated standard errors. The Durbin-Watson statistic is the most commonly used test for this problem. If the value is two, we can assume that there is no autocorrelation. If it is zero, then there is perfect positive correlation and if it is four, then perfect negative correlation exists. To test Durbin Watson's null and alternate hypothesis, the following decision rules have been established, using d_L and d_U as the critical bounds:

No autocorrelation if $d_U \leq d \leq 4 - d_U$; *Positive autocorrelation if* $d < d_L$; *Negative autocorrelation if* $d > 4 - d_L$

However, since our regression contains an autoregressive variable, we cannot use the Durbin-Watson test. We use the Breusch-Godfrey(Serial LM) test to detect autocorrelation. Fixing autocorrelation is difficult in our case as the model may be mis-specified, that is, we might have omitted some important variables, or have an incorrect functional form. This is a certain weakness of the APT model as the model itself does not specify the factors. Also, we omit examination of GARCH and ARCH autocorrelation from this study. As we deal with economic time series, we expect sluggishness or inertia or 'momentum' and therefore some degree of

[22] Gujarati Porter, p 400

autocorrelation. Also the time series may not be stationary, further contributing to autocorrelation.

Also, since we are dealing with firm specific and macroeconomic variables, trends of which are highly interdependent, we may also suffer from the problem of multicollinearity. This in turn would make the t ratios insignificant. In this study we primarily use two methods to detect multicollinearity- correlation matrix and auxiliary regressions.

The fourth assumption, regarding the normal distribution of disturbance terms can be verified informally using graphical analysis and formally using the Jarque-Bera test of normality. If the p-value of the JB statistic is sufficiently high, we do not reject the normality assumption.

In this paper, we chose not to use Chow's breakpoint test as the sample period 2000-2005 did not experience any significant macroeconomic fluctuations. After the dot com crash in March 2000 the economy experienced a period of steady growth. Also, we chose not to use Ramsey's RESET test to investigate model misspecification as the structure specification proposed by the APT theory- a linear multifactor model, is consistent with the model used in this paper. This paper tests and evaluates APT only.

Variables

The following section lists and explains the importance of all the regressors used in the model. Unless stated otherwise, all variables have monthly periodicity.

1. *Number of shares traded (TRAD)*

This refers to the number of common shares traded monthly, listed on national stock exchanges and over the counter for companies in the NASDAQ system. The number of shares traded is used as a proxy for the liquidity of the firm's stock. According to modern finance theory, only systematic risks affect a risky asset's returns. However, it has been shown that liquidity is a very important component of asset returns. Chordia and Swaminathan find that trading volume is a significant determinant of the lead-lag patterns observed in stock returns[23]. Less liquid stocks generally offer investors higher returns because a liquidity premium that the investor must be compensated with. The expected sign of the coefficient is negative. An increase in liquidity should lower asset returns.

2. *Price to Earning Ratio (PE)*

This is defined as $P\ E\ Ratio = \frac{Price\ per\ share}{Annual\ Earnings\ per\ share}$

A high P/E ratio implies that investors are paying a higher price for one unit of earning compared to a lower P/E ratio stock. Normally, stocks with higher earnings growth are traded at a P/E higher compared to the industry average. It is important to note here that a company's P/E ratio alone does not carry much interpretable information. One must compare a company's P/E to the industry or sector average. This also implies that the P/E ratio contains information about the industry sector, as companies belonging to a particular sector tend to have similar P/E's. P/E ratio is a proxy for the market's expectation of growth in the company's stock. Holding everything else equal, a high P/E would imply increase in stock price in the future. Therefore, the expected sign of this factor's coefficient is positive.

3. *Market Capitalization (CAP)*

Is defined as $Market\ cap = (price\ per\ share) X\ (number\ of\ shares\ outstanding)$.

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[23] Chordia, Swaminathan, Trading Volume and Cross-Autocorrelations in Stock Returns, 2000, http://www.cis.upenn.edu/~mkearns/finread/Chordia_lead_lag.pdf (April 2010)

According to Jeffrey and Artemiza's research, shares outstanding have a strong predictive ability of stock returns[24]. The numbers of shares outstanding changes with events such as IPO issues, exercise of stock options and warrants, stock merger/splits, share repurchase. Generally speaking an increase in market cap implies growth of a company. Therefore the expected sign of this factor's coefficient is positive.

4. *Previous month's return (LAG)*

We expect a mean reversion of an asset's return; i.e. the stock return is expected to rise in the future when it currently at a low level relative to the mean and expected to fall when high. Research by Poterba and Summers(1988) supports this as they found negative correlation in stock returns[25].

Also, extremely high levels of stock returns are caused by temporary events whose effect fades over time, and extremely low levels of returns are not sustainable as the drift of a stock price is positive in the long term due to economic growth. Because of mean reversion, the sign of this variable's coefficient is expected to be negative. For example, if unexpected positive news causes a stock to rise by 10% in a month, the next month's return would be expected to be negative. Hence the negative sign of this variable's coefficient. The return on the asset is measured by taking logarithmic monthly returns.

5. *CPI (CPI)*

[24] Pontiff, Woodgate, Shares Outstanding and Cross Sectional Returns, 2005 papers.ssrn.com/sol3/papers.cfm?abstract_id=679143

[25] Porteba, Summers, Mean Reversion in Stock Prices: Evidence and Implications, Journal of Financial Economics Volume 22, Issue 1, October 1988, Pages 27-59

Changes in the consumer price index are used as a proxy for unanticipated inflation. The relationship between unexpected inflation and stock returns in the United States is inconclusive .Bodie 1976, Jaffe and Mandelker 1976, Fama and Schwert found that the relationship was significantly negative while Pearce and Roley 1985, Hardouvelis 1988 found that there was no significant relationship[26]. It is interesting to note that studies done studies done in 1976 were following the oil embargo in the United States while in the late 1980's the country did not have to face such a crisis. Therefore the relationship between the dependent and the independent variable might have changed over time. However, the sign of the variable's coefficient is still expected to be negative. Following IMF's guidelines, the CPI has been lagged by two months, so as to allow for its effect to be incorporated in stock prices. The change in CPI is measured by log returns. Data from the source was obtained in seasonally adjusted form

6. *Money Supply (MS)*

M3 money supply has been used as a proxy for this variable. The reason for choosing M3 over M2 is that M3 also includes institutional money market mutual fund balances and large time deposits. The relationship between money supply and stock prices has been studied in several markets. A strong positive correlation between money supply and stock market returns has been observed historically[27]. However, many argue that changes in money supply are caused by changes in overall level of the markets. In either case, the expected sign of the variable is positive. For instance, an increase in stock prices provides an incentive to liquidate long term

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[26] William Schwert, The Adjustment of Stock Prices to Information about Inflation, http://schwert.ssb.rochester.edu/jfin81a.pdf, p1 (April 2010)

[27] J Allan Rudolph, The Money Supply and Common Stock Prices, http://www.jstor.org/stable/4470899?seq=2, p 19-25 (April 2010)

deposits. The money liquidated is then used to buy assets. Therefore the demand deposits tend to increase, increasing the M1 money supply. If this is the case, then money supply is not a good predicting factor in our model even though it might be statistically significant in explaining stock returns. However, it should also note that stock prices only respond to changes in the money supply in the long run. Therefore observing such an effect might be out of scope of this study's sample period. .The variable has been lagged by two months. The change in Money supply is measured by log returns. Data from the source was obtained in seasonally adjusted form

7. *Industrial Production (IND)*

A strong relation between industrial production and stock market returns has always been noted. The index has been used by economists to measure to forecast future GDP levels and performance of the economy[28]. Ilan Cooper and Richard Priestley investigated the relationship between future stock returns and unrevised industrial production[29]. They concluded that industrial production significantly predicts U.S stock returns and the r-squared for the regression was 0.02, 0.05 and 0.11 at monthly, quarterly, and annual time horizons respectively. It should be noted that the r-squared value was significantly higher for yearly stock returns as compared to monthly returns. This might again indicate that short term changes in the industrial production index do no produce an immediate change in an asset's returns. The expected sign for this variable is positive. The variable has been lagged by two months. The changes are measured by monthly log returns and the data was obtained in seasonally adjusted form.

[28] Peter Young, Industrial Production and Stock Returns, http://ir.lib.sfu.ca/retrieve/3688/etd2332.pdf, p31 (April 2010)
[29] Cooper, Priestley, Time Varying Risk Premia and the Output Gap, Review of Financial Studies, Forthcoming http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1128107,

8. Price of Oil (OIL)

Oil being the most crucial commodities and a basic input for most industries should significantly affect stock returns. However, the expected sign for the coefficient of this factor should depend on the industry. Oil companies should generally profit from an unanticipated increase in oil prices and other firms should exhibit lower stock returns. Other firms, whose costs increase with an increase in oil price, should be negatively affected by an increase in oil prices. The changes are measured by monthly logarithmic returns on oil prices.

9. Risk Premium (RPREM)

This is the difference between an BAA bond yield and an AAA corporate bond yield of the same maturity, also more precisely known as the credit spread. It is defined as:

$$Monthly\ change\ in\ risk\ premium = \log((Y_{BAA(t)} - y_{AAA(t)})/(Y_{BAA(t-1)} - y_{AAA(t-1)}))$$

where $Y_{BAA(t)}$ is the yield on a BAA bond, and $y_{AAA(t)}$ is the yield on an AAA bond.

It reflects the additional yield an investor can earn from a security whose credit risk is greater compared to a safer security. Generally BAA bonds offer higher yields than AAA bonds as they have a greater risk of default. Gomes and Schmid found out that credit spread is an important determinant of economic fluctuations[30]. They show that credit spreads forecast recessions by predicting future movements in corporate investments. A very simplistic analysis of supply and demand shows that the expected sign of this variable would be negative. As the risk premium increases, riskier bonds offer higher returns to investors. As riskier bonds can be considered a substitute for equities, investors rebalance their positions by selling equities and buying these

[30] Gomes and Schmid, Equilibrium Credit Spreads and the Macroeconomy, 2009, http://finance.wharton.upenn.edu/~gomesj/Research/CreditMarkets.pdf, p21 (April 2010)

riskier bonds. This implies a decrease in demand of equities and therefore a drop in returns. However, the firm's debt-equity and asset exposure may also play a significant role in determining the final outcome of this variable's effect.

10. Yield spread (YSP)

Yield spread refers to the difference between the short term bond yield and the long term bond yield. For this study, the yield spread has been calculated by subtracting the three month Treasury bill yield from the ten year Treasury bond yield. The absolute value of the yield is not of use, as we are only concerned with the unanticipated changes in the yield spread. So the changes in the yield spread are measured as

$$Monthly\ change\ in\ yield\ spread = \log((Y_t - y_t)/(Y_{t-1} - y_{t-1}))$$

where 'Y' is the yield on a 10 year bond and 'y' is the yield on a 3 month treasury bill. Modi and Taylor find that interest rate term spreads have significant power in predicting real economic activity[31]. As stock prices generally go up with real economic growth, the expected sign for this variable would be positive. However, we firmly believe that the effect of a relative increase in long term interest rates would affect different companies differently so the final effect of this variable would be very firm specific.

11. Market return (SP500)

[31] Mody, Taylor, The High-Yield Spread as a Predictor of Real Economic Activity: Evidence of a Financial Accelerator for the United States, *IMF Staff Papers* © 2003, http://www.jstor.org/stable/4149938 (April 2010)

For this study, the return on the S&P 500 has been used as a proxy for the market return. This factor derives from the CAPM model where it is the only independent variable. The coefficient of this variable, conventionally called the beta in the CAPM model represents the ratio of the change in asset's return to the change in market return. For example, if beta is equal to 1.5, and the market portfolio goes up by 10 percent, then the security's return is supposed to go up by 15%. Since in most cases, both the security return and market return move in the same direction, the expected sign of the variable's coefficient is positive. It is measured as monthly log returns on the SP500 index.

12. Size factor (SMB)

Fama-French discovered, in their three factor model that smaller firms generally exhibit higher returns[32]. Of course, these higher returns are a result of additional risk, that is, higher standard deviation of returns. This factor was found to be significant in explaining equity returns in past researches and therefore has been included in this model. It is defined as

$$SMB = return\ on\ small\ cap\ market\ index - return\ on\ large\ cap\ market\ index$$

The large cap index used in SP500 and the small cap index used is SP600 small cap.

13. Exchange rate (EXR)

We use the Euro-Dollar rate as a proxy for this variable. Firms are affected by a change in exchange rates either directly, if they engage in foreign trade, or indirectly, if the firm inputs and outputs are affected by exchange rates. Although there is no theoretical or empirical consensus on the relationship between two variables, Hwang in 1999 found that stock prices do not have a

[32] Fama, French, 1993, p4

significant impact on exchange rate but currency devaluation has a significant positive impact in the long run but an insignificant negative effect in the short run[33]. Hwang concluded that the depreciation of the Canadian Dollar led to more competitiveness of the export market and increases the stock prices of the firm in the long run. However, in explaining a particular firm's returns we do not have an 'a priori' sign of the variable as a firm's exposure to exchange rate varies vastly.

[33] Hwang, The relationship between stock prices and exchange rates: Evidence from Canada, International Advances in Economic Research, http://www.springerlink.com/content/070074q290003g52/ 1999.

IV. Data

Monthly data over the period of six years, from January 2000 to December 2005 was collected for each variable. It might have been better if we performed this study used weekly or even daily data, but only monthly data is available for some variables used. We would have risked a structural change in the model if we chose a longer observation period. According to Brealey et al (2006), five years is the recommended length of data to use in most financial analysis[34]. Firm specific data- returns, market capitalization, shares traded, P/E ratio was obtained from COMPUSTAT North America. Macroeconomic data was obtained from the Federal Reserve. No value for any variable was dropped from the study as we believe outliers are an essential feature of equity markets. Wherever applicable (Money Supply, Industrial Production and CPI), the data was obtained seasonally adjusted.

For firm specific variables (P/E ratio, Market Cap, and number of shares traded), the absolute value of the variables is relevant to the study. Market Cap is measured in Dollars while P/E ratio and number of shares traded are unit less. For the rest of the variables, changes in the variable are important, as they represent the unanticipated component. Therefore, we have taken monthly logarithmic returns for these variables except for two cases- Yield Spread and Risk Premium. These time series contained negative values, so we had to take percentage returns. We preferred logarithmic returns over percentage returns as: i) log returns are time additive. For example we can sum all the monthly returns over the sample period, obtain the net return on the equity for the sample period. This would not have been the case if we took percentage returns. ii) they render the time series stationary. A log transformation also helps in reducing heteroscedasticity as it

[34] Brealey, R., Myers, S., Allen F. 2006. “Corporate finance”. 8th edition. Boston: McGraw-Hill/Irwin.

compresses the scale in which variables are being measured. For these reasons log returns are preferred by academics for stochastic time series modeling.

Descriptive Stats: Macroeconomic variables

Table 1 presents the descriptive statistics for the macroeconomic variables. All variables exhibit a positive mean return except for the SP500 index. Also, the sum column represents the net change over the sample period. It shows that the SP500 index declined by about 7%. The small cap index minus big cap index factor increased by about 31%, which means that small cap stocks clearly outperformed big cap stocks over the time frame. Industrial production, oil prices and SP500 returns exhibit a negative skewness which implies that they have a long left tail. Only four factors- SP500, Oil, Industrial production and Exchange rate are relatively normally distributed as indicated by the p values of Jarque Bera statistic. However, it should also be noted that the rest of the variables might have been distributed normally if we dropped outliers from the dataset. For example, with a mean of 25.7, the yield spread has minimum and maximum values ranging from -388.88 to 2100. Histograms of theses macroeconomic variables show that the variables which are not distributed normally have significant outliers.

Descriptive Stats: Equities

Table 2 presents the descriptive statistics for monthly data for each of the twenty equities. Except for QLogic, Cisco, Microsoft and Wal-mart, all other equities had positive monthly returns. There was a huge range of the net return over the 6 years period. Small cap firms had very high net returns with as much as 112% for Tractor Supply and 89% for ITT Educational Services. Technology stocks, on the other hand displayed severely negative returns- (-34)% for Microsoft and (-49)% for Cisco. This is because of the NASDAQ crash in early 2000. Apple, despite being a tech stock showed very impressive returns. This shows that firm specific factors can be very influential while determining a stock return. Most stocks had a standard deviation of 3-6% with the exception of 11% for QLogic. 9 of the 20 stocks were distributed normally as indicated by the p-values of the JB statistic. Again, due to outliers the other 11 stocks failed the JB test. P/E ratios for 9 stocks were distributed normally and only 3 stock's market capitalizations were distributed normally.

It should be noted that in previous researches on equities, the Kolmogorov-Smirnov test has yielded better results as a normality test than the JB statistic. That is, more equities and regressors qualify for normal distribution under the Kolmogorov-Smirnov test.

V. Regression results

Using the White's Test to check heteroscedasticity we observe that only 5 stocks exhibit heteroscedasticity as the chi-square for 13d.f and a P=0.05 is 22.36. It should be noted that we had to exclude the cross terms from the White test, as with 13 regressors we would have consumed all degrees of freedom. Table 3 has been attached showing the results of the test.

As our regression contained an autoregressive term, we could not use the Durbin Watson test to test autocorrelation. Therefore, a Breusch-Godfrey Serial LM test with two lags was used. At P=0.05 only 5 stocks suffered from Autocorrelation. Both autocorrelation and heteroscedasticity has been correction using the Newey-West method of all of the equities. This decreases the standard error of the estimates and hence increases the t-values. Table 4 showing the Serial LM test results has been attached.

According to Gujarati & Porter, a high r-squared and low t-values for regressors is a classic feature of presence of multicollinearity[35]. We however, do not suffer from such an occurrence in most cases as shown later in the regression results. Also, after conducting auxiliary regressions(for each variable) for each equity, we found out that the r-squared for the auxiliary regression was almost always less than the r-squared for the overall regression. Both these factors indicate that multicollinearity is not a significant problem. We chose not to analyse the correlation matrix as with 13 regressors it cannot give us an accurate picture of multicollinearity. The matrix, however, is attached for reference.

[35] Gujarati, Porter p354

Table 5 contains the regression results for all of the twenty equities. In comparison with most other multi-factor models, our model explains the equity returns very well. R-squared values range from about 27% for Landsystem to about 74% for Goldman Sachs. The average R-squared value for all the 20 equities is 46.8%.. Two firms- Landsystem and Trimble fail the F-test at 95% confidence level, which tests for all the beta coefficients being zero at the same time. However, they pass the test at 90% confidence interval. The t-values are indicated under each of the regression coefficients. Since we have 14 regressors, one intercept term and 72 observations, the t-values for 58 degrees of freedom are - 1.67 at 95% confidence interval and 1.29 at 90% confidence interval. We choose to do a one tailed test as we have strong directional sense of the hypothesis a priori. 10 out of the 20 equities showed normal distribution of the residual term at P=0.05. Again, the presence of a few outliers may entirely disrupt the normality assumption.

The market index, SP500 was found to be significant at 90% confidence interval for all the 20 equities. This implies that this factor is the single-most important factor in explaining equity returns. Also, all the coefficients were positive, which implies that all the equities grow with an increase in the SP500 index. The LAG variable was found to be significant for 15 equities which confirm the phenomenon of mean reversion on a monthly basis of equity returns as signs of the coefficients for all 15 are negative, in accordance with our expectations. This means, for example that if the return for this month of an equity is positive, the expected return, holding everything else constant, is negative. This is a very important result in finance, especially in developing trading strategies. The TRAD variable, which stands for the number of shares traded per month was found to be significant for 11 stocks, with the sign of the coefficient (negative) according to our expectation for 9 out of these 11 stocks. Apart from decreased returns due to increased liquidity, this negative sign could also mean that high trading only occurs when institutional clients short sell a company stock anticipating a decrease in its value. PE was significant for 13 stocks with all of them having the sign of coefficient (positive) as we expected. The market cap factor showed mixed results- it was positive for large cap companies and negative for mid cap companies. This might imply that as the mid cap companies grow in size, holding everything else equal, their returns tend to lower. This explanation is also in accordance with the multistage dividend discount model which says that firms in their infancy have an above average growth rate. Money supply was the least significant of regressors in the time series regression. It is interesting to note that OIL had positive signs oil producers like Exxon Mobil and Devon Energy, and negative for rest of the firms. Thor industries, which are a vehicle manufacturer, displayed a strong negative t-value for the Oil prices factor. As expected, the SMB factor was positive for mid cap firms and negative for large cap firms. The factors, Yield Spread, Risk premium and Exchange rate had mixed signs. This could an indication that theses factors depended on the company's structure and business. For example, a firm holding large amounts of U.S. currency would suffer and have lower returns if the Exchange rate dropped. So this firm would have a positive sign of the EXR variable. Therefore, the variables YSP, EXR, and RPREM factors give us an insight of the individual firm's structure. This could especially be useful for hedging purposes where the manager needs to identify individual factors instead of an overall market performance.

With the factor coefficients obtained in the time series regression, we performed a cross sectional regression. The results of the regression are attached in Table 6. Mean returns of the 20 equities was the dependent variable and the factor coefficients, the independent variables. This regression yielded a very strong r-squared value of 97.2%. 9 out of the 13 factors were statistically significant at a 90% confidence interval using a one tailed test. 9 priced factors in the model provide us with an exceptionally well explanation of cross sectional average returns. However, it is important to note that the set of significant factors are different for the two regressions. CPI, MS, IND, YSP were significant in the cross sectional regression but significant for only a few firms in the time series regression.

VI. Conclusion

According to Fama, an asset pricing model cannot be expected to completely describe the actual markets. If the model contributes to a greater understanding of the market, it is considered to be a success. In this study, the average r-squared value for 20 equities was about 46%. This can be considered a very good result compared to Chen (1985) in the US stock market (results ranging from 4% to 27.8% in different sub-periods from1963 to 1978) and Cheng (1995) in the UK (11% in the period January 1965 -December 1988)[36]. We conclude that autoregressive factor combined with the macroeconomic and firm specific factors are successful in explaining a significant proportion of equity returns. The cross sectional results are extremely promising. The empirical aim of this study was to find out the effectiveness of the APT in explaining American equity returns and identifying significant factors. At least six factors- LAG, TRAD, PE, CAP, SMB, SP500 were found to be significant for more than half the equities in the study. 9 of the 13 factors were significant for the cross sectional regression. The rest of the regressors were significant for some equities and not for the others. Therefore it is important to note that the individual structure of the company cannot be ignored, as proposed by the CAPM model, while creating an asset pricing model.

An average r-squared of 46% means that only about half the variance in returns in explained by the independent variable and the other half is noise. Events such as announcement of a new CEO, charges of fraud against the firm, which have a very significant impact on asset prices cannot be properly priced in any of the variables in this model. If the sole aim is to predict

[36] Chen, N. 1983. "Some empirical tests of the theory of arbitrage pricing". The Journal of Finance, Vol. 38, No. 5, 1393–1414

returns, advanced contemporary models such as ones using neural networks, which continuously adapt to changing market conditions and ‘learn’ from daily news might be way more accurate in explaining monthly returns.

To improve our model’s forecasting ability, better measures of rate of change could be used like the GARCH and Kalman/Weiner filter. As we have a large number of independent variables in the model, principal component analysis could have be used as a guide in determining factors more accurately. Also as short term stock prices are believed to follow a random walk path, yearly returns over a larger period of time could have been used instead of monthly returns. Our sample size of 20 firms might not guarantee robustness of the model over the entire U.S. equity market. It could also be the case that the relationship between the dependent and the independent variable might not be linear. However, in testing for non-linear relationship we leave the realm of the Arbitrage pricing theory.

Appendices

CPI: Consumer Price Index; MS:Money Supply; IND: Industrial Production; OIL: Oil price; RPREM: Risk Premium; YSP: Yield Spread; SP500: SP-500 return; SMB: Size Factor; EXR: Exchange Rate
RET: Equity Return; TRAD: Shares Traded; PE: P/E Ratio; CAP: Market Cap

Table 1: Descriptive statistics for Macroeconomic variables

	CPI	MS	IND	OIL	RPREM	YSP	SP500	SMB	EXR
Mean	0.102088	0.273161	0.036148	0.496803	0.238255	25.70285	-0.098306	0.443715	0.096347
Median	0.094562	0.250266	0.032931	1.055057	0	-3.721655	0.137452	0.39928	0.044062
Maximum	0.593879	0.876467	0.589788	7.093691	18.29307	2100	4.009572	6.31115	2.689773
Minimum	-0.165626	-0.080619	-0.758001	-8.232355	-6.775178	-388.8889	-5.062187	-5.669317	-1.894616
Std. Dev.	0.11095	0.191532	0.231526	3.417962	3.78153	254.662	1.917815	1.655234	1.087512
Skewness	0.951116	0.754189	-0.456204	-0.525854	1.45724	7.60218	-0.263111	0.038579	0.394464
Kurtosis	7.056664	3.918263	3.678733	2.751857	8.804214	62.9738	2.97415	6.735693	2.406201
Jarque-Bera	60.22502	9.355241	3.879496	3.502993	126.5493	11484.09	0.832732	41.88406	2.925011
Probability	0	0.009301	0.14374	0.173514	0	0	0.659439	0	0.231655
Sum	7.350355	19.66758	2.602688	35.76981	17.15436	1850.605	-7.07802	31.94745	6.937015
Sum Sq. Dev.	0.874003	2.604596	3.805916	829.4552	1015.298	4604544	261.1392	194.5258	83.97049
Observations	72	72	72	72	72	72	72	72	72

Table 2: Descriptive statistics for equities: Page 1 of 2

AIG	RET	TRAD	PE	CAP		**Devon Energy**	RET	TRAD	PE	CAP
Mean	-0.033138	1.35E+08	26.12665	1.75E+11		Mean	0.806003	53707383	26.85313	1.15E+10
Maximum	9.277767	4.25E+08	40.38406	2.30E+11		Maximum	11.51748	88471600	485.3333	3.05E+10
Minimum	-8.118831	58245600	11.85315	1.29E+11		Minimum	-12.87411	12555000	-62.96053	3.02E+09
Std. Dev.	3.160159	64616625	8.278533	2.37E+10		Std. Dev.	4.488956	17215748	93.46608	7.20E+09
Jarque-Bera	2.591896	389.9816	3.434464	0.882857		Jarque-Bera	2.142319	1.238467	809.9796	12.01911
Probability	0.273638	0	0.179562	0.643117		Probability	0.342611	0.538357	0	0.002455
Sum	-2.385949	9.70E+09	1881.119	1.26E+13		Sum	58.03221	3.87E+09	1933.425	8.31E+11
Apple	RET	TRAD	PE	CAP		**Eagle Materials**	RET	TRAD	PE	CAP
Mean	0.620392	3.31E+08	-1.584574	1.49E+10		Mean	0.689687	4456304	13.16346	9.25E+08
Maximum	16.24991	9.21E+08	300.2	6.08E+10		Maximum	8.778143	22692600	20.31482	2.15E+09
Minimum	-37.41074	1.42E+08	-897.5	5.14E+09		Minimum	-14.37868	660000	3.952595	4.21E+08
Std. Dev.	7.700862	1.66E+08	194.8105	1.30E+10		Std. Dev.	4.194841	4535336	4.70933	4.72E+08
Jarque-Bera	177.9457	34.72328	342.5119	55.60186		Jarque-Bera	21.53264	51.63004	6.989616	12.7505
Probability	0	0	0	0		Probability	0.000021	0	0.030355	0.001703
Sum	44.66826	2.38E+10	-114.0893	1.07E+12		Sum	49.65749	3.21E+08	947.7692	6.66E+10
Bank of America	RET	TRAD	PE	CAP		**Exxon Mobil**	RET	TRAD	PE	CAP
Mean	0.367509	2.47E+08	12.0476	1.21E+11		Mean	0.200558	2.68E+08	17.8436	2.88E+11
Maximum	6.936762	4.38E+08	16.84667	1.90E+11		Maximum	8.882261	5.53E+08	36.59539	4.05E+11
Minimum	-11.03352	1.47E+08	8.285788	6.51E+10		Minimum	-5.37748	1.86E+08	9.751736	2.15E+11
Std. Dev.	2.926499	53519770	1.836343	3.82E+10		Std. Dev.	2.263325	74776377	5.633573	4.43E+10
Jarque-Bera	28.7894	18.58175	6.501112	9.091472		Jarque-Bera	20.46898	74.57261	16.82574	6.385007
Probability	0.000001	0.000092	0.038753	0.010612		Probability	0.000036	0	0.000222	0.041069
Sum	26.46061	1.78E+10	867.4269	8.70E+12		Sum	14.44015	1.93E+10	1284.739	2.07E+13
Cisco	RET	TRAD	PE	CAP		**Goldman Sachs**	RET	TRAD	PE	CAP
Mean	-0.687996	1.34E+09	15.6069	1.75E+11		Mean	0.183655	72119937	15.13056	4.37E+10
Maximum	14.27531	2.78E+09	211.8151	5.33E+11		Maximum	11.46546	2.05E+08	22.1201	5.92E+10
Minimum	-19.87876	7.36E+08	-642	7.65E+10		Minimum	-10.29924	18720600	10.1414	3.16E+10
Std. Dev.	6.186377	3.76E+08	146.7937	1.17E+11		Std. Dev.	4.217134	27250249	3.064161	6.93E+09
Jarque-Bera	8.615105	55.09843	485.6581	49.87143		Jarque-Bera	2.378414	161.2869	3.236464	1.836417
Probability	0.013466	0	0	0		Probability	0.304463	0	0.198249	0.399234
Sum	-49.53571	9.68E+10	1123.697	1.26E+13		Sum	13.22316	5.19E+09	1089.401	3.14E+12
Citi	RET	TRAD	PE	CAP		**Helix Energy**	RET	TRAD	PE	CAP
Mean	0.090543	2.98E+08	15.77563	2.28E+11		Mean	0.884552	16230872	31.74353	1.07E+09
Maximum	9.558974	7.25E+08	22.56039	2.81E+11		Maximum	14.91335	39016418	67.14286	2.82E+09
Minimum	-6.270865	1.85E+08	10.40351	1.50E+11		Minimum	-11.90935	5232800	16.43192	4.75E+08
Std. Dev.	3.146323	78993220	2.837541	2.77E+10		Std. Dev.	5.252635	7781705	11.23892	5.60E+08
Jarque-Bera	0.910864	472.0188	2.816639	7.924344		Jarque-Bera	2.069027	16.21773	8.961227	44.7045
Probability	0.634174	0	0.244554	0.019022		Probability	0.355399	0.000301	0.011326	0
Sum	6.51913	2.15E+10	1135.845	1.64E+13		Sum	63.68776	1.17E+09	2285.534	7.72E+10

Table 2: Descriptive statistics for equities: Page 2 of 2

ITT	RET	TRAD	PE	CAP
Mean	1.227936	9693528	27.40813	1.36E+09
Maximum	12.74924	33127500	47.88889	2.84E+09
Minimum	-23.60892	2653800	12.5	2.95E+08
Std. Dev.	6.537628	6341753	6.351333	7.18E+08
Jarque-Bera	25.95442	142.7773	9.673374	5.349323
Probability	0.000002	0	0.007933	0.06893
Sum	88.4114	6.98E+08	1973.385	9.79E+10
Landstar	RET	TRAD	PE	CAP
Mean	1.238989	10350931	19.13437	1.09E+09
Maximum	8.227113	22104664	33.73684	2.51E+09
Minimum	-6.463345	4500800	9.033401	3.75E+08
Std. Dev.	3.467012	3391173	6.502631	6.20E+08
Jarque-Bera	1.37601	34.75185	3.735433	10.06302
Probability	0.502578	0	0.154476	0.006529
Sum	89.20719	7.45E+08	1377.675	7.83E+10
Microsoft	RET	TRAD	PE	CAP
Mean	-0.484382	1.51E+09	36.48688	3.09E+11
Maximum	14.85351	2.57E+09	59.69101	5.57E+11
Minimum	-18.27847	9.68E+08	21.43443	2.31E+11
Std. Dev.	4.938777	3.49E+08	9.28001	5.67E+10
Jarque-Bera	18.58086	20.47608	3.553486	155.476
Probability	0.000092	0.000036	0.169188	0
Sum	-34.87552	1.09E+11	2627.055	2.22E+13
Oshkosh	RET	TRAD	PE	CAP
Mean	1.089229	8920475	16.47434	1.41E+09
Maximum	7.408803	26602800	21.59633	3.30E+09
Minimum	-13.94134	3232400	10.20487	4.41E+08
Std. Dev.	3.695104	3538872	3.141077	8.69E+08
Jarque-Bera	37.84504	178.5028	3.86972	9.81333
Probability	0	0	0.144445	0.007397
Sum	78.42446	6.42E+08	1186.152	1.02E+11
Pool Corp	RET	TRAD	PE	CAP
Mean	1.19613	7821494	20.66995	9.83E+08
Maximum	10.05464	24834539	28.2126	2.05E+09
Minimum	-7.33792	2229188	13.19665	2.74E+08
Std. Dev.	3.459748	3403025	3.691608	5.20E+08
Jarque-Bera	0.075705	189.7712	3.39615	7.815207
Probability	0.962855	0	0.183036	0.020089
Sum	86.12133	5.63E+08	1488.236	7.08E+10

Qlogic	RET	TRAD	PE	CAP
Mean	-0.542686	2.51E+08	60.33419	4.25E+09
Maximum	31.61911	8.50E+08	283.6364	1.14E+10
Minimum	-37.19015	53812412	18.38346	1.76E+09
Std. Dev.	11.60186	1.76E+08	55.12047	1.91E+09
Jarque-Bera	12.25896	27.85503	110.0464	58.87579
Probability	0.002178	0.000001	0	0
Sum	-39.07336	1.81E+10	4344.061	3.06E+11
Thor	RET	TRAD	PE	CAP
Mean	1.002042	5388768	14.71998	1.06E+09
Maximum	11.69535	12086800	23.51815	2.27E+09
Minimum	-9.760433	711200	6.857639	2.37E+08
Std. Dev.	5.258212	3470247	4.464848	6.55E+08
Jarque-Bera	1.778736	4.182331	2.883226	6.655411
Probability	0.410915	0.123543	0.236546	0.035875
Sum	72.14704	3.88E+08	1059.838	7.66E+10
Tractor	RET	TRAD	PE	CAP
Mean	1.55795	7888573	17.56236	8.62E+08
Maximum	23.93731	19941858	32.68605	2.20E+09
Minimum	-9.987294	1128800	3.853627	65338437
Std. Dev.	6.308861	4539397	7.795955	6.67E+08
Jarque-Bera	6.419819	2.587547	5.407027	6.577587
Probability	0.04036	0.274234	0.06697	0.037299
Sum	112.1724	5.68E+08	1264.49	6.21E+10
Trimble	RET	TRAD	PE	CAP
Mean	0.543391	17665072	3.025691	9.38E+08
Maximum	20.39972	43739400	47.99143	2.09E+09
Minimum	-26.89386	6026700	-233.3333	2.84E+08
Std. Dev.	6.812867	7932448	54.28628	5.61E+08
Jarque-Bera	31.89519	21.32368	263.7292	8.346226
Probability	0	0.000023	0	0.015404
Sum	39.12412	1.27E+09	217.8498	6.75E+10
Walmart	RET	TRAD	PE	CAP
Mean	-0.235263	1.96E+08	30.74739	2.30E+11
Maximum	6.296168	4.46E+08	45.2	2.76E+11
Minimum	-10.1251	1.06E+08	17.05058	1.82E+11
Std. Dev.	3.004809	58969446	7.655109	2.04E+10
Jarque-Bera	4.173206	82.61836	2.49679	0.563662
Probability	0.124108	0	0.286965	0.754401
Sum	-16.93893	1.41E+10	2213.812	1.66E+13

Table 3: White's Test results

Sample: 2000M01 2005M12			
Included observations: 72			
Dependent Variable: RESID^2			
		Obs*R-squared	Prob. Chi-Square(13)
AIG		9.342494	0.7466
Apple		10.45848	0.6561
Bank of America		15.75414	0.2627
Cisco		25.7096	0.0186
Citi		24.15633	0.0297
Devon Energy		13.08586	0.4412
Eagle		38.68956	0.0002
Exxon Mobil		14.92326	0.3122
Goldman Sachs		9.281426	0.7514
Helix		19.38477	0.1116
ITT Educational		9.978375	0.6957
Landsystem		6.100992	0.9424
Microsoft		31.14239	0.0032
Oshkosh		15.71025	0.2651
Pool Corp		11.17489	0.5962
Qlogic		17.4448	0.1798
Thor		19.32342	0.1134
Tractor		13.00182	0.4477
Trimble		44.246	0
Walmart		5.819734	0.9525

Table 4: Breusch-Godfrey Serial LM Test results

Dependent Variable: RESID			
Sample: 2000M01 2005M12			
Included observations: 72			
		Obs*R-squared	Prob. Chi-Square(2)
AIG		0.010536	0.9947
Apple		0.360006	0.8353
Bank of America		3.820715	0.148
Cisco		2.947367	0.2291
Citi		2.296884	0.3171
Devon Energy		19.20338	0.0001
Eagle		5.820558	0.0545
Exxon Mobil		1.126201	0.5694
Goldman Sachs		8.263797	0.0161
Helix		0.438955	0.8029
ITT Educational		7.385988	0.0249
Landsystem		1.072203	0.585
Microsoft		2.205253	0.332
Oshkosh		0.423754	0.8091
Pool Corp		2.960268	0.2276
Qlogic		1.677333	0.4323
Thor		1.456663	0.4827
Tractor		2.492622	0.2876
Trimble		6.974237	0.0306
Walmart		6.779263	0.0337

Table 5: Time Series regression results

Shaded t-statistics indicate significance at 95% confidence level(one tailed). Highlighted t-statistics indicate significance at 90% confidence level(one tailed).

	C	LAG	TRAD	PE	CAP	CPI	MS	IND	OIL	RPREM	SMB	SP500	EXR	YSP	r-squared	F-Test
AIG	1.017	-0.2106	-2.10E-08	-0.0675	2.55E-11	-1.386	-1.2343	2.38749	-0.268	-0.026	-0.5951	0.63518	-0.5801	-0.000394	0.597854	6.6328
	0.363	-2.8022	-4.109244	-1.2024	1.62231	-0.7281	-0.8698	1.77945	-3.251	-0.472	-3.1228	3.78365	-1.8618	-0.651347		0
Apple	-3.03	-0.0352	-3.86E-09	-0.001	1.94E-10	-5.0387	8.08146	1.08104	0.109	-0.17	0.76807	2.00041	1.86521	-4.62E-05	0.388199	2.83093
	-1.49	-0.3324	-0.325891	-0.4451	1.41231	-0.6728	2.79012	0.30355	0.363	-1.121	2.30415	5.49738	2.08713	-0.024644		0.00333
Bank of America	-3.82	-0.3754	-8.80E-09	0.606	-8.71E-12	6.68591	-1.6942	-0.6675	0.089	0.0609	0.06441	0.77835	-0.1602	0.000721	0.43685	3.46093
	-1.35	-2.521	-1.5571	2.78118	-1.25731	1.80056	-0.8792	-0.4729	1.057	1.0099	0.25442	4.71299	-0.4127	1.080512		0.00054
Cisco	0.966	-0.0241	-9.21E-10	-0.0019	4.56E-13	-5.8124	1.59758	1.35197	-0.015	-0.226	0.05846	2.04834	-0.0511	-0.005072	0.548108	5.41147
	0.337	-0.1862	-0.466342	-0.573	0.10965	-1.3609	0.4674	0.63242	-0.07	-1.587	0.10641	8.29624	-0.0887	-4.563326		3E-06
Citi	-3.26	-0.1091	3.64E-10	0.28329	-2.81E-12	2.95231	-2.0981	0.70139	-0.104	-0.024	-0.2655	1.12697	-0.3227	-0.000504	0.683377	9.62948
	-1.16	-1.5229	0.07451	2.90624	-0.33049	1.29078	-1.1928	0.68166	-1.613	-0.277	-1.6788	7.13033	-1.521	-1.225734		0
Devon Energy	4.362	-0.2787	-1.16E-07	0.00622	2.31E-10	1.59955	-2.1952	3.20589	0.364	0.2322	0.4664	0.99942	0.03302	0.001117	0.453774	3.70639
	1.975	-3.9566	-3.097609	1.33369	3.1368	0.29295	-1.0715	1.56454	1.924	1.2875	1.03994	4.47489	0.09096	1.907943		0.00027
Eagle	-0.9	-0.148	-2.91E-07	0.19589	2.58E-09	2.42692	-7.4493	-2.7449	-0.205	-0.018	0.16253	0.43386	-0.7506	0.002323	0.370525	2.62617
	-0.42	-1.249	-1.793574	1.51167	1.93922	0.58031	-2.1705	-2.4232	-1.009	-0.23	0.25238	1.97122	-1.3724	2.949872		0.00604
Exxon Mobil	-3.93	-0.1504	-1.58E-08	0.03253	3.02E-11	-2.2464	-1.906	-0.1058	0.054	0.0148	-0.2349	0.4343	-0.1088	0.000153	0.439809	3.50279
	-1.49	-1.6499	-4.327219	0.7302	3.30506	-0.848	-1.6595	-0.0975	1.071	0.1969	-2.3159	3.29553	-0.5206	0.284245		0.00048
Goldman Sachs	-18	-0.2343	1.65E-08	0.3929	2.56E-10	-3.363	1.14008	2.53614	-0.083	-0.229	0.27542	1.14054	0.65572	-0.002608	0.740595	12.7376
	-4.37	-3.1951	1.390657	3.1624	4.38272	-1.1412	0.7303	1.99384	-0.89	-2.023	1.667	8.06594	2.49367	-3.555324		0
Helix	-2.86	-0.2064	-2.61E-07	0.07637	5.95E-09	-9.0014	-0.7376	4.63868	-0.053	0.2441	0.64518	1.32907	0.26958	0.003321	0.474786	4.03317
	-1.19	-2.6432	-2.525854	1.60772	3.49017	-1.6522	-0.3488	1.65333	-0.28	1.7308	1.45087	4.18805	0.5097	4.695692		0.00011
ITT Educational	-5.08	-0.353	-3.89E-07	0.40864	-8.82E-10	4.79136	0.62836	-0.5402	-0.102	-0.267	0.20339	1.01491	-1.4654	0.004749	0.389357	2.84476
	-1.29	-3.4497	-2.205861	3.00021	-1.06236	0.69402	0.12009	-0.2054	-0.499	-2.046	0.36499	3.30878	-1.7899	3.491131		0.0032
Landsystem	-2.15	-0.194	1.71E-08	0.21069	-1.62E-09	6.22684	0.5708	-0.7889	0.052	0.0141	0.76228	0.41746	0.75037	0.001117	0.273574	1.68023
	-0.78	-2.0129	0.123411	1.4667	-1.15118	1.43814	0.18854	-0.3457	0.407	0.2157	3.77971	2.22998	1.49993	1.175543		0.08999
Microsoft	-2.11	-0.2528	3.14E-12	-0.0245	8.25E-12	-5.2088	2.60626	-1.7384	0.095	-0.083	-0.5442	1.49697	0.24091	0.004352	0.474278	4.02496
	-0.48	-2.7767	0.001893	-0.4542	0.60758	-1.0025	0.73881	-0.647	0.484	-0.588	-1.6066	4.61316	0.3571	4.488269		0.00011
Oshkosh	-4.44	-0.2012	-2.94E-07	0.65639	-1.23E-09	-11.185	1.65864	0.98431	-0.148	0.0342	0.19215	0.73904	-0.0261	0.000526	0.44677	3.60299
	-1.19	-1.6501	-2.40923	2.48177	-1.92	-2.5572	0.76873	0.69698	-1.333	0.5417	0.58124	3.26047	-0.0671	0.511342		0.00036
Pool Corp	-8.46	-0.1549	4.97E-08	0.68748	-4.70E-09	0.10622	0.10302	1.7114	-0.27	-0.141	0.23626	0.7317	-0.6318	-0.000955	0.470173	3.9592
	-2.31	-1.5211	0.447166	3.33842	-2.99753	0.02312	0.05542	1.14459	-2.449	-1.619	0.70149	3.35046	-1.8443	-1.287593		0.00013
Qlogic	-12.7	-0.1644	1.12E-08	-0.0424	2.50E-09	-4.5464	6.09556	0.34307	0.173	-0.57	1.4769	3.03811	-0.3493	-0.01212	0.555704	5.58028
	-2.22	-1.6171	1.882885	-0.5515	1.11143	-0.4335	1.0402	0.09387	0.45	-1.868	1.49627	4.34511	-0.2512	-6.938682		2E-06
Thor	-3.88	-0.0916	-4.18E-07	0.5292	7.95E-11	1.94979	-2.7403	-1.4746	-0.48	-0.18	0.72571	0.82342	-0.2814	0.000918	0.457677	3.76519
	-1.77	-0.6926	-1.78408	3.65291	0.07953	0.35713	-0.7514	-0.6565	-2.113	-1.727	1.92068	2.4437	-0.5403	1.091419		0.00023
Tractor	-4.13	-0.1334	-9.96E-08	0.69151	-7.21E-09	0.64063	1.49526	-2.8654	-0.171	0.0193	0.98041	1.48592	0.89835	0.003366	0.356171	2.46816
	-1.03	-1.0209	-0.636292	3.52772	-4.18183	0.08932	0.31835	-0.8928	-0.777	0.1842	2.40684	4.50204	1.13051	1.923946		0.00958
Trimble	1.382	-0.1627	-1.03E-07	0.01252	-1.31E-10	8.24733	0.58431	0.18996	0.176	0.193	0.38241	1.86865	0.66548	-0.000741	0.29095	1.83074
	0.317	-1.3991	-0.41658	0.94015	-0.08837	1.18892	0.12456	0.06328	0.876	0.8145	1.07697	3.27268	0.78775	-0.27556		0.05949
Walmart	-16.2	-0.3135	-2.12E-09	-0.1079	8.77E-11	3.72308	-1.9437	-2.6222	-0.155	0.0851	-0.3778	0.24335	-0.315	-0.000376	0.515467	4.74637
	-2.77	-4.2751	-0.379149	-1.2847	3.0807	1.5873	-1.0029	-2.4744	-1.788	1.4229	-1.8551	1.355	-0.9491	-0.418214		1.6E-05

Table 6: Cross sectional regression results

Shaded t-statistics indicate significance at 95% confidence level(one tailed).

Dependent Variable: MEAN				
Method: Least Squares				
Date: 04/29/10 Time: 10:13				
Sample: 1 20				
Included observations: 20				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.932674	0.149496	6.238805	0.0008
LAG	1.490578	0.531143	2.806359	0.0309
TRAD	-699549.5	636265.2	-1.099462	0.3137
PE	0.480085	0.247751	1.937775	0.1008
CAP	-46873115	27099985	-1.729636	0.1344
CPI	0.021144	0.010524	2.009128	0.0913
MS	0.069449	0.038636	1.797508	0.1224
IND	0.07	0.029916	2.339933	0.0578
OIL	0.148173	0.287839	0.514777	0.6251
RPREM	0.712142	0.552392	1.289196	0.2448
SMB	0.827659	0.134288	6.163301	0.0008
SP500	-0.47733	0.101117	-4.720564	0.0033
EXR	-0.220417	0.144357	-1.526881	0.1776
YSP	78.09481	18.77606	4.159275	0.0059
R-squared	0.972343	Mean dependent var		0.485755
Adjusted R-squared	0.912419	S.D. dependent var		0.658397
S.E. of regression	0.194847	Akaike info criterion		-0.237178
Sum squared resid	0.227792	Schwarz criterion		0.459834
Log likelihood	16.37178	Hannan-Quinn criter.		-0.101114
F-statistic	16.22625	Durbin-Watson stat		2.076932
Prob(F-statistic)	0.001302			

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